Heart Disease Prediction after Affecting COVID-19 using Machine Learning Algorithms

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Abstract

Covid19 has done serious revolution in health care system. Still research is undergoing how it impacts the cardio vascular system. The diagnosis of cardiac disease associated with COVID-19 is significant, and determining the precise cause and making the necessary diagnostics requires a great deal of effort and perseverance. But if discovered, it has the power to significantly alter a patient's life and put them back on the path to leading a heart-healthy life. A heart attack or heart failure may be more likely if you have a severe or even mild form of COVID-19. The virus that causes COVID-19 seldom infects the cardiac muscle. However, the virus can lead to issues with entire body, including harm to your heart. This work focuses on the prediction of heart disease for covid-19 affected patients using machine learning algorithms KNN and support vector machines. Forty eight attributes with minimum number of samples for different age group of patients were taken for this research work. The findings of prediction results shown moderate accuracy because of minimum number of samples. SVM model achieves more accuracy than KNN.

Keywords : COVID-19,Post-COVID-19, Machine Learning, cardio vascular disease and Prediction.

1. Introduction

Even after being exposed to [5]COVID-19, some people still have health issues. Aware of the risk factors and potential symptoms associated with post-COVID-19 syndrome.Symptoms that appear more than four weeks after contracting COVID-19 can include a range of new, recurring, or persistent symptoms, together referred to as post-COVID-19 syndrome. Post-COVID-19 syndromes can cause incapacity and last for months or years in some persons. Studies indicate that 1 in 5 adults aged 18 to 64 have at least one medical problem that may be related to COVID-19 within a month to a year after contracting the virus. One out of every four adults 65 years of age and older has at least one health issue that may be related to COVID-19.

The following are the most often reported symptoms of post-COVID-19. They are fatigue, symptoms that worsen with physical or mental exertion, high temperature,and respiratory symptoms in the lungs such as dyspnea with cough. The other potential signs and symptoms consist of mental health disorders or neurological symptoms, such as trouble in thinking, headaches, sleep issues, giddiness, loss of taste or smell, sadness, or anxiety, the other symptoms include Muscle or joint pain, heart-related symptoms or disorders such as thumping heartbeat and chest pain. In terms of Symptoms of digestion such as stomach pain and diarrheawill also suffer. The next most severe suffer will be blood clots and blood vessel problems, such as pulmonary embolism.

The possibility of organ damage exists. Heart, kidney, skin, and brain damage are possible outcomes for individuals who suffered from severe COVID-19 sickness. Moreover, immune system issues and inflammation may arise. How long these impacts could persist is unknown. Additional illnesses like diabetes or problems with the heart or neurological system could arise as a result of the impacts.Another possible factor could be prior experience with severe COVID-19. Intensive care units in hospitals are frequently necessary for the treatment of individuals with severe COVID-19 symptoms. Excessive weakness and PTSD, a mental illness brought on by a horrific experience, may ensue from this.

Those who had a serious COVID-19 illness, particularly if they required hospitalization or intensive care, are considered risk factors. Before contracting the COVID-19 virus, already certain medical issues could have been present in the patient's body. Severe COVID could make a heart condition worse. However, it is unknown how the corona virus would affect people who already have cardiac problems. There are various varieties of heart attacks, type 1 heart attack and type 2 heart attacks. A blood clot obstructing an artery in the heart causes a type 1 heart attack. Increased cardiac strain, such as a rapid heartbeat, low blood oxygen levels, or anemia, can result in type 2 heart attacks because the heart muscle isn't receiving enough oxygen from the blood to perform this additional job. According to Post, "in patients with an abnormal EKG during acute COVID-19 [17], elevated troponin levels are linked to higher mortality, but not in patients with a normal EKG."

Dr. Hindoyan says, our knowledge of how COVID-19 impacts the cardiovascular system is still growing. Finding the diagnosis and the definitive etiology of COVID-19-related cardiac illness requires a great deal of effort and perseverance. But if discovered, it has the power to significantly alter a patient's life and put them back on the path to leading a heart-healthy life.

The objective of this work is finding the number of patients who have heart issues after affecting covid19 and its impacts. Then the patients are suggested how to recover from this impacts. The goal of this research is to develop a model using KNN and SVM and evaluating its performance using metrics.

2. Review of Literature

Gomes et.al.[1] investigated the impacts of cardiac function after affecting COVID-19 using machine learning techniques. The publicly available database of ECG images was used. Feature extraction, Attribute Selection and classification were performed by the author. The LeNet, ResNet and VGG16 networks were used for analysis. The author concluded that COVID-19 would not create any heart disease. The better results obtained for VGG16 and Random Forest network

Pourhomayoun M et.al.[2] Designed and developed a new predictive model based on AI and ML techniques to find the risk of patients after affecting covid19. The samples were collected from various countries. AI technology is used to find who needs immediate treatment. KNN, SVM, ANN, RF, DT and logistic regression algorithms were implemented to predict the death rate of patients. The evaluation of algorithms is done for finding which one performs better.

Ardabili S.F et.al. [3] presented a comparative and performance analysis of machine learning and soft computing models to find critical illness outbreaks of covid19 patients. The multi-layered perceptron and adaptive network-based fuzzy inference system were implemented to predict the critical illness of covid19 patients. The author suggested machine learning was an efficient tool to determine the complexities of the affected patients. SEIR (susceptible-exposed-infectious-removed) model is combined with machine learning model to find the severity of the patients.

Munblit, D. et.al.[4] Although there are more studies looking at the post-COVID-19 syndrome, there is disagreement on what important outcomes to measure and how this new disease should be characterized and diagnosed in clinical practice. For clinical services and research purposes, it is imperative to optimize and standardize outcome metrics for this significant patient population to facilitate data comparison and pooling. Many months after the initial acute infection, a significant percentage of COVID-19 patients continue to have symptoms, such as exhaustion, dyspnea, and neurological issues like cognitive impairment. There is growing evidence that this illness, also known as post-acute sequelae of SARS-CoV-2 infection (PASC) or post-COVID-19 syndrome, may become a major global health burden. It is commonly referred to as protracted COVID.

NT Pramathesh Mishra et.al.[5] Globally, the COVID-19 has had a severe impact on the economy in addition to public health and society. Among the main worries about the pandemic disease extenuation are significant drops in income, a rise in unemployment, and disruptions in the transportation, utilities, and industrial sectors. In addition, the majority of the nations' governments miscalculated the risks posed by the COVID-19 pandemic and generally responded appropriately to the disasters that struck their nations. Based on current understanding and accessible literature, the author illustrated in this overview the several facets of pre- and post-COVID-19 consequences throughout global social and economic phases. Additionally, the evidence-based information on dangers, social effects, technological advancements, moral dynamics, stress, and adapting to pre- and post-COVID-19 circumstances has been compiled.

Moulaei, K. et.al.[6] Hospitalized individuals with COVID-19 are always at danger of dying from the virus. Predicting death in hospitalized COVID-19 patients may be possible with machine learning (ML) techniques. Thus, the purpose of this study was to evaluate many machine learning algorithms for predicting COVID-19 mortality using patient data at the time of initial admission and to select the most effective algorithm as a prediction tool for decision-making.

Gong, B. et.al.[7] During the pandemic, a lot of people postponed or avoided seeking medical attention, which could result in long-term health issues. Furthermore, COVID-19 patients may continue to suffer symptoms like exhaustion, dyspnea, and muscle weakness, which may have an effect on their long-term health. When analyzing the effects of the post-pandemic period on health, machine learning (ML) can be an extremely useful technique. This article uses machine learning techniques to help find patterns and insights in the massive amounts of data from public health databases, electronic health records, and other sources. By analyzing health data, the suggested machine learning models can spot trends and patterns that could point to future health issues.

Gupta A et.al.[8] Deep neural networks are used to develop a binary classifier based on a stacking ensemble for the prediction of heart disorders following COVID-19 infection. The suggested model is verified through comparison with alternative baseline methodologies, including support vector machines, random forests, decision trees, and artificial neural networks. The suggested method gets the highest accuracy of 93.23% and performs better than other baseline procedures, according to the results. Furthermore, when compared to alternative methods for the prediction of cardiac illnesses, the findings of specificity (95.74%), precision (95.24%), and recall (92.05%) further demonstrate the usefulness of the chosen strategy. Keywords: machine learning, stacking ensemble, K-fold cross-validation, and post-COVID-19.

SmritiJojo et.al.[9] Based on historical time-series data, the author has created a flutter-based mobile application that employs machine learning to forecast the COVID-19 epidemic for the future week. The COVID-19 facts and forecast for India are provided by the application called COVID_19 India. Numerous prospects in research, data science, development, AI and machine learning implementations, and information technology integration in the healthcare industry are made possible by this initiative.

Nalbandian A, et.al. [10] It is now acknowledged that COVID-19 is a multi-organ illness with a wide range of symptoms. There are growing reports of long-lasting consequences following acute COVID-19 infection, which are similar to post-acute viral symptoms reported in survivors of previous virulent coronavirus epidemics. A thorough analysis of the most recent research has been done on the etiology, organ-specific consequences, and post-acute COVID-19. In conclusion, the author addresses pertinent factors for the multidisciplinary treatment of COVID-19 survivors and put forth a plan for identifying individuals who are highly susceptible to post-acute COVID-19 and coordinating their care via COVID-19 clinics.

SanzidaSolayman, Sk et.al. [11] In order to create an intelligent web application, this project will analyze automatic COVID-19 identification with the use of machine learning algorithms. Preprocessing methods for the dataset include feature engineering, eliminating null values, and synthetic oversampling (SMOTE). We then trained and assessed various classifiers, including ensemble models (adaptive boosting and extreme gradient boosting), deep learning (artificial neural network, convolutional neural network, and long short-term memory), logistic regression, random forest, decision tree, k-nearest neighbor, support vector machine (SVM), and others. The prediction findings have been interpreted by applying Explainable AI within the LIME framework. On the used open-source dataset collected from the Israeli Ministry of Health website, the hybrid CNN-LSTM algorithm utilizing the SMOTE technique outperformed the other models.

Ghafouri-Fard S et.al. [12] Recurrent neural networks, multilayer perceptrons, long short-term memory, and adaptive neuro-fuzzy inference systems are some of the most often utilized techniques in this area. We evaluated the effectiveness of various machine learning techniques in forecasting the COVID-19 pandemic. To compare the accuracy of the models, the following performance metrics were chosen: mean absolute error (MAPE), R2 coefficient of determination (R2), root means squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). R2 values for artificial neural networks

(ANN) and bidirectional long short-term memory (LSTM) have varied from 0.64 to 1. R2 values for the Multilayer Perceptron (MLP), Autoregressive Integrated Moving Average (ARIMA), and Adaptive Neuro-Fuzzy Inference System (ANFIS) are likewise close to 1. The models with greatest MAPE values were LSTM and ARIMA. All together, these models

Meraihi. Y.et.al. [13] This work provides a summary of over 160 machine learning-based strategies created to counteract COVID-19. Elsevier, Springer, ArXiv, MedRxiv, and IEEE Xplore are some of the places they originate from. Supervised learning-based approaches and Deep learning-based approaches are the two groups into which they are categorized after analysis. The ML algorithm that is being utilized in each category is described, along with a list of its many parameters. The parameters that are specified for every algorithm are compiled into several tables. The problems that are addressed (detection, diagnosis, or detection), the data types that are examined (text, X-ray, CT, or time series, clinical data, etc.), and the metrics that are assessed (accuracy, precision, sensitivity, specificity, F1-Score, and AUC) are among them. In addition to discussing the data gathered, the study offers several figures that illustrate

Sumayh S. et.al.[14] 287 COVID-19 patient samples from Saudi Arabia's King Fahad University Hospital were used in the investigation. Three classification algorithms—logistic regression (LR), random forest (RF), and extreme gradient boosting (XGB)—were used to evaluate the data. The data were first preprocessed using a variety of preprocessing methods. Moreover, data partitioning was done using 10-k cross-validation, and data imbalance was reduced using SMOTE. Twenty clinical features that were found to be relevant for predicting survival in comparison to deceased COVID-19 patients were used in the experiments. The findings demonstrated that, with an accuracy of 0.95 and an area under the curve (AUC) of 0.99, RF performed better than the other classifiers. The suggested methodology effectively identifies at-risk COVID-19 patients early on, which can help decision-makers and medical professionals.

Maitham G. et.al. [15] A thorough investigation was carried out, involving a group of 352 COVID-19 patients from various parts of Iraq. Important clinical data were carefully gathered, including demographics, comorbidities, test values, and imaging results. To build predictive models, machine learning methods were utilized. Training and testing subset of the dataset was created in order to thoroughly evaluate the model's performance. The results highlight the need for close patient observation, especially for those with known risk factors. In addition, this study recommends future research to improve models' accuracy.

3. Methodology

According to recent studies, some of the peoples have an increased risk of cardiovascular problems, including heart failure, irregular heartbeats, and strokes. Notably, even among those with minor cases of COVID-19 who were not hospitalized, there was a greater risk of heart disease. The risk persists irrespective of demographic attributes such as age, race, or gender, or the presence of antecedent illnesses like obesity or hypertension. We now need to distinguish between patients who had heart problems before and those who now have more severe cardiac problems as a result of having COVID-19 [18]. COVID-19 brought special difficulties to the medical field in general and cardiology in particular. The principal signs of a heart attack include, feeling weak, dizzy, or faint, shortness of breath, discomfort or pain in the arms, shoulders, neck, jaw, or back and chest discomfort or pain, which can cause pressure or squeezing in the center or left side of the chest and fluctuate in intensity.

A dataset is an assortment of information gathered from multiple COVID-19-affected patients, representing their post-recovery medical records. This data includes a variety of attributes, and only the necessary data is used in order to prevent inaccurate data predictions. Additionally, both redundant and missing values are added to the data to fix it. There are 48 attributes. Dataset is downloaded from the internet. The link is given below.

https://data.mendeley.com/datasets/yw4jhs5n9d/1/files/4fd80677-1759-42e1-bd3e-56d92386ea9f

The COVID-19 pandemic in India is a part of the worldwide pandemic of coronavirus disease 2019 (COVID-19). A second wave beginning in March 2021 was much more devastating than the first, with shortages of vaccines, hospital beds, oxygen cylinders and other medical supplies in parts of the country. Covid 19 infection affected both male and female gender ages ranging between 17 to 70 years old. Covid 19 also had significant impact on vital signs Temperature above 37.5 °C, peripheral oxygen saturation below 90%, respiratory rate below 10 or above 25 breaths per minute, heart rate below 40 bpm or above 150 bpm, and mean arterial pressure below 65 mmHg, Systolic and diastolic blood pressure ranged as 150 and 88 mm of hg. BMI also increased from normal to severe obesity (35.9). Epi-pericardial or epicardial fat necrosis (EFN) is a self-limited inflammatory process occurring in the mediastinal fat surrounding the heart. After acute coronavirus disease 2019, many patients with rheumatic and musculoskeletal diseases continue to have persistent symptoms. Low TAPSE levels are associated with poor COVID-19 disease outcomes. TAPSE levels are modulated by disease severity, and their prognostic utility may be skewed by pre-existing patient comorbidities. TAPSE 3 and TAPSE 6 ranged between 19 to 23.

Pericarditis can happen while patients are sick with COVID-19 or after recovery. Pulmonary Artery Pressure (PAP) significantly increased to 30 to 54 while pre-covid normal was 20. After covid 19 infection, Ebstein Anomaly (EA) (Cardiac Abnormality) was elevated to 2.3. Pericardial effusion (Buildup of fluid around the heart) was 1.5 to 4.8. Overall after covid 19 infection there is a higher risk of getting many cardiac related diseases.

Table 1. Dataset Attributes with allowed range for human body

Attribute	Description	Data type	Normal Range	Range in the dataset
WAVES	Covid'19 Wave 1,2,3	102 non-null int64	1-3	1,2,3
GENDER	Male-1 , Female-2	102 non-null int64	1,2	1,2
AGE	Age of a patient	102 non-null int64	30-55	17 to 55
BPSIST	BP Systolic	102 non-null int64	150.09+/- 22.20	120 to 145
BPDIAST	BP Diastolic	102 non-null int64	88.84 +/-13.92	70 - 90
HR	Heart Rate	102 non-null int64	> 70	70 - 90
BMI	Body Mass Index	102 non-null float64	<30	19.03 - 35.98
WEEKSS IN CE INFECTION	Carbapenem-resistant Enterobacteriaceae	102 non-null int64	<4	4 - 8
PULMONARY INJURY		102 non-null int64	35 - 50	5 - 40
PCFS	paracardial fat	102 non-null int64	<4mm	1- 4

PCSF3	paracardial fat	102 non-null int64	<4mm	0-2
PCSF6	paracardial fat	102 non-null int64	<4mm	0-2
RCP	Reitan Catheter Pump	102 non-null float64	36 - 42	11.14 - 90.67
RV	Right ventricular	102 non-null float64	3 - 5 mm	2.6 - 4.1
RA	Rheumatoid Arthritis	102 non-null float64	3	3.2 - 4.3
TAPSE	Tricuspid Annular Plane Systolic Excursion	102 non-null float64	17.09±5.09mm 10.56±3.96mm in newborns 20.95±6.54mm in the 13- to 18-year-old group.	12 - 22
TAPSE3	Tricuspid Annular Plane Systolic Excursion3	102 non-null float64	>16 mm	19 - 23
TAPSE6	Tricuspid Annular Plane Systolic Excursion6	102 non-null float64	15-25mm	14-23
VMAX	velocity of contractile element	102 non-null float64	3.38	2.54 - 3.46
PAPS	pulmonary artery pressure	102 non-null float64	14±3 mmHg with an upper limit of 20 mmHg	30.80- 54. 84
TRVMAX3	TR velocity max	102 non-null float64	TRV ≤2.5 m/s as the upper limits of normal	1.34 - 2.9
PAPS3	Pulmonary Artery Pressure	102 non-null float64	**21 ± 4 mm Hg**	12.39 -37.71
TRVMAX6	TR velocity max	102 non-null float64	TRV ≤2.5 m/s as the upper limits of normal	1.34 - 2.95
PAPS6	Pulmonary Artery Pressure	102 non-null float64	**21 ± 4 mm Hg**	12.84-39.81
GLSRV	Global Longitudinal Strain of the Right Ventricle	102 non-null int64	mean, −1.88, 95%CI, −2.10 to −1.59	>18
GLSRV3	Global Longitudinal Strain of the Right Ventricle	102 non-null int64	mean, −1.88, 95%CI, −2.10 to −1.59	19-31
GLSRV6	Global Longitudinal Strain of the Right Ventricle	102 non-null int64	mean, −1.88, 95%CI, −2.10 to −1.59	25-31
FAC	Fractional area change	102 non-null float64	Normal fractional area change is **above 35**%. In this example, the fractional area change is diminished (26%)	25.78 – 37.89

FAC3	Fractional area change3	102 non-null float64	fractional area change is **above 35**%.	30.31-37.06
FAC6	Fractional area change6	102 non-null float64	fractional area change is **above 35**%.	34-37.74
MAPSE	Mitral annular plane systolic excursion	102 non-null int64	13±3 to 17±3	6 - 17
MAPSE3	Mitral annular plane systolic excursion	102 non-null int64	13±3 to 17±3	9-18
MAPSE6	Mitral annular plane systolic excursion	102 non-null int64	13±3 to 17±3	10-20
EF	Effusion	102 non-null float64	50 % - 70 %	30 % - 60 %
EF3	Effusion	102 non-null int64	50 % - 70 %	42 % - 70 %
EF6	Effusion	102 non-null int64	50 % - 70 %	49 %-70%
GLSLV	Global longitudinal strain of the left ventricle	102 non-null int64	42 – 59 mm	-7 to - 24
GLSLVS3	Global longitudinal strain of the left ventricle	102 non-null int64	42 – 59 mm	-14 to 25
GLSLV6	Global longitudinal strain of the left ventricle	102 non-null int64		-19 to - 28
EA	Ebstein Anomaly	102 non-null float64	1.00 +/-0.66	0.6 – 2.3
EE	Early diastolic mitral to Annular Tissue Velocity Ratio	102 non-null float64	14.66 +/-6.91	2.89 -16.77
EE3	Early diastolic mitral to Annular Tissue Velocity Ratio	102 non-null float64	14.66 +/-6.91	8.23 – 16.67
EE6	Early diastolic mitral to Annular Tissue Velocity Ratio	102 non-null float64	14.66 +/-6.91	8.23 – 16.67
LAVI	Left Atrial Volume Index	102 non-null float64	32 ± 11 ml/m^2	13.91 – 39.82
LVMI	Left Atrial Myocardial Infarction	102 non-null float64	49 – 115 g/m2	65 - 145
PERICARD	Inflammation of the Pericardium,	102 non-null float64	between 15 and 50 milliliters	1.2 -7.1 ml
PERICARD3	Inflammation of the Pericardium,	102 non-null float64	between 10–50 ml	0.8 – 3.8 ml
PERICARD6	Inflammation of the Pericardium,	102 non-null float64	between 10–50 ml	0.8 – 4 ml
EFFUSION	Buildup of too much fluid in the double-layered, saclike structure around the heart (pericardium)	102 non-null float64	at least 10 mm thick	1.5 – 4.8

K-Nearest Neighbour

The machine learning algorithm used for prediction is K-Nearest Neighbor and Support Vector Machine. KNN is non parametric supervised machine learning algorithm. KNN identifies the closest point. To identify the closest point, it uses distance formula. The Euclidean distance formula is

$$D(x1,x2) = \sqrt{(X_2-X_1)^2+(Y_2-Y_1)^2} \qquad (1)$$

Where
X_2 = 2nd data point in feature attribute

X_1= 1st data point in feature attribute

Y_2 = 2nd data point in target attribute

Y_1 = 1st data point in target attribute

The class with the highest probability is allocated to the input x once the distance has been calculated. The conditional probability function of KNN is given by

$$P(y = j|X = x) = \frac{1}{K} \sum_{i \in \mathcal{A}} I(y^{(i)} = j) \qquad (2)$$

Where

X – Feature attribute
y – Target attribute
$I(y^{(i)}=j)$ - Indicator variable
A – set of k nearest neighbor observations
KNN finds at the k observations nearer to test observation x

It evaluates to be 1 when (xi,yi) is a member of class j, otherwise 0.When KNN is used to solve a problem, it does not assume any certain functional form. K-NN performs substantially better when the scale of all the data is the same. When there are few input variables (p), KNN performs well. but, when there are many inputs, it will perform not as much as we expect. The steps to be performed are

Step 1 : Repeat the loop varying i from 1 to n
Step 2 : Distance is calculated by using formula
Step 3 : Check if distance is less than nearest distance then assign distance to nearest distance.
Step 4 : Determine the nearest point anf fix the target value of nearest point.

Support Vector Machine

$$w^T x + b = 0 \qquad (3)$$

W - The normal vector of the hyperplane
b - The offset or distance of the hyperplane
The distance between a data point x and the decision boundary can be calculated as

$$D_i = w^T x + b = 0 \, / \, ||w|| \ (4)$$

||w|| represents the Euclidean norm of the weight vector w.

For Linear SVM classifier

$$Y = \begin{cases} 1 & w^T x + b \geq 0 \\ 0 & w^T x + b < 0 \end{cases} \quad (5)$$

To ensure a successful recovery from COVID-19, scheduling a follow-up examination with primary care physician is one of the most crucial things if a patient has COVID-19 infection and is experiencing cardiac problems. These are a few tests to be recommended by doctor. Routine testing for labs and blood pressure, EKG or ECG, Echocardiogram, Magnetic Resonance Imaging (MRI), B-type Natriuretic peptide (BNP), High-sensitivity C-Reactive Protein (CRP) and Exercise stress test. These tests are all useful in determining a person's risk factors.

4. Results and Discussion

Severe COVID-19 increases the risk of arrhythmias (irregular heartbeats) and weakens the cardiac muscle. Heart failure or heart attacks following COVID-19 are among the additional issues that might arise from overexerting the heart during the healing process. Figure 1 shows the attack of covid19 in the heart. There may be a connection between COVID-19 and cardiovascular disease (CVD), according to recent data. A CVD risk modifier that is often overlooked is COVID-19, which includes risk factors such arterial hypertension and diabetes mellitus [16].

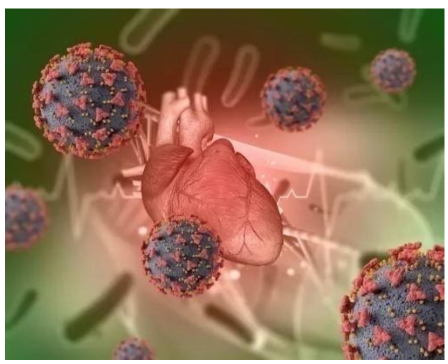

Figure 1. Covid 19 attack in heart

Table 2 shows the combined incidence of age wise MI-CAD and MINOCA. Most people are affected at the age of 50 to 70. Previously believed to be innocuous, MI with non-obstructive coronary artery (MINOCA) has recently been found to have a death rate similar to acute coronary syndrome with obstructive coronary disease. More care has to be taken for the people who are in the age of 50 to 70.

Table 2. Incidence of Age wise MI-CAD and MINOCA combined

Age	Incidence of MI-CAD and MINOCA combined
Over 50	18%
50–59	27%

60–69	26%
70–79	18%
80–89	12%

Table 3 shows the Incidence of age wise heart attack per 100,000 people. CHD is thought to affect 16.3 million Americans who are 20 years of age or older, representing a 7% prevalence. The prevalence is 6.1 percent for women and 8.3 percent for men. The highest frequency of CHD is found in non-Hispanic white men (8.5 percent), followed by Mexican American men (6.3 percent) and non-Hispanic Black men (7.9 percent). The greatest rate of CHD in women is 7.6 percent among non-Hispanic Black women, 5.8 percent among non-Hispanic white women, and 5.6 percent among Mexican American women (Roger et al., 2010). According to data from the National Heart, Lung, and Blood Institute (NHLBI)-funded Strong Heart Study, the incidence of CHD among American Indians aged 45 to 74 was 17.9 per 1,000. The people who have age above 40 will suffer a lot.

Table 3. Incidence of heart attack per 100,000 people

Age	Incidence of heart attack per 100,000 people
20–29	2.1
30–39	16.9
40–49	97.6

Globally, cardiovascular disease is the primary cause of illness and mortality. Despite this, women are generally less likely than males to suffer CVD. Numerous studies have demonstrated that women had a higher fatality rate and a worse prognosis following an acute cardiovascular (CV) incident [19].

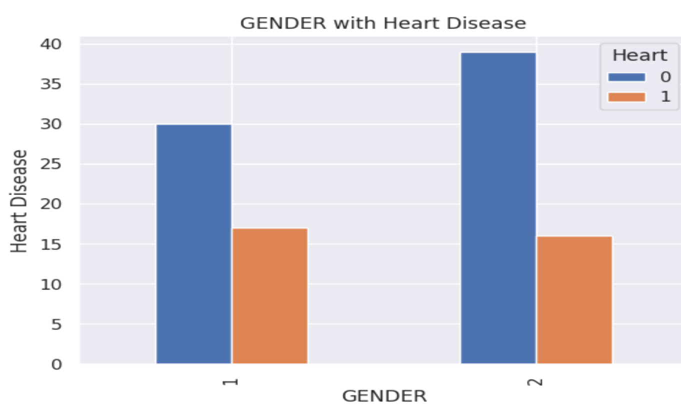

Figure 2. Gender with Heart Disease

The acute problems have been increased for the patients during / after COVID-19. Comparison and analysis is made for the post-acute cardiovascular problems of patients in hospitalized and non-hospitalized COVID-19 first, second, and third pandemic waves. The gender wise distribution in three waves are shown in figure 3.

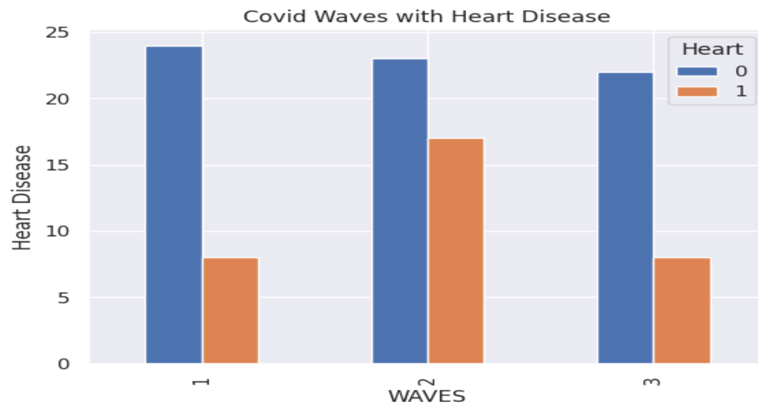

Figure 3. Gender with Heart Disease in Waves

Over 55-year-olds are more vulnerable to cardiac after affecting covid 19. Individuals who already have a cardiac ailment, such as heart failure or coronary artery disease, are more vulnerable. The age wise heart disease affected patients are shown in figure 4.

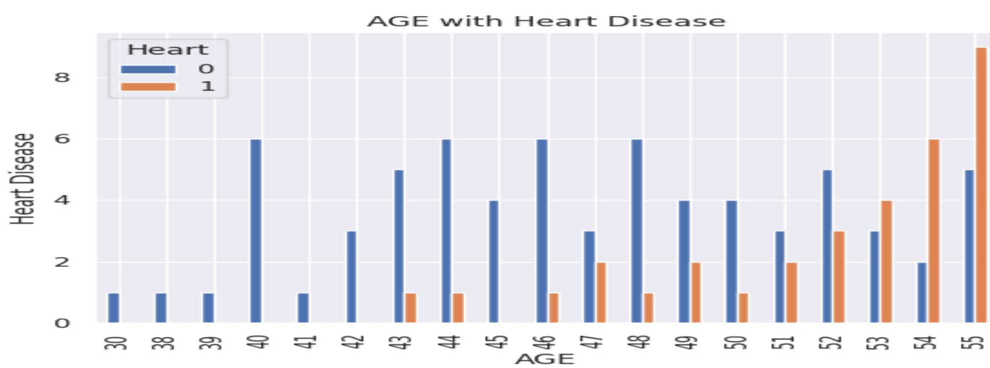

Figure 4. Age with Heart Disease

Males and older adults may have greater rates of COVID-19 infection and mortality because to associated risk factors, co-morbid diseases, and biological variations based on gender and age. The age with gender distribution of covid 19 affected patients are shown in figure 5.

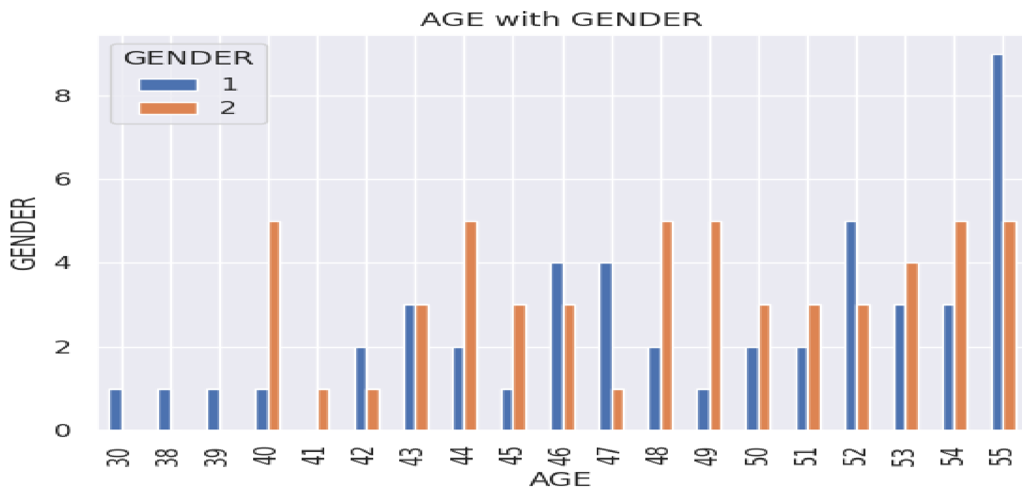

Figure 5. Age with Gender

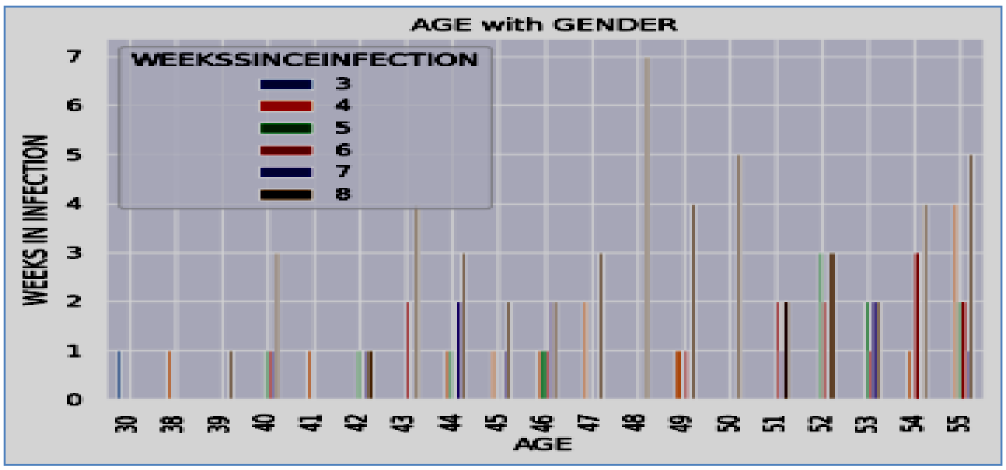

Figure 6. Age, Gender with Weeks Infection

While the model is learning on training data, test data's main purpose is to assess the trained model's performance on unseen datasets. Assessing the model's performance is a simpler task than learning the model. The model may overfit and performs poorly when applied to novel data patterns that are not present in the training set if the training data set is small. Thus, as the amount of the training dataset increases, model performance usually improves.Therefore, the SVM classifier achieves 76.92 as the accuracy. The prediction of disease for 26 patients is shown in the result.In the below results of figure 7, the number 1 indicates the patient has symptoms of heart related risks and 0 indicates there is no risk at all.

```
SVM Prediction:
[0 0 0 0 1 0 0 0 1 0 1 1 1 0 0 0 0 1 1 1 0 1 1 0 0 1]
SVM Classifier:
Accuracy: 0.7692307692307693
Precision: 0.6363636363636364
Recall: 0.7777777777777778
Confusion Matrix :
[[13  4]
 [ 2  7]]
```

Figure 7. SVM Prediction

Feature similarity is the method used by the KNN algorithm to forecast the values of any new data points. In other words, a value is assigned to the new point according on how much it resembles the points in the training set. The KNN classifier achieves 73.07 as the accuracy. The prediction of disease for 26 patients is shown infigure 8.

```
KNN Prediction:
[0 0 0 0 1 0 1 0 1 0 1 0 1 1 1 0 0 0 1 1 0 0 0 0 0 1]
Accuracy : 0.7307692307692307
Precision: 0.6
Recall: 0.6666666666666666
Confusion Matrix :
[[13  4]
 [ 3  6]]
```

Figure 8. KNN Prediction

The frequency with which a machine learning model accurately forecasts the result is known as accuracy. By dividing the number of accurate predictions by the total number of predictions, you can determine accuracy. The accuracy, precision and recall obtained is shown in Table 4.

Table 4. Performance Analysis of SVM and KNN

Algorithm	Accuracy	Precision	Recall
SVM	76.92	0.63	0.77
KNN	73.07	0.6	0.66

Accuracy is a valuable metric when working with balanced classes and when overall model “correctness” is prioritized over the ability to forecast a particular class. Accuracy is calculated by the following formula

Accuracy = Correct Predictions / All Predictions

Compared to KNN, SVM has somewhat greater accuracy which is shown in figure 9.

The frequency with which a machine learning model accurately predicts the positive class is measured by a parameter called precision. Precision can be computed by dividing the total number of instances the model predicted as positive (including true and false positives) by the number of correct positive predictions (true positives). It can be specified as

Precision = True Positive / True Positive + False Positive

The frequency with which a machine learning model properly detects positive examples (true positives) out of all the real positive samples in the dataset is known as recall. Recall can be computed by dividing the number of positive instances by the number of true positives. The latter comprises false negative results (missed cases) and true positives (successfully discovered patients). It can be written as
Recall = True Positive / True Positive + False Negative

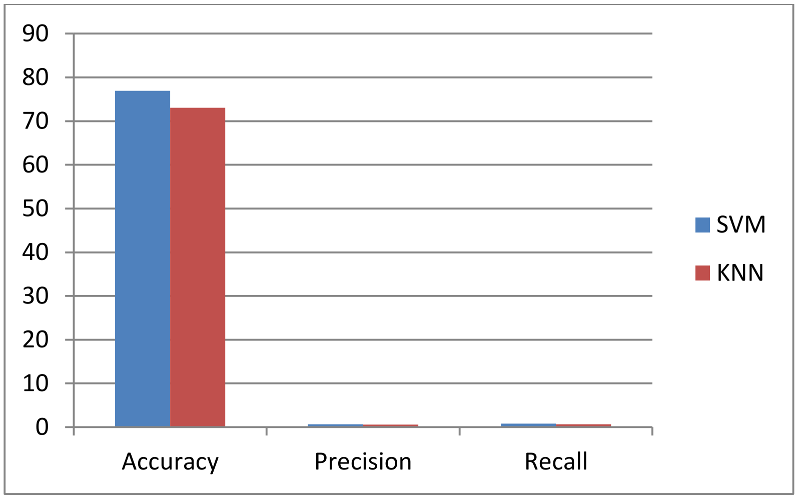

Figure 9. Performance Analysis Chart of SVM and KNN

Overall, the result findings achieve that The accuracy of SVM is better than KNN. The precision and recall of both the model performs with same level.……..

5. Conclusion

For classification problems, the KNN and SVM algorithms are both employed. KNN is a voting-based technique that uses the class of an object's closest neighbors in the decision space to classify it. SVM, on the other hand, divides classes into input spaces by drawing a hyperplane, then classifications objects according to which side of the hyperplane they fall on. Regarding precision, although the accuracy with which they classify the data is positive for both algorithms, the SVM offers substantially higher classification accuracy and classification speed than the KNN.The selection of K essentially determines how well KNN performs. KNN uses whole training dataset memorization to function. KNN considers the k-nearest data points in the training set depending on a given distance metric whenever a new data point is provided for prediction.

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