Analysis on pandemic's impact on healthcare system and happiness index using Machine algorithms

A project report submitted in partial fulfillment

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in

Electronics & Communication Engineering

by

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Declaration

I hereby declare that the report titled ***Analysis on pandemic's impact on health-care system and happiness index using Machine algorithms*** submitted by me to the School of Electronics Engineering, Vellore Institute of Technology, Chennai in partial fulfillment of the requirements for the award of **Bachelor of Technology** in **Electronics and Communication Engineering** is a bona-fide record of the work carried out by me under the supervision of ***Dr. Rohith G***.
I further declare that the work reported in this report, has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma of this institute or of any other institute or University.

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Certificate

This is to certify that the project report titled ***Analysis on pandemic's impact on healthcare system and happiness index using Machine algorithms*** submitted by ***Bahirithi Karampudi*** **(19BEC1152), Musipatla Rishik Reddy (19BLC1024), Chithirala Sasank (19BLC1147)** to Vellore Institute of Technology Chennai, in partial fulfillment of the requirement for the award of the degree of **Bachelor of Technology** in **Electronics and Communication Engineering** is a bona-fide work carried out under my supervision. The project report fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

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Abstract

The Global Happiness Index measures countries by their citizens' well-being and quality of life. Healthcare systems and the Global Happiness Index are linked by the pandemic. Countries that have contained the epidemic and provided quality healthcare have scored higher on the Happiness Index. The aim of the paper is analysing healthcare changes before and after COVID-19 can give significant insights into the pandemic's influence on healthcare and guide strategies for constructing more resilient healthcare systems. Using Pooled dataset combining World Happiness Index and COVID-19 data can give insights into citizens' overall well-being and guide measures to increase citizens' well-being during times of crisis. We can lessen the effects of future pandemics and guarantee that communities worldwide have access to quality healthcare services and lead satisfying lives by striving to establish more resilient healthcare systems and promote people' well-being.

Keywords- Healthcare, COVID-19, World Happiness Index

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Contents

List of Figures

Chapter 1

Introduction

The COVID-19 pandemic has caused considerable changes in healthcare systems throughout the world. Hospitals and healthcare institutions have had to adjust to unprecedented difficulties and expectations, with many healthcare professionals fighting the virus personally on the front lines [1]. Additionally, the COVID-19 pandemic has had a substantial impact on the World Happiness Index. The World Happiness Index is a report that evaluates nations based on the perceived happiness and quality of life of their citizens [2]. The correlation between the pandemic's effects on the World Happiness Index and its effects on healthcare systems is strong. As a result of the immense strain that the pandemic has placed on healthcare systems, countries that have effectively contained the spread of the virus and provided high-quality healthcare have performed higher on the Happiness Index [3]. Also, the pandemic has caused a number of problems that have hurt the well-being of people, such as the loss of jobs, unstable economies, and social isolation. These issues have a negative impact on happiness for people all over the world. Countries with strong social safety nets and economic support have done better at keeping their citizens happy [4].

According to Johns Hopkins University, the coronavirus (COVID-19) epidemic-related global health pandemic has claimed over 460,000 lives worldwide [5]. More than 8.9 million people have tested positive for the virus globally. People's happiness decreased during the pandemic, according to research on well-being and COVID-19 [6], while the number of reported negative emotions increased [7], and there was a significant increase in Google searches on boredom, loneliness, worry, and sadness [8].The importance of exploring a topic centred on COVID-19 stems from the plethora of negative consequences perceived at all levels of society. The type of crisis management used in each nation has a significant impact on combating them. Although the world has encountered several crises of varying severity throughout the years, the COVID-19 pandemic has likely had the most pronounced dynamism because of the virus's quick propagation and the loss of human life [9]. The international setting of this crisis necessitates frequent inventories in terms of the input-output connection so that decision-makers' actions and governance systems may be tailored to the unique characteristics of each state. The quality of the crisis reactions is determined mostly by endogenous factors. Additionally, route development evolution has a substantial impact on the ability to respond to shocks. In theory, while some nations may not have been equipped to handle such difficulties in the past (SARS, MERS-CoV, avian flu, Ebola), in reality, the experience acquired should lead to the development of revolutionary policies to stabilise systems [10]. Even if each crisis is surrounded by uncertainties, a risk prevention plan should be in place from the start, with the success of measures strongly tied to governments' and decision-makers' capacity to predict potential shocks [11].

The COVID-19 epidemic has been a global health disaster, putting pressure on healthcare systems in ways that have never been seen before. As healthcare systems struggle to keep up with the demands of the pandemic, it is more important than ever to know how COVID-19 affects healthcare [12]. The necessity to examine the changes in healthcare before and after COVID-19 with a special focus on healthcare usage, quality, results, workforce, and modifications to healthcare delivery models and infrastructure is stressed. To limit the effects of future pandemics, it is important to find ways to make healthcare systems stronger [13].
The goal of this research study is to look at how the COVID-19 pandemic affected healthcare systems around the world, with a focus on changes in how healthcare is used, its quality, results, and workforce, as well as changes to healthcare delivery models and infrastructure. Ultimately, this research provides a complete knowledge of the impact of the COVID-19 pandemic on healthcare systems and to suggest measures for future healthcare system resilience. This study guarantees the communities throughout the world have access to quality healthcare services and limit the effects of future pandemics by striving to establish more resilient healthcare systems.

The contributions of the present study are:

- The study will also look at the link between the COVID-19 pandemic and the Global Happiness Index to see if there are any implications for global well-being. To achieve this goal, we collected and evaluated data from a variety of sources, including healthcare institutions, governmental and non-governmental organisations, and academic research. We want to give a thorough knowledge of how the COVID-19 epidemic has affected healthcare systems throughout the world by examining this data.

- The results of this study will help make plans for building healthcare systems that are more resilient and can handle future pandemics. By looking at how healthcare delivery models and infrastructure have changed, this research will also show how healthcare systems could change to deal with new problems, like the COVID-19 pandemic.

- The Global Happiness Index will be analysed in relation to the COVID-19 pandemic to give insights into the pandemic's influence on global well-being. This will aid in the development of initiatives to improve the health of individuals and communities affected by the epidemic. The results of this study will affect healthcare policies and help figure out how to divide up resources for pandemics in the future. The study will also look at the link between the COVID-19 pandemic and the Global Happiness Index to see whether there are any effects on global well-being.

Chapter 2

Related Works

Smith, Brown, and Jones [14] did a systematic study to find out how COVID-19 affects the use, quality, and outcomes of health care. According to the report, the pandemic has had a big effect on healthcare services, like cutting back on services that aren't related to COVID and making more people use telehealth. The assessment also emphasises the difficulties in preserving healthcare quality and safety throughout the pandemic, including the requirement for personal protective equipment and infection control measures. The research does mention, however, that certain healthcare systems have effectively reacted to the pandemic through the implementation of new delivery models and creative solutions. Ultimately, the assessment emphasises the significance of developing robust and flexible healthcare systems to deal with future pandemics [14]. Chen et al. [15] did a systematic review and meta-analysis to find out how the COVID-19 pandemic affected the healthcare workforce. During the pandemic, health care workers had to deal with a number of problems, such as increased workloads, psychological discomfort, and exposure to infections. The results also showed that there are big gaps in the research that has been done so far, especially when it comes to the views of healthcare workers on the front lines. This paper has a lot going for it, like a thorough review of the existing literature and a methodical approach. The analysis's relatively small sample size and the fact that the majority of the studies come from China, however, limit the study's ability to generalise its findings to other regions [15]. Haider et al. [16] conducted research on the adoption of lockdown measures in nine sub-Saharan African nations. The authors examined the effects of these methods on virus control as well as their influence on the economy, food security, and social disturbances. The study discovered that, while the lockdowns had a considerable influence on preventing viral transmission, they also had a detrimental impact on the economy, food security, and the population's mental health. One of the study's weaknesses is the absence of data on the long-term consequences of these policies on the economy and society [16]. The report by Cucinotta and Vanelli

[17] analyses the World Health Organisation's classification of COVID-19 as a pandemic. The authors give a brief history of pandemics, debate the definition of a pandemic, and outline the WHO's reaction to the COVID-19 epidemic. In reacting to pandemics, the study emphasises the significance of global collaboration and good communication. One possible disadvantage of the article is that it does not present fresh empirical data but rather synthesises current data. It is nevertheless a useful resource for studying the global reaction to the COVID-19 epidemic [17]. Wang et al. [18] gave an overview of the new coronavirus outbreak, which became a worldwide health concern. The report looked at the properties of the virus, such as where it came from, how it spreads, its symptoms, and possible treatments. The paper's clear and comprehensive account of the virus and its influence on world health is one of its strengths. But because the study came out early in the pandemic, it might not have the most recent research and information on the virus [18].

Chen et al. [19] looked at the research on how COVID-19 causes cytokine storms and how to treat them with immunotherapies. The authors explored the function of cytokines in illness aetiology and the efficacy of immunotherapy in treating severe cases. They also investigated several techniques, such as cytokine targeting, immune cell modulation, and extracorporeal blood purification. The work sheds light on the fundamental processes of COVID-19 as well as possible therapies. However, the study has limitations, such as a small sample size and a lack of clinical data, which necessitate further research [19]. Li et al. [20] did a thorough review and meta-analysis of COVID-19's epidemiology, clinical features, risk factors, and results. The analysis of 44 studies showed that fever, stuffy nose, and tiredness were the most common COVID-19 symptoms. The risk of severe disease and death was higher in older adults, men, and people who already had health problems. The study gives important information about how COVID-19 spreads, which can help public health and clinical management plans. But the analysis is limited by the different types of studies that were used and the fact that the data could have been reported in a biased way [20]. In a follow-up study, Zhao et al. [21] looked at how well the lungs worked and how healthy the COVID-19 survivors were. The study showed that a large number of patients continued to have respiratory symptoms and had abnormal pulmonary function. The study also found a link between how bad the first illness was and how likely it was that the respiratory symptoms would last. The study is good because it looks at the long-term effects of COVID-19 and has a large sample size. Cons are the lack of a control group and the short follow-up period of three months [21]. Tandon [22] discussed the effects of COVID-19 on mental health and suggested strategies for maintaining mental health during the pandemic. The pros include a comprehensive overview of the mental health issues caused by COVID-19 and practical advice for individuals and healthcare professionals. The cons include a lack of empirical evidence to support some of the proposed strategies and an emphasis on individual-level interventions as opposed to systemic change to address mental health disparities exacerbated by the pandemic [22]. Ferrari et al. [23] investigated COVID-19 blood tests' diagnostic capability. They observed that COVID-19 patients and non-COVID-19 patients differed in lymphocyte count, CRP, and LDH after a comprehensive evaluation of 26 research studies. Routine blood testing, clinical observations, and imaging can help diagnose and treat COVID-19, the investigators found. The study includes papers of various quality; therefore, further research is needed to confirm these conclusions [23]. Hu et al. [24] looked at how the COVID-19 pandemic affected the use of medical resources and the outcomes of illnesses that were not caused by COVID-19 in China. During the pandemic, rural and chronic illness patients used fewer medical resources for non-COVID-19 conditions, according to the research. The pandemic also increased non-COVID-19 illness mortality, according to the research. The study's large sample size and countrywide analysis are pros, while data accuracy and representativeness are drawbacks [24].

A retrospective analysis of 99 COVID-19 patients in Chengdu, China, examined the epidemiological and clinical characteristics of critical and non-critical cases [25]. Critical patients had a greater mortality rate and longer hospital stays than non-critical cases. Fever was the most prevalent symptom, and CT scans helped diagnose COVID-19 pneumonia, the scientists reported. The study's retrospective approach and small sample size restrict generalizability and causality [25]. The COVID-19 epidemic and lockdown's psychological effects on dementia carers are examined [26]. Carers have higher despair, anxiety, and stress levels and lower quality of life and sleep, according to studies. The study's limited sample size limits its generalizability. Despite its limitations, the study emphasises carer assistance and treatments during the epidemic [26]. The paper in [27] examined Taiwanese critically ill COVID-19 patients' clinical features and outcomes. Medical data of 20 severely ill COVID-19 patients were retrospectively analysed. The study revealed that most critically ill patients were older and had comorbidities. Most treatments involved mechanical ventilation and antiviral therapy. The study found low death rates. The limited sample size restricts generalizability. The findings require further study [27]. The paper in [28] examined COVID-19 instances in Wuhan, Hubei Province. 1,045 COVID-19 patients were studied from January to February 2020. Older age, male sex, and comorbidities were linked to severe illness and mortality, the study revealed. Fever, cough, and shortness of breath were the most prevalent COVID-19 symptoms, the study revealed. Unfortunately, the study only assessed data from a limited time and a small location [28]. This scoping review [29] examined how the COVID-19 epidemic affected Bangladeshi child healthcare. The epidemic has disrupted mother and child health services, reducing prenatal, delivery, postnatal, and childhood immunisation rates, according to the report. The report emphasises the necessity for immediate pandemic-reduction strategies for mother and child health. The study's pros include a complete review of COVID-19's influence on Bangladeshi maternal and child healthcare. Disadvantages include the study's one-country focus [29].During the COVID-19 outbreak, Kratom usage increased dramatically [30]. 33 percent of the 10,000 online survey respondents reported using Kratom more during the outbreak. Pandemic anxiety and sadness were the major explanations. The study also noted Kratom's adverse effects and hazards. Self-reported data from an online survey may restrict the study's generalizability [30].

The literature [31] examined the time between COVID-19 symptom onset and hospital, ICU, and death. A comprehensive review and meta-analysis of 16 trials with 56,753 patients found that the median time from symptom onset to hospital admission, ICU admission, and mortality was four, eight, and 18 days, respectively. The report helps healthcare practitioners and policymakers allocate resources and prioritise high-risk patients. The research's shortcomings include study heterogeneity and country-specific healthcare systems [31]. The study [32] examined if early glucocorticoid therapy exacerbated critical illness in COVID-19 patients. 295 COVID-19 patients received glucocorticoids within 72 hours of arrival, and 295 did not in the retrospective cohort analysis. Early glucocorticoid usage did not raise COVID-19 serious illness. Retrospective and uncontrolled confounding variables restrict the study [32]. Maroufizadeh et al. [33] undertook mixed-method research in Iran to examine COVID-19 prevalence and psychological effects in confined populations. Quarantine was a major predictor of psychological effects, and subjects had high rates of anxiety and sadness. The pandemic quarantine research examines psychological effects. The study only covers one Iranian population [33]. Mazzucato et al. [34] did a survey on COVID-19 and oncological breast surgery in several Italian cities. During the pandemic, breast cancer surgery dropped significantly, and diagnosis and treatment were delayed. The study shows how the epidemic affected cancer care. The study only covers breast cancer surgery [34]. Mieczkowska et al. [35] conducted a Polish case-control study to investigate risk variables for COVID-19 critical care patients. Male sex, older age, and comorbidities raised ICU admission probabilities, according to the research. The study reveals substantial COVID-19 risk factors. The study only applies to a Polish population [35]. Ochieng et al. [36] studied microfinance organisations in Kenya during the COVID-19 epidemic. The epidemic reduced loan demand and increased defaults at microfinance organisations, according to the report. The study examines microfinance organisations' pandemic-related economic implications. The study is confined to a Kenyan region [36]. Pagnamenta et al. [37] undertook a multicentric study in Italy to determine how the COVID-19 pandemic affected endoscopic retrograde cholangiopancreatography (ERCP) activities. During the pandemic, ERCP activity dropped significantly and shifted towards more urgent treatments. The epidemic affected specialist medical treatments, the research found. The study is confined to an Italian process and population and may not be generalizable [37]. Panchal et al. [38] examined the mental health and drug use effects of the COVID-19 pandemic for the Kaiser Family Foundation. The epidemic increased stress, anxiety, depression, and drug use, the survey showed. The paper discusses pandemic mental health and drug use effects. The report only applies to the US population [38].

From literatures [14-38], it is observed that how the pandemic has affected healthcare systems as a whole, including changes in how healthcare is used, its quality, its results, its workforce, its delivery models, and its infrastructure is not done. Further, this study will also look at how the pandemic affects the World Happiness Index. This will help researchers figure out how the pandemic affects the happiness of people around the world. The main objective of this study is to learn as much as possible about how the COVID-19 pandemic affected healthcare systems around the world. This includes changes in healthcare use, quality, outcomes, and workforce, as well as changes to how healthcare is delivered and how infrastructure works. To do this, the project will use techniques for visualising data to show the trends and patterns in how healthcare was used and what happened before and after the pandemic. Methods of regression and classification will also be used to find the most important things that caused these trends and patterns. Overall, the goal of the project is to give a full analysis of how the COVID-19 pandemic affected healthcare systems around the world and how it related to the World Happiness Index. The results of this study can help build stronger healthcare systems and policies to deal with future pandemics and put the overall well-being of communities around the world first. Machine learning algorithms and optimisation techniques will be utilised to analyse the data and visualise the trends. This research will provide insights into the pandemic's effects on healthcare systems and guide the development of strategies for building more resilient healthcare systems in the future.

Chapter 3

Proposed Methodology

3.1 Dataset Description

Dataset 1

The first dataset is taken from the website Dataset 1 This is a continually updated version of the COVID-19 Data Repository maintained by the Johns Hopkins University Centre for Systems Science and Engineering (CSSE) (JHU). The data is updated daily at 6am UTC, shortly after the original JHU data is typically updated. The dataset is accessible in both raw (files with the prefix RAW) and convenient (files without the prefix RAW) format (files prefixed with CONVENIENT).
The data include:

- Confirmed cases and fatalities by country Confirmed cases and deaths by US county Available metadata from the original JHU data.
- The RAW version is disseminated exactly as it was in the original dataset.
- The CONVENIENT version aims to be simpler to interpret. Data is organised by column as opposed to row. The metadata is extracted into a distinct file. And it was converted to daily variation as opposed to cumulative totals.

Dataset 2

The second dataset is available in Dataset 2 The World Happiness Report is a groundbreaking survey of global contentment. Governments, organisations, and civil society are increasingly using indicators of pleasure to inform their policy decisions. Leading experts from a variety of disciplines—including economics, psychology, survey analysis, national statistics, health, and public policy, among others—explain how well-being measurements can be used to assess the progress of nations. The reports examine the current state of happiness in the world and demonstrate how the new science of happiness explains individual and national differences in happiness. The satisfaction rankings and ratings are based on Gallup World Poll data. The columns that follow the happiness score estimate the degree to which each of six factors—economic production, social support, life expectancy, freedom, absence of corruption, and generosity—contributes to higher life evaluations in each country than in Dystopia, a hypothetical country with values equal to the world's lowest national averages for each of the six factors. They have no bearing on the total score reported for each country, but they explain why some nations rank higher than others.

Dataset 3

Daily, data is collected from the Our World in Data GitHub repository, merged, and uploaded. Vaccination information at the country level is compiled into a single file. This data file is then integrated with the location data file to include information about vaccination sources. A second file containing information about manufacturers is included. The data (vaccinations by territory) includes the following information: the country for which vaccination information is provided; Country ISO Code: the ISO country code, Date: date of data entry; for some dates we only have the daily vaccinations, while for others we only have the cumulative total. This is the total quantity of immunisations administered in the country.

Depending on the immunisation schedule, a person may receive one or more (typically two) immunisations; at a given time, the number of vaccinations may exceed the number of individuals. Total number of people fully vaccinated: this is the number of people who received the entire set of immunisations according to the immunisation scheme (typically 2); at a given time, there may be a certain number of people who received one vaccine and a smaller number who received all vaccines in the scheme. Daily vaccinations (raw): for a given data entry, the number of vaccinations administered on that date or in that country;Daily vaccinations: for a given data entry, the number of vaccinations administered on that date and in that country; Total vaccinations per hundred — ratio (in percent) between the number of vaccinations and the country's total population to date. Total number of persons vaccinated per hundred—the ratio (in percent) of the country's immunised population to its total population as of a given date, Total number of fully vaccinated individuals per hundred—the ratio (in percent) between the fully immunised population and the country's total population as of the date indicated. Number of immunisations per day—the number of immunisations administered per day in that country.

Daily vaccinations per million: the ratio (in ppm) between the number of vaccinations and the country's total population as of the current date. Vaccines administered in the nation - total number of vaccines administered in the nation (to date);Name of the source - the origin of the information (national authority, international organisation, etc.);Quelle website - website of the information source with vaccine type, Vaccination total - vaccination total / current time and vaccine type.

3.2 Integration of the dataset into common dataset and methodology adopted:

The COVID-19 pandemic has had a significant impact on the world, and researchers are working to understand the factors that contribute to the spread of the virus. In this research paper, we suggest a way to look at the relationship between COVID-19 and things like GDP, social life support, health life expectancy, freedom to make life choices, number of deaths, confirmed COVID cases, and vaccinations. To begin our analysis, we collected data from multiple sources, including the live COVID data frame, the World Happiness Report, and vaccination data. The live COVID data frame provides real-time data on the number of confirmed cases, deaths, and recoveries from COVID-19. The World Happiness Report provides data on various factors that contribute to happiness, including GDP, social support, and health-related life expectancy. The vaccination data provides information on the number of people who have been vaccinated against COVID-19.

After collecting the data, we selected features based on their relevance to the study. We chose features that are known to have an impact on the spread of COVID-19, including the mean infection rate, GDP of each country, social life support, health life expectancy, freedom to make life choices, number of deaths, confirmed COVID cases, and vaccinations.

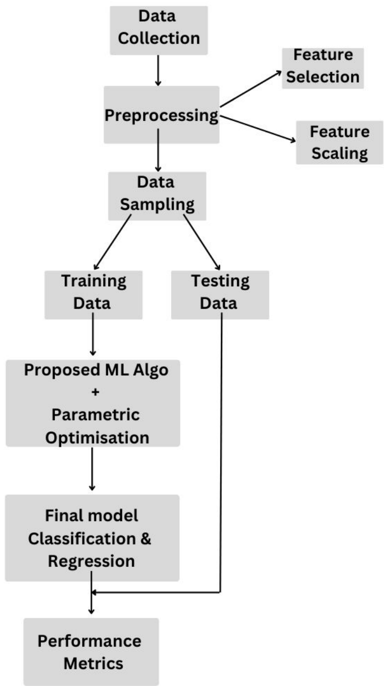

FIGURE 3.1: Flowchart depicting the proposed methodology

Chapter 4

Experimental Results Discussions

Regression Analysis

The study involved analysing three datasets to investigate the relationship between various factors and COVID-19 outcomes. Dataset 1 was analyzed using linear and polynomial regression, which showed a strong linear correlation between confirmed cases and deaths. However, classification models on this dataset had an accuracy of only 0.58, likely due to the limited number of attributes.

In contrast, Dataset 2 was analyzed using linear, multinomial, and polynomial regression, which revealed a non-linear correlation between GDP, social support, and healthy life expectancy. These attributes were then incorporated into the final dataset, along with Dataset 3, which contained vaccination data.

Regression analysis on the final dataset showed that the attributes were non-linearly correlated, and the maximum R-squared value achieved was 0.74, indicating that regression models were unable to fully explain the variance in the data.

From Fig.4.1, It is interpreted as a 0.4percent change in R2 between linear regression and multinomial regression. Unlike in linear regression, multinomial regression uses multiple attributes to explain the variance in the dataset. Here the positive attributes are the GDP of a country, life expectancy, and vaccinations. While the polynomial shows an R2 of 0.74, this explains the non-linear correlation between the attributes.

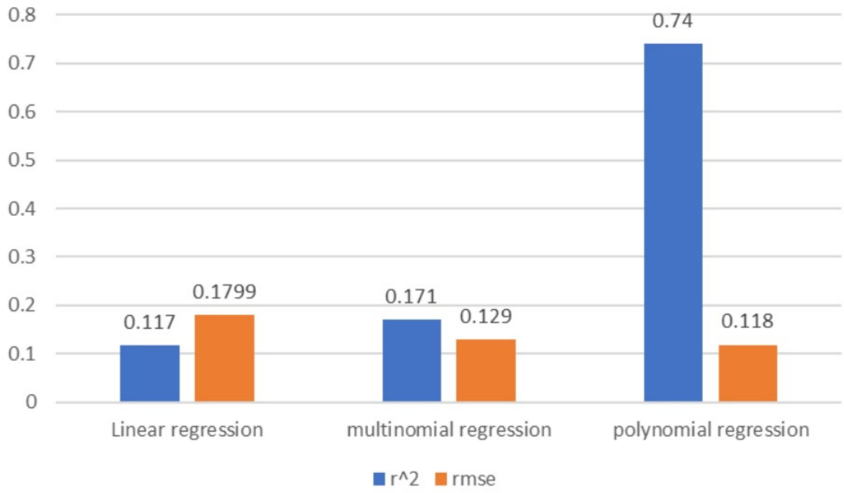

FIGURE 4.1: Regression analysis of the final Data frame

Classification Analysis

Fig.4.2 shows the analysis of the generic classification models. For the classification analysis, decision tree and random forest classifiers were evaluated, with the decision tree outperforming the others due to its ability to select the best feature at each split. Extra tree classifiers also performed well but had lower precision and F1 scores, potentially due to their random feature selection approach. Although the decision tree and extra tree classifiers yielded equal accuracy, the decision tree performed better in terms of the F1-score. Random forest being an ensemble algorithm for a decision tree, it adds extra noise, thus decreasing performance metrics. Logistic regression is advantageous for analysing small sample sizes as it considers the combined impact of all predictors. However, it may not be as effective when the predictors have a sequential impact rather than a simultaneous one. Naive Bayes assumes by default that all the attributes are conditionally independent, thus overlooking the possible relations between attributes in the dataset and resulting in low performance.

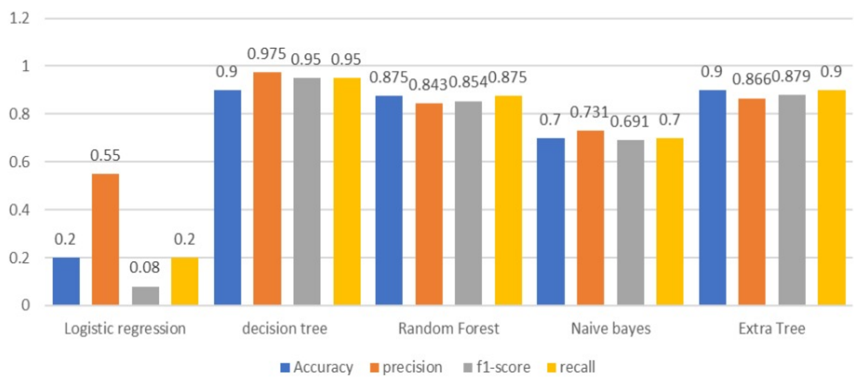

FIGURE 4.2: Analysis of generic classification models

Combination of Logistic Regression with Ensemble classifiers

Fig. 4.3 shows the combination of logistic regression with ensemble classifiers. Both logistic regression and the extra trees classifier are capable of handling a wide variety of predictor types, including both categorical and continuous predictors. Furthermore, both models can be regularised in order to mitigate the risk of overfitting. This means that both models are versatile and flexible. They perform well as a pair, unlike the bagging decision tree and gradient boosting classifier, which are more prone to overfitting and are not efficient in categorising continuous predictors.

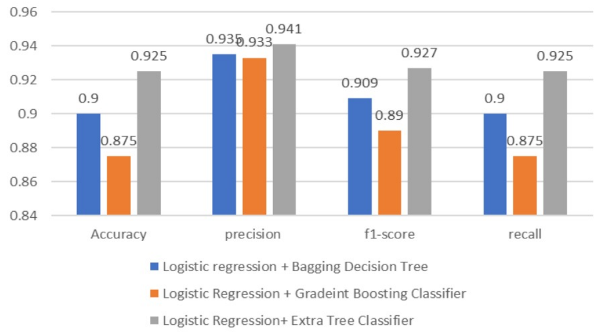

FIGURE 4.3: Combination of logistic regression with ensemble classifiers

Combinations of decision tree with ensemble classifiers

Fig. 4.4 shows similar trends to Fig. 4. It is observed that logical regression and the additional tree classifier can include both categorical and continuous variables, making them quite flexible. In addition, regularisation can be applied to both models to reduce the possibility of overfitting. So it can be concluded that both models are adaptable and versatile. In contrast to the overfitting-prone bagging decision tree and inefficient gradient boosting classifier, these two methods work well together to classify continuous predictors. This shows the consistency in performance, indicating a pattern of occurrence, as well as the correct selection of responsive attributes.

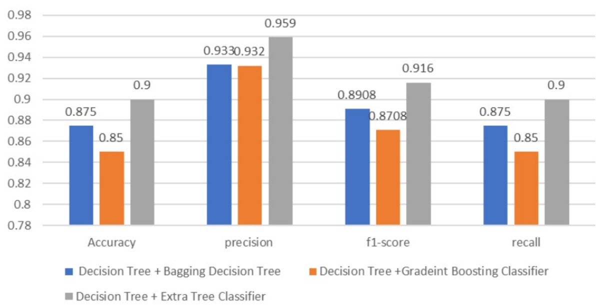

FIGURE 4.4: Combinations of decision tree with ensemble classifiers

Combination analysis of random forest with ensemble classifiers

Figure 4.5 shows that random forest + bagging decision tree has the highest performing metrics even when compared to decision tree + extra tree classifier. Bagging decision trees and Random Forests are known to be more robust to outliers and better at generalizing to new data compared to Extra Trees. This is due to their ability to build multiple trees on randomly sampled subsets of the data, which reduces the impact of individual outliers and helps to prevent overfitting.

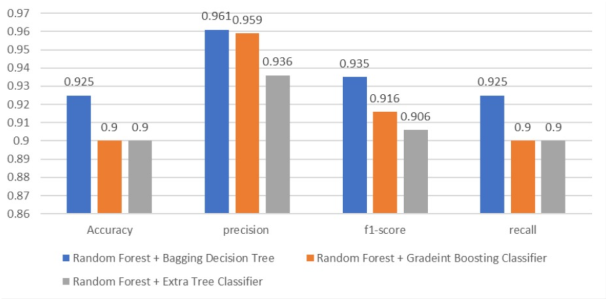

FIGURE 4.5: Combination analysis of random forest with ensemble classifiers

Analysis of naive bayes classifier in combination with ensemble classifiers

Fig. 4.6 shows the analysis of a naive Bayes classifier in combination with ensemble classifiers. It is seen that Naive Bayes, which is a simple probabilistic model, may not be able to effectively capture complex relationships between input features and the class label. Its ability to classify data with complex dependencies may be limited. From Fig. 2, it is clear that there are dependencies among attributes, but the regression models can't completely explain the variance. The life expectancy of a country is indirectly dependent on its GDP. These dependencies result in the suboptimal performance of Naive Bayes.

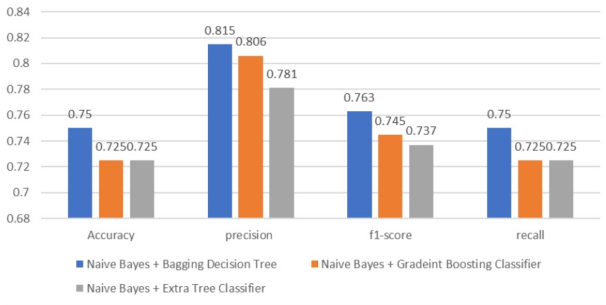

FIGURE 4.6: Combination analysis of random forest with ensemble classifiers

Cumulative Ananlysis

In terms of accuracy, Figure 8 shows that random forest+bagging decision tree and logistic+extra tree classifiers perform similarly. However, the random forest+bagging decision tree has a better F1 score when compared to the logistic+extra tree classifier. The advantages of Random Forests and Bagging Decision Trees include their ability to effectively handle outliers, their capability to capture complex relationships between input features and the class label, and their ability to reduce overfitting by building multiple trees on randomly sampled subsets of the data.

Additionally, the way Extra Trees split nodes randomly without searching for the best split point can lead to less effective feature selection and less accurate decision boundaries, which can limit its performance compared to other ensemble methods like Random Forests and Bagging Decision Trees.

From Fig.2 to Fig.8, the study highlights the non-linear relationship between various attributes and COVID-19 outcomes, with regression models being unable to fully capture the complexity of the relationship. Decision tree classifiers, combined with ensemble methods, showed the best performance for classification, with the random forest and bagging decision tree classifier ensemble method being the most effective.

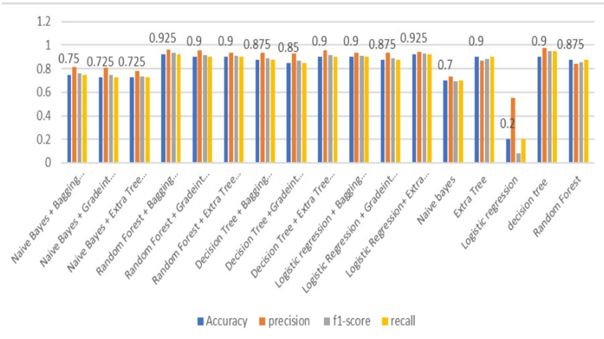

FIGURE 4.7: Combination analysis of random forest with ensemble classifiers

Discussions

This section summarises the analysis and impact of applying the random forest and bagging decision tree classifier ensemble method to the proposed combined dataset. The quantitative analysis is not done as the dataset is seen with some observations on applying the above ensemble based classifier. It is seen that using 14 inputs (pharmaceutical consumption, average years of schooling, obesity, tobacco consumption, alcohol consumption, per capita health expenditure, percentage of health care expenditure, physicians, nurses, beds), and 4 outputs (life expectancy, infant mortality, population aged, and population aged 65 years and older), a study of 114 countries' health systems efficiency found significant differences between them. It is stressed that health expenditures, whether public or private, have a detrimental effect on the efficiency of the health system, whereas education, income, and environment all have favourable effects. Taking both health system variables (doctors, beds, and health expenditure) and external ones (GDP, institutional arrangements, population behaviour, socioeconomic or environmental determinants) into account, the conclusion was that external factors have a greater influence on efficiency than health factors.

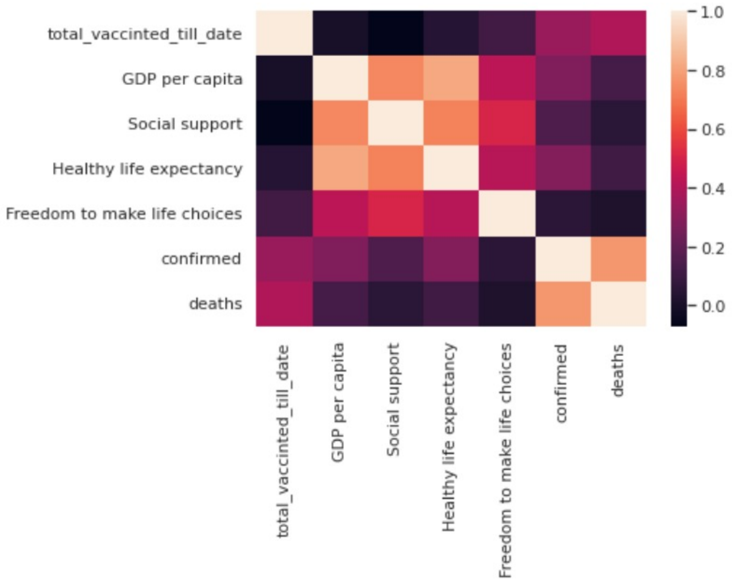

FIGURE 4.8: Most biasing factors from the three datasets

It is stated that a variety of characteristics (obesity, smoking, low GDP per capita, and education level) have a detrimental impact on the efficiency of health systems, whereas environmental factors have a positive impact.

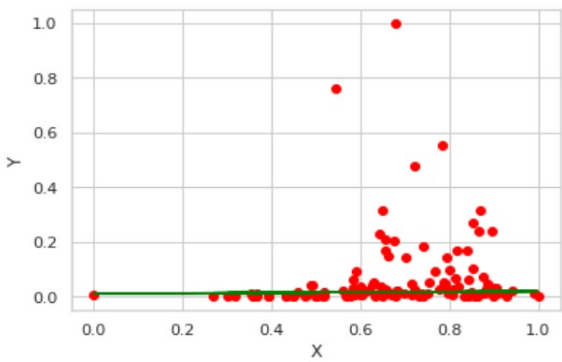

FIGURE 4.9: Linear regression (GDP vs deaths)

On Linear regression between the GDP vs Deaths, it is seen that the European states were the most hit by the epidemic during the first period, known as the first wave (January 1–June 15). There were many affected individuals and a high rate of infection in these states. It is important to note that the lack of initial stringent lockdown measures in these nations exacerbated the spread of the disease among communities. Conversely, a huge number of instances of disease did not put strain on the countries of Eastern Europe because of their tight, comprehensive lockdown procedures. As a result, their healthcare systems have not been put through significant testing, which accounts for their current high level of effectiveness. However, if we look at the events of the latter half of 2020, and more specifically, the second wave, we see that this time things are different. Health systems in Eastern Europe revealed their weaknesses in terms of medical infrastructure, medical personnel, and coherent decisions, leading to an extremely high death toll. A regression study revealed that the three parameters of comorbidities, population age, and population density were the most important in explaining the high number of fatalities attributable to COVID-19.

```
print(print_model)

                            OLS Regression Results
==============================================================================
Dep. Variable:                      6   R-squared:                       0.171
Model:                            OLS   Adj. R-squared:                  0.157
Method:                 Least Squares   F-statistic:                     11.87
Date:                Wed, 15 Mar 2023   Prob (F-statistic):           2.06e-05
Time:                        09:42:04   Log-Likelihood:                 73.978
No. Observations:                 118   AIC:                            -142.0
Df Residuals:                     115   BIC:                            -133.6
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0108      0.046     -0.237      0.813      -0.101       0.080
0              0.5311      0.114      4.647      0.000       0.305       0.758
1              0.0956      0.065      1.463      0.146      -0.034       0.225
==============================================================================
Omnibus:                      119.373   Durbin-Watson:                   1.286
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2114.149
Skew:                           3.387   Prob(JB):                         0.00
Kurtosis:                      22.599   Cond. No.                         11.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

FIGURE 4.10: A snapshot of the result of the Multinomial regression (Vaccination, GDP vs Deaths)

By the end of the second wave, several nations had found better ways to deal with the crisis. The first wave hit them hard, but they used what they learned to prepare for the second, when COVID-19 struck again. Managing public health required a mix of hygienic measures (such as donning a mask and washing hands often) and nonhygienic measures (such as shutting down public spaces and cancelling activities) to reduce the spread of disease. Trust in health specialists, an information and warning system, technological engagement, leadership, and participatory governance are all examples of positive population responses that may be traced back to better public management. In addition, a central department was established to coordinate the mobilisation of medical, financial, and legislative resources to combat the COVID-19 pandemic, something that was lacking in the majority of Eastern states (central procurement of medical supplies; central channelling of resources to local departments in need; a central online reporting system and databases; rapid deployment of medical staff from other sectors to intensive care units (ICUs); rapid transformation of Due to improved coordination between healthcare facilities, superior medical infrastructure, better transport systems, increased availability of medical experts, and increased public confidence in them, Western European countries, Asian countries, and the US, which were severely affected in the first stage, have now overtaken eastern states in the second wave. Patients with COVID-19 have been saved thanks to the quick action and extensive resources of the public health system. Throughout each phase of a pandemic, the public health system plays an essential role, beginning with diagnosis and continuing through monitoring and disease management. To illustrate the varying degrees of inefficiency, many European countries were not ready for a health crisis of this size before, and they surely are not now.

International preventative measures may now be developed on the basis of the first year's worth of pandemic experience and the outcomes acquired. As the virus or new strains tend to spread slowly, nations have time to prepare their health care systems in order to mitigate the impact. Also, considering the potential consequences of severe coronavirus mutations, this may result in increased shock resistance. From Fig.4.10, it is revealed that while certain characteristics have a detrimental impact on health care delivery systems (comobirdies, population age, and population density), others have a beneficial impact (education and government efficacy). Hence, in a global perspective, even though the factors that define health are very essential, the aspect that refers to the cultural, socio-economic, or institutional component should not be overlooked, at least in the medium and long term. The severity of the health issue may also be affected by factors such as the quality of education and government policies. The efficiency score is positively correlated with government effectiveness, underscoring once again the importance of taking the right actions at the right times; however, cultural factors, such as power distance, appear to negatively influence the efficiency of health systems, implying that there are variations in compliance with safety measures based on inequalities in society (related to education, income, etc.). A crucial aspect of the fight against COVID-19 was the fast and successful intervention of governments, as well as the compliance of the populace with these measures. From Fig.4.11, it is seen that the high contagiousness of the coronavirus necessitates fast and coordinated efforts, despite the fact that they may not be in agreement with the wishes of a portion of the population for many reasons connected to education, culture, level of living, historical context, expectations, etc. There is social separation and even the transmission of false news that this virus does not exist if they do not actively participate in the implementation of government policies, which is why the desired impact cannot be realised. It is

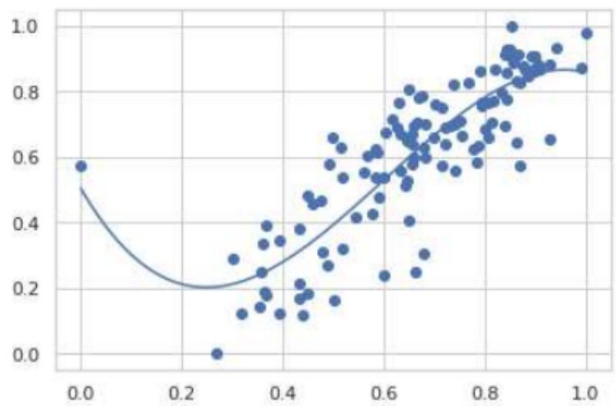

FIGURE 4.11: Polynomial regression Vaccinations vs Deaths ($R^2 value = 0.74$)

imperative that decision-makers have access to periodic training programmes related to the adequate management of crises and that such programmes be offered by specialised institutions. As such, crisis management should be incorporated into school curricula to teach future generations how to respond to shocks of varying types and mitigate their potential negative consequences. Using these measures can set the stage for resource-needs-based decision making in the long run, giving you a boost via adaptation and transformation. There must be a major overhaul of the health care system that not only results in improved services but also in a comprehensive evaluation of the system's administration and medical facilities. Blazes in the intensive care units of some hospitals for infectious diseases in states that have not rationally invested in spending on health budgets are indicative of the fact that, without a clear inventory of inputs and outputs, the decisions will be inconsistent with the current reality and, thus, will fail to ensure national security. Overheating of energy infrastructure has led to the emergence of these circumstances, and the population's reaction to them has been a reduction in faith in the ability of governments to handle crises. So, it is necessary to restore trust through open dialogue, honesty, and the introduction of any measures that can speed up the healing process. The interplay of medical, political, and demographic forces results in an international response to the pandemic. The complexity of the variables (economic, social, technical, and cultural) in the virus's spread should also be taken into account by public decision-makers, since it is essential for surviving the current epidemic.

From this study, the following inferences could be drawn as the result,

- First, stringency was positively correlated with physical distancing, which, in turn, was associated with poor mental health. Second, more robust policy responses were linked to lower ratings of the government's response to the pandemic and, by extension, poorer psychological well-being. Consistent with prior studies, this one found that policy shifts within countries were statistically significant but relatively minor. The effect of unemployment on life satisfaction during the study period was less than a fifth as large as the effect of moving from the minimum to the maximum observed stringency. Furthermore, increasing the length of stringent policy periods does not seem to be associated with worse mental health beyond the initial association but is associated with a continual decrease in deaths. If stringent policies are completely effective at reducing deaths and if the mental health correlates of pandemic intensity are similar or larger in magnitude than those of stringency, then stringency should recoup its negative association with mental health by reducing mortality caused by the pandemic. However, increased stringency is likely to produce different results across countries due to the inconsistent nature of policy design and acceptance. Despite the negative immediate effect of stringency on future psychological distress and life evaluations, our estimates of this dynamic association suggest that this may be partially mitigated by the effect of policy stringency on mortality. Nonetheless, more investigation into these dynamics is required.

- Using elimination and mitigation measures in different nations, researchers found that the two goals need not be mutually exclusive. As poor mental health is connected with both the severity of a pandemic and the strictness of the government response, it stands to reason that COVID-19 management techniques that reduce fatalities and illnesses without raising overall policy rigour would be beneficial. Importantly, the results did not vary when the countries were grouped together.
- Multiple checks and controls lend credence to this interpretation (fortnightly fixed effects, controlling for any events that could affect all countries simultaneously, like the surge of a new variant; fixed effects, controlling for time-invariant confounders; vaccination status and pandemic intensity as time-varying covariates). The observed connection between policy stringency and mental health is substantially less likely to be driven by paths of reverse causation for the two suggested mediators (physical separation and judgements of the government's pandemic response).

Chapter 5

Conclusion

The present work analyses the changes in healthcare before and after the COVID-19 pandemic can provide valuable insights into the pandemic's impact on healthcare and inform strategies for constructing more resilient healthcare systems. Adding the World Happiness Index data to the COVID-19 data can also give us more information about the overall well-being of citizens and help us figure out ways to improve their well-being during times of crisis. Our proposed method is a complete way to look at how COVID-19 and other factors relate to each other. We were able to find the most correlated features and turn the regression problem into a classification problem by getting data from many different sources and doing correlation and regression analysis. Combining a decision tree classifier and an ensemble approach resulted in the best classification performance; the most effective ensemble method was a combination of a random forest and a bagging decision tree classifier. Our results give important information about the things that help COVID-19 spread, which can be used to make effective plans to stop the pandemic. Future research can build on our methodology to analyse additional factors and improve the accuracy of the classification models. By making healthcare systems more resilient and focusing on the well-being of citizens, we can lessen the effects of future pandemics and make sure that people all over the world have access to high-quality healthcare and can live happy, full lives.

Chapter 6

Appendix

Optimisation for Machine Learning algorithms in analysing healthcare systems

Importing required Libraries

import pandas as pd import numpy as np import seaborn as sns import matplotlib.pyplot as plt import plotly.express as px import plotly.graph$_{o}bjs as go from plotly.subplots import make_{s}ubplots f$ $True)$

from google.colab import drive drive.mount('/content/drive')

import io corona$_{d}ataset_{c}sv = pd.read_{c}sv("/content/drive/MyDrive/capstone/RAW_{g}lobal_{c}onfirmed_{c}$

corona$_{d}ataset_{c}sv.shape$

corona$_{d}ataset_{c}sv.drop(['Lat',' Long'], axis = 1, inplace = True)$

corona$_{d}ataset_{c}sv.head(10)$

Aggregating the rows with country

corona$_{d}ataset_{a}ggregated = corona_{d}ataset_{c}sv.groupby("Country/Region").sum()$

corona$_{d}ataset_{a}ggregated.head(10).sum(axis = 1)$

corona$_{d}ataset_{a}ggregated.shape$

Visualizing data related to a country for example India,China,Spain,Italy

corona$_{d}ataset_{a}ggregated.loc['India'].plot()$

corona$_{d}ataset_{a}ggregated.loc['China'].plot() corona_{d}ataset_{a}ggregated.loc['Italy'].plot() corona_{d}ataset_{a}g$

TO GET THE RATE AT WHICH CASES ARE GROWING(DIFFERENTIATING THE CURVE)

corona$_{d}ataset_{a}ggregated.loc['China'].diff().plot()$

corona$_{d}ataset_{a}ggregated.loc['India'].diff().plot()$

Find max infection rates for China and India

corona$_{d}ataset_{a}ggregated.loc['China'].diff().max()$

corona$_{d}ataset_{a}ggregated.loc['India'].diff().max()$

corona$_{d}ataset_{a}ggregated.loc['India',:]$

Finding average infection rates

corona$_{d}ataset_{a}ggregated.loc['China'].diff().mean()$

corona$_{d}ataset_{a}ggregated.loc['India'].diff().mean()$

Find maximum infection rate for all of the countries.

countries = list(corona$_{d}ataset_{a}ggregated.index)ave_{i}nfection_{r}ates = []forcountryincountries :$ $ave_{i}nfection_{r}ates.append(corona_{d}ataset_{a}ggregated.loc[country].diff().mean())corona_{d}ataset_{a}ggreg$ $ave_{i}nfection_{r}ates$

corona$_{d}ataset_{a}ggregated.head()$

Create a new dataframe with only needed column

corona$_{d}ata = pd.DataFrame(corona_{d}ataset_{a}ggregated['meaninfectionrate'])$

corona$_{d}ata.head(10)$

Importing the world happiness report

world$_{h}appiness_{r}eport = pd.read_{c}sv("/content/drive/MyDrive/capstone/world_{h}appiness_{r}eport_{2}022.$

world$_{h}appiness_{r}eport.dtypes$

world$_{h}appiness_{r}eport.shape$

Dropping useless Columns

columns$_{t}o_{d}ropped = ['Whisker-high','Whisker-low','Dystopia(1.83)+residual','RANK','Happine$ $1, inplace = True)$

world$_{h}appiness_{r}eport.head()$

Changing the indices of the dataframe

world$_{h}appiness_{r}eport.set_{i}ndex([\prime Country\prime], inplace = True)world_{h}appiness_{r}eport.head()$

Joining the two datasets

data = world$_{h}appiness_{r}eport.join(corona_{d}ata, how = "inner")data.head()$

pip install covid

from covid import Covid

covid = Covid() covid.get$_{d}ata()len(covid.get_{d}ata())$

df=pd.DataFrame(data=covid.get$_{d}ata())df.head()$

df.drop(['latitude','longitude','id'],axis=1,inplace=True) df.head()

df.set$_{i}ndex(\prime country\prime, inplace = True)df.head()$

final=df.join(corona$_{d}ata, how =\prime\ inner\prime)len(final)$

final.head()

Joining Data from covid library and World Happiness Index

data1 = world$_{h}appiness_{r}eport.join(final, how = "inner")$

data1.head(10)

Scaling data

data1.drop(['active','recovered','last$_{u}pdate\prime], axis = 1, inplace = True)data1.head()$

from sklearn.preprocessing import MinMaxScaler scaler = MinMaxScaler() scaled = scaler.fit$_{t}ransform(data1)$

from pandas import DataFrame datax = DataFrame(scaled) datax.head()

Vaccinations

pip install wordcloud

import pandas as pd import numpy as np import matplotlib.pyplot as plt import plotly.express as px import plotly.graph$_{o}bjectsasgoimportmatplotlib.patchesasmpatchesfromplotly.su$
$True)sns.set(style = "whitegrid")importplotly.figure_{f}actoryasfffromplotly.colorsimportn_{c}olors$

df = pd.read$_{c}sv("/content/drive/MyDrive/capstone/country_{v}accinations.csv")df.head()$

df.isnull().sum()

df.fillna(value = 0, inplace = True) df.total$_{v}accinations = df.total_{v}accinations.astype(int)df.people_{v}ac$
$df.people_{v}accinated.astype(int)df.people_{f}ully_{v}accinated = df.people_{f}ully_{v}accinated.astype(int)df.dail$
$df.daily_{v}accinations_{r}aw.astype(int)df.daily_{v}accinations = df.daily_{v}accinations.astype(int)df.total_{v}ac$
$df.total_{v}accinations_{p}er_{h}undred.astype(int)df.people_{f}ully_{v}accinated_{p}er_{h}undred = df.people_{f}ully_{v}accin$
$df.daily_{v}accinations_{p}er_{m}illion.astype(int)df.people_{v}accinated_{p}er_{h}undred = df.people_{v}accinated_{p}er_{h}u$
$df.date.str.split('-', expand = True)date$

df['year'] = date[0] df['month'] = date[1] df['day'] = date[2] df.year = pd.to$_{n}umeric(df.year)df.month =$
$pd.to_{n}umeric(df.month)df.day = pd.to_{n}umeric(df.day)df.date = pd.to_{d}atetime(df.date)df.head()$

df.describe()

df.country.unique()

country$_{w}ise_{t}otal_{v}accinated = forcountryindf.country.unique() : vaccinated = 0foriinrange(len(df))$
$ifdf.country[i] == country : vaccinated+ = df.daily_{v}accinations[i]country_{w}ise_{t}otal_{v}accinated[countr$
$vaccinatedmadeaseperatedictfromthedfcountry_{w}ise_{t}otal_{v}accinated_{d}f = pd.DataFrame.from_{d}ict(co$
$index', columns = ['total_{v}accinted_{t}ill_{d}ate'])converteddicttodfcountry_{w}ise_{t}otal_{v}accinated_{d}f.sort_{v}alues$
$total_{v}accinted_{t}ill_{d}ate', ascending = False, inplace = True)country_{w}ise_{t}otal_{v}accinated_{d}f$

datar = country$_{w}ise_{t}otal_{v}accinated_{d}f.join(data1, how = "inner")$

datar

Correlation Matrix

datar.corr()

sns.heatmap(datar.corr())

Visualization of the results

Plotting GDP vs maximum Infection rate

x = data['GDP per capita'].values y = data['mean infection rate'].values sns.scatterplot(x,y) VISUALISATION IS DIFFICULT BECAUSE OF DIFFERENCE Y SCALE AND X-SCALE

x = data['GDP per capita'] y = data['mean infection rate'] sns.scatterplot(x,np.log(y))

sns.regplot(x,np.log(y))

Plotting Social support vs maximum Infection rate

x = data['Social support'] y = data['mean infection rate'] sns.scatterplot(x,np.log(y))

sns.regplot(x,np.log(y))

Plotting Healthy life expectancy vs maximum Infection rate

x = data['Healthy life expectancy'] y = data['mean infection rate'] sns.scatterplot(x,np.log(y))

sns.regplot(x,np.log(y))

Plotting Freedom to make life choices vs maximum Infection rate

x = data['Freedom to make life choices'] y = data['mean infection rate'] sns.scatterplot(x,np.log(y))

sns.regplot(x,np.log(y))

Performing linear regression

from sklearn.linear$_m odelimportLinearRegressionregression_m odel = LinearRegression()$

x = datax.iloc[:, -6].values GDP y = datax.iloc[:, -1].values deaths x= x.reshape(-1,1) regression$_m odel.fit(x, y)GDPvsDeaths$

y$_p redicted = regression_m odel.predict(x)$

from sklearn.metrics import mean$_s quared_e rror, r2_s coremse = mean_s quared_e rror(y, y_p redicted)$

mse

rmse = np.sqrt(mean$_s quared_e rror(y, y_p redicted))r2 = r2_s core(y, y_p redicted)$

rmse

r2

GDP alone cannot explain variance of deaths

Gradient descent approach

m = 0 c = 0 L = 0.00001 epochs = 10000 the number of iterations to perform gradiation X = datax.iloc[:, -6].values attributes to determine dependant variable/ Class Y = datax.iloc[:, -1].values dependant variable/ Class n = float(len(X)) n

for i in range(epochs): Y$_p red = m * X + cThecurrentpredictedvalueofYD_m = (-2/n) * sum(X * (Y - Y_p red))DerivativewrtmD_c = (-2/n) * sum(Y - Y_p red)Derivativeofcm = m - L * D_m Updatemc = c - L * D_c Updatecprint(m, c)$

Y$_p red = m*X+cplt.scatter(X, Y, color = "red")plt.plot(X, Y_p red, color = "green")plt.xlabel("X")plt.$

Outliers of the Data Frame

Social support index vs Deaths due to covid x = datax.iloc[:, -5].values attributes to determine dependant variable/ Class y = datax.iloc[:, -1].values dependant variable/ Class x= x.reshape(-1,1) regression$_{m}odel.fit(x, y)$

y$_{p}redicted = regression_{m}odel.predict(x)$

mse = mean$_{s}quared_{e}rror(y, y_{p}redicted)mse$

rmse = np.sqrt(mean$_{s}quared_{e}rror(y, y_{p}redicted))r2 = r2_{s}core(y, y_{p}redicted)r2$

Healthy Life Expectancy Vs Deaths due to covid

x = datax.iloc[:, -4].values attributes to determine dependant variable/ Class y = datax.iloc[:, -1].values dependant variable/ Class x= x.reshape(-1,1) regression$_{m}odel.fit(x, y)y_{p}redicted = regression_{m}odel.predict(x)mse = mean_{s}quared_{e}rror(y, y_{p}redicted)mse$

rmse = np.sqrt(mean$_{s}quared_{e}rror(y, y_{p}redicted))r2 = r2_{s}core(y, y_{p}redicted)r2$

datar.head(10)

from sklearn.preprocessing import MinMaxScaler scaler = MinMaxScaler() scaled = scaler.fit$_{t}ransform(datar)$

from pandas import DataFrame data$_{s}caled = DataFrame(scaled)data_{s}caled.head()$

from sklearn.linear$_{m}odelimportLinearRegressionregression_{m}odel = LinearRegression()fromsklear$

x = data$_{s}caled.iloc[:, -7].valuestotalvaccinatedy = data_{s}caled.iloc[:, -1].valuesdeathsx = x.reshape(-1, 1)regression_{m}odel.fit(x, y)y_{p}redicted = regression_{m}odel.predict(x)mse = mean_{s}quared_{e}rror(y, y_{p}redicted)mse$

rmse = np.sqrt(mean$_{s}quared_{e}rror(y, y_{p}redicted))r2 = r2_{s}core(y, y_{p}redicted)r2print(rmse)$

x = data$_{s}caled.iloc[:, -7].valuesattributestodeterminedependantvariable/Classy = data_{s}caled.iloc[: , -2].valuesconfirmedx = x.reshape(-1, 1)regression_{m}odel.fit(x, y)y_{p}redicted = regression_{m}odel.pr mean_{s}quared_{e}rror(y, y_{p}redicted)np.sqrt(mse)$

rmse = np.sqrt(mean$_{s}quared_{e}rror(y, y_{p}redicted))r2 = r2_{s}core(y, y_{p}redicted)r2$

Multinomial regression

Performing multinomial regreesion on (Vaccination,GDP) vs Deaths due to Covid

data$_{s}caled$

from sklearn.metrics import mean$_{s}quared_{e}rror, r2_{s}corefromsklearnimportlinear_{m}odelimportstatsmo data_{s}caled[[0, 1]]herewehave2variablesformultipleregression.Ifyoujustwanttouseonevariableforsim df['Interest_{R}ate']forexample.Alternatively, youmayaddadditionalvariableswithinthebracketsY = data_{s}caled[6]$

with sklearn regr = linear$_{m}odel.LinearRegression()regr.fit(X,Y)Yp = regr.predict(X)print('Interce$
$, regr.intercept_{)}print('Coefficients :', regr.coef_{)}print('Rsqaure :')print(regr.score(X,Y))rmse =$
$np.sqrt(mean_{s}quared_{e}rror(Y,Yp))print(rmse)$

Performing multinomial regreesion on (Vaccination,GDP) vs Deaths due to Covid using stastical models

X = sm.add$_{c}onstant(X)addingaconstant$

model = sm.OLS(Y, X).fit() predictions = model.predict(X)

print$_{m}odel = model.summary()print(print_{m}odel)$

Polynomial Regression

X = data$_{s}caled[0]Vaccinatedlistofdifferentcountries Y = data_{s}caled[5]CovidConfirmedcases$

Polynomial regression (Vaccinations vs Confirmed cases)

import numpy as np mymodel = np.poly1d(np.polyfit(X, Y, 3)) myline = np.linspace(0.6, 0.8, 100)

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show()

Rsquare value of Vaccinations vs Confirmed cases

print(r2$_{s}core(Y, mymodel(X)))$

Polynomial regression (Vaccinations vs Deaths)

X = data$_{s}caled[0]Vaccinatedlist Y = data_{s}caled[6]Deathsduetocovid$

import numpy as np mymodel = np.poly1d(np.polyfit(X, Y, 3)) myline = np.linspace(0.6, 0.7, 100)

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show() print("R2 value of Vaccinations vs Deaths:") print(r2$_{s}core(Y, mymodel(X)))$

Polynomial Regression (GDP vs social support)¶

X = data$_{s}caled[1]Y = data_{s}caled[2]$

import numpy as np mymodel = np.poly1d(np.polyfit(X, Y, 3)) myline = np.linspace(0, 1, 100)

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show() print("R2 value of Gdp vs social support:") print(r2$_{s}core(Y, mymodel(X)))$

Polynomial Regression (GDP vs Health Life expectancy)

X = data$_{s}caled[1]GDPY = data_{s}caled[3]HLP$

from sklearn.metrics import mean$_{s}quared_{e}rrorimportnumpyasnpmymodel = np.poly1d(np.polyfit(X,$
$np.linspace(0, 1, 100)$

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show() print("R2 value of gdp vs HLP:") print(r2$_{s}core(Y, mymodel(X)))rmse = np.sqrt(mean_{s}quared_{e}rror(Y, mymodel(X)))print(rm$

Polynomial Regression (Social Support vs HLP)

X = data$_{s}caled[2]socialsupportY = data_{s}caled[1]HLP$

import numpy as np mymodel = np.poly1d(np.polyfit(X, Y, 3)) myline = np.linspace(0, 1, 100)

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show() print("R2 social support vs HLP:") print(r2$_{s}core(Y, mymodel(X)))$

Polynomial Regression (Confirmed vs Deaths)

X = data$_{s}caled[5]ConfirmedY = data_{s}caled[6]Deaths$

from sklearn.metrics import mean$_{s}quared_{e}rrorimportnumpyasnpmymodel = np.poly1d(np.polyfit(X,$
$np.linspace(0, 1, 100)$

plt.scatter(X, Y) plt.plot(myline, mymodel(myline)) plt.show() print("R2 Confirmed vs Deaths:") print(r2$_{s}core(Y, mymodel(X)))rmse = np.sqrt(mean_{s}quared_{e}rror(Y, mymodel(X)))print(r$

df

df$_{n}ew = pd.DataFrame(data = covid.get_{d}ata())df_{n}ew.head()$

df$_{n}ew.drop(['latitude', 'longitude', 'id', 'active', 'recovered', 'last_{u}pdate'], axis = 1, inplace = True)df_{n}ew.head()$

death = df$_{n}ew['deaths'].tolist()$

series = pd.Series(death)

series

quantile$_{2}0 = series.quantile(0.20)quantile_{4}0 = series.quantile(0.40)quantile_{6}0 = series.quantile(0.60$
$series.quantile(0.80)$

quantile$_{7}0 = series.quantile(0.70)quantile_{7}0$

max(death)

import matplotlib.pyplot as plt plt.plot(df$_new['country'], df_new['deaths']$)

classes = [] ax=0 b=0 c=0 d,e = 0,0 for i in death: if(i¡quantile$_20) : classes.append(0)ax+ = 1elif(i >= quantile_20andi <= quantile_40) : classes.append(1)b+ = 1elif(i >= quantile_40andi <= quantile_60) : classes.append(2)c+ = 1elif(i >= quantile_60andi <= quantile_80) : classes.append(3)d+ = 1else : classes.append(4)e+ = 1$

print(ax) print(b) print(c) print(d) print(e)

df$_new['class'] = classesdf_new.head(25)$

df$_new.set_index(['country'], inplace = True)df_new.head()$

df$_new.drop(['confirmed','deaths'], axis = 1, inplace = True)df_new$

data$_class = datar.join(df_new, how = "inner")data_class$

from sklearn.model$_selectionimporttrain_test_splitfromsklearn.linear_modelimportLogisticRegressionf$

Load the dataset X = data$_class.drop("class", axis = 1)y = data_class["class"]$

Split the dataset into training and testing sets X$_train, X_test, y_train, y_test = train_test_split(X, y, test_size$ 0.333)

Train the classifier

clf1 = DecisionTreeClassifier() clf1.fit(X$_train, y_train)$

Predict the class labels y$_pred = clf1.predict(X_test)$

Evaluate the classifier acc = accuracy$_score(y_test, y_pred)print("Accuracy : ", acc)$

from sklearn.preprocessing import LabelBinarizer

label$_binarizer = LabelBinarizer().fit(y_train)y_onehot_test = label_binarizer.transform(y_test)y_onehot_t$

label$_binarizer.transform([0])$

class$_of_interest = 0class_id = np.flatnonzero(label_binarizer.classes_ = = class_of_interest)[0]class_id$

clf0 = LogisticRegression() clf0.fit(X$_train, y_train)$

y$_pred = clf0.predict(X_test)acc = accuracy_score(y_test, y_pred)print("Accuracy : ", acc)$

from sklearn.naive$_bayesimportGaussianNBgnb = GaussianNB()gnb.fit(X_train, y_train)y_pred = gnb.predict(X_test)acc = accuracy_score(y_test, y_pred)print("Accuracy : ", acc)$

y

X$_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.333)$

from sklearn.metrics import confusion$_matrix, accuracy_score, classification_report$

def evaluate(model, X$_train, X_test, y_train, y_test) : y_test_pred = model.predict(X_test)y_train_pred =$ $model.predict(X_train)$

print("TRAINIG RESULTS: ===================================")
clf$_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict = True))print(f"CON$
$confusion_matrix(y_train, y_train_pred)")print(f"ACCURACYSCORE : accuracy_score(y_train, y_train_p$
$clf_report")$

print("TESTING RESULTS: ===================================")
clf$_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict = True))print(f"CONFU$
$confusion_matrix(y_test, y_test_pred)")print(f"ACCURACYSCORE : accuracy_score(y_test, y_test_pred) :$
$clf_report")$

from sklearn.ensemble import BaggingClassifier from sklearn.tree import DecisionTreeClassifier

tree = DecisionTreeClassifier() bagging$_clf = BaggingClassifier(base_estimator = tree, n_estimators =$ $2500, random_state = 42)bagging_clf.fit(X_train, y_train)$

evaluate(bagging$_clf, X_train, X_test, y_train, y_test)$

scores = 'Bagging Classifier': 'Train': accuracy$_score(y_train, bagging_clf.predict(X_train)),'Test' :$ $accuracy_score(y_test, bagging_clf.predict(X_test)),,$

scores

clf0 = LogisticRegression() clf0.fit(X$_train, y_train)evaluate(clf0, X_train, X_test, y_train, y_test)$

gnb = GaussianNB() gnb.fit(X$_train, y_train)evaluate(gnb, X_train, X_test, y_train, y_test)$

clf1 = DecisionTreeClassifier() clf1.fit(X$_train, y_train)evaluate(clf1, X_train, X_test, y_train, y_test)$

from sklearn.ensemble import RandomForestClassifier

rf$_clf = RandomForestClassifier(random_state = 42, n_estimators = 2000)rf_clf.fit(X_train, y_train)ev$

from sklearn.ensemble import ExtraTreesClassifier

ex$_tree_clf = ExtraTreesClassifier(n_estimators = 2000, max_features = 7, random_state =$ $42)ex_tree_clf.fit(X_train, y_train)evaluate(ex_tree_clf, X_train, X_test, y_train, y_test)$

from sklearn.ensemble import GradientBoostingClassifier

grad$_boost_clf = GradientBoostingClassifier(n_estimators = 100, random_state = 42)grad_boost_clf.fit($

from sklearn.svm import SVC svm$_clf = SVC(gamma =' scale')svm_clf.fit(X_train, y_train)evaluate(sv$

ex$_tree_clf = ExtraTreesClassifier()bagging_clf = BaggingClassifier(base_estimator =$
$ex_tree_clf, n_estimators = 1500, random_state = 42)bagging_clf.fit(X_train, y_train)$

evaluate(bagging$_clf, X_train, X_test, y_train, y_test)$

Logistic+ others

from sklearn.ensemble import VotingClassifier from sklearn.linear$_modelimportLogisticRegressionfrom$

estimators = [] ex$_tree_clf = ExtraTreesClassifier(n_estimators = 2000, max_features =$
$7, random_state = 10)estimators.append(('Extratree', ex_tree_clf))$

grad$_boost_clf = GradientBoostingClassifier(n_estimators = 100, random_state = 42)estimators.appen$
$LogisticRegression()logis.fit(X_train, y_train)$

estimators.append(('logistic regression',logis)) tree = DecisionTreeClassifier() bagging$_clf =$
$BaggingClassifier(base_estimator = tree, n_estimators = 1500, random_state = 42)estimators.append($

voting = VotingClassifier(estimators=estimators) voting.fit(X$_train, y_train)$

evaluate(voting, X$_train, X_test, y_train, y_test)$

decision tree + others

from sklearn.ensemble import VotingClassifier from sklearn.linear$_modelimportLogisticRegressionfrom$

estimators = [] ex$_tree_clf = ExtraTreesClassifier(n_estimators = 2000, max_features =$
$7, random_state = 10)estimators.append(('Extratree', ex_tree_clf))$

grad$_boost_clf = GradientBoostingClassifier(n_estimators = 100, random_state = 42)estimators.appen$
$DecisionTreeClassifier()estimators.append(('Decisiontree', Dtree))$

tree = DecisionTreeClassifier() bagging$_clf = BaggingClassifier(base_estimator = tree, n_estimators =$
$1500, random_state = 42)estimators.append(('Decisiontreebagging', bagging_clf))$

voting = VotingClassifier(estimators=estimators) voting.fit(X$_train, y_train)$

evaluate(voting, X$_train, X_test, y_train, y_test)$

Random forest + others

from sklearn.ensemble import VotingClassifier from sklearn.linear$_modelimportLogisticRegressionfrom$

estimators = [] ex$_t ree_c lf = ExtraTreesClassifier(n_e stimators = 2000, max_f eatures = 7, random_s tate = 10) estimators.append(('Extratree', ex_t ree_c lf))$

grad$_b oost_c lf = GradientBoostingClassifier(n_e stimators = 100, random_s tate = 42) estimators.appen$

rf$_c lf = RandomForestClassifier(random_s tate = 42, n_e stimators = 2000) estimators.append(('Rand$

tree = DecisionTreeClassifier() bagging$_c lf = BaggingClassifier(base_e stimator = tree, n_e stimators = 1500, random_s tate = 42) estimators.append(('Decisiontreebagging', bagging_c lf))$

voting = VotingClassifier(estimators=estimators) voting.fit(X$_t rain, y_t rain)$

evaluate(voting, X$_t rain, X_t est, y_t rain, y_t est)$

Naive bayes + others

estimators = [] ex$_t ree_c lf = ExtraTreesClassifier(n_e stimators = 2000, max_f eatures = 7, random_s tate = 10) estimators.append(('Extratree', ex_t ree_c lf))$

grad$_b oost_c lf = GradientBoostingClassifier(n_e stimators = 100, random_s tate = 42) estimators.appen$

gnb = GaussianNB() estimators.append(('naive bayes',gnb))

tree = DecisionTreeClassifier() bagging$_c lf = BaggingClassifier(base_e stimator = tree, n_e stimators = 1500, random_s tate = 42) estimators.append(('Decisiontreebagging', bagging_c lf))$

voting = VotingClassifier(estimators=estimators) voting.fit(X$_t rain, y_t rain)$

evaluate(voting, X$_t rain, X_t est, y_t rain, y_t est)$

data$_c lass$

data$_c lass.shape$

y

from numpy import unique, argmax import tensorflow.keras.models n$_f eatures = X_t rain.shape[1] n_c lass$ $len(unique(y)) y_c lass = LabelEncoder().fit_t ransform(y) X_t rain, X_t est, y_t rain, y_t est, y_t rain_c lass, y_t est$ $train_t est_s plit(X, y, y_c lass, test_s ize = 0.33, random_s tate = 1)$

from sklearn.metrics import accuracy$_s core, mean_a bsolute_e rror from sklearn.model_s election import train$ $Input(shape = (n_f eatures,)) hidden1 = Dense(20, activation =' relu', kernel_i nitializer =' he_n ormal')(visible) hidden2 = Dense(10, activation =' relu', kernel_i nitializer =' he_n ormal')(hidden1$ $Dense(1, activation =' linear')(hidden2) classification output out_c las = Dense(n_c lass, activation =' softmax')(hidden2) define model model = Model(inputs = visible, outputs = [out_r eg, out_c las]) compile$ $['mse',' sparse_c ategorical_c rossentropy'], optimizer =' adam') plot graph of model plot_m odel(model, to_f ile$ $model.png', show_s hapes = True) fit the keras model on the dataset model.fit(X_t rain, [y_t rain, y_t rain_c lass]$

$500, batch_size = 32, verbose = 2)makepredictionsontestsetyhat1, yhat2 = model.predict(X_test)calcula$ $mean_absolute_error(y_test, yhat1)print('MAE : evaluateaccuracyforclassificationmodelyhat2 =$ $argmax(yhat2, axis = -1).astype('int')acc = accuracy_score(y_test_class, yhat2)print('Accuracy :$

from sklearn.neural$_networkimportMLPClassifierclf = MLPClassifier(hidden_layer_sizes =$ $(6, 5), random_state = 5, verbose = True, learning_rate_init = 0.1)$

Fit data onto the model clf.fit(X$_train, y_train)evaluate(clf, X_train, X_test, y_train, y_test)$

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Analysis on pandemic's impact on healthcare system and happiness index using Machine algorithms

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Abstract:

The Global Happiness Index measures countries by their citizens' well-being and quality of life. Healthcare systems and the Global Happiness Index are linked by the pandemic. Countries that have contained the epidemic and provided quality healthcare have scored higher on the Happiness Index. The aim of the paper is analysing healthcare changes before and after COVID-19 can give significant insights into the pandemic's influence on healthcare and guide strategies for constructing more resilient healthcare systems. Using Pooled dataset combining World Happiness Index and COVID-19 data can give insights into citizens' overall well-being and guide measures to increase citizens' well-being during times of crisis. We can lessen the effects of future pandemics and guarantee that communities worldwide have access to quality healthcare services and lead satisfying lives by striving to establish more resilient healthcare systems and promote people' well-being.

Keywords- Healthcare, COVID-19, World Happiness Index

1. Introduction:

The COVID-19 pandemic has caused considerable changes in healthcare systems throughout the world. Hospitals and healthcare institutions have had to adjust to unprecedented difficulties and expectations, with many healthcare professionals fighting the virus personally on the front lines [1]. Additionally, the COVID-19 pandemic has had a substantial impact on the World Happiness Index. The World Happiness Index is a report that evaluates nations based on the perceived happiness and quality of life of their citizens [2]. The correlation between the pandemic's effects on the World Happiness Index and its effects on healthcare systems is strong. As a result of the immense strain that the pandemic has placed on healthcare systems, countries that have effectively contained the spread of the virus and provided high-quality healthcare have performed higher on the Happiness Index [3]. Also, the pandemic has caused a number of problems that have hurt the well-being of people, such as the loss of jobs, unstable economies, and social isolation. These issues have a negative impact on happiness for people all over the world. Countries with strong social safety nets and economic support have done better at keeping their citizens happy [4].

According to Johns Hopkins University, the coronavirus (COVID-19) epidemic-related global health pandemic has claimed over 460,000 lives worldwide [5]. More than 8.9 million people have tested positive for the virus globally. People's happiness decreased during the pandemic, according to research on well-being and COVID-19 [6], while the number of reported negative emotions increased [7], and there was a significant increase in Google searches on boredom, loneliness, worry, and sadness [8].The importance of exploring a topic centred on COVID-19 stems from the plethora of negative consequences perceived at all levels of society. The type of crisis management used in each nation has a significant impact on combating them. Although the world has encountered several crises of varying severity throughout the years, the COVID-19 pandemic has likely had the most pronounced dynamism because of the virus's quick propagation and the loss of human life [9]. The international setting of this crisis necessitates frequent inventories in terms of the input-output connection so that decision-makers' actions and governance systems may be tailored to the unique characteristics of each state. The quality of the crisis reactions is determined mostly by endogenous factors. Additionally, route development evolution has a substantial impact on the ability to respond to shocks. In theory, while some nations may not have been equipped to handle such difficulties in the past (SARS, MERS-CoV, avian flu, Ebola), in reality, the experience acquired should lead to the development of revolutionary policies to stabilise systems [10]. Even if each crisis is surrounded by uncertainties, a risk prevention plan should be in place from the start, with the success of measures strongly tied to governments' and decision-makers' capacity to predict potential shocks [11].

The COVID-19 epidemic has been a global health disaster, putting pressure on healthcare systems in ways that have never been seen before. As healthcare systems struggle to keep up with the demands of the pandemic, it is more important than ever to know how COVID-19 affects healthcare [12]. The necessity to examine the changes in healthcare before and after COVID-19 with a special focus on healthcare usage, quality, results, workforce, and modifications to healthcare delivery models and infrastructure is stressed. To limit the effects of future pandemics, it is important to find ways to make healthcare systems stronger [13].

The goal of this research study is to look at how the COVID-19 pandemic affected healthcare systems around the world, with a focus on changes in how healthcare is used, its quality, results, and workforce, as well as changes to healthcare delivery models and infrastructure. Ultimately, this research provides a complete knowledge of the impact of the COVID-19 pandemic on healthcare systems and to suggest measures for future healthcare system resilience. This study guarantees the communities throughout the world have access to quality healthcare services and limit the effects of future pandemics by striving to establish more resilient healthcare systems.

The contributions of the present study are

- The study will also look at the link between the COVID-19 pandemic and the Global Happiness Index to see if there are any implications for global well-being. To achieve this goal, we collected and evaluated data from a variety of sources, including healthcare institutions, governmental and non-governmental organisations, and academic research. We want to give a thorough knowledge of how the COVID-19 epidemic has affected healthcare systems throughout the world by examining this data.
- The results of this study will help make plans for building healthcare systems that are more resilient and can handle future pandemics. By looking at how healthcare delivery models and infrastructure have changed, this research will also show how healthcare systems could change to deal with new problems, like the COVID-19 pandemic.
- The Global Happiness Index will be analysed in relation to the COVID-19 pandemic to give insights into the pandemic's influence on global well-being. This will aid in the development of initiatives to improve the health of individuals and communities affected by the epidemic. The results of this study will affect healthcare policies and help figure out how to divide up resources for pandemics in the future. The study will also look at the link between the COVID-19 pandemic and the Global Happiness Index to see whether there are any effects on global well-being.

2. Related Works

Smith, Brown, and Jones [14] did a systematic study to find out how COVID-19 affects the use, quality, and outcomes of health care. According to the report, the pandemic has had a big effect on healthcare services, like cutting back on services that aren't related to COVID and making more people use telehealth. The assessment also emphasises the difficulties in preserving healthcare quality and safety throughout the pandemic, including the requirement for personal protective equipment and infection control measures. The research does mention, however, that certain healthcare systems have effectively reacted to the pandemic through the implementation of new delivery models and creative solutions. Ultimately, the assessment emphasises the significance of developing robust and flexible healthcare systems to deal with future pandemics [14]. Chen et al. [15] did a systematic review and meta-analysis to find out how the COVID-19 pandemic affected the healthcare workforce. During the pandemic, health care workers had to deal with a number of problems, such as increased workloads, psychological discomfort, and exposure to infections. The results also showed that there are big gaps in the research that has been done so far, especially when it comes to the views of healthcare workers on the front lines. This paper has a lot going for it, like a thorough review of the existing literature and a methodical approach. The analysis's relatively small sample size and the fact that the majority of the studies come from China, however, limit the study's ability to generalise its findings to other regions [15]. Haider et al. [16] conducted research on the adoption of lockdown measures in nine sub-Saharan African nations. The authors examined the effects of these methods on virus control as well as their influence on the economy, food security, and social disturbances. The study discovered that, while the lockdowns had a considerable influence on preventing viral transmission, they also had a detrimental impact on the economy, food security, and the population's mental health. One of the study's weaknesses is the absence of data on the long-term consequences of these policies on the economy and society [16]. The report by Cucinotta and Vanelli [17] analyses the World Health Organisation's classification of COVID-19 as a pandemic. The authors give a brief history of pandemics, debate the definition of a pandemic, and outline the WHO's reaction to the COVID-19 epidemic. In reacting to pandemics, the study emphasises the significance of global collaboration and good communication. One possible disadvantage of the article is that it does not present fresh empirical data but rather synthesises current data. It is nevertheless a useful resource for studying the global reaction to the COVID-19 epidemic [17]. Wang et al. [18] gave an overview of the new coronavirus outbreak, which became a worldwide health concern. The report looked at the properties of the virus, such as where it came from, how it spreads, its symptoms, and possible treatments. The paper's clear and comprehensive account of the virus and its influence on world health is one of its strengths. But because the study came out early in the pandemic, it might not have the most recent research and information on the virus [18].

Chen et al. [19] looked at the research on how COVID-19 causes cytokine storms and how to treat them with immunotherapies. The authors explored the function of cytokines in illness aetiology and the efficacy of immunotherapy in treating severe cases. They also investigated several techniques, such as cytokine targeting, immune cell modulation, and extracorporeal blood purification. The work sheds light on the fundamental processes of COVID-19 as well as possible therapies. However, the study has limitations, such as a small sample size and a lack of clinical data, which necessitate further research [19]. Li et al. [20] did a thorough review and meta-analysis of COVID-19's epidemiology, clinical features, risk factors, and results. The analysis of 44 studies showed that fever, stuffy nose, and tiredness were the most common COVID-19 symptoms. The risk of severe disease and death was higher in older adults, men, and people who already had health problems. The study gives important information about how COVID-19 spreads, which can help public health and clinical management plans. But the analysis is limited by the different types of studies that were used and the fact that the data could have been reported in a biased way [20]. In a follow-up study, Zhao et al. [21] looked at how well the lungs worked and how healthy the COVID-19 survivors were. The study showed that a large number of patients continued to have respiratory symptoms and had abnormal pulmonary function. The study also found a link between how bad the first illness was and how likely it was that the respiratory symptoms would last. The study is good because it looks at the long-term effects of COVID-19 and has a large sample size. Cons are the lack of a control group and the short follow-up period of three months [21]. Tandon [22] discussed the effects of COVID-19 on mental health and suggested strategies for maintaining mental health during the pandemic. The pros include a comprehensive overview of the mental health issues caused by COVID-19 and practical advice for individuals and healthcare professionals. The cons include a lack of empirical evidence to support some of the proposed strategies and an emphasis on individual-level interventions as opposed to systemic change to address mental health disparities exacerbated by the pandemic [22]. Ferrari et al. [23] investigated COVID-19 blood tests' diagnostic capability. They observed that COVID-19 patients and non-COVID-19 patients differed in lymphocyte count, CRP, and LDH after a comprehensive evaluation of 26 research studies. Routine blood testing, clinical observations, and imaging can help diagnose and treat COVID-19, the investigators found. The study includes papers of various quality; therefore, further research is needed to confirm these conclusions [23]. Hu et al. [24] looked at how the COVID-19 pandemic affected the use of medical resources and the outcomes of illnesses that were not caused by COVID-19 in China. During the pandemic, rural and chronic illness patients used fewer medical resources for non-COVID-19 conditions, according to the research. The pandemic also increased non-COVID-19 illness mortality, according to the research. The study's large sample size and countrywide analysis are pros, while data accuracy and representativeness are drawbacks [24].

A retrospective analysis of 99 COVID-19 patients in Chengdu, China, examined the epidemiological and clinical characteristics of critical and non-critical cases [25]. Critical patients had a greater mortality rate and longer hospital stays than non-critical cases. Fever was the most prevalent symptom, and CT scans helped diagnose COVID-19 pneumonia, the scientists reported. The study's retrospective approach and small sample size restrict generalizability and causality [25]. The COVID-19 epidemic and lockdown's psychological effects on dementia carers are examined [26]. Carers have higher despair, anxiety, and stress levels and lower quality of life and sleep, according to studies. The study's limited sample size limits its generalizability. Despite its limitations, the study emphasises carer assistance and treatments during the epidemic [26]. The paper in [27] examined Taiwanese critically ill COVID-19 patients' clinical features and outcomes. Medical data of 20 severely ill COVID-19 patients were retrospectively analysed. The study revealed that most critically ill patients were older and had comorbidities. Most treatments involved mechanical ventilation and antiviral therapy. The study found low death rates. The limited sample size restricts generalizability. The findings require further study [27]. The paper in [28] examined COVID-19 instances in Wuhan, Hubei Province. 1,045 COVID-19 patients were studied from January to February 2020. Older age, male sex, and comorbidities were linked to severe illness and mortality, the study revealed. Fever, cough, and shortness of breath were the most prevalent COVID-19 symptoms, the study revealed. Unfortunately, the study only assessed data from a limited time and a small location [28]. This scoping review [29] examined how the COVID-19 epidemic affected Bangladeshi child healthcare. The epidemic has disrupted mother and child health services, reducing prenatal, delivery, postnatal, and childhood immunisation rates, according to the report. The report emphasises the necessity for immediate pandemic-reduction strategies for mother and child health. The study's pros include a complete review of COVID-19's influence on Bangladeshi maternal and child healthcare. Disadvantages include the study's one-country focus [29].During the COVID-19 outbreak, Kratom usage increased dramatically [30]. 33% of the 10,000 online survey respondents reported using Kratom more during the outbreak. Pandemic anxiety and sadness were the major explanations. The study also noted Kratom's adverse effects and hazards. Self-reported data from an online survey may restrict the study's generalizability [30].

The literature [31] examined the time between COVID-19 symptom onset and hospital, ICU, and death. A comprehensive review and meta-analysis of 16 trials with 56,753 patients found that the median time from symptom onset to hospital admission, ICU admission, and mortality was four, eight, and 18 days, respectively. The report helps healthcare practitioners and policymakers allocate resources and prioritise high-risk patients. The research's shortcomings include study heterogeneity and country-specific healthcare systems [31]. The study [32] examined if early glucocorticoid therapy exacerbated critical illness in COVID-19 patients. 295 COVID-19 patients received glucocorticoids within 72 hours of arrival, and 295 did not in the retrospective cohort analysis. Early glucocorticoid usage did not raise COVID-19 serious illness. Retrospective and uncontrolled confounding variables restrict the study [32]. Maroufizadeh et al. [33] undertook mixed-method research in Iran to examine COVID-19 prevalence and psychological effects in confined populations. Quarantine was a major predictor of psychological effects, and subjects had high rates of anxiety and sadness. The pandemic quarantine research examines psychological effects. The study only covers one Iranian population [33]. Mazzucato et al. [34] did a survey on COVID-19 and oncological breast surgery in several Italian cities. During the pandemic, breast cancer surgery dropped significantly, and diagnosis and treatment were delayed. The study shows how the epidemic affected cancer care. The study only covers breast cancer surgery [34]. Mieczkowska et al. [35] conducted a Polish case-control study to investigate risk variables for COVID-19 critical care patients. Male sex, older age, and comorbidities raised ICU admission probabilities, according to the research. The study reveals substantial COVID-19 risk factors. The study only applies to a Polish population [35].

Ochieng et al. [36] studied microfinance organisations in Kenya during the COVID-19 epidemic. The epidemic reduced loan demand and increased defaults at microfinance organisations, according to the report. The study examines microfinance organisations' pandemic-related economic implications. The study is confined to a Kenyan region [36]. Pagnamenta et al. [37] undertook a multicentric study in Italy to determine how the COVID-19 pandemic affected endoscopic retrograde cholangiopancreatography (ERCP) activities. During the pandemic, ERCP activity dropped significantly and shifted towards more urgent treatments. The epidemic affected specialist medical treatments, the research found. The study is confined to an Italian process and population and may not be generalizable [37]. Panchal et al. [38] examined the mental health and drug use effects of the COVID-19 pandemic for the Kaiser Family Foundation. The epidemic increased stress, anxiety, depression, and drug use, the survey showed. The paper discusses pandemic mental health and drug use effects. The report only applies to the US population [38].

From literatures [14-38], it is observed that how the pandemic has affected healthcare systems as a whole, including changes in how healthcare is used, its quality, its results, its workforce, its delivery models, and its infrastructure is not done. Further, this study will also look at how the pandemic affects the World Happiness Index. This will help researchers figure out how the pandemic affects the happiness of people around the world. The main objective of this study is to learn as much as possible about how the COVID-19 pandemic affected healthcare systems around the world. This includes changes in healthcare use, quality, outcomes, and workforce, as well as changes to how healthcare is delivered and how infrastructure works. To do this, the project will use techniques for visualising data to show the trends and patterns in how healthcare was used and what happened before and after the pandemic. Methods of regression and classification will also be used to find the most important things that caused these trends and patterns. Overall, the goal of the project is to give a full analysis of how the COVID-19 pandemic affected healthcare systems around the world and how it related to the World Happiness Index. The results of this study can help build stronger healthcare systems and policies to deal with future pandemics and put the overall well-being of communities around the world first. Machine learning algorithms and optimisation techniques will be utilised to analyse the data and visualise the trends. This research will provide insights into the pandemic's effects on healthcare systems and guide the development of strategies for building more resilient healthcare systems in the future.

3. Proposed Methodology

3.1 Dataset Description

Dataset-1:

The first dataset is taken from the website https://nf1s.github.io/covid/john_hopkins/#list-countries. This is a continually updated version of the COVID-19 Data Repository maintained by the Johns Hopkins University Centre for Systems Science and Engineering (CSSE) (JHU). The data is updated daily at 6am UTC, shortly after the original JHU data is typically updated. The dataset is accessible in both raw (files with the prefix RAW) and convenient (files without the prefix RAW) format (files prefixed with CONVENIENT).

The data include:

Confirmed cases and fatalities by country Confirmed cases and deaths by US county Available metadata from the original JHU data

- The RAW version is disseminated exactly as it was in the original dataset.
- The CONVENIENT version aims to be simpler to interpret. Data is organised by column as opposed to row. The metadata is extracted into a distinct file. And it was converted to daily variation as opposed to cumulative totals.

Dataset-2:

The second dataset is available in https://www.kaggle.com/datasets/ajaypalsinghlo/world-happiness-report-2022.

The World Happiness Report is a groundbreaking survey of global contentment. Governments, organisations, and civil society are increasingly using indicators of pleasure to inform their policy decisions. Leading experts from a variety of disciplines—including economics, psychology, survey analysis, national statistics, health, and public policy, among others—explain how well-being measurements can be used to assess the progress of nations. The reports examine the current state of happiness in the world and demonstrate how the new science of happiness explains individual and national differences in happiness. The satisfaction rankings and ratings are based on Gallup World Poll data. The columns that follow the happiness score estimate the degree to which each of six factors—economic production, social support, life expectancy, freedom, absence of corruption, and generosity—contributes to higher life evaluations in each country than in Dystopia, a hypothetical country with values equal to the world's lowest national averages for each of the six factors. They have no bearing on the total score reported for each country, but they explain why some nations rank higher than others.

Dataset-3:

Daily, data is collected from the Our World in Data GitHub repository, merged, and uploaded. Vaccination information at the country level is compiled into a single file. This data file is then integrated with the location data file to include information about vaccination sources. A second file containing information about manufacturers is included. The data (vaccinations by territory) includes the following information: the country for which vaccination information is provided; Country ISO Code: the ISO country code, Date: date of data entry; for some dates we only have the daily vaccinations, while for others we only have the cumulative total. This is the total quantity of immunisations administered in the country.

Depending on the immunisation schedule, a person may receive one or more (typically two) immunisations; at a given time, the number of vaccinations may exceed the number of individuals. Total number of people fully vaccinated: this is the number of people who received the entire set of immunisations according to the immunisation scheme (typically 2); at a given time, there may be a certain number of people who received one vaccine and a smaller number who received all vaccines in the scheme. Daily vaccinations (raw): for a given data entry, the number of vaccinations administered on that date or in that country;Daily vaccinations: for a given data entry, the number of vaccinations administered on that date and in that country; Total vaccinations per hundred — ratio (in percent) between the number of vaccinations and the country's total population to date. Total number of persons vaccinated per hundred—the ratio (in percent) of the country's immunised population to its total population as of a given date, Total number of fully vaccinated individuals per hundred—the ratio (in percent) between the fully immunised population and the country's total population as of the date indicated. Number of immunisations per day—the number of immunisations administered per day in that country.

Daily vaccinations per million: the ratio (in ppm) between the number of vaccinations and the country's total population as of the current date. Vaccines administered in the nation - total number of vaccines administered in the nation (to date);Name of the source - the origin of the information (national authority, international organisation, etc.);Quelle website - website of the information source with vaccine type, Vaccination total - vaccination total / current time and vaccine type.

3.2 Integration of the dataset into common dataset and methodology adopted:

The COVID-19 pandemic has had a significant impact on the world, and researchers are working to understand the factors that contribute to the spread of the virus. In this research paper, we suggest a way to look at the relationship between COVID-19 and things like GDP, social life support, health life expectancy, freedom to make life choices, number of deaths, confirmed COVID cases, and vaccinations. To begin our analysis, we collected data from multiple sources, including the live COVID data frame, the World Happiness Report, and vaccination data. The live COVID data frame provides real-time data on the number of confirmed cases, deaths, and recoveries from COVID-19. The World Happiness Report provides data on various factors that contribute to happiness, including GDP, social support, and health-related life expectancy. The vaccination data provides information on the number of people who have been vaccinated against COVID-19.

After collecting the data, we selected features based on their relevance to the study. We chose features that are known to have an impact on the spread of COVID-19, including the mean infection rate, GDP of each country, social life support, health life expectancy, freedom to make life choices, number of deaths, confirmed COVID cases, and vaccinations.

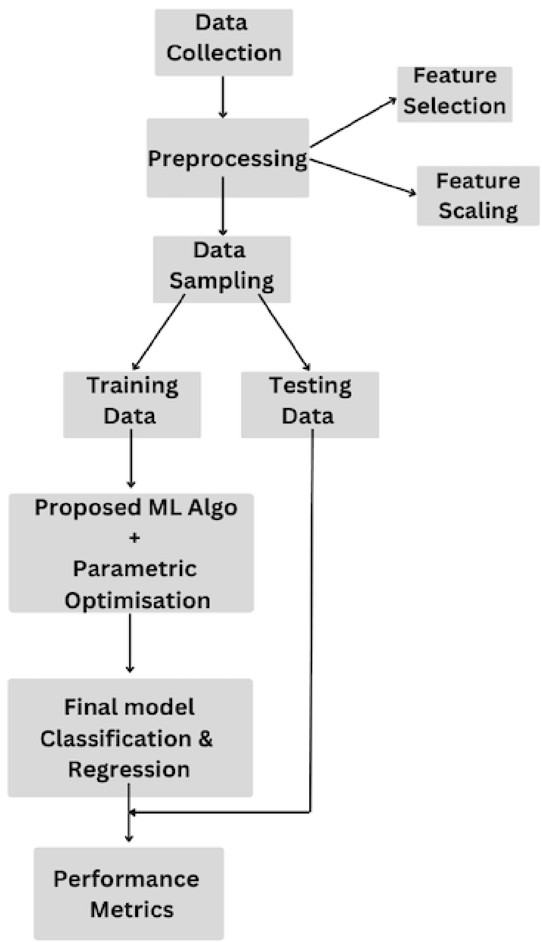

Fig.1 Proposed Methodology

Fig.1 shows the proposed methodology flow chart. To identify the most correlated features, we performed a correlation analysis. Correlation analysis is a statistical technique that measures the strength of the relationship between two variables. We found that the mean infection rate, GDP of each country, social life support, health life expectancy, freedom to make life choices, number of deaths, confirmed COVID cases, and vaccinations were the most correlated features.

Next, we did regression analysis with the following feature sets: GDP vs. deaths (linear regression), vaccination and GDP vs. deaths (multinomial regression), and vaccinations vs. deaths (polynomial regression).Regression analysis is a statistical technique that measures the relationship between two or more variables. The goal of regression analysis is to figure out how the independent and dependent variables are related. In our study, the dependent variable is the number of deaths, and the independent variables are GDP, vaccinations, and the mean infection rate.

We used inter-quantile ranges to divide the data into 5 classes and change the regression problem into a classification problem. The classes include very low, low, medium, high, and very high. We then utilised various classifiers and obtained the accuracy. A classifier is a machine learning algorithm that is used to predict the class of a given data point. In our study, we used various classifiers, including decision trees, random forests, and support vector machines.

To further improve the accuracies, we utilised ensemble methods like bagging and boosting. Ensemble methods are machine learning algorithms that combine multiple models to improve the accuracy of the predictions. Bagging is a technique that involves training multiple models on different subsets of the data and then combining the predictions of the models. Boosting is a technique that involves training multiple models sequentially, with each model learning from the errors of the previous model.

4. Experimental Results

The study involved analysing three datasets to investigate the relationship between various factors and COVID-19 outcomes. Dataset 1 was analyzed using linear and polynomial regression, which showed a strong linear correlation between confirmed cases and deaths. However, classification models on this dataset had an accuracy of only 0.58, likely due to the limited number of attributes.

In contrast, Dataset 2 was analyzed using linear, multinomial, and polynomial regression, which revealed a non-linear correlation between GDP, social support, and healthy life expectancy. These attributes were then incorporated into the final dataset, along with Dataset 3, which contained vaccination data.

Regression analysis on the final dataset showed that the attributes were non-linearly correlated, and the maximum R-squared value achieved was 0.74, indicating that regression models were unable to fully explain the variance in the data.

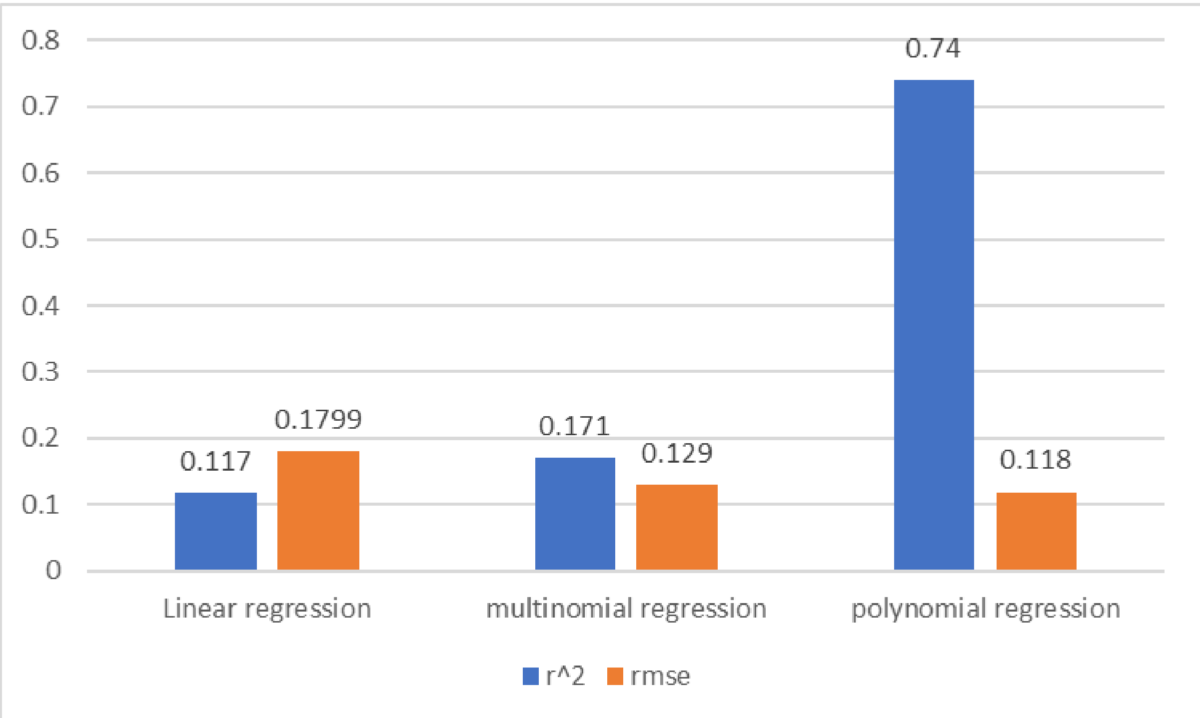

Fig.2. Regression analysis of the final Data frame.

From Fig.2, It is interpreted as a 0.4% change in R^2 between linear regression and multinomial regression. Unlike in linear regression, multinomial regression uses multiple attributes to explain the variance in the dataset. Here the positive attributes are the GDP of a country, life expectancy, and vaccinations. While the polynomial shows an R^2 of 0.74, this explains the non-linear correlation between the attributes.

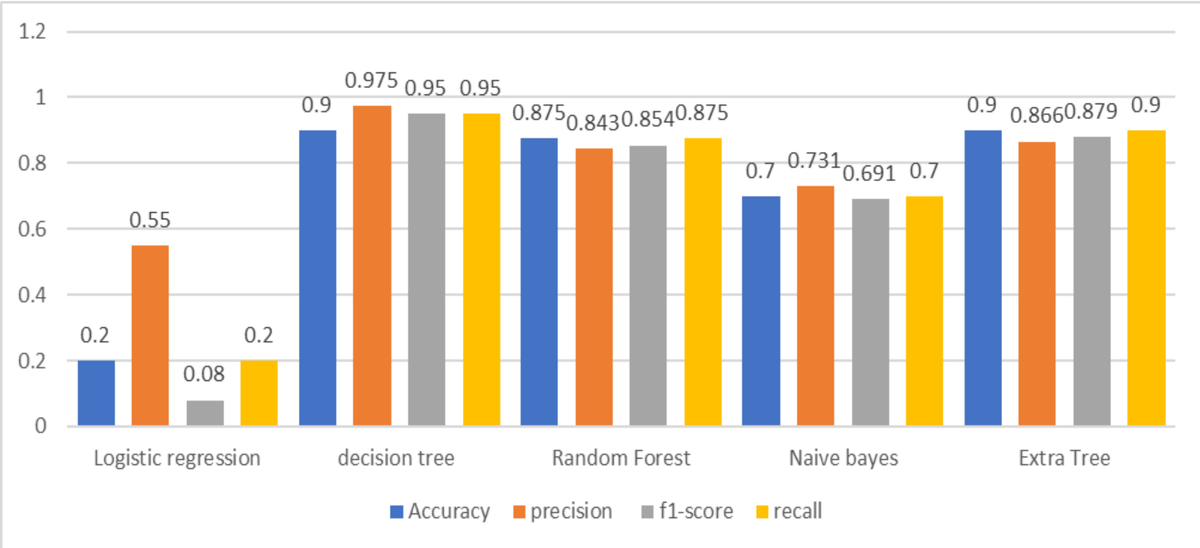

Fig.3. Analysis of generic classification models

Fig. 3 shows the analysis of the generic classification models. For the classification analysis, decision tree and random forest classifiers were evaluated, with the decision tree outperforming the others due to its ability to select the best feature at each split. Extra tree classifiers also performed well but had lower precision and F1 scores, potentially due to their random feature selection approach. Although the decision tree and extra tree classifiers yielded equal accuracy, the decision tree performed better in terms of the F1-score. Random forest being an ensemble algorithm for a decision tree, it adds extra noise, thus decreasing performance metrics. Logistic regression is advantageous for analysing small sample sizes as it considers the combined impact of all predictors. However, it may not be as effective when the predictors have a sequential impact rather than a simultaneous one. Naive Bayes assumes by default that all the attributes are conditionally independent, thus overlooking the possible relations between attributes in the dataset and resulting in low performance.

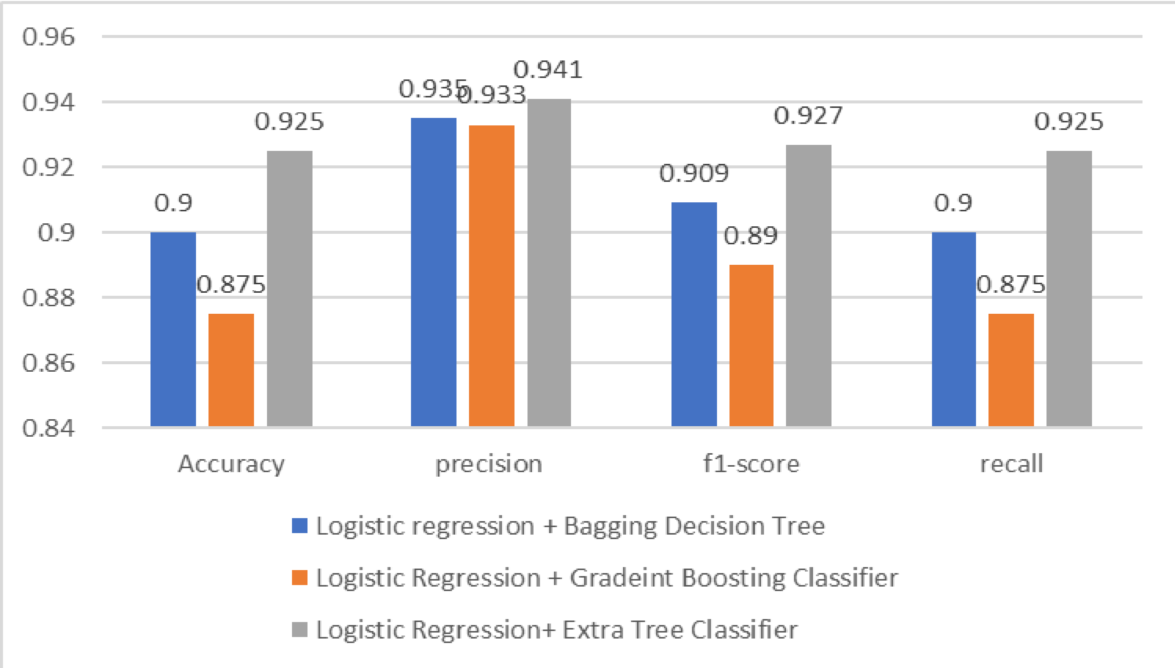

Fig.4. Combination of logistic regression with ensemble classifiers

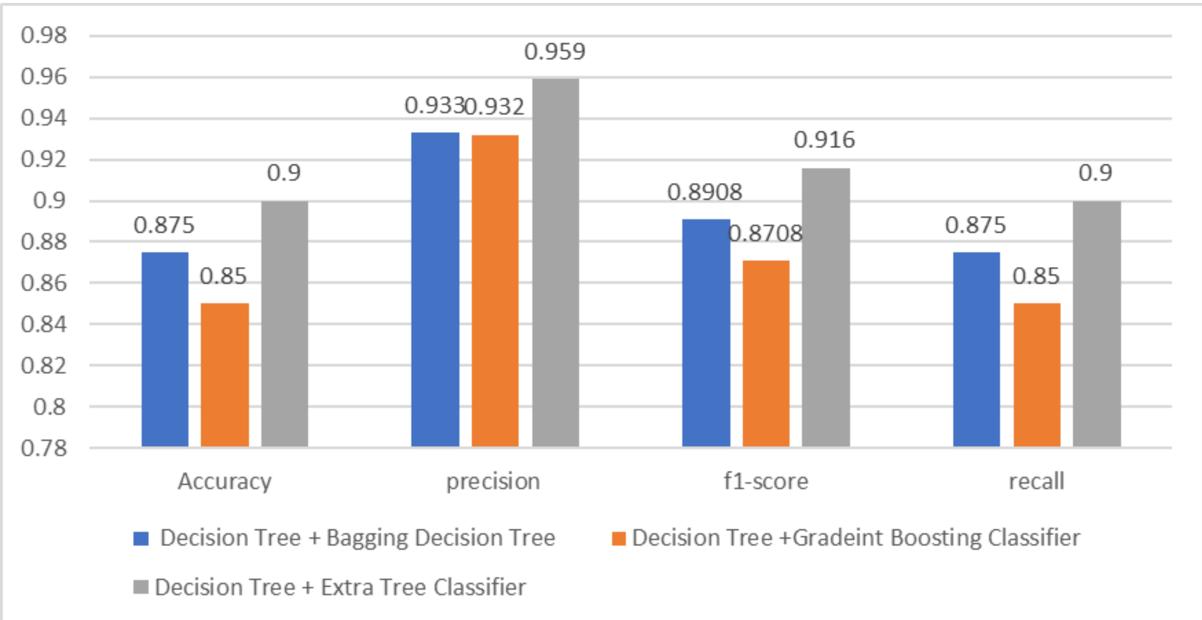

Fig5. Combinations of decision tree with ensemble classifiers

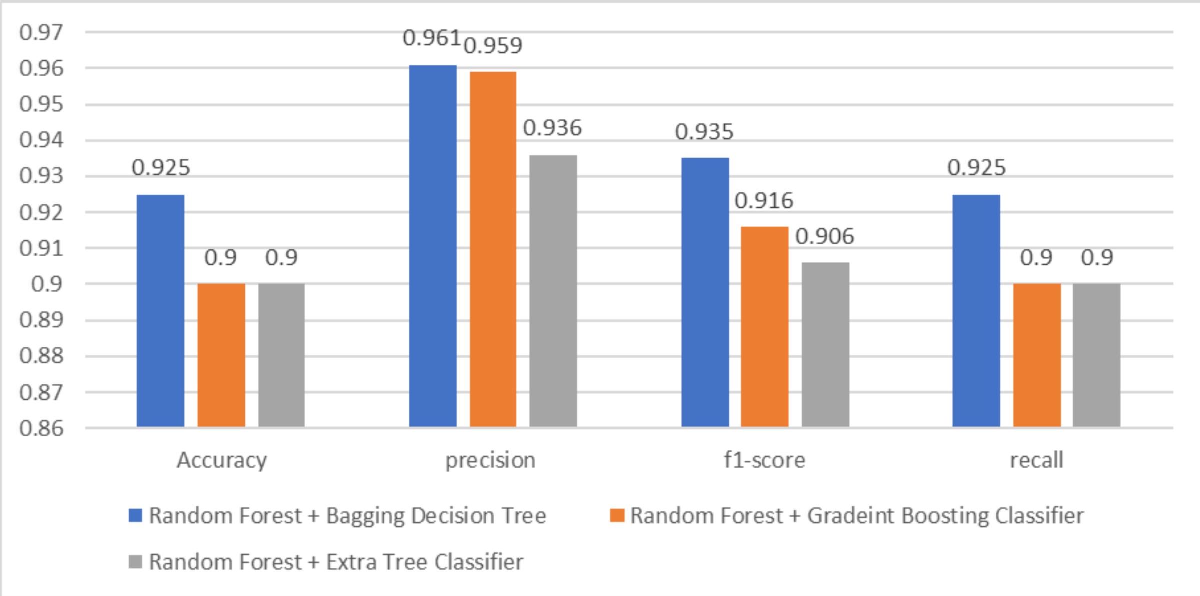

Fig6. Combination analysis of random forest with ensemble classifiers

Fig. 4 shows the combination of logistic regression with ensemble classifiers. Both logistic regression and the extra trees classifier are capable of handling a wide variety of predictor types, including both categorical and continuous predictors. Furthermore, both models can be regularised in order to mitigate the risk of overfitting. This means that both models are versatile and flexible. They perform well as a pair, unlike the bagging decision tree and gradient boosting classifier, which are more prone to overfitting and are not efficient in categorising continuous predictors.

Fig. 5 shows similar trends to Fig. 4. It is observed that logical regression and the additional tree classifier can include both categorical and continuous variables, making them quite flexible. In addition, regularisation can be applied to both models to reduce the possibility of overfitting. So it can be concluded that both models are adaptable and versatile. In contrast to the overfitting-prone bagging decision tree and inefficient gradient boosting classifier, these two methods work well together to classify continuous predictors. This shows the consistency in performance, indicating a pattern of occurrence, as well as the correct selection of responsive attributes.

Figure 6 shows that random forest + bagging decision tree has the highest performing metrics even when compared to decision tree + extra tree classifier. Bagging decision trees and Random Forests are known to be more robust to outliers and better at generalizing to new data compared to Extra Trees. This is due to their ability to build multiple trees on randomly sampled subsets of the data, which reduces the impact of individual outliers and helps to prevent overfitting.

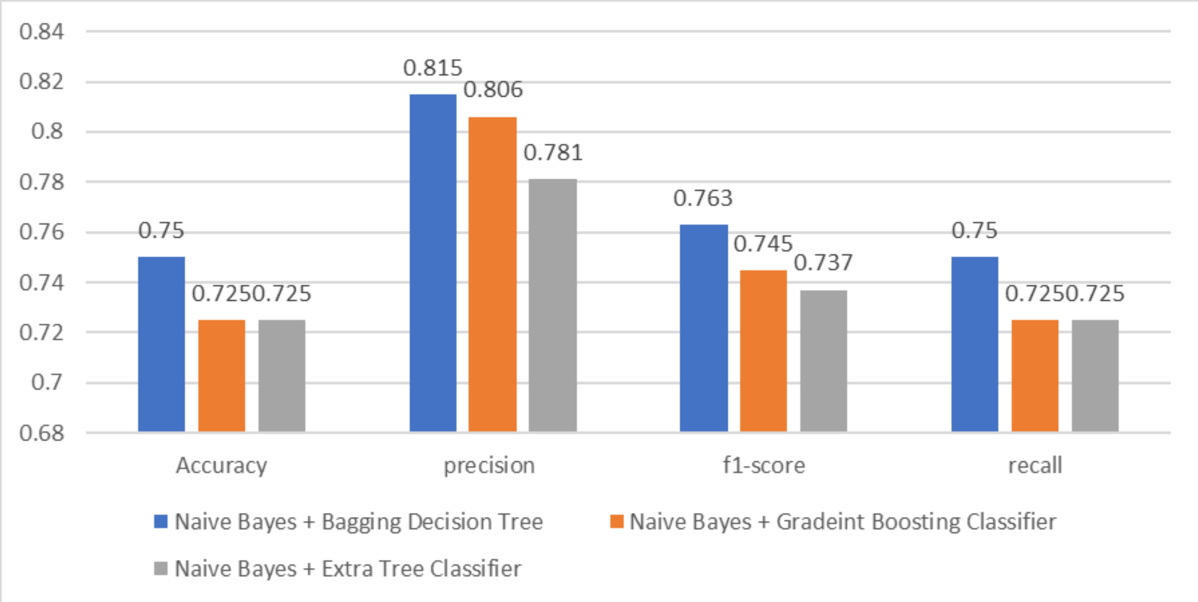

Fig7. Analysis of naive bayes classifier in combination with ensemble classifiers

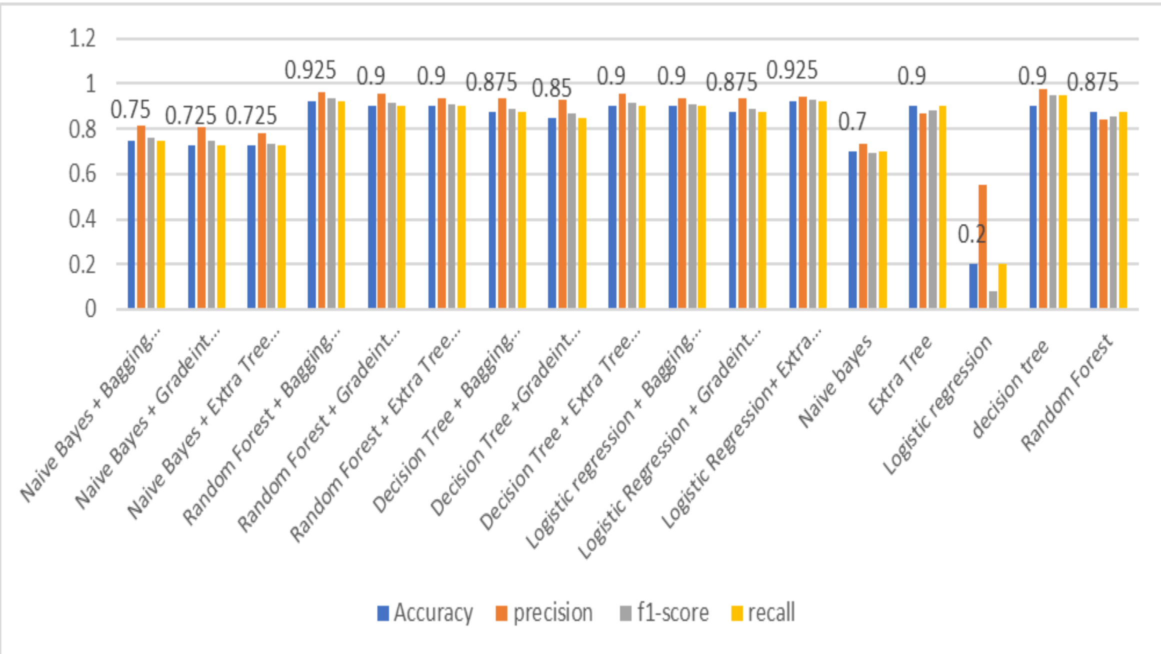

Fig8. Aggregated classification analysis of all the combinations

Fig. 7 shows the analysis of a naive Bayes classifier in combination with ensemble classifiers. It is seen that Naive Bayes, which is a simple probabilistic model, may not be able to effectively capture complex relationships between input features and the class label. Its ability to classify data with complex dependencies may be limited. From Fig. 2, it is clear that there are dependencies among attributes, but the regression models can't completely explain the variance. The life expectancy of a country is indirectly dependent on its GDP. These dependencies result in the suboptimal performance of Naive Bayes.

In terms of accuracy, Figure 8 shows that random forest+bagging decision tree and logistic+extra tree classifiers perform similarly. However, the random forest+bagging decision tree has a better F1 score when compared to the logistic+extra tree classifier. The advantages of Random Forests and Bagging Decision Trees include their ability to effectively handle outliers, their capability to capture complex relationships between input features and the class label, and their ability to reduce overfitting by building multiple trees on randomly sampled subsets of the data. Additionally, the way Extra Trees split nodes randomly without searching for the best split point can lead to less effective feature selection and less accurate decision boundaries, which can limit its performance compared to other ensemble methods like Random Forests and Bagging Decision Trees.

From Fig.2 to Fig.8, the study highlights the non-linear relationship between various attributes and COVID-19 outcomes, with regression models being unable to fully capture the complexity of the relationship. Decision tree classifiers, combined with ensemble methods, showed the best performance for classification, with the random forest and bagging decision tree classifier ensemble method being the most effective.

5. Discussion

This section summarises the analysis and impact of applying the random forest and bagging decision tree classifier ensemble method to the proposed combined dataset. The quantitative analysis is not done as the dataset is seen with some observations on applying the above ensemble based classifier. It is seen that using 14 inputs (pharmaceutical consumption, average years of schooling, obesity, tobacco consumption, alcohol consumption, per capita health expenditure, percentage of health care expenditure, physicians, nurses, beds), and 4 outputs (life expectancy, infant mortality, population aged, and population aged 65 years and older), a study of 114 countries' health systems efficiency found significant differences between them. It is stressed that health expenditures, whether public or private, have a detrimental effect on the efficiency of the health system, whereas education, income, and environment all have favourable effects. Taking both health system variables (doctors, beds, and health expenditure) and external ones (GDP, institutional arrangements, population behaviour, socioeconomic or environmental determinants) into account, the conclusion was that external factors have a greater influence on efficiency than health factors.

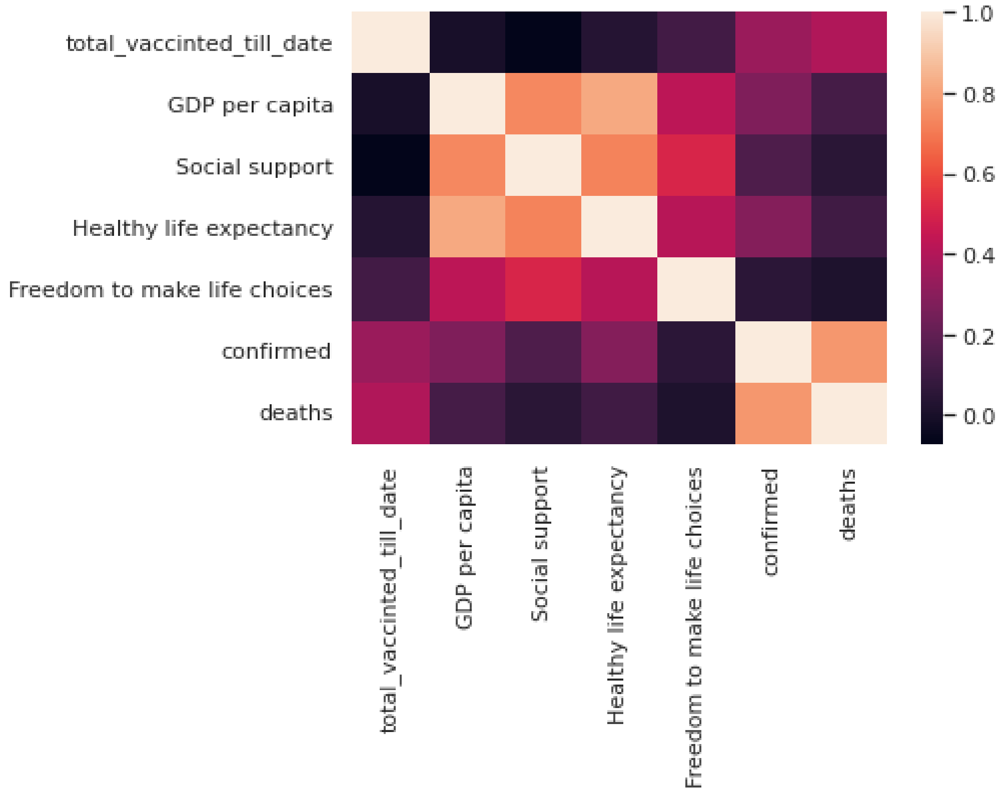

Fig.9 Most biasing factors from the three datasets

It is stated that a variety of characteristics (obesity, smoking, low GDP per capita, and education level) have a detrimental impact on the efficiency of health systems, whereas environmental factors have a positive impact.

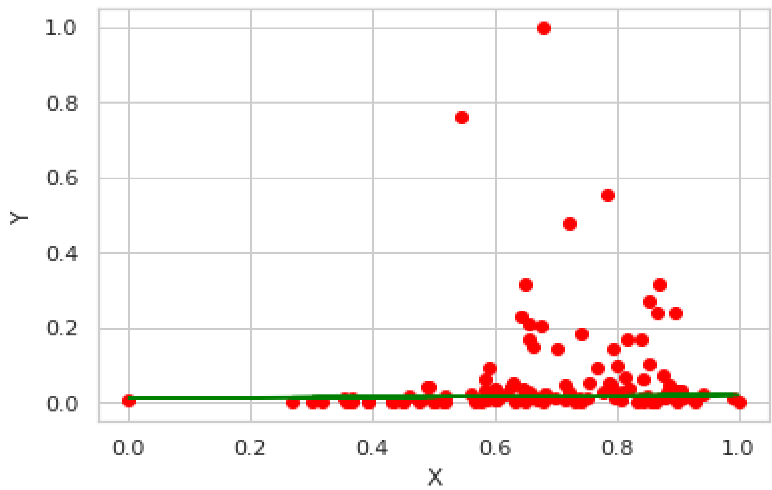

Fig.10 Linear regression (GDP vs deaths)

On Linear regression between the GDP vs Deaths, it is seen that the European states were the most hit by the epidemic during the first period, known as the first wave (January 1–June 15). There were many affected individuals and a high rate of infection in these states. It is important to note that the lack of initial stringent lockdown measures in these nations exacerbated the spread of the disease among communities. Conversely, a huge number of instances of disease did not put strain on the countries of Eastern Europe because of their tight, comprehensive lockdown procedures. As a result, their healthcare systems have not been put through significant testing, which accounts for their current high level of effectiveness. However, if we look at the events of the latter half of 2020, and more specifically, the second wave, we see that this time things are different. Health systems in Eastern Europe revealed their weaknesses in terms of medical infrastructure, medical personnel, and coherent decisions, leading to an extremely high death toll. A regression study revealed that the three parameters of comorbidities, population age, and population density were the most important in explaining the high number of fatalities attributable to COVID-19.

```
print(print_model)

                            OLS Regression Results
==============================================================================
Dep. Variable:                      6   R-squared:                       0.171
Model:                            OLS   Adj. R-squared:                  0.157
Method:                 Least Squares   F-statistic:                     11.87
Date:                Wed, 15 Mar 2023   Prob (F-statistic):           2.06e-05
Time:                        09:42:04   Log-Likelihood:                 73.978
No. Observations:                 118   AIC:                            -142.0
Df Residuals:                     115   BIC:                            -133.6
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.0108      0.046     -0.237      0.813      -0.101       0.080
0              0.5311      0.114      4.647      0.000       0.305       0.758
1              0.0956      0.065      1.463      0.146      -0.034       0.225
==============================================================================
Omnibus:                      119.373   Durbin-Watson:                   1.286
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             2114.149
Skew:                           3.387   Prob(JB):                         0.00
Kurtosis:                      22.599   Cond. No.                         11.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Fig.11 A snapshot of the result of the Multinomial regression (Vaccination, GDP vs Deaths)

By the end of the second wave, several nations had found better ways to deal with the crisis. The first wave hit them hard, but they used what they learned to prepare for the second, when COVID-19 struck again. Managing public health required a mix of hygienic measures (such as donning a mask and washing hands often) and nonhygienic measures (such as shutting down public spaces and cancelling activities) to reduce the spread of disease. Trust in health specialists, an information and warning system, technological engagement, leadership, and participatory governance are all examples of positive population responses that may be traced back to better public management. In addition, a central department was established to coordinate the mobilisation of medical, financial, and legislative resources to combat the COVID-19 pandemic, something that was lacking in the majority of Eastern states (central procurement of medical supplies; central channelling of resources to local departments in need; a central online reporting system and databases; rapid deployment of medical staff from other sectors to intensive care units (ICUs); rapid transformation of Due to improved coordination between healthcare facilities, superior medical infrastructure, better transport systems, increased availability of medical experts, and increased public confidence in them, Western European countries, Asian countries, and the US, which were severely affected in the first stage, have now overtaken eastern states in the second wave. Patients with COVID-19 have been saved thanks to the quick action and extensive resources of the public health system. Throughout each phase of a pandemic, the public health system plays an essential role, beginning with diagnosis and continuing through monitoring and disease management. To illustrate the varying degrees of inefficiency, many European countries were not ready for a health crisis of this size before, and they surely are not now.

International preventative measures may now be developed on the basis of the first year's worth of pandemic experience and the outcomes acquired. As the virus or new strains tend to spread slowly, nations have time to prepare their health care systems in order to mitigate the impact. Also, considering the potential consequences of severe coronavirus mutations, this may result in increased shock resistance. From Fig.11, it is revealed that while certain characteristics have a detrimental impact on health care delivery systems (comobirdies, population age, and population density), others have a beneficial impact (education and government efficacy). Hence, in a global perspective, even though the factors that define health are very essential, the aspect that refers to the cultural, socio-economic, or institutional component should not be overlooked, at least in the medium and long term. The severity of the health issue may also be affected by factors such as the quality of education and government policies. The efficiency score is positively correlated with government effectiveness, underscoring once again the importance of taking the right actions at the right times; however, cultural factors, such as power distance, appear to negatively influence the efficiency of health systems, implying that there are variations in compliance with safety measures based on inequalities in society (related to education, income, etc.). A crucial aspect of the fight against COVID-19 was the fast and successful intervention of governments, as well as the compliance of the populace with these measures.

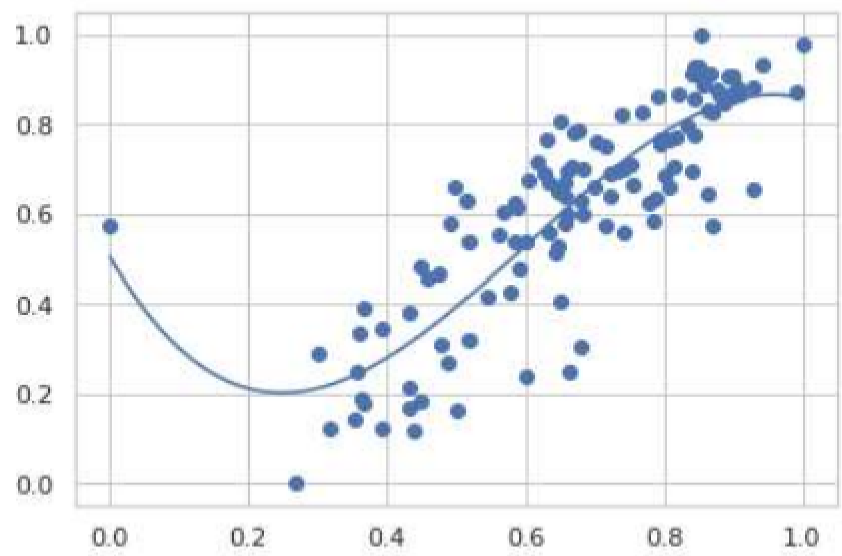

Fig. 12 Polynomial regression Vaccinations vs Deaths (R^2 value= 0.74)

From Fig.12, it is seen that the high contagiousness of the coronavirus necessitates fast and coordinated efforts, despite the fact that they may not be in agreement with the wishes of a portion of the population for many reasons connected to education, culture, level of living, historical context, expectations, etc. There is social separation and even the transmission of false news that this virus does not exist if they do not actively participate in the implementation of government policies, which is why the desired impact cannot be realised. It is imperative that decision-makers have access to periodic training programmes related to the adequate management of crises and that such programmes be offered by specialised institutions. As such, crisis management should be incorporated into school curricula to teach future generations how to respond to shocks of varying types and mitigate their potential negative consequences. Using these measures can set the stage for resource-needs-based decision making in the long run, giving you a boost via adaptation and transformation. There must be a major overhaul of the health care system that not only results in improved services but also in a comprehensive evaluation of the system's administration and medical facilities. Blazes in the intensive care units of some hospitals for infectious diseases in states that have not rationally invested in spending on health budgets are indicative of the fact that, without a clear inventory of inputs and outputs, the decisions will be inconsistent with the current reality and, thus, will fail to ensure national security. Overheating of energy infrastructure has led to the emergence of these circumstances, and the population's reaction to them has been a reduction in faith in the ability of governments to handle crises. So, it is necessary to restore trust through open dialogue, honesty, and the introduction of any measures that can speed up the healing process. The interplay of medical, political, and demographic forces results in an international response to the pandemic. The complexity of the variables (economic, social, technical, and cultural) in the virus's spread should also be taken into account by public decision-makers, since it is essential for surviving the current epidemic.

From this study, the following inferences could be drawn as the result,

- First, stringency was positively correlated with physical distancing, which, in turn, was associated with poor mental health. Second, more robust policy responses were linked to lower ratings of the government's response to the pandemic and, by extension, poorer psychological well-being. Consistent with prior studies, this one found that policy shifts within countries were statistically significant but relatively minor. The effect of unemployment on life satisfaction during the study period was less than a fifth as large as the effect of moving from the minimum to the maximum observed stringency. Furthermore, increasing the length of stringent policy periods does not seem to be associated with worse mental health beyond the initial association but is associated with a continual decrease in deaths. If stringent policies are completely effective at reducing deaths and if the mental health correlates of pandemic intensity are similar or larger in magnitude than those of stringency, then stringency should recoup its negative association with mental health by reducing mortality caused by the pandemic. However, increased stringency is likely to produce different results across countries due to the inconsistent nature of policy design and acceptance. Despite the negative immediate effect of stringency on future psychological distress and life evaluations, our estimates of this dynamic association suggest that this may be partially mitigated by the effect of policy stringency on mortality. Nonetheless, more investigation into these dynamics is required.
- Using elimination and mitigation measures in different nations, researchers found that the two goals need not be mutually exclusive. As poor mental health is connected with both the severity of a pandemic and the strictness of the government response, it stands to reason that COVID-19 management techniques that reduce fatalities and illnesses without raising overall policy rigour would be beneficial. Importantly, the results did not vary when the countries were grouped together.
- Multiple checks and controls lend credence to this interpretation (fortnightly fixed effects, controlling for any events that could affect all countries simultaneously, like the surge of a new variant; fixed effects, controlling for time-invariant confounders; vaccination status and pandemic intensity as time-varying covariates). The observed connection between policy stringency and mental health is substantially less likely to

be driven by paths of reverse causation for the two suggested mediators (physical separation and judgements of the government's pandemic response).

6. Conclusion

The present work analyses the changes in healthcare before and after the COVID-19 pandemic can provide valuable insights into the pandemic's impact on healthcare and inform strategies for constructing more resilient healthcare systems. Adding the World Happiness Index data to the COVID-19 data can also give us more information about the overall well-being of citizens and help us figure out ways to improve their well-being during times of crisis. Our proposed method is a complete way to look at how COVID-19 and other factors relate to each other. We were able to find the most correlated features and turn the regression problem into a classification problem by getting data from many different sources and doing correlation and regression analysis. Combining a decision tree classifier and an ensemble approach resulted in the best classification performance; the most effective ensemble method was a combination of a random forest and a bagging decision tree classifier. Our results give important information about the things that help COVID-19 spread, which can be used to make effective plans to stop the pandemic. Future research can build on our methodology to analyse additional factors and improve the accuracy of the classification models. By making healthcare systems more resilient and focusing on the well-being of citizens, we can lessen the effects of future pandemics and make sure that people all over the world have access to high-quality healthcare and can live happy, full lives.

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