Abstract  World Health Organization (WHO) declared new coronavirus disease, COVID-19 as a pandemic in January 2020 and stated that support is needed for mental health and psychosocial wellbeing during this pandemic. Machine learning is the subset of artificial intelligence which can provide resources to overcome the current mental health crisis during COVID-19. It provides the opportunity to solve challenges with the ability to learn from experiences automatically. This chapter gives useful insight to assess the feasibility and efficacy of artificial intelligence and psychosocial support during the COVID-19 outbreak. The demographic data of Namibia during the infestation period of COVID-19 spread is presented and analysed by statistical methods about age, citizen and gender. Further in this study, a regression model is developed, which gives the relationship between the independent variable which is the date of infestation and a dependent variable which is the number of patients, and the available data is being used to predict the future value of infected COVID-19 outbreak in a similar environment.

Keywords  Artificial intelligence · COVID-19 · Psychosocial support · Mental health

1 Introduction

World Health Organization (WHO) declared new coronavirus disease, COVID-19 as a pandemic in January 2020 [1]. World Health Organization and public health authorities mentioned that this time of crisis is developing stress throughout the world population. World Health Organization stated that support is needed for mental health and psychosocial wellbeing during this pandemic. World Health Organization released a series of messages for the healthcare workers, general population, team
leaders, managers in health services, elderly people, care of children, people with severe health conditions and their careers, and for people in self-isolation [1].

Advancement in computing power, machine learning and data collection methods are developing an interest in artificial intelligence (AI). The effective usage of AI into healthcare can improve quality of care. Artificial intelligence can provide resources to overcome the current mental health crisis during COVID-19. There is a lack of mental health professionals in Namibia and other countries [2]. Artificial Intelligence can provide psychosocial support that an individual can access all the time remotely in the present scenario. Artificial intelligence can be helpful to analyse data faster, advise appropriate treatments and monitor the progress of patient’s.

The demographic data of Namibia during COVID-19 spread is presented and analysed by statistical methods about age, citizen and gender. Various statistical methods are required with certain assumptions to analyses massive data generated during COVID-19. In industrial revolution 4.0, AI is a pivotal approach to analyse a large amount of data efficiently. This chapter gives useful insight to assess the feasibility and efficacy of artificial intelligence and psychosocial support during the COVID-19 outbreak. Machine learning is a subset of AI, and it provides the opportunity to solve science challenges with the ability to automatically learn from their experiences and increase the speed of data interpretation and analysis. The chapter analyses distribution of infestation in different gender, citizens and age group by Chi-square test for association. Simple linear regression analysis was also conducted to predict the relationship between the two variables [3, 4].

1.1 Motivation

With the speedy progression in technology and its application in the medical field, scientists and medical doctors are now looking forward to cure many disease. Research has been done to develop an image aided examination method using CT scan images to find out the pneumonia infection from the lungs. This study also proposes a method to compute the rate of infection in the lungs using the pixel level ratio of the lung region, which is infected [5]. Another study developed an optimised forecasting model by using a new algorithm called a polynomial neural network with corrective feedback. This algorithm is capable of predicting and has comparatively lowest prediction error. This model is advantageous to produce forecast during COVID-19 outbreak [6]. The proposed model helps to detect COVID-19 positive cases using a light-weight CNN-tailored shallow architecture. This model also needs a few parameters, and it has no false positive and chest X-rays is used to find out COVID-19 infected cases [7].

A study suggests that using Composite Monte Carlo (CMC) simulation, which is enriched by adding deep learning network and fuzzy rule induction is a better way to get stochastic understandings about the epidemic spread. The researchers suggested that instead of merely applying Monte Carlo (MC), deep learning incorporated CMC
can be used in combination with fuzzy rule induction so that the decision-makers can get the benefit to forecasting the epidemic in China and the rest of the world [8].

The research proposed a model (Artificial Intelligence Model for COVID-19 Diagnosis and Prediction—AIMDP) using artificial intelligence to diagnose and predict patients infected by COVID-19. Mainly the model has two tasks, firstly the Diagnosis Module (DM), which is responsible for detecting the patient suffering from COVID-19 at an early stage and with accuracy using CT scans. This model also distinguishes it from other viral infections. The DM is based on Convolutional Neural Networks and can process a large number of CT scans in a few seconds. Secondly, the Prediction Module (PM) is for predicting capability of the patient to respond to the treatment based on various factors such as medical condition, age, stage of infection etc. Whale Optimization Algorithm was used in PM to select genuine cases. The results show good performance for both the modules using a large dataset of CT images [9].

As COVID-19 has now attained pandemic status. The WHO has given specific guidelines to manage the problem for both biomedical as well as a psychological aspect. At this stage, preventive action is very crucial but to provide psychosocial support to people suffering from COVID-19 is also essential. According to the researcher best knowledge, a few published literature exists on artificial intelligence and psychosocial support during the COVID-19 outbreak.

Further, the chapter is organised as follows: Sect. 2 gives an update on COVID-19 in Namibia. Recent studies are included in Sect. 3, under the psychosocial support heading. In Sect. 4, some insight is given related to statistical and machine learning methods. Section 5 includes statistical results and discussion. In Sect. 6, linear regression for machine learning is described. Results of regression-machine learning are shown in Sect. 7. Lastly, the conclusion and future scope are mentioned in Sect. 8.

2 Update on COVID-19 in Namibia

The test for COVID-19 was conducted on two traveller’s couple who came to Namibia from Madrid Spain and were immediately quarantined on 13th March 2020 when positive results were found, and contact tracing commenced. This was intensified to ensure that all contacts are traced in order to prevent community spread [3].

The President of the Republic of Namibia addressed the country and said, “The health of Namibians is the first priority. Appropriate precautionary measures must be taken” [4]. The first three cases were travel-related [10]. “As emphasised in my statement, the Health of Namibians is the highest priority. It is why on March 17, 2020, the Government declared the State of Emergency and responded with urgent and aggressive measures to contain the spread of the novel Corona Virus into our communities” [11].

In light of the rising travel-related six cases up to March 24, 2020, of COVID-19 disease in Namibia, Cabinet decided to strengthen the national response and some measures were adopted [11]. State of emergency—COVID-19 regulations: Namibian constitution was Proclamation by the President of the Republic of Namibia
on Saturday 28 March 2020 [12]. The period of lockdown started on 28 March 2020 and ends on 17 April 2020, inclusive of the first and the last day. To date cummatically, 16 confirmed cases are reported in the country. No new confirmed case is reported from 2 April 2020. Three cases are related to local transmission, and 13 cases are imported [13].

3 Psychosocial Support

The coronavirus disease (COVID-19) has been spread in Namibia and all over the world. This COVID-19 pandemic has provoked attention countrywide. It is the need of the hour to look at the psychological effects of quarantines and their family members. People suffering from COVID-19 have psychological distress, and this leads to numerous problems like depression, anxiety, feeling of fear, aloneness, rejection and specially stigmatisation [14].

Besides physical distress, it is normal for COVID-19 patients to go through psychological distress and other mental and physical health-related complications. Psychologists and social workers are not the exceptions as they have to do counselling sessions with the infected patients, family members and relatives. The ministry of health and social services of Namibia has taken several steps to provide psychosocial support by arranging health education, psychosocial support and post counselling services to people under quarantine, COVID-19 confirmed cases and their families. The psychosocial support services are also available through radio talks [13].

As this pandemic is contagious, it is not possible to have one-on-one or face to face counselling sessions. So it is suggested to have online-based mental health intervention programs and counselling. This is feasible by incorporating technology, big data and AI for COVID-19 readiness and preparedness [15]. Mainly psychologists administer different types of psychological tests, assessments, and questionnaires to the patient suffering from COVID-19 to assess their mental state by having contact with each other, by doing this there are chances that the disease can spread vastly. Therefore, we can overcome this problem if all the assessments and their analysis are conducted and assisted with AI and ML algorithms. AI can also bring therapy to more people and at an affordable price [16]. Another difficulty the psychologists are facing in diagnosing the mental health status of the COVID-19 patients. To know about the mental state, regular interactions are needed as symptoms of these disorders change frequently. In this situation of a pandemic, it becomes difficult to have face to face counselling, and it is also not safe to be in contact with the patients frequently.

So there is a need to have additional approaches for counselling and analysing data using AI, such as audio and video analysis because these methods have better objectivity and also have good predictive value. These tools can also monitor the progress of patients. In this situation with limited resources, there is a need for various methods using AI for psychosocial counselling which are readily available and are more productive. By using AI, it becomes easy and fast to analyse extensive data and give a better prediction for the treatment [17].
If AI is successfully integrated into healthcare, it could improve the quality of care of the patients suffering from COVID-19 disease. By introducing AI in psychosocial interventions, this will lead to improving patient outcome like their mental state, and will also balance the workload of health care workers and also to analyse the big data in this situation. It will also be helpful to monitor the trend in which the disease is spreading [17].

Artificial intelligence can serve as an effective way for psychologists to make the best of the time they spend with their clients, and also to bridge any type of gap in access. Data analysis using artificial intelligence can assist psychologists in making their diagnosis faster and accurate and in giving the treatment as soon as possible. Besides this, other programs in which AI is incorporated will allow the psychologists to observe the patients remotely as the positive cases need frequent consultations and this regular touch with the psychologist the patients will feel safe. Programmes incorporating AI can also be helpful to collect data without getting in contact with the patients suffering COVID-19 and analysis can be done faster and accurate. At present, there is a need for such technology to be integrated into counselling sessions to provide psychosocial interventions so that both the patients and the clinicians can get all the benefits by maintaining social distance. For this study, the researcher could only analyse demographic data.

4  Statistical and Machine Learning Methods

The chapter analyses the patients infected by COVID-19 in Namibia. For this study, the author gathered the data for the infected cases by COVID-19 and the date of symptoms onset within one month in Namibia. Patients data are collected from the Ministry of Health and Social Services, Republic of Namibia [13].

4.1 Statistical Models

Firstly the Statistical Package for the Social Sciences (SPSS), the software package is used to analyse the infected cases by COVID-19 and to find out the association between gender, age and citizen [18].

4.2 Machine Learning Models

Further, the researcher has developed the mathematical regression analysis model, which gives the relationship between infected cases by COVID-19, which is the dependent variable, and date of symptoms onset, which is the independent variable. This regression model is implemented with the help of Python 3.7, as it is
an object-oriented and platform-independent programming language used for multidisciplinary research and development in machine learning. In this study, Python3.7 and Jupyter Notebook are used to generate plots and establish regression model for COVID-19 data of Namibia [19]. This study has linear and quadratic regression and built a basic machine-learning model with COVID-19 dataset of Namibia.

The linear regression model is expressed as:

$$\hat{y} = b_0 + b_1 x$$

where $x$ denotes the independent variable and the dependent variable is denoted by $y$. In regression, equation $b_0$ is the constant term, which intercepts the regression line on the vertical axis ($y$) and $b_1$ is called as the regression coefficient. The importing statements and codes of Python 3.7 for scatter plot and regression equation are:

**Algorithm for scatter plot**

```python
# Import 'COVID-19 Patients' data from csv file to DataFrame
import pandas as pd
# Import for creating plots.
import matplotlib.pyplot as plt

# Import library for graphics
import seaborn as sns
# Import library for scientific computing
import numpy as np
# Import library for data visualization

# Read the csv file contents into a DataFrame
data = pd.read_csv("Namibia COVID-19.csv")
data

data.plot('Date of Symptoms Onset','Patients', style='o')
plt.ylabel('COVID-19 Patients')
plt.title('COVID-19 Patients')
plt.show()
```

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plt.ylabel('COVID-19 Patients')
plt.title('COVID-19 Patients')
plt.show()
```
Algorithm for regression equation

```python
# from pandas import DataFrame
import statsmodels.api as sm
date_sym=data['Date of Symptoms Onset']
pat=data['Patients']
# Adding a constant
date_sym=sm.add_constant(date_sym)
# Fit regression model
model=sm.OLS(pat, date_sym)
results=model.fit()
# Analysis result of the developed model
print(results.summary())
```

5 Statistical Results and Discussion

Tables 1, 2 and 3 show that several COVID-19 infested males (75%) were significantly higher than females (25%) $P = 0.043$. Nevertheless, the difference between Namibian and non-Namibian citizens was non-significant $P = 0.130$. Though 68.8% infested persons were Namibians and 31.2% were non-Namibians. The trend was almost the same in both the genders. In males, 66.7% Namibians and 33.3% non-Namibians similarly in females, 75.0% were Namibians, and 25.0% were non-Namibians. This distribution was also independent as Fisher’s exact probability was 1.00.

Table 4 shows that maximum infestation was in the age group 14–34 years (50%) it was followed by 35–59 (31.2%), 60–79 (12.5%) and was minimum in 1–14 (6.2%) age group.

### Table 1  Males and females infested with COVID-19 in Namibia

|        | Female | Male | $\chi^2$ | DF | P    |
|--------|--------|------|----------|----|------|
| Count  | 4      | 12   | 4.00     | 1  | 0.043|
| %      | 25.0   | 75.0 |          |    |      |

### Table 2  Namibian and non-Namibian citizens infested with COVID-19

|        | Non-Namibian | Namibian | $\chi^2$ | DF | P    |
|--------|--------------|----------|----------|----|------|
| Count  | 5            | 11       | 2.250    | 1  | 0.130|
| %      | 31.2         | 68.8     |          |    |      |
Table 3  Relationship between citizens and genders

| Citizen          | Gender | Male | Female |
|------------------|--------|------|--------|
| Non-Namibian     | Count  | 4    | 1      |
|                  | % within gender (%) | 33.3 | 25.0   |
| Namibian         | Count  | 8    | 3      |
|                  | % within gender (%) | 66.7 | 75.0   |

Fisher’s exact probability = 1.00

Table 4  Distribution of COVID-19 infestation in different age groups

| Age (year) | 1–14 | 15–34 | 35–59 | 60–79 | $\chi^2$ | DF | P  |
|------------|------|-------|-------|-------|----------|----|----|
| Count      | 1    | 8     | 5     | 2     | 7.500    | 3  | 0.056 |
| %          | 6.2  | 50.0  | 31.2  | 12.5  |          |    |     |

Table 5 indicates that in each age group, male were more infested than females. This distribution indicated that infestation was associated with the movement of persons.

The age group and gender are having more movement having more infestation and change according to the movement of other age groups. However, on account of a smaller sample, the $\chi^2$ test was not justified.

Table 6 presents the relationship between age and citizenship of the COVID-19 positive cases. The trend of infected patients was the same in both Namibians and non-Namibian citizens and was similar to the age group except a few exceptions. In Namibians, the maximum frequency was in the most active age group 15–34 (54.5%) followed by 35–59 (27.3%).

The age group 1–14 and 60–79 having an equal frequency, i.e. 9.1%. Similarly, in non-Namibians, more frequency was in the age group 15–34 and 34–59, i.e. 40%

Table 5  Relationship between age and gender

| Age in years | 1–14 | Count | Male | Female |
|--------------|------|-------|------|--------|
|              |      |       | 1    | 0      |
|              |      | % within gender (%) | 8.3  | 0.0    |
| 15–34        |      | Count | 5    | 3      |
|              |      | % within gender (%) | 41.7 | 75.0   |
| 35–59        |      | Count | 4    | 1      |
|              |      | % within gender (%) | 33.3 | 25.0   |
| 60–79        |      | Count | 2    | 0      |
|              |      | % within gender (%) | 16.7 | 0.0    |
Table 6  Relationship between age and citizen

| Age in years | Count | Citizenship |
|--------------|-------|-------------|
|              |       | Namibian | Non-Namibian |
| 0–14         | 1     | 1 | 0 |
|              | % within citizen (%) | 9.1 | 0.0 |
| 15–34        | 6     | 2 | 4 |
|              | % within Citizen (%) | 54.5 | 40.0 |
| 35–59        | 3     | 2 | 4 |
|              | % within citizen (%) | 27.3 | 40.0 |
| 60–79        | 1     | 1 | 2 |
|              | % within citizen (%) | 9.1 | 20.0 |

Table 7  The determinant of quadratic regression analysis

| Sn | Type of patients  | R square | Variability explained (%) |
|----|-------------------|----------|----------------------------|
| 1. | All               | 0.980    | 98.00                      |
| 2. | Male              | 0.992    | 99.20                      |
| 3. | Female            | 0.977    | 97.70                      |
| 4. | Namibian          | 0.956    | 95.60                      |
| 5. | Non Namibian      | 0.825    | 82.50                      |
| 6. | Age 14–34         | 0.972    | 97.20                      |
| 7. | Age 35–59         | 0.902    | 90.20                      |
| 8. | Age 60–79         | 1.000    | 100.00                     |

in each. Rest of the 20% patients were in the age group 60–79 the youngest one age group 1–14 did not have any patient. Chi-square test again on account of a smaller sample size could not be justified.

From the Table 7 the determinant of quadratic regression analysis revealed that the date explains 98.00% of change in several patients. It was true in all the groups of patients but, varies from 90.2 (age 35–59) to 100% (age 60–79).

The analysis of variance for quadratic regression analysis (Table 8) revealed that regression explained the variability of patients significantly in all the groups except females, non-Namibian and age group 35–59.

6 Linear Regression for Machine Learning

Linear regression algorithm is one of the frequently used algorithm in statistics. It is a type of supervised machine learning and is used to create a linear regression model for the analysis of the tasks.
Table 8 ANOVA for quadratic regression analysis

| Sn | Type of patients | DF Reg | DF Err | MS Reg | MS Err | P    |
|----|------------------|--------|--------|--------|--------|------|
| 1. | All              | 2      | 13     | 166.589| 0.525  | 0.000|
| 2. | Male             | 2      | 9      | 70.937 | 0.125  | 0.000|
| 3. | Female           | 2      | 1      | 2.442  | 0.115  | 0.152|
| 4. | Namibian         | 2      | 8      | 52.607 | 0.598  | 0.000|
| 5. | Non Namibian     | 2      | 2      | 4.124  | 0.876  | 0.175|
| 6. | Age 14–34        | 2      | 5      | 20.422 | 0.231  | 0.000|
| 7. | Age 35–59        | 2      | 2      | 4.512  | 0.488  | 0.098|
| 8. | Age 60–79        | 1      | 0      | 0.5    | –      | –    |

6.1 Regression Analysis

Linear regression model is used to express the association between the dependent and independent variables.

The use of a linear regression model is to describe the relationships between the dependent variable and a set of independent variables. The principle behind the simple linear regression model is that there is only one independent and one dependent variable.

The goodness-of-fit measure of the regression model measures with the help of the coefficient of determination called R-squared (R²). So, the strength of the relationship between the independent variable and the dependent variable is measured by R-squared.

The estimated regression equation is used for estimation and prediction values. With the help of regression analysis, the model for significant can be tested. So it determines how well the model fits the data and can be used for the hypothesis testing. Thus, the regression analysis technique is beneficial where the cause and effect have to be measured between variables. This model can be used for process optimisation. If there are many independent variables, we can say which independent variable is a more important variable that affects the dependent variable.

The simple linear regression model shows the relationship between the dependent variable (y) and an independent variable (x) and also an error term.

The simple linear regression model is:

\[ y = \beta_0 + \beta_1 x + \epsilon \] (2)

where \( \beta_0 \) and \( \beta_1 \) are called parameters of the model, and \( \epsilon \) is a random variable known as the error term.

Independent variable (x) itself is not enough to predict the dependent variable (y) as there may be some unknown variable other than x and the error due to that unknown variable is called error term.
The estimated linear regression equation is the expectation of \( E(y) = \hat{y} = \beta_0 + \beta_1 x \), where \( \beta_0 \) is the y-intercept of the regression line, \( \beta_1 \) is the slope of the regression line, and \( E(y) \) or \( \hat{y} \), is the expected value of \( y \) for a given \( x \) value.

When a comparison is made between the linear regression model and the estimated linear regression equation, an error term is also present in the equation because the error was minimised by using least squares method during the formation of the equation.

**Least squares method**

The principle behind the least square method is the sum of the square of the error has to be minimised so that line is the best.

**Least square criterion:** \[ \min \sum (y_i - \hat{y})^2 \] (3) where \( y_i \) is the observed value of the dependent variable for the \( i \)th observation and \( \hat{y} \), is the estimated value of the dependent variable. Therefore, an error is the total of the square of the difference of actual value minus the predicted value of the dependent variable. This sum of the error square has to be minimised.

The beauty of this error squared the transformation is if there is a lesser deviation, there is a lesser penalty and if there is a larger deviation larger penalty. For example, for the low value the difference of \( y_i - \hat{y} \), is 0.4 then the square is 0.16 but for high value, suppose the deviation is four then the square is 16.

### 6.2 Estimation Process

In Fig. 1, we assume a regression model \( y = \beta_0 + \beta_1 x + \epsilon \) and this regression will be predicted with the help of regression equation, and that is expected value \( E(y) = \hat{y} = \beta_0 + \beta_1 x \). In the population regression model \( y = \beta_0 + \beta_1 x + \epsilon \) the unknown parameters are \( \beta_0 \), \( \beta_1 \), and \( \epsilon \). However, the unknown parameters are \( \beta_0 \) and \( \beta_1 \). Furthermore, there is no error term in the population regression equation.

We have to estimate the value of \( \beta_0 \) and \( \beta_1 \). If the estimated value of \( \beta_0 \) and \( \beta_1 \) that means there is no relation between the independent variable (\( x \)) and the dependent variable (\( y \)).

In this chapter, the gathered sample data for COVID-19 infested cases in Namibia are the date of symptoms onset (\( x \)) as an independent variable and patient (\( y \)) as the dependent variable. With the help of the data, a regression equation \( \hat{y} = b_0 + b_1 x \) is developed and is applicable only for the sample data.

Hence, \( \hat{y} = b_0 + b_1 x \), where \( x \) is an independent variable and \( \hat{y} \) is the estimated dependent variable and \( b_1 \) is the slope of the sample regression equation line and \( b_0 \) is the intercept (the value of \( y \) when \( x = 0 \)).

Now we have to estimate whether the value of the slope of the sample regression equation line \( b_1 \), and the intercept \( b_0 \) is valid even for the population (slope of the population regression model \( \beta_1 \), and the intercept \( \beta_0 \)).
So with the help of the sample regression equation, we can construct the population regression model. Expected regression equation at the population level is $\hat{y} = \beta_0 + \beta_1 x$ however, when we estimate the value of $\beta_0$, it may not be significant at population-level.

However, with the help of a sample mean ($\bar{x}$) we have predicted population parameter mean ($\mu$), with the help of sample variance ($s^2$) we have predicted the population variance ($\sigma^2$) and with the help of sample proportion ($p$), we have predicted population proportion ($P$).

We have some $x$ and $y$ value from the sample and predicted regression equation $\hat{y} = \beta_0 + \beta_1 x$. Now we have to validate whether this relationship is valid even for the population.

Sometimes when a regression equation is constructed with the help of sample data, there is an association between an independent variable ($x$) and the dependent variable ($y$). However, when we test with the population, there is no relation between $x$ and $y$.

Therefore, there is a difference between regression modelling and hypothesis testing. In hypothesis testing, only one parameter is tested at a time and can predict the mean or variance or population proportion.
6.3 Regression Model

Now a regression model is constructed with the help of sample data, and we will test this model in the population level. With the help of sample data, we have to find out the value of $b_1$ which is called the slope. The slope is the covariance divided by the variance of the independent variable. The slope ($b_1$) is calculated as:

$$\text{Slope (} b_1 \text{)} = \frac{\text{CoV}(x, y)}{\text{Var}(x)} \quad (4)$$

$$\text{CoV} (x, y) = \sigma_{x,y} = \frac{\sum(x - \bar{x})(y - \bar{y})}{n - 1} \quad (5)$$

The variance formula includes only the independent variable (x).

$$\text{Correlation Coefficient} = \frac{\text{CoV}(x, y)}{\sigma_x \sigma_y} \quad (6)$$

$$\text{Variance}(x) = (s^2) = \frac{\sum(x - \bar{x})^2}{n - 1} \quad (7)$$

$$\text{Slope (} b_1 \text{)} = \frac{\text{CoV}(x, y)}{\text{Var}(x)} = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sum(x - \bar{x})^2} \quad (8)$$

Therefore, the slope ($b_1$) for the estimated regression equation is calculated by the following formula using least squares method:

$$\text{Slope (} b_1 \text{)} = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sum(x - \bar{x})^2} \quad (9)$$

Now we have to calculate y-intercept ($b_0$) for the estimated regression equation using the least squares equation:

$$\bar{y} = b_0 + b_1 \bar{x} \quad (10)$$

$$b_0 = \bar{y} - b_1 \bar{x} \quad (11)$$

where:

- $\bar{x}$ mean value for independent variable
- $\bar{y}$ mean value for dependent variable
- $n$ total observations.
7 Results of Regression-Machine Learning

Linear regression or Ordinary Least Squares regression (OLS) results are shown in Table 9. The linear regression model is \( \hat{y} = -4.5343 + 0.6320x \), where \( x \) is the date of symptom and \( y \) is the patient (Table 9). Regression analysis will evaluate:

\[
\hat{y} = -4.5343 + 0.6320x \tag{12}
\]

7.1 Plot at Mean Value of Date of Symptoms Onset and Infected Cases

```python
date_sym = data['Date of Symptoms Onset']
pat = data['Patients']
plt.figure()
sns.regplot(date_sym, pat, fit_reg=True)
plt.scatter(np.mean(date_sym), np.mean(pat), color='green')
```

In Fig. 2, the X-axis is the date of symptoms onset (independent variable), and

| Table 9 | OLS regression results |
|---------|------------------------|
| Dep. variable: | Patients | R-squared: | 0.954 |
| Model: | OLS | Adj. R-squared: | 0.950 |
| Method: | Least Squares | F-statistic: | 287.3 |
| Date: | Sat, 18 Apr 2020 | Prob (F-statistic): | 1.00e-10 |
| Time: | 17:01:15 | Log-likelihood: AIC: | -22.603 |
| No. observations: | 16 | BIC: | 49.21 |
| Df residuals: | 14 | | 50.75 |
| Df model: | 1 | | |
| Covariance type: | Nonrobust | | |
| const | coef | std err | t | P>|t| | [0.025 | 0.975 |
| Date of symptoms onset | -4.5343 | 0.814 | -5.573 | 0.000 | -6.279 | -2.789 |
| | 0.6320 | 0.037 | 16.949 | 0.000 | 0.552 | 0.712 |
| Omnibus: | 1.160 | Durbin-Watson: | 0.457 |
| Prob(Omnibus): | 0.560 | Jarque-Bera (JB): | 0.881 |
| Skew: | -0.291 | Prob(JB): | 0.644 |
| Kurtosis: | 2.008 | Cond. No. | 67.0 |

Note: Standard Errors assume that the covariance matrix of the errors is correctly specified. Kurtosis test only valid for \( n \geq 20 \)
the Y-axis is the number of patients (dependent variable). The confidence interval is very narrow when $x = \bar{x}$. The estimated regression equation $-4.5343 + 0.6320 \times x$ provides an estimate of the relationship between the dates of symptoms onset $x$ and patients $y$. If the date is increased by one unit, patients will be increased by 0.6320 unit.

The F test value is 287.3 for the entire model, which shows the $P$-value = 0.000. The results show a statistically significant linear correlation between the two variables. Coefficient of determination (R squared) value tells how well the regression predictions estimate the actual data points.

The value for R squared is between 0 and 1 that states that how well the line fits the data set. An $R^2$ of 1 represents that the regression predictions fit the data perfectly. The value closer to 1, the better the line fits the data set and to draw correlation conclusions from the graph, so we want to be reasonably close to 1. So with an $R^2$ of 0.954 (Table 9), we can conclude that the variance of $y$ (number of patients on the date) explains 95.4% by the $x$ (date of symptoms onset).

8 Conclusions

In Namibia, the first COVID-19 infested patient was found on 9th March 2020. After that, the increase in the number of patients was reported with the increasing
date following quadratic regression. This trend was true for all the type of patients viz., males, females, Namibian, non-Namibian and different age groups. Except for gender, no significant difference between the groups was there. The frequency of COVID-19 positive was significantly higher in males than in females. The frequency revealed that positive cases were more in the more exposer/movable group. Further, this study develops a linear regression model, which gives the relationship between the independent variable and dependent variable. The available data is being used to predict the future value of infected COVID-19 cases in a similar environment.

In this study, the researcher mainly attempts to see the trend in which the COVID-19 pandemic will spread in future using machine learning and the analysis is conducted based on only one-month data. Overall, AI can benefit and support mental health specialists in doing their work. Algorithms are capable of analysing data much faster in comparison to humans, can recommend possible treatments, can easily keep an eye on a patient’s recovery and can also alert the practitioner if there are any concerns. At present, in Namibia, there are no data available related to psychological variables to see the effect on the COVID-19 positive cases. In this COVID-19 crisis, AI and a human practitioner should work together to provide appropriate psychosocial support to the community. In future, this work can be extended if related data is available, and the analysis will be done by using artificial intelligence.

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