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Machine learning based model for detecting depression during Covid-19 crisis

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ABSTRACT

Covid-19 has impacted negatively on people all over the world. Some of the ways that it has affected people include such as Health, Employment, Mental Health, Education, Social isolation, Economic Inequality and Access to healthcare and essential services. Apart from physical symptoms, it has caused considerable damage to mental health of individuals. Among all, depression is identified as one of the common illnesses which leads to early death. People suffering from depression are at a higher risk of developing other health conditions, such as heart disease and stroke, and are also at a higher risk of suicide. The importance of early detection and intervention of depression cannot be overstated. Identifying and treating depression early can prevent the illness from becoming more severe and can also prevent the development of other health conditions. Early detection can also prevent suicide, which is a leading cause of death among people with depression.

Millions of people have affected from this disease. To proceed with the study of depression detection among individuals we have conducted a survey with 21 questions based on Hamilton tool and advise of psychiatrist. With the use of Python's scientific programming principles and machine learning methods like Decision Tree, KNN, and Naive Bayes, survey results were analysed. Further a comparison of these techniques is done. Study concludes that KNN has given better results than other techniques based on the accuracy and decision tree has given better results in the terms of latency to detect the depression of a person. At the conclusion, a machine learning-based model is suggested to replace the conventional method of detecting sadness by asking people encouraging questions and getting regular feedback from them.

Introduction

Sudden outbreak of the Covid-19 pandemic was an unexpected shock to the countries. Every country's well-being is dependent on its citizens' health but individuals may experience panic as a result of such outbreaks. There are several reasons that Every country's well-being is dependent on its citizens' health. When a large portion of the population is

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unhealthy, it can lead to decreased productivity, increased absenteeism, and higher healthcare costs. This can negatively impact the country's economic growth and development. When individuals are suffering from poor health, they may be less able to participate in social activities, and may also be more likely to experience social isolation. The health of a nation's population can also have an impact on its political stability. For example, a population suffering from poor health may be more likely to experience political unrest and social conflict. A healthy population is vital for achieving a high quality of life for all citizens. When a significant portion of the population is unhealthy, it can lead to decreased life expectancy, increased disability, and reduced overall well-being. A healthy population is important for the educational development of a country. Poor health can lead to absenteeism and lower academic performance, which can negatively impact the overall educational attainment of the population.

The World Health Organization (WHO) officially designated COVID-19 as the new designation for the novel coronavirus on February 11, 2020, citing concern about the virus's potential for worldwide spread. The mental health of people affected and those who are close to them is always at risk when a disease suddenly goes into pandemic. It is more common for people who have been identified or are suspected to experience stress, despair, rage, and other psychological issues. Patients may fear passing away, and medical professionals treating COVID-19 patients may fear that the virus will infect their loved ones, friends, or other close associates. [1]. Excess deaths are defined as deaths that surpass what would be expected under "normal" conditions. It includes deaths that have been positively confirmed as well as COVID-19 deaths that have been incorrectly identified and registered as well as fatalities brought on by the broader crisis scenario. [2,3]. This provides a more thorough and dependable estimate than solely certified COVID-19 deaths. Some countries only keep track of COVID-19 deaths that occur in hospitals or among people who've already tested positive for the virus [4,5]. Furthermore, many nations are unable to properly quantify or record the causes of morbidity and mortality due to inadequate or underfunded health information systems. A few examples of how this can occur are; Lack of access to health information: When health information systems are inadequate or underfunded, it can be difficult for healthcare providers to access important patient information, such as medical history and test results. This can lead to misdiagnosis, delayed treatment, and increased morbidity and mortality. Inaccurate or incomplete data: Inadequate or underfunded health information systems can lead to inaccurate or incomplete data, which can in turn lead to poor decision-making by healthcare providers. This can result in inappropriate treatment, increased morbidity and mortality. Limited surveillance and monitoring capabilities: An underfunded health information system may not have the capability to conduct adequate surveillance and monitoring of disease outbreaks and other public health threats. This can lead to delays in identifying and responding to outbreaks, which can result in increased morbidity and mortality [6,7].

Lockdowns have been established as a result of the COVID-19 outbreak in a number of countries, and this has been associated with an increase in domestic violence and violence between intimate partners. As a result of financial insecurity, stress, and uncertainty, there has been an increase in aggressiveness, and abusers are now able to control a significant portion of their victims' day-to-day lives in the house. The COVID-19 pandemic has had an impact on educational systems around the world, forcing almost all schools, colleges, universities, and other educational institutions to close their doors. Not only do students, their families, and communities suffer when a school is closed, but also the economy and society at large. The effects were significantly worse for underprivileged kids and their families. Depression can have significant effects on children and their families, especially when they are living in poverty or underprivileged conditions. Some of the effects of depression that may be worse for underprivileged children and their families include, Poor academic performance: Children experiencing depression may have difficulty concentrating, which can lead to poor academic performance and difficulty completing school work. This can be further exacerbated for underprivileged children who may have limited access to resources such as tutoring or educational enrichment programs. Limited access to mental health services: Children from underprivileged backgrounds may have limited access to mental health services, which can make it difficult for them to receive an accurate diagnosis and appropriate treatment for depression. This lack of access can be due to lack of knowledge, fear of stigmatization, or financial barriers. Increased stress: Children from underprivileged backgrounds may experience increased stress due to their living conditions, which can exacerbate symptoms of depression. This can include exposure to violence, poverty, food insecurity and lack of stable housing.

This led to disruptions in schooling, poor nutrition, difficulty with childcare, and a financial burden for families who were unable to work. The labor market is going to feel the effects of COVID-19 to a major degree. Some of the ways in which the labor market is likely to be affected include: Job Losses: The pandemic has led to widespread job losses across many industries, including hospitality, travel, retail, and entertainment. Many businesses have been forced to close or scale back operations, leading to a sharp increase in unemployment. Reduced hours and wages: Even for those who have not lost their jobs, many have experienced reduced hours and wages as a result of the pandemic. This is particularly true for workers in industries that have been hit hard, such as hospitality and retail. Remote work: The pandemic has accelerated the trend towards remote work, as many businesses have been forced to shift their operations online. This has led to a change in the nature of work, as well as a change in the way in which businesses operate.

Many of us are in a bad situation right now since our income has completely dried up and some companies have fired staff in order to avoid paying for the time that COVID-19 has been active in the nation. Many of us are now in dire financial problems as a result of this. [8]. Covid-19 established a permanent trend for marketing to adopt a similarly adaptable approach. A corporation may discover as the crisis develops that its message was ineffective or that its supply chain was unable to meet demand, posing an urgent issue with its public relations and/or advertising. [9,10]. The good outcome of the crisis was the establishment of a marketing flexibility philosophy that is likely to persist. Companies have been forced to be more flexible in their marketing strategies, as traditional methods of reaching customers such as in-person events, trade shows, and print advertising have become less effective. As a result, companies have turned to digital marketing channels such as social media, email marketing, and online advertising. This shift has led to an increase in the use of data analytics and targeting techniques, which has allowed companies to better understand their customers and tailor their marketing efforts to specific segments of their audience. This comprises continual customer listening and market sensing for marketing objectives as well as to help the entire firm grasp the consumer mood zeitgeist [11,12]. It also implies quicker decision-making processes and improved flexibility in critical areas like as media, finance, and creative [13,14].

Daily, millions of people experience depression, yet only a small fraction of them receive adequate treatment. Doctors used to conduct face-to-face interviews with sad persons and use diagnostic criteria defined by a licensed psychologist to diagnose depression. These interviews are typically conducted one-on-one and can include a variety of different types of questions and assessments. Some of the ways in which doctors conduct face-to-face interviews with sad persons include: Structured diagnostic interviews: Doctors may use structured diagnostic interviews, such as the Diagn Interview Schedule for Children or the Structured Clinical Interview for DSM-5, to assess for the presence of specific symptoms of depression and other mental health disorders. Clinical observation: During the interview, doctors may also observe the individual's behavior, nonverbal communication, and overall demeanor to gain insight into their emotional state. Open-ended questions: Doctors may ask open-ended questions to encourage the individual to share their thoughts and feelings about their experiences. Standardized questionnaires: Standardized questionnaires such as the Patient Health Questionnaire (PHQ-9) or the Beck Depression Inventory (BDI) may be used to assess the severity of depression symptoms and monitor changes over time. Physical examination: The doctor may also conduct a physical examination to rule out any underlying medical conditions that may be contributing to the individual's symptoms.

A depressed individual is unhappy, anxious, and hopeless all of the time, loses interest in daily activities, and suffers from a variety of physical and mental health issues. Depression is serious social problems that is become more prevalent during Covid-19. Many people are affected by this disease, yet only a small percentage of them receive therapy. When compared to other mental health issues, depression ranks second in the world. Suicide is a result of depression. Depression is the primary cause of suicide among young people. Early disease detection is essential to halting its global spread and preventing young individuals from committing suicide. When depression is identified early, individuals can receive appropriate care and support before their symptoms become severe. This can help to reduce the duration and severity of the illness, and improve the chances of recovery. Early detection also allows for the identification and support of individuals who may be at high risk for suicide. Suicide is the second leading cause of death among young individuals, and early identification and intervention can help to prevent suicide and save lives. Depression comes in a variety of forms. Depression in its early stages is easily treatable. However, a person suffering from severe depression needs special attention and care [15]. Although there are some similarities, depression is not the only emotion that can be felt following a horrific occurrence or the loss of a loved one [16,17]. Grief does not usually result in self-hatred or a loss of identity, although depression commonly does. While someone is mourning, positive thoughts and joyful remembrance of the dead typically coexist with emotional sorrow [18,19]. Sadness is a continuous feeling in those suffering from major depression. It's vital to remember that feeling melancholy on occasion is a normal part of life. Everyone has terrible and unsettling experiences. However, if you constantly feel gloomy or hopeless, you may be depressed [20,21]. Different studies have revealed the use of machine learning approach for detection of depression. Techniques such as supervised and unsupervised learning are used for classification of text. Supervised learning is a technique where a model is trained on labeled data, meaning that the model is provided with both input data and the corresponding correct output. The model then learns to make predictions on new, unseen data. In the case of text classification, the input data would be text documents, and the output label could be a category such as "positive" or "negative" sentiment. Some examples of supervised learning algorithms for text classification include logistic regression, support vector machines (SVMs), and naive Bayes. Unsupervised learning, on the other hand, is a technique where the model is not provided with labeled data, but instead must find patterns or structure in the input data on its own. One example of an unsupervised learning technique for text classification is clustering, where the model groups similar documents together. Another example is topic modeling, where the model learns to identify the main themes or topics present in a set of documents.

Supervised learning techniques include Nave Bayes Classification, Neural Networks, Support Vector Machines, and Maximum Entropy. On the other hand, unsupervised learning techniques include lexicon-based learning, dictionary-based learning and corpus-based learning [22]. The objectives of our study are: To analyze the existing machine learning techniques of detecting depression and to propose the Python based scientific programming model for identifying depression with the help of collective responses. Common machine learning techniques: characteristics, benefits, and drawbacks of common machine learning techniques now used in research on healthcare outcomes is shown in Table 1.

There are several machine learning techniques that have been used to detect depression, including: Supervised learning: In this technique, a model is trained on labeled data, where the input is text data such as social media posts, text messages, or speech transcripts and the output is a depression diagnosis. The model learns to make predictions on new, unseen data. Some examples of supervised learning algorithms used in depression detection include logistic regression, decision trees, and support vector machines. Unsupervised learning: This technique is used to identify patterns or structure in the input data, without the need for labeled data. In the case of depression detection, unsupervised learning algorithms such as clustering or topic modeling can be used to identify patterns in the text data that are indicative of depression. Natural Language Processing (NLP): NLP is a set of techniques used to analyze and understand human language. NLP can be used to

Table 1
Common Machine learning techniques: characteristics, benefits and drawbacks.

Methods	Intuition	Advantages	Disadvantages
Regularization	Estimators that include a greater number of covariates, particularly correlated covariates, should be penalized so as to reduce overfitting (multicollinearity)	Improves generalizability and helps provide consistent results that are less sensitive to modest changes in estimator choices. Produces more minimalistic (simple) estimators.	When there are multiple predictors that are highly associated with one another, it is possible to choose the "wrong" predictor. This makes the computation more difficult.
Factor analysis, principal component analysis, K-means, hierarchical clustering, and neural networks are examples of unsupervised learning techniques	By assessing how strongly significant traits of the people or organisations represented in the data correspond with one another, one can group the data into basic "dimensions"	May help researchers organize people or institutions based on preset criteria by identifying underlying commonalities in tough or noisy data.	It is impossible to measure accuracy; rather, the intuition and experience of the researchers is what defines how valuable the outcome is.
Decision trees	The data should be sequentially separated into categories based on the values of particular attributes.	Easily open to multiple interpretations.	Having a tendency to be too tight.
Boosting gradient machines made of a group of decision trees	Fit a number of decision trees to weighted resampled subsets of the data, with the predictions of one tree's failures guiding the improvement of the next tree based on those failures.	Among modern machine learning techniques, typically performs best (lowest error between expected and observed outcomes) when dealing with tabular data.	Because inference involves more work from the researchers to "tune" the estimators to get optimal performance, it is more effective for prediction because it does not explain the mechanism underlying the outcomes.
Ensemble of decision trees: random forest	One can either a) average the generated trees (for regression) or b) select the tree with the majority of votes after applying several decision trees to bootstrap-resampled copies of the data (for classification).	The estimators can be easily "tuned" by researchers to ensure that they are quick to implement and running at maximum efficiency.	Does not explain the process by which the outcome was achieved; as a result, prediction rather than inference are its main applications.
Neural networks, deep learning	A series of data transformations that yields abstractions or generalisations from the data by repeatedly iterating through many layers of transformations and using the outputs of one set of transformations as inputs for the next.	can help in the prediction of outcomes with extremely complex, nonlinear linkages and interactions and can be used to more accurately assess the risk of an outcome from extremely large, noisy, nontabular datasets.	High processing power is needed, additional study is needed to "tune" the estimators for best performance, and because the results' mechanism is unknown, prediction is preferred to inference.
Machine learning meta-learners	creates a summary forecast of an outcome among them by using many machine learning algorithms.	Even if the underlying machine learning estimators do not contain the "actual" prediction function, ensembles can nevertheless provide a very accurate approximation.	It requires a lot of time and computing resources, does not explain how a result arises, making it better for prediction than inference, and may even encourage "fishing" among many methods to achieve high performance without an explanation from the start.

extract features from the text data such as sentiment, emotion, and language structure, which can then be used as inputs to a machine learning model. Deep Learning: Deep learning algorithms such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have also been used for depression detection from text data. These algorithms are able to learn complex representations of the input data, and have been shown to be effective at detecting patterns in text data that are indicative of depression.

Literature review

Many academics have demonstrated that the information provided by the user can aid in determining a person's mental level. As a result, the user overview in SNS makes it simple to acquire all of the information linked to an individual's attitude and negativism. By using SNS as a data source and artificial intelligence as a selection tool in this study, the author provided a novel technique to categorize users [23]. By organizing the UGC using two separate classifiers—Vector Machine Support and Naive Bayes Support—the author develops the model. Patients are then classified into one of four categories: minimum, medium, moderate, or severe depression. It was intended for the three outcomes' outputs, including sentiment analysis, SVM results, and Naive Bayes results [24]. Recognizing one's feelings or opinions is the aim of a feeling evaluation. Methodologies for sensitivity analysis may provide useful tools and methods for monitoring mental illness and depression. This study offers useful techniques for diagnosing depression. Identification and applications of sentimental analysis [25]. With the use of social media, it is simple to identify depression from people's messages. The author of this study uses cognitive theory, machine learning methods, and approaches to natural language processing to extract emotions from text in order to investigate a person's state of depression. The author distinguished between SVM, NB, and ME classifiers on sentence-level sentiment analysis for the sadness aspect and recognised the voting model and feature selection technique. The result shows that SVM is larger than Naive Bayes and Maximum Entropy classifiers. [26]. According to the experts, sadness and other mental diseases can be detected in various online contexts. Technological advancements in natural language manage and machine learning approaches are beneficial [27]. In this study, the author uses four cutting-edge machine learning classifiers—Naive Bayes, J48, BF Tree, and One R—to optimize sentiment analysis. Three manually created datasets—two from Amazon and one from IMDB movie reviews—are used in the testing [28]. The amount of effort put into using machine learning and natural language processing techniques to identify depression. In this research, a system is developed for tracking tweets from Twitter users as well as sending updates when the worried individual is noticed. This type of six-author strategy also allows social workers to reach out to disturbed persons in the early stages of their illness [29]. Sentiment analysis is a branch of NLP study that aims to characterize textual subjectivity and aids in the extraction and classification of people's ideas, beliefs, perceptions, judgments, evaluations, and emotions regarding services. Sentiment analysis can be divided into a number of categories, including such as Polarity classification, Subjectivity classification, Aspect-based sentiment analysis, Emotion detection, Stance detection, Irony detection and Multi-language sentiment analysis. Various fields such as marketing, politics, and sociology are being investigated using this technique. Here is a more detailed look at how each field has been affected: Marketing: The COVID-19 pandemic has had a profound impact on the marketing industry. With businesses shutting down and consumers spending more time at home, digital marketing has become even more important. Politics: The COVID-19 pandemic has had a significant impact on politics. Governments around the world have had to respond quickly to the crisis, implementing measures such as lockdowns and travel bans. The pandemic has also highlighted existing political and economic inequalities and has led to increased public scrutiny of government handling of the crisis. Sociology: The COVID-19 pandemic has had a significant impact on society. The pandemic has highlighted existing social inequalities, with marginalized communities and low-income households being disproportionately affected. The pandemic has also led to increased isolation and loneliness, as well as increased stress and mental health issues [30]. Sentiment analysis is a relatively young field of Natural Language Processing (NLP) research that seeks to discover the subjective components of written text as well as extract and categorize the opinions and sentiments represented in that content. The term "sentiment analysis" refers to the study of people's emotions, ideas, opinions, attitudes, evaluations, assessments, and reactions to particular services, items, people, organizations, issues, themes, and events as well as their features.

Emotion analysis is a means of automatically representing qualities in other people's ideas regarding specific items, services, or experiences. Opinion mining is a term used to describe the enormous potential of the views being analysed. Building an automated system that can recognize and classify emotions is the aim of sentiment analysis. [31]. Emotion analysis refers to the technique of identifying and interpreting the emotions expressed in textual material. The technique of identifying and interpreting emotions expressed in textual material is known as sentiment analysis or opinion mining. This technique is used to automatically extract subjective information from text, such as opinions, appraisals, evaluations, appraisals, affect, or sentiments. There are several techniques that can be used for sentiment analysis, including Machine Learning, Natural Language Processing, Rule-based systems and Hybrid systems Based on the emotions expressed in the text, such as fear, fury, happiness, grief, affection, motivation, or neutral, the tasks of emotion detection and classification can be completed quickly. These emotions include, among others, fear, fury, joy, grief, affection, and motivation. Sentiment analysis is an important part of how organisations connect with customers through their websites and online portals [32,33]. In collaborative post processing recommendation systems, emotion comprehension and sentiment analysis are essential. assembling and displaying relevant materials to customers who have similar responses to a particular product Based on a variety of criteria, sentiment analysis can be divided into a number of categories. [34,35]. Depending on the scope, it can be divided into three categories: sentiment classification at the word level, sentiment analysis at the sentence level, and sentiment analysis at the sub-sentence or phrase level. [36,37]. The highest level of communication in society is social networking. Because of the widespread use of social networking, it is clear that most people shun one-on-one engagement. It involves multiple stakeholders, such as healthcare providers, community organizations, government agencies, and individuals affected by depression. This kind of communication would involve the following key elements include Raising awareness, Encouraging help-seeking behaviors, Providing access to resources, Training healthcare providers, Coordination and collaboration and Data collection and analysis. Social networking has its particular civilization, which spreads interpersonal contact between individuals, groups, and cultures around the world. This is the main reason why many prefer it over face-to-face interaction. In addition, the hybridization technique has been utilised to improve classification accuracy in sentiment analysis. The machine learning classification algorithm used to classify sentiment tweets into positive, negative, and neutral has a 90% accuracy rate. There are several machine learning classification algorithms that can be used to classify sentiment in tweets. Some of the most popular ones include such as Naive Bayes, Logistic Regression, Support Vector Machines, Random Forest, Deep Learning [38].

An internal model that recognizes the polarization of signals in machine learning is one that has the ability to identify the orientation or direction of the signal without the need for normalization. This means that the model can distinguish between signals that are positively or negatively polarized, even if the magnitude or intensity of the signal is not standardized. This can be useful in many applications where the direction or orientation of the signal is more important than its absolute value, such as image or speech recognition. By using an internal model that recognizes the polarization of signals, the need for normalization is reduced, allowing the model to focus on the more important information and make faster and more accurate predictions. The internal model recognises the polarization of the signals in this publication, obviating the necessity for normalization. The algorithm's performance improves with this internal model. The algorithmic technique, in addition to the findings, illustrates the application's well-organized functioning, and this strategy is also effective for preventing suicide attempts due to cyber-depression [39]. The author of this essay proposed a method for separating people into displayer and non-displayer depression. The developed strategy uses Facebook as a reliable tool for noticing independent depression patterns [40]. The author looked at spatial patterns and used GIS methodologies to analyze social media. The program uses GIS technology to classify distressed Twitter users and analyze spatial sketch. This strategy can help to enhance depression behavior policies [41]. Machine learning, lexicon-based, and hybrid systems all have different classifiers. The classifier must evaluate the risks associated with each categorization decision. A mathematical approach to pattern classification is known as Bayesian decision theory. Comparing and contrasting various classification choices is the major objective. The main goals are to identify the reasons why some NB classifiers perform better than others and to assess how much the standard judgement technique is the optimum course of action. The study of probabilistic binary classifiers, according to the author, will benefit from a new viewpoint provided by this new geometrical knowledge of the decision function. Naive Bayes (NB) classifiers are a family of simple probabilistic classifiers based on applying Bayes' theorem with strong (naive) independence assumptions between the features. These classifiers have been widely used in text classification tasks, due to their simplicity, speed and good performance in many cases. Some reasons why some NB classifiers may perform better than others include: Feature engineering: The performance of a NB classifier can be heavily influenced by the features used as input. Some feature engineering techniques, such as stemming and stop-word removal, can help improve the performance of a NB classifier by removing noise and irrelevant information from the text data. Data preprocessing: Data preprocessing techniques such as data cleaning, normalization, and feature scaling can also play a crucial role in improving the performance of a NB classifier. Model tuning: The performance of a NB classifier can also be improved by fine-tuning the model's parameters, such as the smoothing parameter or the prior probabilities. Training dataset: The performance of a NB classifier is heavily influenced by the quality and size of the training dataset. A NB classifier trained on a large, high-quality dataset is more likely to perform well than a classifier trained on a small or low-quality dataset. [42]

According to the author, data analysis in the psychology industry can be used to identify dissatisfied users of social online applications. Emotion analysis is presented first, according to the author, like the application of terminology and manufactured criteria like measure depression. This hypothesised process is then used to create a depression detection model, but this depression model is based on Chinese terminology [43].

A popular classification method is the Naive Bayes classifier. This classifier is straightforward to recognize, and classifiers are much easier to use. The experimental results have proven the efficacy of this algorithm versus different techniques [44]. The word feature level of text categorization performs well under the Naive Bayes assumption of attribute independence when there are multiple attributes, the independence assumption allows the parameters of each attribute to be learned separately, greatly simplifying the learning process. These parameters may include such as Textual features, Demographic features, Behavioral features, Physiological features and Social support. By learning these parameters separately, the algorithm is able to focus on one aspect of the data at a time, rather than trying to process all of the information simultaneously. This greatly simplifies the learning process and can lead to more accurate detection of depression. There are two different event models. The multi-variate approach makes use of a document event model, where characteristics of the event are the binary occurrence of words. Here, the model—which is a more straightforward model—fails to take into account word repetitions inside the same page. Instead, a multinomial model should be utilized, where a multinomial distribution takes into account numerous word occurrences, if multiple word occurrences are significant. In this case, the words cause the happenings. Following **Algorithm 1** explains the step-by-step procedure implemented in python based scientific programming to detect the depression:

1. Open web-app
2. Fill Details:
2.1. Enter: personal details
2.2. Answer: lifestyle questions
2.3. Answer: behavioral questions
2.4. Enter: 7-day sentiment records
2.5. Submit Form
3. Prepare data by scaling, missing value treatment, and dimensionality reduction as required.
4. Provide prepared data to model
5. Predict a class value for new data:
Input: Training dataset T,
F= (fi, f2, f3,.., fn) in testing dataset. // value of the predictor variable
Output: A class of testing dataset.
Step:
5.1. Read the training dataset T;
5.2. Calculate the mean and standard deviation of the predictor variables in each class;
5.3. Repeat
Calculate the probability of f; using the gauss density equation in each class;
Until the probability of all predictor variables (fi, f2, f3,.., fn) has been calculated.

5.4. Calculate the likelihood for each class;
5.5 Get the greatest likelihood;
5.6: The class with greatest likelihood will be our predicted class
6. Set depression level as per predicted class
6.1. If the predicted class is 1: then depression level → mild
6.2. If the predicted class is 2: then depression level → moderate
6.3. If the predicted class is 3: then depression level → severe
7. Return: depression level

As cases of the coronavirus sickness 2019 (COVID19) grew, panic buying occurred all around the world, indicating that the condition was more of a psychological problem than a public health one. We know very little about how the pandemic has affected psychological impacts, stress, anxiety, and depression. This longitudinal study conducted two surveys of the general public between the initial outbreak and the peak epidemic four weeks later, gathering information on demographics, symptoms, awareness, concerns, and COVID-19 preventative measures. [45]. to assess the levels of stress, anxiety, and depression that doctors felt during the Covid-19 outbreak, as well as any associated conditions in both clinical and non-clinical contexts. During the Covid-19 outbreak, an online survey is run to learn more about the psychological responses of healthcare professionals and related topics. The following subjects are covered in three subsections: 1) Socioeconomic and demographic data 2) Information on a person's employment condition 3) A questionnaire called the Depression Anxiety and Stress Scale-21 evaluates depression, anxiety, and stress (DAS-21) [46]. The purpose of this study was to discover characteristics among young individuals residing in the United States during the COVID-19 era that were linked to PTSD, anxiety, and depressive symptoms. This cross-sectional online survey looked at 898 participants between April 13, 2020, and May 19, 2020, roughly one month after the US proclaimed a state of emergency due to COVID-19 and before the initial easing of restrictions across the 50 US states. Asian Americans were less likely than whites to report having serious mental health issues, whereas Hispanics/Latinos were less likely to report having severe anxiety. One of these components is the initial suggestions for the clinical care of mental health issues related to COVID-19. [47].

Sentiment analysis is a subfield of NLP research that helps in the extraction and categorization of people's ideas, opinions, perceptions, judgments, evaluations, and emotions surrounding services. Its goal is to characterize textual subjectivity. There is no need for normalization because the internal model recognises the polarization of the signals in this publication. With this internal model, the algorithm performs better. Machine learning, lexicon-based, and hybrid systems all have different classifiers. The classifier must evaluate the risks associated with each categorization decision. Rumours, a flood of information in the media and on the internet, changes in daily routines, economic shifts, stigma, solitude, and guilt all lead to heightened anxiety. The latter three parts must be dealt with by patients and their families [48,49]. Anxiety is often characterised by anxiety, ruminating, and a fear of developing or transmitting a disease to others. It can also manifest as unease, jitteriness, shaking, tachycardia, tightness of the chest, and difficulty breathing [50,51].

The different people which are affected by this disease. Depression is a mental health disorder that can affect people of all ages, genders, and backgrounds. Some of the different groups of people who may be particularly affected by depression include: Women: Women are more likely to experience depression than men, with hormonal changes, pregnancy, and menopause being some of the risk factors. Seniors: As people age, they may experience increased feelings of isolation and loneliness, which can increase the risk of depression. Children and adolescents: Children and adolescents are also at risk of depression, particularly if they experience bullying, trauma, or family conflict. People with chronic illnesses: People with chronic illnesses such as cancer, heart disease, or diabetes may be at an increased risk of depression due to the physical and emotional toll of their condition. People with a family history of depression: If someone has a family member who has been diagnosed with depression, they may be at a higher risk of developing the condition themselves. People who have experienced significant life changes: People who have recently experienced a traumatic event, such as the loss of a loved one, a divorce, or a job loss, may be more likely to develop depression. People who struggle with substance abuse: People who struggle with substance abuse may also be at a higher risk of developing depression, as substance abuse can be both a cause and a symptom of depression. People with low socioeconomic status: People with low socioeconomic status may have a higher risk of developing depression due to increased stressors and fewer resources to manage them.

Major challenges faced by the individuals post pandemic.

1. Impact of social isolation and quarantine on mental health:

Right after the quarantine period is complete, people typically exhibit post-traumatic stress disorder (PTSD) symptoms as emotional instability, rage, insomnia, and despair. Alcohol misuse, post-traumatic stress disorder (PTSD), feelings of worry, wrath, and sorrow, as well as changes to behavioural patterns like avoiding crowded settings and methodically washing hands, are just a few of the significant and pervasive long-term effects. Patients may continue to have these psychological symptoms after the quarantine period is ended for anything between a few months and three years.

2. After the recovery from Covid-19, mental health difficulties

When COVID-19 patients need to be hospitalised during the acute stage of the illness, delirium is a usual symptom that shows up. The prevalence of anxiety, depression, and post-traumatic stress disorder may be higher in this patient population than in previous corona virus outbreaks, severe acute respiratory syndrome (SARS), or Middle East Respiratory Syndrome (MERS), despite the fact that the information on long-term psychiatric issues in this patient population is still not fully understood.

3. Impact of mental health on front-line healthcare workers

During the Covid-19 pandemic, up to 60% of physicians, nurses, and medical residents frequently report psychological effects such anxiety, melancholy, and insomnia (Que et al.;, 2020). These symptoms are expected to linger for a number of years after the pandemic has passed. HCPs who practised respiratory medicine experienced a noticeably greater degree of psychological symptoms, such as anxiety, depression, and post-traumatic stress symptoms, a year after the SARS pandemic in 2003. I was becoming bothered by these signs.

4. Social injustices, the post-COVID-19 economic downturn, and its effects on mental health

The prevalence of mental health conditions such anxiety, depression, substance use disorders, and suicidal ideation has been shown to rise during economic downturns. Post-recession mental health problems appear to be linked to decreased socioeconomic position, job insecurity, unemployment, and the incidence of pre-existing psychiatric diseases.

5. Pandemic stigma associated with COVID-19

The stigmatization of people with HIV/AIDS and COVID-19 survivors is to blame for cases of harassment, stereotyping, discrimination, social isolation, and even physical violence. Anxiety, depression, and emotional disturbance are among the mental health conditions that are more prevalent in stigmatised individuals.

Research methodology

From review of literature, it is identified that many methods and equipment are employed to identify depression. Techniques like machine learning, lexicon-based analysis, supervised learning, unsupervised learning and deep learning techniques etc. are being used to identify that the person is depressed or not. The action plan is based on texts, photographs, videos, as well as emotions, among other things. Between all of these procedures, it is analysed that most of the studies are based on tools and questionnaire. Such tools and questionnaire use the negative aspects of life to detect the depression. In our work we have proposed the pattern to study positive aspects of life with weekly surveys for the detection of depression.

Data collection

To apply machine learning techniques on the survey dataset, questions were framed with responses such as yes, no, sometimes and not applicable. To detect the depression of an individual a threshold value is defined in the range of 0–21(score). If obtained score is 0–6 then individual is not depressed and if computed scored of individuals the individual is in between 7 and 14, has mild depression. If obtained score is 15–20 then the individual has moderate depression. If the score is 21, in that case the individual has severe depression. Three threshold levels are used such as 7, 15, and 21 for the detection of depression. Question description with received response (in%) is presented in Table 2 below.

Data description

The Hamilton Rating scale, which is utilised by the majority of psychiatrists, is employed in a survey of 21 questions to determine a person's mental condition. The Hamilton Depression Rating Scale is the instrument that is most frequently used to assess depression symptoms (HAM-D or HDRS). It has been used in a number of significant research on depression and its treatment. Doctors must utilize the tool to evaluate the patient's symptoms following an organised or unstructured discussion with the patient to learn about their symptoms. The overall score is calculated by adding the individual points for each question. Depression is typically absent or in remission when a score falls below 7.

- Mild depression is represented by scores of 7 to 17.
- Scores of 18 to 24 indicate mild depression.
- Scores of 25 and higher indicate serious depression.

While people with moderate depression commonly remit spontaneously or respond to psychological (talking) therapies, those with severe depression are more likely to benefit from a mix of treatments that may involve biological therapy like drugs.

The majority of depression studies consider therapy to have "responded" when a patient's score decreases by more than 50%. Remission usually refers to a score of less than 7.

The survey yielded a total of 1694 records. A survey may ask about a person's age, gender, education, occupation, annual income, marital status, place of residence, whether they have a pet, their use of social media, and other personal and professional information. After the collection of responses from the questionnaire, the four positive questions are added such as there is a pet at home, social media usage of individual, is there any park nearby home. After adding the positive questions, there will be the one-week survey of an individual basis on sentiment scale. A purified version of data after completing Exploratory Data Analysis (EDA) is compiled and analysed during the study. Fig. 1 shows sentiment scale for weekly record.

Table 2
Question description with received response (in%) is presented.

Question Description	Response [%]			
	Yes	No	Sometimes	NA
Losing interest in social activities	21.1	27.0	51.9	–
Loss of Energy or excessive tiredness	30.3	24.2	45.4	–
Losing excitement in activities those used to excite earlier.	22.8	26.3	51.0	–
Prefer sitting alone	23.4	25.3	51.3	–
Less interactive as per people's point of view	37.9	62.1	–	–
Persistently feels sadness of mood.	36.5	63.5	–	–
Often noticed having frequent crying spells.	38.5	38.5	23.1	–
Less Confident	63.9	40.2	–	–
Facing difficulties in planning and executing tasks	52.0	32.2	15.8	–
Have you become indecisive?	55.0	45.0	–	–
Facing concentration issues.	58.1	41.9	–	–
Persistently Feeling of self-worthlessness	51.8	48.2	–	–
Feeling of empty and emotional numbing	60.5	39.5	–	–
Feeling of hopelessness	62.2	37.8	–	–
Do you feel that nobody understands you?	60.4	39.6	–	–
Do you have sleeping disturbance?	29.0	54.5	16.5	–
Feeling changes in Appetite and Significant Weight lose	54.8	45.2	–	–
Feeling often restless or being slowed	36.8	63.2	–	–
Ever thought of attempting suicide (Deliberate self-harm/death wishes/ ideation / made plans / attempted)	40.4	59.6	–	–
Do you think these symptoms are present persistently for more than two weeks?	40.0	43.2	–	16.8
Do you feel these symptoms put a significant impact on your Social / Occupational /Family or other important areas of your life?	68.1	13.4	–	18.5

sentiment	lonely	sad	not_happy	feel_nothing	neutral	happy	very_happy
sentiment_scale	-3	-2	-1	0	1	2	3

Fig. 1. Sentiment scale for weekly records.

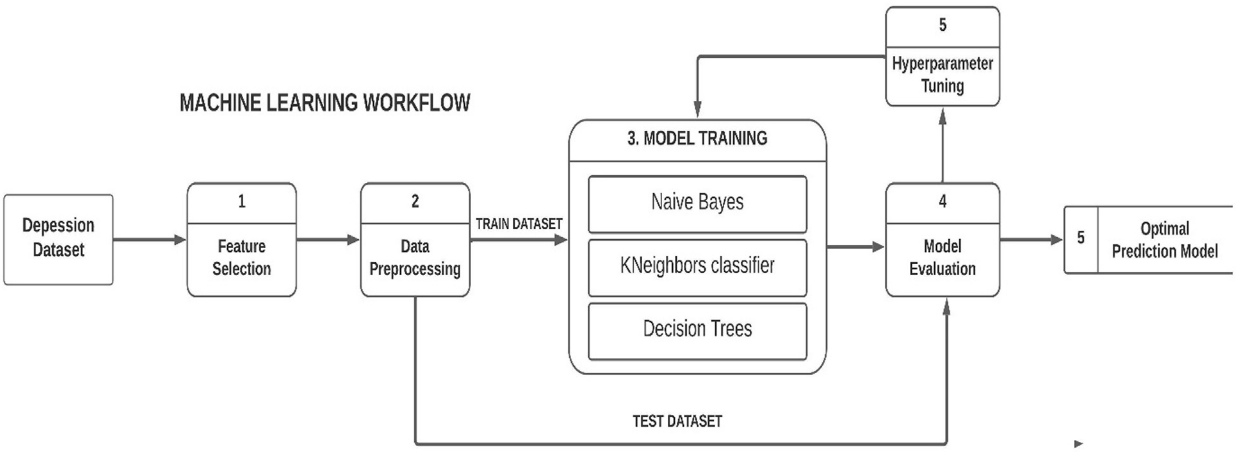

Fig. 2. Workflow of scientific programming based proposed model.

Proposed methodology

The depression dataset will be used for feature selection in the model that was proposed, which is shown in Fig. 2. Following the completion of the initial processing of the data, the model will next be trained using various machine learning approaches, including Naive Bayes, KNN, and Decision Tree. The questionnaire for the pre-processed data will be based on the Hamilton tool, and it will cover positive characteristics such as whether or not an individual has a pet and whether or not there is a park nearby. In addition, the weekly comments of individuals will be included in the pre-processed data. At the end, the model will be assessed to determine whether it provided the best possible prediction.

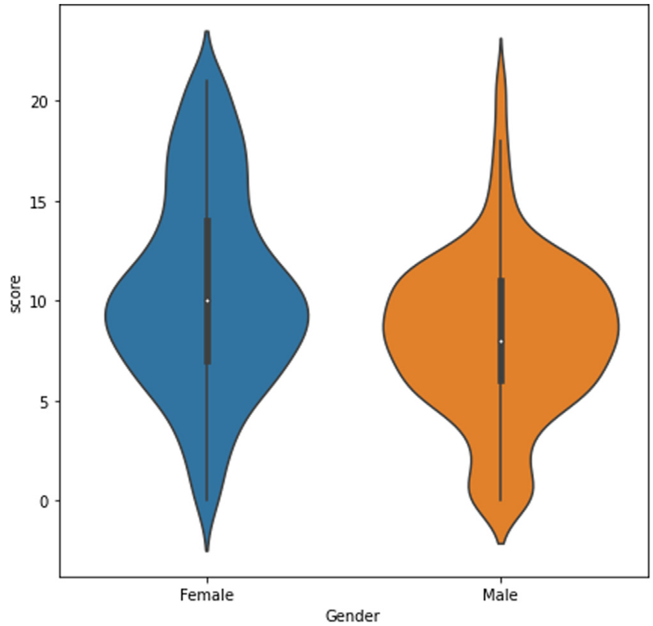

Fig. 3. Depression level on the basis of Gender.

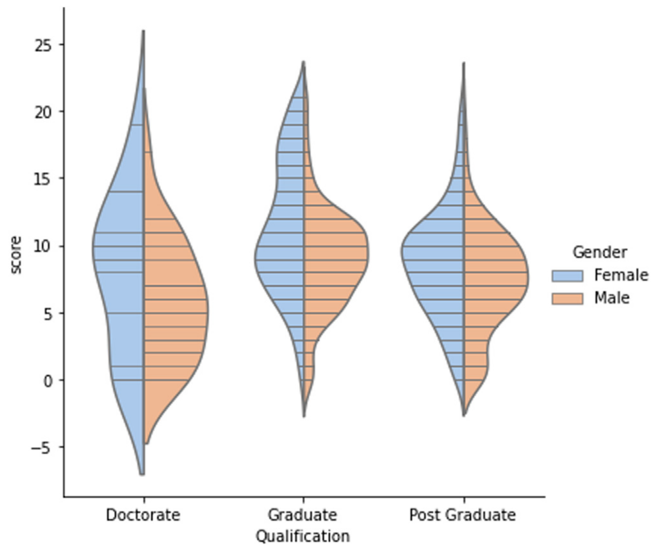

Fig. 4. Depression on the basis of qualification.

Results and discussions

We have presented the scientific programming-based analysis implemented in Python, on the basis of categorical analysis Fig. 3 presents that most of the males seem to have depression score between 5 and 12 while on the other hand females seem to have a more distributed score value. 56 percentages of females are identified as suffering from depression as compared to males.

Fig. 4 represents that most people with doctorate have less depression level instead of graduate and postgraduates. Also, females with graduation have more distributed depression scores than ones with higher degrees. At the graduate level, 60 percent of females have a higher level of depression instead of males.

Fig. 5 shows the depression level in males and females on the basis of annual income. Study shows that females with no income seem to have less stress such as housewives. Also, the males with high income (as per dataset) have less stress but on the other hand males with no income and low income have the highest level of depression. It has been observed that females have high level of depression as comparative to males.

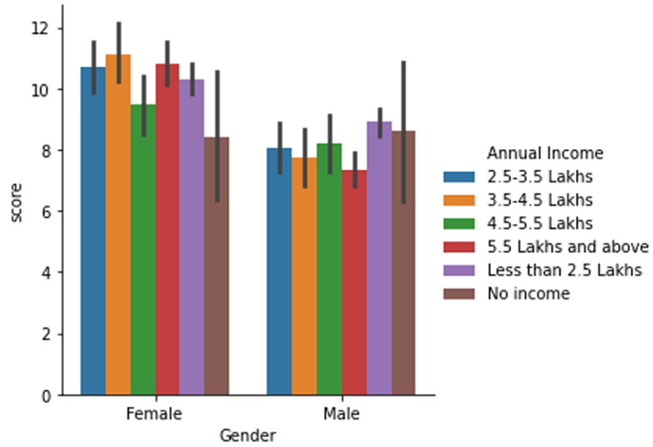

Fig. 5. Depression level depends on annual income.

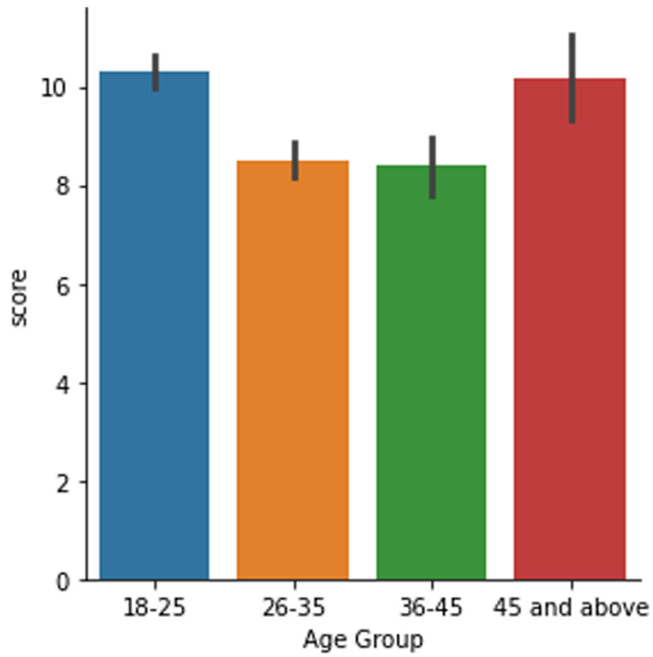

Fig. 6. Depression level on different Age Groups.

Fig. 6 shows that people with age-group 18–25 are suffering from depression because they are facing concentration issues. They have stress about their studies and future. People in the age-group above 45 have high depression scores because they are facing difficulties in planning and executing tasks. They have the stress of children's marriage and their retirement stress. We have 1694 records in the dataset and it is observed that the average score of 18–25 age and above 45 age is high than others which shows a higher level of depression.

Fig. 7 represents that people in age group who are married and become indecisive and restless have a high level of depression because they have a number of responsibilities in their lives such as household, children's studies, their needs, etc. On the other hand people in same age group, those who are unmarried are taking stressed about their future and studies. Moreover, people are of age above 45 whether they are married or unmarried they have also suffered from a high level of depression.

Fig. 8 analysis is based on residential areas. It is observed that the people living in urban areas seem to have a high depression score due to loss of energy and excessive tiredness because in the cities people's needs are very high whether the person is married or unmarried. But in rural areas, the facilities are on average so the needs of people are not much higher than in the urban areas.

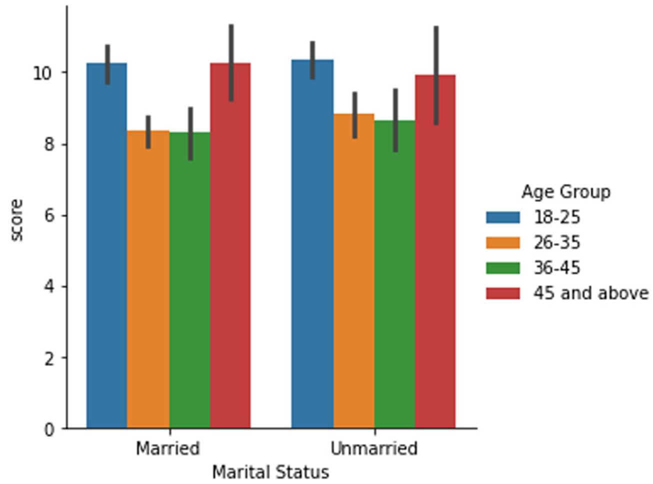

Fig. 7. Depression level at marital status.

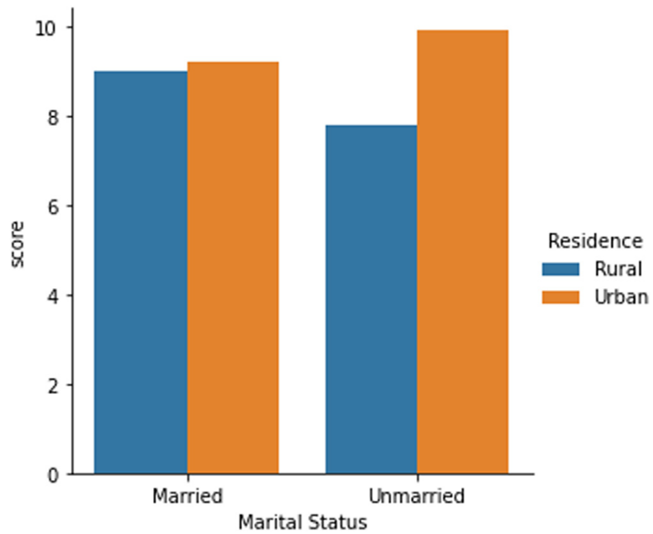

Fig. 8. Depression level at residential facilities.

Scientific programming based comparative analysis of Decision tree, KNN, and Naïve Bayes

Fig. 9(a) Study shows for depression level 0: Out of (145 + 0) 145 zero depression level people, our model predicted 145 correctly. And for 0 people our model predicted them with depression level as 1 while in actuality they were of depression level 0. For depression level 1: Out of (43 + 282 + 11) 336 depression level people, our model predicted 282 correctly. And for 43 people our model predicted them with a depression level of 0 while in actuality they were of depression level 1 and for 11 people our model predicted them with a depression level of 2 while in actuality they were of depression level 1. For depression level 2: Out of (67 + 12 + 0) 79-two depression level people, our model predicted 67 correctly. And for 12 people our model predicted them with a depression level of 1 while in actuality they were of depression level 2. Finally, the accuracy of Naïve Bayes is 88.21%.

In Fig. 9(b) It has been observed that for depression level 0: out of (131 + 14) 145 zero depression level people, our model predicted 131 correctly and for 14 people our model predicted them with depression level as 1 while in actuality they were of depression level 0. For depression level 1: out of (20 + 303 + 13) 336 depression level people, our model predicted 303 correctly. And for 20 people our model predicted them with a depression level of 0 while in actuality they were of depression level 1 and for 13 people our model predicted them with a depression level of 2 while in actuality they were of depression level 1. For depression level 2: out of (1 + 10 + 68) 79 two depression level people, our model predicted 68 correctly. And for 10 people our model predicted them with a depression level of 1 while in actuality they were of depression level 2. Finally, the accuracy of the Decision Tree is 89.64%.

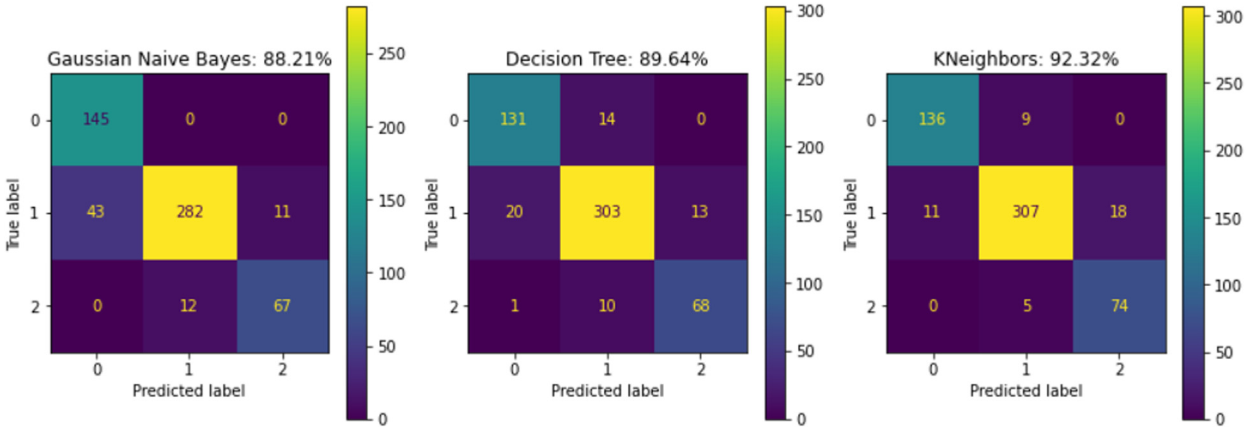

Fig. 9. Confusion matrix of the Decision tree, Naïve Bayes and KNN.

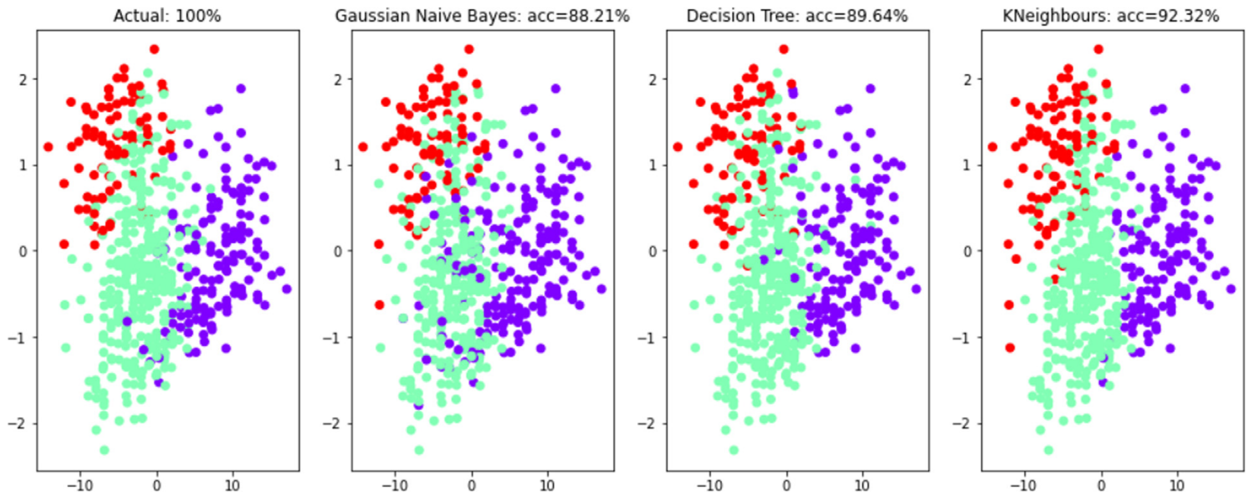

Fig. 10. Comparison of Actual values and predicted values.

In Fig. 9(c) This Confusion Matrix shows that for depression level 0: out of (136 + 9) 145 zero depression level people, our model predicted 136 correctly. and for 9 people our model predicted them with depression level as 1 while in actuality they were of depression level 0. For depression level 1 out of (11 + 307 + 18) 336 depression level people, our model predicted 307 correctly. And for 11 people our model predicted them with depression level as 0 while in actuality they were of depression level 1. Rest for 18 people our model predicted them with a depression level of 2 while in actuality they were of depression level of 1. For depression level 2: out of (0 + 5 + 74) 79 two depression-level people, our model predicted 74 correctly. And for 5 people our model predicted them with a depression level of 1 while in actuality they were of depression level 2. Finally, the accuracy of KNN is 92.32%.

Fig. 10 shows after the comparison of the confusion matrix there is also the comparison in the form of a plot of actual data and predicted data.

Conclusion

There is a global economic crisis as a result of the COVID-19 epidemic. Countries that face the risk of losing human life have expressed alarm over this circumstance. In order to address the issue and safeguard both an individual's and society's mental health, a prompt and effective system is required. In our work, we suggested a machine learning algorithm based on scientific programming to identify an individual's mental state, such as whether or not they are depressed. Python-based scientific programming principles have been used to use machine learning approaches in order to identify depression via survey forms. The analysis of the comparison outcomes is done with the aid of methods like Decision Tree, KNN, and Naive Bayes. The earlier questionnaires relied on negative questions to identify depression, but the suggested methodology also included positive questions and weekly records. Results showed that, for detecting depression in a person, KNN performed better than other strategies in terms of accuracy, while the decision tree performed better in terms of latency.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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