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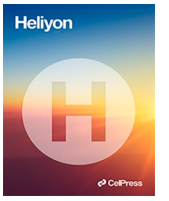

Research article

Machine learning predictive modeling of the persistence of post-Covid19 disorders: Loss of smell and taste as case studies

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ABSTRACT

The worldwide health crisis triggered by the novel coronavirus (COVID-19) epidemic has resulted in an extensive variety of symptoms in people who have been infected, the most prevalent disorders of which are loss of smell and taste senses. In some patients, these disorders might occasionally last for several months and can strongly affect patients' quality of life. The COVID-19-related loss of taste and smell does not presently have a particular therapy. However, with the help of an early prediction of these disorders, healthcare providers can direct the patients to control these symptoms and prevent complications by following special procedures. The purpose of this research is to develop a machine learning (ML) model that can predict the occurrence and persistence of post-COVID-19-related loss of smell and taste abnormalities. In this study, we used our dataset to describe the symptoms, functioning, and disability of 413 verified COVID-19 patients. In order to prepare accurate classification models, we combined several ML algorithms, including logistic regression, k-nearest neighbors, support vector machine, random forest, extreme gradient boosting (XGBoost), and light gradient boosting machine (LightGBM). The accuracy of the loss of taste model was 91.5 % with an area-under-cure (AUC) of 0.94, and the accuracy of the loss of smell model was 95 % with an AUC of 0.97. Our proposed modelling framework can be utilized by hospitals experts to assess these post-COVID-19 disorders in the early stages, which supports the development of treatment strategies.

1. Introduction

The novel coronavirus has caused a rapidly spreading disease known as COVID-19, which was declared a pandemic by the world health organization (WHO) in 2020 [1]. The pandemic has caused significant socioeconomic hardships in various countries and communities around the world. Researchers have conducted many studies to identify the most effective strategies for mitigating the impact of the pandemic and preventing possible future outbreaks [2–5]. Around 10–15 % of all respiratory infections caused by viruses affect the upper respiratory system in the human body, and this includes more than 200 different types of viruses, including

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coronaviruses. Furthermore, the engagement of the neurological, gastrointestinal, and hematological systems gives rise to various health complications. The prevalent manifestations of this condition typically include dry coughs, breathing difficulties, elevated body temperature, and nasal congestion. On the other hand, less frequently encountered symptoms consist of headaches, muscle pain (myalgia), diarrhea, fatigue, loss of smell, and loss of taste [6–14]. Even after the passage of several years and as the pandemic enters its waning phases, many individuals have reported persistent symptoms following their recovery from the acute infection. Loss of smell and taste are dominant symptoms associated with the predication diagnosis of COVID-19 [15–23]. Multiple terms are used to describe the same syndrome, such as "long COVID-19″, "long haulers", "long-term COVID-19 effects", and "permanent COVID-19 symptoms" [6]. These terms represent a novel and specific definition that captures the aftermath of the unknown pathophysiology associated with COVID-19 infection. It involves the persistence of acute infection symptoms for a duration exceeding four weeks or the onset of new symptoms after the initial four-week period. Furthermore, recent research has established that the duration should extend to twelve weeks and beyond, particularly when the symptoms cannot be attributed to alternative diagnoses. Long haulers, as individuals experiencing prolonged COVID-19 symptoms are often referred to, suffer from a wide range of symptoms that influence various organs in the body, significantly impeding their ability to carry out daily activities [6]. Despite the considerable attention and research dedicated to COVID-19 in recent years, there remains a significant knowledge gap concerning the underlying mechanisms responsible for the manifestation of symptoms associated with this disease [6,24–29]. The researchers discovered that loss of smell and loss of taste are notable persistent symptoms among these patients, regardless of the duration of their illness. Numerous studies have consistently supported the notion that the loss of taste and smell are the most prevalent symptoms that can persist even after recovery [15–18, 30–36], and significantly affects an individual's quality of life [24,37–39]. As a result, an early expectation of persistent COVID-19 symptoms helps develop a guide to preventing complications and controlling any hazardous issues in a patient's life [38,39]. The Long COVID-19 syndrome poses a burden on the healthcare system and has economic implications, as patients have reported reduced working hours and decreased workload [40]. In the recent literature, prediction model utilizing COVID-19 symptoms such as fever, tiredness, loss of taste, and loss of smell, has been reported [25–27,35,36,41]. Most of the time, once the body heals from the infection, these symptoms go away on their own within a few weeks. However, in some patients, these disorders might occasionally last for several months. The COVID-19-related loss of taste and smell does not presently have a particular therapy. To assist control these symptoms, patients can take the following actions:

- Maintain proper dental hygiene. Regular tooth brushing and mouthwash use will help to lessen the accumulation of germs in your mouth, which can enhance the sense of taste.
- Try smell training, which involves being exposed to various scents, such as those of spices or essential oils, to improve the sense of smell.
- Use nasal saline sprays to aid sense of smell and nasal passageways stay clean.
- A healthcare provider should be consulted in case the patient has chronic or severe loss of smell and taste. The healthcare provider may be able to suggest further treatment options or make a referral to a specialist. It's crucial to remember that loss of smell and taste can be a sign of other diseases, so if the patient encounters these symptoms, especially if they continue or are coupled with other symptoms, they should consult a specialist right once.

Owing to recent significant advancements in artificial intelligence tools, machine learning (ML)-based prediction models have emerged as valuable tools for predicting multiple diseases based on their associated symptoms and diagnostic data. These predictive models aid clinicians in better understanding, diagnosing and managing symptom persistence, preventing complications, and improving patients' quality of life [42–44]. Moreover, they can provide optimum prediction and insight into the patient's future health situation. Utilizing accurately predicting models aid healthcare providers in identifying individuals who are at a higher risk of experiencing ongoing symptoms. This information can help clinicians proactively monitor and manage these patients, ensuring appropriate care and support. Furthermore, these models can guide personalized treatment strategies. By identifying individuals who are more likely to experience persistent symptoms, healthcare providers can tailor interventions and therapies to address specific needs. This targeted approach can potentially improve patient outcomes and enhance the effectiveness of treatment plans. Additionally, they can draw interactions and correlations between different symptoms. From a public health perspective, these models can contribute to resource allocation and planning. Moreover, the use of these predictive models can facilitate early intervention and preventive measures. Additionally, public health campaigns can be developed to raise awareness about self-management strategies, symptom monitoring, and the importance of seeking timely medical assistance. Therefore, the objective of this study is to develop an accurate ML models to predict loss of taste and smell senses during infection and after recovery from COVID-19.

2. Methods

2.1. Study design, setting, and participants

A cross-sectional study was conducted in the Qassim region of Saudi Arabia in the period between January 2021 and March 2022. This region is in the country's central region and has 1.5 million people, 165 public health centers, and 19 government hospitals, offering medical care in various disciplines. Therefore, patients who received a COVID-19-positive PCR diagnosis in the Qassim region made up the target population. The Epi Info Stat calculator was used to calculate the sample size. According to the Saudi centers for disease control and prevention (2d February 2021), there were 14,129 COVID-19-positive cases in the region. For the sake of this investigation, we calculated the sample size under the assumption that COVID-19 prevalence is 50 %; at a design impact of 2.0, a 95 %

confidence level, and a 5 % margin of error. A convenience sampling method was used to select positive PCR COVID-19 cases. COVID-19 surveillance data was collected through the official government-registered system HESN surveillance. The inclusion criterion was adult-confirmed patients with positive PCR results recorded in the surveillance system.

In order to collect the dataset, a well-structured questionnaire called the COVID-19 Yorkshire Rehabilitation Scale (C19-YRS) was adopted [45,46]. The original C19-YRS questionnaire comprising 22 items, each rated on an 11-point numerical scale ranging from 0 (no presence of the symptom) to 10 (extremely severe level or impact). It is divided into four subscales: symptom severity score (range: 0–100), functional disability score (range: 0–50), additional symptoms (range: 0–60), and overall health (range: 0–10) [47–49]. Over 18-year-old patients who had been identified in Tetamman clinics as having COVID-19 positivity (based on WHO criteria) were contacted to conduct the study. A total of 35 questions were included in the questionnaire, divided into three categories. In the first section, questions were asked regarding the patient's age, gender, history of comorbidities, family size, smoking status, and exercise frequency. Patients' clinical characteristics were gathered in the second component, including their initial and two-week symptoms, medication status, immunization status, and length of isolation. A third section was used to assess the patient's clinical condition utilizing the C19-YRS checklist. It sought to highlight the enduring symptoms and their degrees of severity in relation to the pre-infection condition in a bio-psycho-social manner. Furthermore, each symptom was classified into three severity levels according to the severity of the Post-COVID-19 Syndrome (PCS) (<3 = mild; $3-5$ = moderate; $6-10$ = severe). As part of the clinical evaluation for the C19-YRS application, every domain of the International Classification of Functioning (ICF) was examined, including body structure and function, activity limitations, and participation restrictions, as well as social and environmental factors. Among the 35 items, ten can be directly or indirectly observed through validation. We, therefore, focused on breathlessness at rest, during dressing and stair climbing, pain or discomfort, exhaustion, depression, anxiety, mobility, personal care, communication, regular activities, and overall health in our dataset.

Machine learning (ML) modeling is known as the process of building systems that can learn and develop on their own through computer programming that is carefully designed based on data-driven models. Therefore, designing algorithms that spontaneously support a system in collecting data and effectively utilizing that data to learn more is the main objective of a successful ML model. Systems are anticipated to analyze the gathered data for patterns and use those patterns to autonomously make important decisions. The framework followed to develop a predicted ML modeling is clarified as follows: Initially, it is essential to gather truthful data so that the ML model can detect the proper trends hidden within the data. The accuracy of the developed ML model essentially depends on the quality of the data fed to ML algorithms. After collecting the dataset, it should be preprocessed to detect missing values, outliers, duplication, or redundant features. Moreover, it is important to visualize the data to comprehend its organization and understand the connections between the different factors and classifications it contains. Additionally, scaling the data or normalization the features is very helpful to speed up computations and assist the algorithms to quickly converge to accurate solutions. Typically, the data was split into two main groups that are randomly selected; the training and testing datasets. After training the model using the training set, it is validated to test its performance and accuracy using the testing set. Best-performance ML algorithms are then calibrated using hyperparameters optimization procedures to increase their accuracies. If a trained model failed during the testing phase, it is retrained using various model configurations. After successful training, the model's success is evaluated utilizing serval evaluation metrics. Finally, the best performance model is deployed, and its inference can be used to make predictions using new unknown data. In the following subsections, we introduce, in detail, this procedure followed to develop our ML modeling of loss of taste and smell senses in infected COVID-19 patients observed during the infection and after recovery.

2.2. Data preprocessing

To improve the computation and convergence of ML algorithms, it is a good practice to standardize or normalize the data. This gives a unified scaling to each feature and speeds up the convergence. Data standardization involves modifying the features so that their means are zero and standard deviations are equal to one. This can be implemented simply by dividing each feature's standard variation by its mean before summing the results. On the other hand, normalization scales the model features to a defined range, typically [0, 1] by subtracting the minimum value for each feature and dividing by the feature range (i.e. max-min).

In this study, we have developed two predictive models; the first one consists of all cases where individuals experienced symptoms related to the loss of smell and taste immediately after confirming their infection with COVID-19. The second model includes cases where individuals experienced these symptoms persistently after a duration of four weeks.

2.2.1. Data related to symptoms during the infection

Table 1 shows the statistical distribution of the collected dataset including positive and negative cases within target groups for the

Table 1
Statistical associations between loss of taste, loss of smell, and reported numbers in sample size of 413 patients.

Loss of taste	Loss of smell	Numbers and percentage
No	No	169 (40.9 %)
No	Yes	47 (3.4 %)
Yes	No	14 (11.4 %)
Yes	Yes	183 (44.3 %)

loss of taste, and loss of smell cases immediately after and during the infection.

Based on the above numbers, we summarize the total numbers as listed in Table 2. Out of the 413 verified COVID-19 patients in our study, 197 (47.7 %) individuals experienced a loss of taste and 230 (56.7 %) experienced a loss of smell. Therefore, based on the given statistics, we can determine that 183 patients experienced both a loss of smell and taste.

Commonly, when building an ML model using a dataset including many features, we may face a typical challenge of feature ranking and selection. This is owing to that not all of the features in the dataset are useful in creating accurate predictive models. Moreover, incorporating all dataset features into the modeling process may even make the prediction accuracy worse, as some of them may include an irrelevant and redundant feature. As a consequence, feature selection is an essential process that should be carefully done before the development ML predictive model.

Correlation is a statistical method that describes how close two factors are to having a linear connection with each other. For instance, two variables x and y will have a higher correlation if the correlation coefficients were close to one and a weak correlation if this coefficient was close to zero. Moreover, the correlation coefficients might be positive to indicate the linear proportional relationship between the two variables, while they might be negative to indicate the inverse proportional behavior.

P-value, also known as probability value or asymptotic significance, is a measure of the likelihood that, if the null hypothesis is correct, a given collection of statistical data, also referred to as the statistical summary, will be higher than or equivalent to the observed results. The p-value for the dataset will change in various ways depending on which characteristics are removed from it. To determine whether to retain a feature or not, one can use these measured p-values. In this modeling, we incorporated both Pearson's correlation coefficient and p-value statistics to evaluate features important relative to the target classes of the loss of taste and loss of smell disorders before and after recovery. The collected dataset contained many features comprising the socio-demographic characteristics of the study population and patients' clinical profile as listed in Table 3.

Among the above-listed features, we selected the most relevant features that were directly or indirectly measurable through validation, as illustrated in Table 4. Based on computed Pearson's correlation coefficients and p-values we selected the most important features that statistically related to the target symptoms, which are the loss of taste and loss of smell. These features included gender, receiving the flu vaccine, short of breathing (SOB) at rest, during dressing and stairs, congestion, sore throat, aches pains/discomfort, headache, tiredness, and nausea. From the correlation analysis, it is worth noticing that the loss of taste and smell senses were strongly correlated to each other as Pearson's correlation coefficient was 0.72. This suggested a high possibility of occurrence of them simultaneously. Based on the results obtained from Table 4, the features' importance ranking, relative to the loss of taste and loss of smell symptoms, is shown in Fig. 1.

2.2.2. Data related to symptoms presistance after four weeks

After 4 weeks of observations for patients who have already recovered from COVID-19, however, some of them still experience persistent loss of smell and loss of smell disorders. Table 5 shows the distribution of positive and negative for loss of taste and loss of smell cases after the recovery. The recovery rate of the loss of taste achieved 70.5 %, the loss of smell was only 61.3 %, and that of both of them is 76.3 %. Therefore, in the adopted dataset, the parentage was 14 % for the loss of taste dataset, and 21.6 % for that the loss of smell, indicating imbalanced datasets.

Considering that the predictor with the greatest contribution to the targeted class has a contribution of 100 % and contributions of the other variables are expressed as percentages. The feature raking was created using an RF classifier and further confirmed by computing Pearson's correlation coefficient and p-values of the level of significance. Therefore, the features importance were ranked in the following order: symptoms continue after two weeks, loss of taste during the infection, loss of sell during the infection, congestion, sorethroat, fever, vomiting, tiredness, and aches pain.

2.3. Machine learning classifiers

More recently, several ML and deep learning models were used for building predictive models of COVID-19 and post-COVID-19-associated disorders [50–53]. Traditional machine learning classifiers such as Logistic regression (LR) [54], K-Nearest Neighbors (KNN) [55], Support Vector Machines (SVM) [56], Random Forest (RF) [57], Extreme Gradient Boosting XGBoost [58], and Light Gradient Boosting Machine (LightGBM) [59] are widely used in various domains including medical problem classification problems. LR is a linear classifier that models the probability of binary or multi-class problems. KNN is a non-parametric method that uses the similarity of data points based on the Euclidean distance metric to classify new data points. SVM separates data points using linear or nonlinear hyperplanes in high-dimensional space. A decision tree classifier partitions a dataset into subsets based on the values of input features to create a tree-like structure of if-then rules which predict the target variable while RF constructs multiple decision trees to classify data. XGBoost and LightGBM are gradient-boosting algorithms that create a sequence of decision trees trained to minimize the loss function. These traditional machine learning classifiers have been used successfully in many real-world applications and have their strengths and weaknesses, which make them suitable for different tasks.

Table 2
Statistical summary of patient experienced loss of taste and smell.

Total number of patients who experienced loss of taste	197 (47.7 %)
Total number of patients who experienced loss of smell	230 (55.7 %)
Total number of patients who experienced both loss of taste and smell simultisnosly	183 (44.3 %)

Table 3
Features list comprising socio-demographic characteristics of the study population and patients' clinical profile.

No.	Feature
1.	Gender (Male, Female)
2.	Age
3.	Education Level
4.	Family Size
5.	Place of residency
6.	Is a current smoker? (None, Active, Former)
7.	Physical exercise (Yes, No)
8.	Chronic illness (Yes, No)
9.	Type of chronic disease (Diabetes Mellitus, Hypertension, Thyroid disease, Asthma, Renal diseases, Low immunity, Cancer)
10.	Others (Cardiac problem, Arthritis, Epilepsy, Facial palsy)
11.	Received flu vaccine? (Yes, No)
12.	COVID-19 Vaccine? (Yes, No)
13.	Type of COVID-19 Vaccine (Strazinka, Pfizer, Jonson & Jonson, Mixed, Unknown, Others)
14.	Admitted to hospital (In-home isolation, Ward patient, ICU)
15.	Isolation weeks (<1 week, 1–2 weeks, 3–4 weeks, <4 weeks)
16.	Symptoms continue after 2 weeks (Yes, No)
17.	Duration of COVID-19 Symptoms (<1 week, 1–2 weeks, 3–4 weeks, <4 weeks)
18.	Swab after recovery (Yes, No)
19.	Is the disease worsening the quality of life? (Yes, No)
20.	Patients' medications (Analgesics, zinc, and vitamin c, Analgesics, Herbal medication, and vitamin c, Respiratory supportive therapy (Oxygen, Ventolin), Azithromycin, analgesics, zinc, vitamin c, vitamin c, zinc, Analgesics, azithromycin, Respiratory supportive therapy (Oxygen, Ventolin), Azithromycin, analgesics, anticoagulant, and zinc.
21.	Respiratory/Cardiac symptoms (Cough, SOB at rest, SOB on walking, SOB on dressing, Congestion or running nose, Sore throat, Chest pain/pressure)
22.	Neurological symptoms (Headache, Loss of smell, Loss of taste, Confusion, Loss of speech, Loss of movement)
23.	Systematic symptoms (Fever, Tiredness, Aches/pains, Skin rash)
24.	GIT symptoms (Nausea, Diarrhea, Vomiting)
25.	Psychological symptoms(Anxiety, Depression)
26.	Other symptoms(Dizziness, Sweating, Bad Dreams, Decrease sight, Indigestion, Hair falling, Coldness, Hallucination, Thirst)

Table 4
Important Features list adopted for developing ML model. The asterisk sign indicates p-value of less than 0.05.

		Loss of taste		Loss of smell	
		R	P	R	P
1	Gender	0.10	0.04*	0.01	0.85
2	Received the Flu vaccine?	−0.06	0.26	−0.14	0.01*
3	SOB at rest during COVID	0.16	0.00*	0.13	0.01*
4	SOB on dressing during COVID	0.14	0.00*	0.12	0.01*
5	SOB on walking during COVID	0.15	0.00*	0.12	0.01*
6	Congestion	0.16	0.00*	0.11	0.02*
7	Sore throat	0.11	0.03*	0.08	0.09
8	Headache	0.13	0.01*	0.12	0.02*
9	Fever	0.18	0.00*	0.14	0.01*
10	Aches pains	0.12	0.01*	0.19	0.00*
11	Tiredness	0.13	0.01*	0.11	0.03*
12	Nausea	0.11	0.02*	0.05	0.34

Among the above mention algorithms, XGBoost is a popular and powerful ML algorithm that has been widely used in various domains including medical data classification. It is designed to address the limitations of traditional gradient-boosting algorithms by incorporating advanced regularization techniques and parallel computing. The algorithm works by creating a sequence of decision trees that are trained to minimize the loss function. Unlike traditional gradient boosting algorithms, XGBoost builds trees in a parallel and optimized way, making it much faster and more efficient. It also includes a technique called gradient-based regularization, which helps to prevent overfitting and improve model accuracy. In addition, XGBoost allows for customized loss functions and evaluation metrics, making it a flexible algorithm that can be tailored to medical applications. Its ability to handle large and complex datasets and its flexibility make it an important tool for data scientists and researchers in the medical field. The mathematical equation for XGBoost classification can be represented as follows: For a given set of input features x, the predicted output y is calculated as:

$$y = \arg_i \max \sum w_j \cdot y_j + b_i \tag{1}$$

where i represents the class label, j represents the index of the decision tree, w_j is the weight of the jth decision tree, y_j is the output of the jth decision tree, and b_i is the bias term for class i. The output of each decision tree is calculated as the sum of the leaf values in the decision path that input x takes through the tree. The final prediction is the class label with the highest predicted probability. XGBoost uses gradient descent to optimize the weights and bias terms and includes advanced regularization techniques such as L_1 and L_2

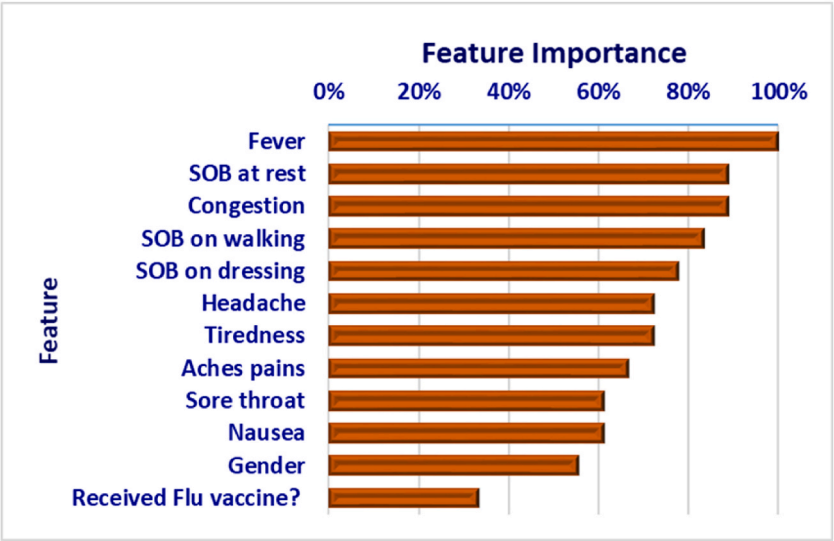


Fig. 1. Features' importance ranking relative to Loss of taste and Loss of smell symptoms. Considering that the predictor with the greatest contribution to the targeted class has a contribution of 100 % and contributions of the other variables are expressed as percentages.

Table 5
Distribution of positive and negative cases within target groups.

Total numbers who recovered from the symptoms	315 (76.3 %)
Total number who still experience loss of taste	58 (14.0 %)
Total number who still experience loss of smell	89 (21.6 %)
Total number who still experience both of them	49 (11.9 %)

regularization to prevent the overfitting problem. Generally, XGBoost is a powerful algorithm that can accurately deal with large and complex datasets.

LightGBM is a gradient-boosting framework that is designed to be faster and more memory-efficient than other gradient-boosting frameworks such as XGBoost. It is an open-source project developed by Microsoft. The following are some of the key differences between LightGBM and XGBoost algorithm:

1) Gradient-based One-Side Sampling (GOSS): LightGBM uses a GOSS technique to select a subset of the data during the training process. This technique selects the instances with larger gradients and keeps all instances with small gradients. This technique helps to decrease the number of instances that need to be evaluated during each iteration, thereby reducing the computational cost.
2) Exclusive Feature Bundling (EFB): LightGBM uses this technique to group the features into bundles based on their importance. The bundles are created by combining the most important features that have similar distributions. EFB reduces the number of features that need to be evaluated during each iteration, which reduces the computational cost.
3) Leaf-wise Tree Growth: LightGBM uses a leaf-wise tree growth algorithm instead of a level-wise tree growth algorithm like XGBoost. The leaf-wise algorithm grows the tree by splitting the leaf with the maximum gain, while the level-wise algorithm splits all leaves at the current level simultaneously. While a leaf-wise algorithm can lead to a higher training speed and better accuracy, it may also lead to overfitting.
4) Histogram-based Gradient Calculation: LightGBM uses a histogram-based approach to calculate the gradients during the training process. This approach reduces memory usage by discretizing the continuous features into discrete bins. The histogram-based approach also enables a fast calculation of the gradients.

Generally, the properties of LightGBM, including its ability to handle large and complex datasets, speed and efficiency, and high accuracy, make it a powerful tool for COVID-19 symptoms prediction. Its versatility and ability to handle a wide range of machine-learning tasks also make it an essential tool for predicting and managing other health-related issues.

Another advantage of LightGBM is its ability to handle imbalanced datasets, which is common in COVID-19 symptom prediction. Overall, while both LightGBM and XGBoost are powerful algorithms for COVID-19 symptoms prediction, LightGBM's speed, ability to handle imbalanced datasets, lower memory footprint, and exclusive feature bundling provide it with some advantages over XGBoost in this application.

Mathematically, LightGBM can be described as follows: Given a training dataset $D = (x_i, y_i)_{i=1}^{n}$, where $x_i \in R^m$ is the feature vector for the i^{th} instance, and $y_i \in R$ is the corresponding label. The goal is to learn a prediction function $F(x)$ that minimize the loss function

$L(y, F(x))$.

LightGBM works by iteratively adding decision trees to the model to minimize the objective function. The objective function can be written as:

$$obj(\Theta) = \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + T_m(x_i)) + \Omega(T_m) + C \tag{2}$$

where $F_{m-1}(x_i)$ is the prediction of the model up to the $(m-1)^{th}$ iteration, $T_m(x_i)$ is the decision tree added at the m^{th} iteration, Θ is the set of hyperparameters including the structure of the tree and the regularization parameters, $\Omega(T_m)$ is the regularization term, and C is a constant term.

The loss function L measures the difference between the true value y_i and the predicted value $F_{m-1}(x_i) + T_m(x_i)$. The regularization term $\Omega(T_m)$ penalizes complex trees to avoid overfitting. The objective function is optimized by gradient boosting, which involves computing the gradients and Hessians of the loss function with respect to the model predictions and using them to fit the decision tree.

At each iteration, LightGBM uses EFB and GOSS techniques to select a subset of instances and features for tree building. EFB groups similar features together to reduce the number of features considered for splitting, while GOSS samples instances based on their gradients to decrease the number of instances considered for splitting.

The decision tree is grown in a leaf-wise manner, where each leaf node is split into two child nodes that maximize the gain in the objective function. Once the decision tree is built, the prediction function $F_m(x)$ is updated as follows:

$$F_m(x) = F_{m-1}(x) + \eta T_m(x) \tag{3}$$

where η is the learning rate, which controls the contribution of each decision tree to the final prediction. The process of adding decision trees and updating the prediction function is repeated until a stopping criterion is achieved, so that a minimum improvement in the objective function or a maximum number of iterations is reached.

2.3.1. Model training

The COVID-19 dataset consists of 413 observations and 16 selected features that were split into two subsets, the training set, and the testing set. The training/validation percentage was 80 %, corresponding to 330 observations, while the testing set percentage was 20 %, corresponding to 83 observations. For the development of the predictive models, several ML classification algorithms were used and fined tuned. These algorithms include LR, SVM, KNN, RF, XGBoost, and LightGBM. The model training of these algorithms typically involves the following steps.

First, the algorithm is initialized with a set of hyperparameters that control the model's behavior, such as the learning rate, number of neighbors, or number of trees. Then, the algorithm is trained on the labeled training dataset, where the input features and target variables are provided. During training, the algorithm iteratively adjusts the model parameters to minimize the loss function that represents the difference between the true and predicted output. The specific optimization algorithm used can vary depending on the algorithm, such as stochastic gradient descent for LR and XGBoost, or tree-building for RF and LightGBM.

Both XGBoost and LightGBM are gradient-boosting algorithms that build a sequence of decision trees to make predictions. Here are some additional details about the model training process for these algorithms. The training process for XGBoost involves fitting decision trees to the data and updating the weights of each training example after each tree is constructed. The objective function for XGBoost includes a regularization term to prevent overfitting, and the algorithm uses a second-order approximation to optimize the objective function more efficiently. XGBoost also includes features such as early stopping to prevent overfitting and automatic handling of missing data. The training process for LightGBM is similar to XGBoost but with some key differences. LightGBM uses a histogram-based approach to bin the features and reduces memory usage and computation time. It also uses GOSS, which is a novel sampling method, to select the most informative training examples for each tree. In addition to these optimizations, LightGBM includes features such as categorical feature handling and multi-threading to further improve the speed and accuracy of the algorithm.

2.3.2. Model evaluation

The performance of the trained model is then evaluated on a separate dataset to assess its performance and identify potential issues such as overfitting. Finally, the hyperparameters may be tuned using techniques such as grid search or random search to optimize the model's performance on the evaluation dataset. Overall, the model training process for these machine learning algorithms involves a combination of hyperparameter tuning, optimization, and evaluation to create an accurate and robust predictive model.

The model performance was determined using several assessment metrics including accuracy, precision, recall, specificity, and F1-score. These metrics are derived from a common classification model evaluation tool termed the confusion matrix. It includes data on actual and predicted classifications. These model assessment metrics are calculated using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Here, the TP was used to denote the number of cases that correctly predicted and identified as loss of taste or loss of smell symptoms. TN denotes the number of cases that were correctly predicted as negative cases that did not experience the loss of smell symptoms. FP and FN denote the number of cases incorrectly predicted as positive and negative cases, respectively.

The accuracy is calculated as the percentage of the truly predicted positive and negative cases to the total number of observations, as given below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

Precision is a considerable metric for evaluating the degree of exactness as it determines the percentage of instances the classifier labeled as positive, with respect to the total predictive positive instances. This can be calculated using the following equation:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

The sensitivity or recall refers to a number of instances of the positive class that were categorized correctly. It can be computed as shown in Equation (6):

$$Senstivity\ or\ Recall = \frac{TP}{TP + FN} \tag{6}$$

The recall is another performance metric utilized to select the best predictive model when there is a high cost associated with an FN.

Specificity determines the chance that the negative label is true since it relates to the conditional probability of true negatives for a given class, as shown by the following Equation:

$$Specificity = \frac{TN}{TN + FP} \tag{7}$$

Another important metric is called the F1-score which is quite helpful when seeking a weighted average of the precision and sensitivity as it represents a harmonic mean of these metrics. Analysis using F1-score mainly focuses on the positive class. A high F1-score value indicates that the model performs well in the positive class, as shown in the following equation:

$$F1 - Score = \frac{2 \times precesion \times recall}{precesion + recall} \tag{8}$$

Although accuracy and F1-score are commonly used to evaluate classification models, sometimes they might produce overly optimistic results, particularly on positively imbalanced datasets. The receiver operating characteristic curve (ROC) [60] is the most widely used assessment curve developed during world war II for controllers of military radar receivers as an effective indicator to differentiate received signals, representing enemy targets, from noise. The area under the curve (AUC) of the ROC curve is a performance metric for classification issues at different threshold levels. AUC shows the degree or measure of separability, while ROC is a probability graph. The ROC curve depicts the true positive rate (TPR) on the y-axis vs the false positive rate (FPR) on the x-axis. It indicates how well the model can differentiate between classes in the dataset. The greater the AUC, the better the algorithm predicts zero classes as zero and one class as one. Similarly, the higher the AUC, the better the model distinguishes between individuals with and without illness.

3. Results and discussion

In this section, we introduce the model performance evaluation developed to predict the symptoms of loss of taste and loss of smell senses using key symptoms as input features of the model. Based on that, the trained and tested model task is to predict the occurrence of these symptoms during the infection with COVID-19 for two weeks. The results are analyzed using accuracy, precision, sensitivity,

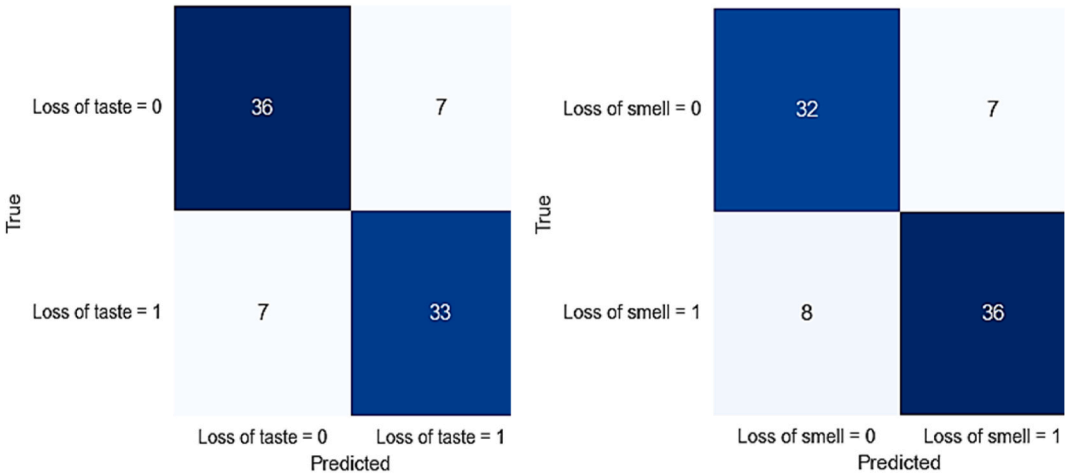


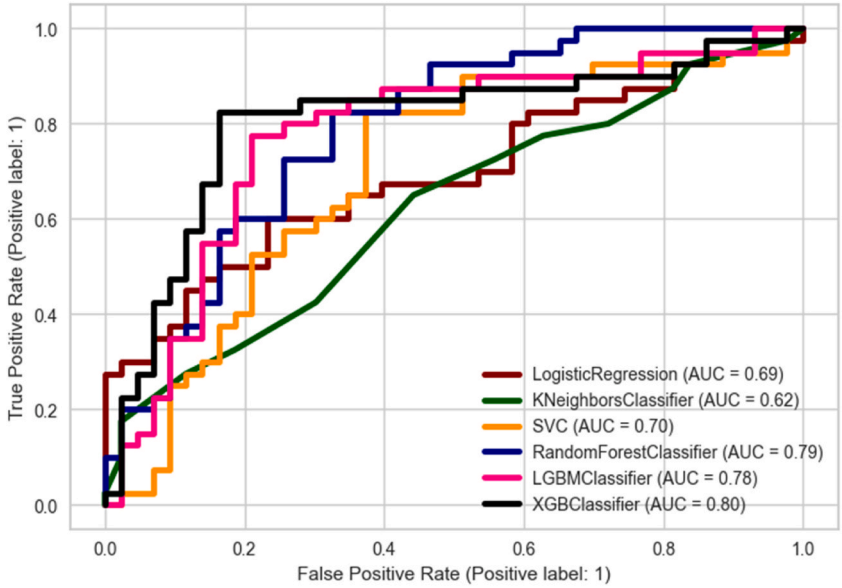
Fig. 2. Confusion matrix of the classification model applied for testing datasets (83 samples) with (a) "loss of taste" and (b) "loss of taste" as the predicted targets. The accuracy of the "loss of taste" model is 83 %, and that of the "loss of taste" is 82 %. These results were achieved using an optimized LightGBM classifier algorithm.

specificity, and F1-Score, for both the training and testing datasets. In the following section, we display other modeling results considering the prediction of these symptoms for more than one month after recovery from the COVID-19 virus.

3.1. Prediction of symptoms during the infection

Fig. 2 displays the confusion matrices of the testing sets comprising 20 % of the dataset (i.e. 83 instances). The numbers of patients who were correctly classified were 69 out of 83, corresponding to 83.13 %, while the misclassified number was 14 out of 83, corresponding to 16.87 %. Likewise, for the loss of smell symptom, the numbers of patients who were correctly classified were 68 out of 83 (81.92 %) and those incorrectly classified were 15 out of 83 (i.e. 18.07 %). Therefore, we consider the overall model accuracy for the loss of taste and loss of smell target classes in the testing dataset computed to be approximately 83 %, and 82 %, respectively.

The ROC plot is a widely used performance metric in binary classification problems, as it provides a visual illustration of the trade-off between the TPR and the FPR at different classification thresholds. In this case, we evaluate the performance of six different



(b)

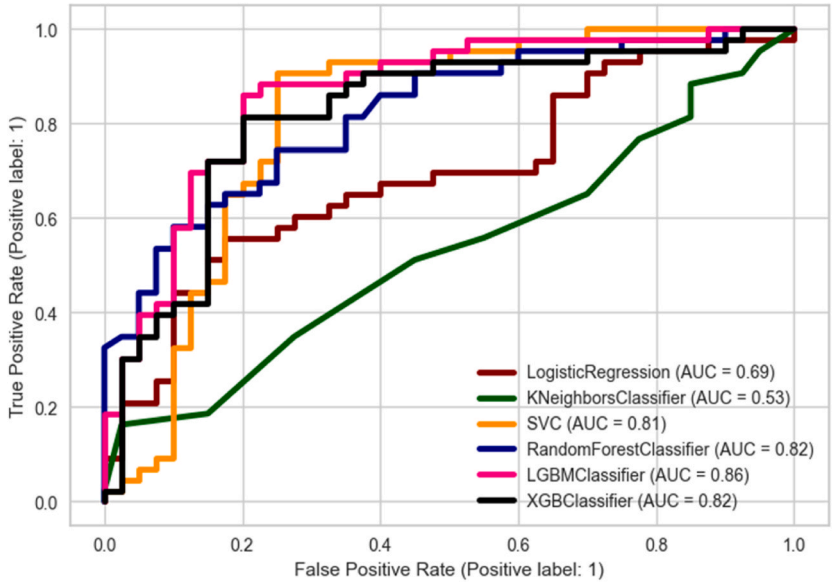


Fig. 3. ROC plot of classifiers used for modeling of (a) loss of taste and (b) loss of smell symptoms before recovery. AUC ranges from 0 to 1, with a higher value indicating better predictive performance. An AUC of 0.5 suggests a model that performs no better than random guessing, while an AUC of 1 represents a perfect classifier. The best performance model, achieved using the XGB classifier, exhibited AUCs of 0.80 and 0.82 for the testing dataset.

algorithms - LR, KNN, SVM, RF, XGBM, and LightGBM for binary classification of loss of taste and loss of smell symptoms before recovery and calculate their performance using the area under the ROC curve (AUC-ROC) metric. The AUC-ROC results are displayed as shown in Fig. 3. For the prediction of the loss of taste symptom, it can be observed that the best-performing algorithms are XGBM with an AUC of 0.80, followed by RF with an AUC of 0.79, and LightGBM with an AUC of 0.78. SVM also performed relatively well with an AUC of 0.70, while LR and KNN had lower AUC values of 0.69 and 0.62, respectively. In addition, for the loss of smell symptom prediction, the best-performing algorithms are LightGBM with an AUC of 0.86, followed by RF and XGBM with an equal AUC value of 0.82. SVM also performed well with an AUC of 0.81, while LR and KNN had lower AUC values of 0.69 and 0.53, respectively.

Table 6 shows the classification results of various models using LR, KNN, SVM, RF, LightGBM, and XGBM. The model's effectiveness has been demonstrated through comparisons of various performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. Results show that the accuracy metric of the XGBM model for loss of taste symptoms has the highest precision value of 83.13 %, followed by LightGBM with 78.31 %, and RF with 71.08 %. LR and SVM have accuracy values of 66.27 % and 63.86 %, respectively, while KNN has the lowest accuracy value of 56.63 %. Considering the results of the precision metric, XGBM again has the highest value of 82.50 %, followed by LightGBM with 77.50 %, and RF with 71.05 %. SVM and LR have precision values of 63.16 % and 68.75 %, respectively, while KNN has the lowest recall value of 56.67 %.

Recall is another considerable performance metric that also measures the classification model's correctness. In this case, XGBM has a recall value of 82.50 %, followed by LightGBM with 77.50 %, and RF with 67.50 %. SVM and LR have recall values of 60.00 % and 55.00 %, respectively, while KNN has the lowest accuracy value of 42.50 %. F1-score, which is the harmonic mean of precision and recall, is a balanced metric that provides an overall performance measure. In this case, XGBM again has the highest F1-measure value of 82.50 %, followed by LightGBM with 77.50 %, and RF with 69.23 %. SVM and LR have F1-measure values of 61.54 % and 61.11 %, respectively, while KNN has the lowest F1-measure value of 48.57 %. The overall results reveal that for the loss of taste model, XGBM achieved the highest model results in all metrics, while for the loss of smell model, the Light-GBM achieved the highest performance in all metrics. Table 7 summarizes all the hyperparameters associated with each ML algorithm that has been utilized.

3.2. Prediction of symptoms persistence

Fig. 4 displays the confusion matrix of the testing datasets for the two target features. The numbers of patients who were correctly classified as experiencing loss of taste symptoms after recovery were 7 out of 10 (70 %) and those who did not were 69 out of 73 (83.6 %). The total number of incorrectly classified cases was 4 + 3 (8.4 %). The average accuracy of this model is 91.5 %. Likewise, the numbers of patients who were incorrectly classified with loss of smell symptoms and non-loss-of-smell were 6 and 1, with 3.3 % and 0.7 % corresponding among all patients in each group. Similarly, overall 97.7 % were correctly, and 1.6 % were incorrectly classified. In the case of the testing dataset, the correct positive and negative predictions for the loss of smell target were 86.7 % and 78.9 %, respectively. On the other hand, the incorrect positive and negative classes were 13.3 % and 21.1 %.

The ROC plot of all models after recovery is shown in Fig. 5. For the loss of taste symptoms, it is observed that the best-performing algorithms are RF with an AUC of 0.96, followed by XGBM with an AUC of 0.95, and LR with an AUC of 0.94. LightGBM and SVM also performed relatively well with an AUC of 0.93 and 0.90, respectively, while KNN has a lower AUC value of 0.87. However, for the loss of smell symptom prediction, the best-performing algorithms are LightGBM, RF, and SVM with equal AUC values of 0.97, followed by LR and XGBM with equal AUC values of 0.96. While KNN had lower AUC values of 0.90. It is noted that most of the examined machine learning algorithms perform well in loss of smell prediction except the KNN algorithm.

It is worth to note that the AUC values do not provide information about the overall accuracy or other performance metrics such as precision and recall, but rather indicate the ability of the algorithm to distinguish between positive and negative samples. Therefore, we cannot conclude that XGB or LightGBM are necessarily the best algorithms overall, as their performance may be affected by other factors such as data size and class imbalance. Table 8 shows the classification results of various models using LR, KNN, SVM, RF, LightGBM, and XGBM. The model's effectiveness has been demonstrated through comparisons of various metrics, including accuracy, precision, recall, F1-score, and AUC. For the loss of taste models, XGBM achieved the highest model results in accuracy, recall, and F1-score metrics with values of 91.57 %, 63.64 %, and 66.67 %, respectively. While the SVM classifier achieved the best precision score of 71.43 %. Regarding the performance of loss of smell models, the Light-GBM achieved the highest performance in accuracy and F1-score metrics with values of 95.18 % and 84.62 %, respectively. The best precision value of 96.67 % was achieved using the RF classifier while the best recall value of 100 % was obtained using XGBM. It is observed that since the prediction of symptoms

Table 6
Summary of models' performance evaluated for different ML algorithms including LR, KNN, SVM, RF, LightGBM, and XGBoost. The performance metrics provide insights into the effectiveness of each model in classifying cases of "loss of taste" and "loss of smell." These metrics include accuracy, precision, recall, F1-score, and AUC.

Model metrics	Loss of taste						Loss of smell					
	LR	KNN	SVM	RF	Light-GBM	XGBM	LR	KNN	SVM	RF	Light-GBM	XGBM
Accuracy (%)	66.27	56.63	63.86	71.08	78.31	**83.13**	54 0.22	49.40	74.70	72.29	**81.93**	79.52
Presicion (%)	68.75	56.67	63.16	71.05	77.50	**82.50**	54.39	50.72	76.19	70.00	**81.82**	80.95
Recall (%)	55.00	42.50	60.00	67.50	77.50	**82.50**	72.09	81.40	74.42	81.40	**83.72**	79.07
F1-score (%)	61.11	48.57	61.54	69.23	77.50	**82.50**	62 0.00	62.50	75.29	75.27	**82.76**	80.00
AUC	0.69	0.62	0.70	0.79	0.78	**0.80**	0.69	0.52	0.81	0.82	**0.86**	0.81

Table 7
Model hyperparameters.

Model	Hyperparameters
LR	C: 1.0; penalty: 'l2'; fit_intercept: True.
KNN	n_neighbors: 50; weights: 'uniform'; algorithm: 'auto'; leaf_size: 30.
SVM	C: 10; kernel: 'rbf'; gamma: 0.1.
RF	n_estimators: 10; criterion: 'gini'; max_depth: 10; min_samples_split: 4; min_samples_leaf: 1.
LightGBM	boosting_type: 'gbdt'; num_leaves: 31; learning_rate: 0.1; n_estimators: 556; max_depth: 1.
XGBoost	booster: 'gbtree'; n_estimators: 218; learning_rate: 0.1; max_depth: 3; reg_lambda = 0.006.

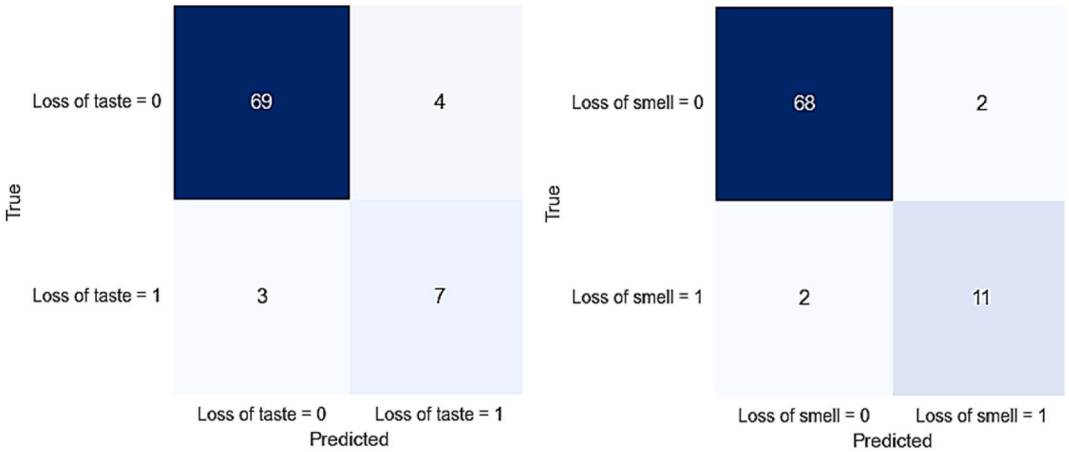


Fig. 4. Confusion matrix of the classification model applied for testing datasets (83 samples) with (a) "loss of taste" and (b) "loss of smell" as the predicted targets. The accuracy of the loss of taste model is 92 % and that of the loss of smell is 95 %. These results were achieved using an optimized LightGBM classifier algorithm.

persistence after recovery suffers from a class imbalance problem, no one classifier performs well in all metrics. However, in the case of Prediction of symptoms during the infection, XGBM and Light-GBM performance dominate other classifiers.

4. Conclusions

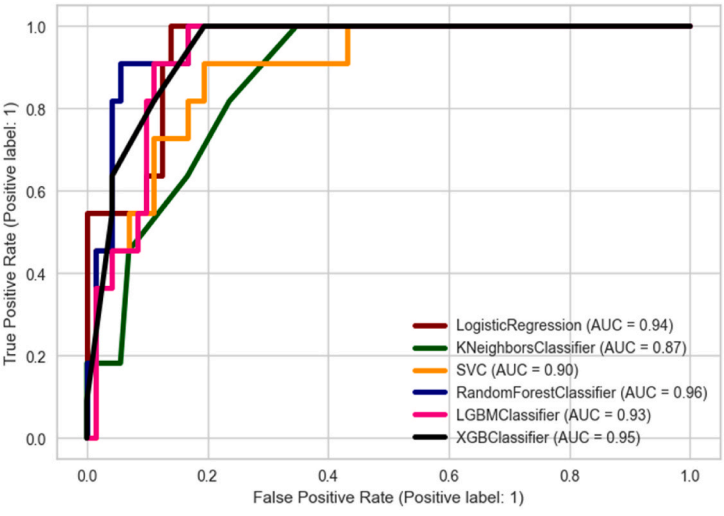
The goal of this work is to provide a comprehensive machine learning (ML) modeling framework for predicting the loss of smell and taste disorders due to infection by COVID-19. For the 413 verified polymerase chain reaction (PCR) test-positive COVID-19 patients enrolled in this investigation, the Saudi ministry of health electronic surveillance system (HESN) database was used. The ML algorithms used to predict COVID-19 diagnosis were applied to 413 cases. For the testing dataset before the recovery, the average accuracy of the loss of taste model was 78 % with an AUC of 0.82 using different ML classifier algorithms. The best performance model's average accuracy for the loss of smell before recovery was 82 %, with an AUC of 0.86. The average accuracy for loss of taste after recovery was 89 % with an AUC of 0.96, and for loss of smell after recovery was 92 % with an AUC of 0.97. As a result, this study introduces accurate predictive ML models to evaluate two major disorders associated with COVID-19. The modified decision tree-based classifiers such as XGBM and Light-GBM exhibits a promising performance in most of the commonly used machine learning metrics. Experts in hospitals can use this modeling to initially determine the incidence and persistence of these associated symptoms. These developed models that accurately predict symptom persistence in COVID-19 recovery can benefit healthcare providers in identifying high-risk individuals and enabling proactive monitoring and care. Tailored treatment strategies can be developed based on these models, leading to improved patient outcomes. Resource allocation and planning can be optimized by identifying those at higher risk, ensuring efficient distribution of healthcare resources. Early intervention and preventive measures can be implemented through public health campaigns targeting at-risk individuals.

Institutional review board statement

This study was approved by the Regional Research Etics Committee, Qassim region (Approval #: 607-44-013238).

Informed consent statement

Informed consent was obtained from all subjects involved in the study.



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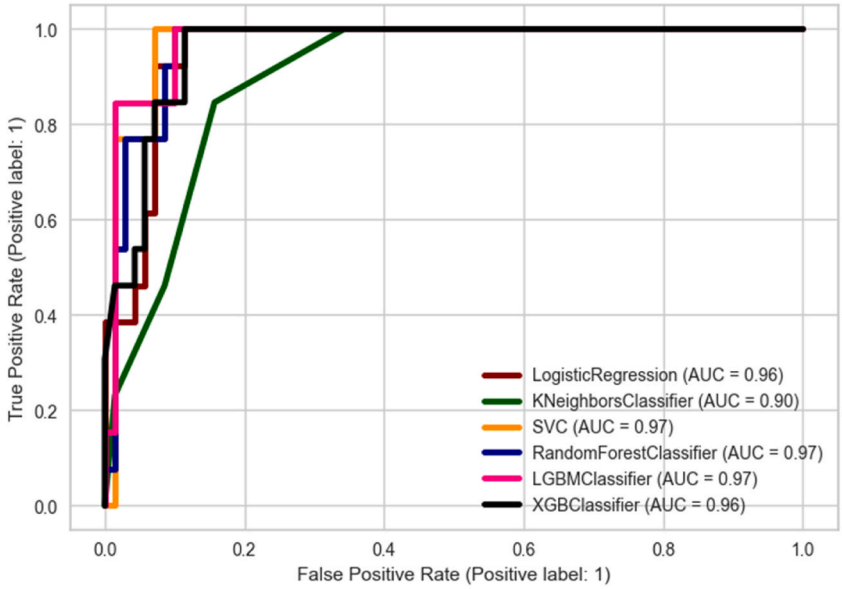

Fig. 5. ROC plot of classifiers used for modeling of (a) loss of taste and (b) loss of smell symptoms after recovery. AUC ranges from 0 to 1, with a higher value indicating better predictive performance. An AUC of 0.5 suggests a model that performs no better than random guessing, while an AUC of 1 represents a perfect classifier. The best performance models were achieved using RF (AUC = 0.96) and LightGBM (AUC = 0.97) classifiers.

Table 8
Summary of models' performance. evaluated for different ML algorithms including LR, KNN, SVM, RF, LightGBM, and XGBoost. The performance metrics provide insights into the effectiveness of each model in classifying cases of "loss of taste" and "loss of smell." These metrics include accuracy, precision, recall, F1-score, and AUC.

Model metrics	Loss of taste						Loss of smell					
	LR	KNN	SVM	RF	Light-GBM	XGBM	LR	KNN	SVM	RF	Light-GBM	XGBM
Accuracy (%)	86.75	89.16	90.36	89.16	85.54	**91.57**	92.77	84.34	90.36	91.57	**95.18**	86.75
Presicion (%)	50.00	100	**71.43**	62.50	46.15	70.00	70.59	50.00	66.67	**96.67**	84.62	54.17
Recall (%)	54.55	18.18	45.45	45.45	54.55	**63.64**	92.31	61.54	76.92	92.31	84.62	**100.0**
F1-score (%)	52.17	30.77	55.56	52.63	50.00	**66.67**	80.00	55.17	71.43	77.42	**84.62**	70.27
AUC	0.94	0.87	0.89	**0.96**	0.93	0.94	0.96	0.90	0.97	0.96	**0.97**	0.96

Data availability statement

Data generated during this study are available from the corresponding authors on request.

CRediT authorship contribution statement

Khaled Alhassoon: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **Mnahal Ali Alhsaon:** Resources, Investigation, Data curation. **Fahad Alsunaydih:** Methodology, Investigation, Data curation. **Fahd Alsaleem:** Methodology, Investigation, Conceptualization. **Omar Salim:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation. **Saleh Aly:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation. **Mahmoud Shaban:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Data curation, Conceptualization.

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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