Psychological Risk Profiling for Post-COVID-19 Anxiety Using Interpretable Ensemble Learning

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Abstract. COVID-19 pandemic has left significant physical and mental health consequences with anxiety disorders being particularly prevalent among recovered patients. This study presents a machine learning framework to predict post-COVID-19 anxiety using data from 1,000 recovered individuals in Bangladesh. Several models including SVM, XGBoost, LightGBM, CNN and a heterogeneous voting ensemble were developed and evaluated. Data preprocessing involved z-score normalization, label encoding and the SMOTE to address class imbalance. For interpretability, SHAP was employed to identify key risk factors influencing predictions. The proposed heterogeneous voting ensemble, combining Random Forest, Gradient Boosting, SVM, Logistic Regression and K-Nearest Neighbors with soft voting achieved superior performance compared to individual models and prior studies. It attained 98% accuracy with MAE of 0.095 and an R^2 value of 0.810 demonstrating strong predictive power and robustness. SHAP based feature importance analysis revealed that pre-existing psychological conditions especially drug addiction and anxiety before COVID-19 were the most influential predictors of post-COVID anxiety. Other critical factors included low energy, age, sleep quality and vaccination status. This study highlights the potential of combining ensemble learning with explainable AI to provide reliable predictions and clinically relevant insights, supporting early detection and targeted mental health interventions for recovered COVID-19 patients.

Keywords: Covid-19, Machine learning, Voting ensemble, SHAP, anxiety, mental health

1 Introduction

The COVID-19 pandemic significantly affected global healthcare systems causing many diseases and deaths [1]. The pandemic severely affected mental health

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worldwide [2]. Mental health disorders represent a leading cause of global disease and disability. Anxiety alone has a worldwide prevalence of approximately 4.05%, with cases increasing by over 55% from 1990 to 2019 [3]. On May 5, 2023, the WHO declared that COVID-19 is no longer a "public health emergency of international concern". This marked the practical end of the pandemic but its negative effects are expected to continue [2]. Patients who have recovered from COVID-19 frequently have persistent mental and physical issues. Mental health issues like depression, anxiety, and stress are common and can significantly affect their overall well-being and quality of life [4]. Physical and mental health problems today are often linked with a history of COVID-19 disease. It is important to examine whether current health problems are related to past COVID-19 infection. Recent studies have explored this using statistical analysis and machine learning methods [5]. Machado et al. [7] used a Random Forest to predict Long COVID risk. The model was optimized for recall to minimize false negatives. This study demonstrates that machine learning can accurately identify the health and social factors linked to Long COVID. Islam et al. [5, 6] studied post-COVID health effects in recovered patients in Bangladesh. They identified 17 key physiological and neurological factors. Statistical analysis revealed strong interrelations among factors such as anxiety was linked with low energy and depression increasing post COVID. Using machine learning the Decision Tree model predicted anxiety with 93.84% accuracy. This study is the first to use ML to analyze both physiological and neurological post COVID factors providing insights for patient care and public health. Alayo et al. [8] first identified key risk factors for suicidal thoughts and behaviours in healthcare workers during COVID-19 using L1-regularized SVC with SHAP values. Then they predicted outcomes with a Random Forest model, achieving high accuracy without class balancing. Abbaspour et al. [9] analyzed data from 50,484 people who received mRNA COVID-19 vaccines to identify factors linked to side effects. They used an XGB model with SHAP and found allergic reactions were tied to allergy history, female sex, younger age as well as prior COVID-19 and Moderna vaccine. Non-allergic reactions were higher with morning vaccination. The study suggests changing vaccination time may lower side effects. Yousif et al. [10] aimed to identify risk factors for post-COVID mental health disorders. They preprocessed the data and trained several machine learning models. Random Forest performed best and feature importance showed age, severe illness, female gender and prior mental health issues as main risk factors. Gupta et al. developed a framework to predict post-COVID heart risks. They used a stacking ensemble with deep neural networks and a LogitBoost meta-learner, which performed better than other models. Rezapour et al. [12] studied how COVID-19 and online learning affected college students mental health. They handled missing values and balanced classes with SMOTE. Machine learning models were trained with SHAP values used for feature importance. Random Forest performed best showing key factors. Alhassoon et al. [13] used data from 413 COVID-19 patients to predict post-COVID loss of smell and taste. Data was preprocessed, standardized and analyzed for feature importance using Pearson's correlation and p-values.Machine Learning models were trained with hyperparameter tuning. Among them Tree-based models (XGBoost, LightGBM, RF) performed best. Many existing methods may be biased because of methodological limitations, limited validation and poor handling of categorical or multi-level data [14]. In response to this need, our objective is:

- To develop a comprehensive machine learning framework for predicting post COVID-19 health effects in recovered patients.
- To evaluate and compare machine learning and deep learning models (SVM, XGBoost, LightGBM, CNN) with voting ensemble method for accurate classification of post COVID health outcomes.
- To identify and analyze key risk factors for post-COVID anxiety using SHAP values to improve model understanding and clinical relevance.
- To address limitations in previous studies by using robust preprocessing, handling class imbalance with SMOTE, and validating the ensemble learning approach.

2 Methodology

This study used data of 1,000 COVID-19 recovered patients in Bangladesh to predict post-COVID health complications such as anxiety. Data preprocessing included z-score normalization, label encoding and SMOTE for class imbalance. Key features were selected using SHAP and a voting ensemble of five classifiers (Random Forest, Gradient Boosting, SVM, Logistic Regression, and K-NN) with soft voting was used for accurate prediction. Figure 1 shows the workflow of the methodology.

2.1 Dataset

We collected the dataset from Islam et al. (2024) [5]. Which came from 1,000 COVID-19 recovered individuals in Bangladesh between July 2022 and August 2023. It includes 600 males and 400 females aged 10–70 years. Dataset includes 13 demographic and medical features. Also it captured responses for 17 post COVID health factors. The responses were validated by two medical professionals to ensure accurate labeling. Ethical approval was granted by the Research and Development wing of Military Institute of Science and Technology (MIST), Dhaka, and informed consent was obtained from all participants. The dataset is balanced, ethically approved and well-suited for statistical analysis and machine learning models. In this research, the target variable was Anxiety after COVID-19.

2.2 Data Preprocessing

At first we handled missing values in the dataset. z-score was applied to the dataset to standardize the data. This method standardizes the data by subtracting the mean and dividing by the standard deviation. It scales all variables

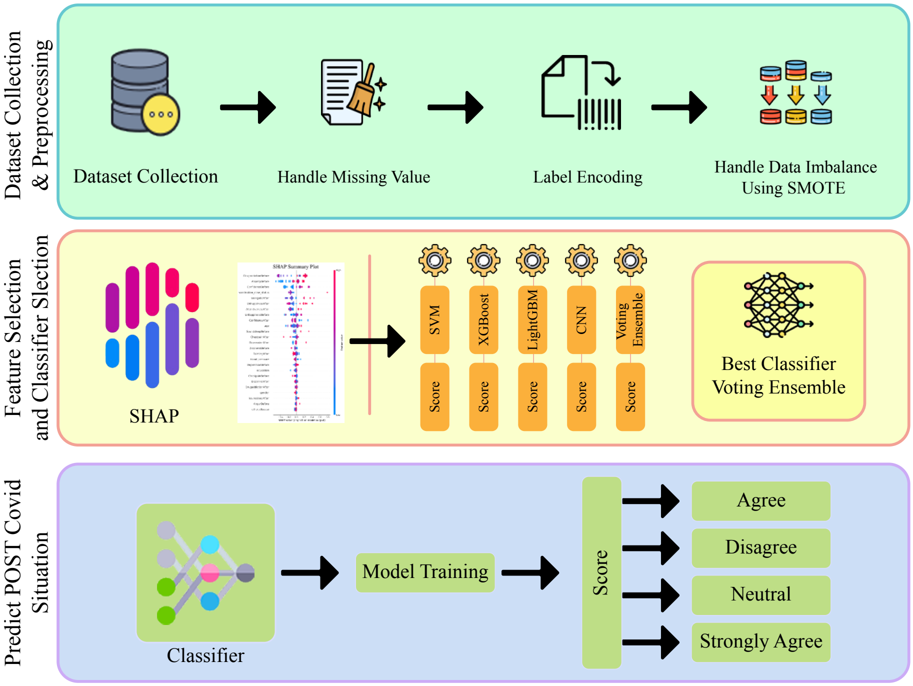

Fig. 1. *Workflow of the proposed methodology for predicting post-COVID-19 health complications, illustrating the sequence of preprocessing, feature analysis and modeling steps.*

on a similar scale enhancing the reliability of further analysis [15]. Then label encoding was applied to convert categorical values into numerical form. It assigns each category as a unique integer making the data suitable for machine learning [16].

2.3 Class Imbalance Handling

SMOTE was applied to handle the problem of class imbalance. It creates synthetic samples of the minority class instead of just duplicating them.This helps the model learn broader decision regions. SMOTE enhances the detection of minority class instances and overall model performance compared to traditional under-sampling or random over-sampling methods [17].

2.4 Feature Importance Analysis

SHAP was applied for feature selection. SHAP assigns an importance value to each feature for a specific prediction. It ensures three key properties. Local accuracy where the explanation matches the models output [19]. Missingness ensures absent features get no contribution. Consistency means a features higher impact does not reduce its attribution. SHAP works by adapting Shapley values from game theory. Each feature is treated as a player in the prediction. Its contribution is calculated by averaging the effect across all possible feature combinations [18, 20]. SHAP calculates feature contributions using a formula based on Shapley values:

$$\phi_i(f,x) = \sum_{z' \subseteq x'} \frac{M!}{|z'|!(M - |z'| - 1)!} [f_x(z') - f_x(z' \setminus i)] \tag{1}$$

Here, M is the total number of features, $z' \subseteq x'$ is a subset of present features, $f_x(z')$ is the model output given that subset of features and $f_x(z' \setminus i)$ is the model output when feature i is excluded. This ensures fair distribution of contributions across all features. SHAP improves trust and transparency by showing which features influenced a prediction.

2.5 Voting Based Ensemble Learning

We applied Heterogeneous Ensemble (Random Forest, Gradient Boosting, SVM, Logistic Regression and K-Nearest Neighbors) for classification. These classifiers were chosen to increase diversity. Heterogeneous Ensemble is an ensemble learning approach that combines different types of base classifiers on the same dataset. Voting is one of the simplest and most widely used combination rules for heterogeneous ensembles [21]. In this experiment soft voting was used. It is used when base classifiers output class probabilities instead of only class labels. Instead of counting votes it averages the predicted probabilities from all models and assigns the class with the highest average probability. Soft voting is better than hard voting because it uses prediction confidence. Soft Voting formulation:

$$H_j(x) = \sum_{i=1}^{T} h_{ij}(x) \tag{2}$$

Here, T = number of classifiers, $h_{ij}(x)$ = probability that classifier i assigns x to class c_j. It takes the average of all probability estimates. The final prediction is the class with the highest average probability [22]. By combining models with different strengths and limitations an ensemble can perform better overall than any single model alone.

The training and testing procedure is conducted using Pytorch, a popular deep learning framework, inside a Python 3.12 setup. The simulations are executed on the Intel Core i9 19400k, 64GB DDR5 60000 Mhz, and 4090 GPU 24GB environment. The datasets and programs used in this research will be available on GitHub at the following link: https://github.com/rudradcruze/post-covid-19-diu-idaa-2025

3 Result

This section presents the results of predicting post-COVID anxiety. We compare models using accuracy and error measures, review class wise performance and examine feature selection methods. We also highlight important health factors and show that our voting ensemble model achieves higher accuracy and reliability than existing approaches.

Table 1. Overall Performance Comparison of Models

Model	Accuracy	MAE	MSE	RMSE	R^2 value
SVM	0.9425	0.1225	0.2725	0.5220	0.8022
XGBoost	0.9644	0.1022	0.3022	0.5497	0.7813
LightGBM	0.9667	0.1000	0.3000	0.5477	0.7829
CNN	0.9767	0.0970	0.2800	0.5291	0.7950
Voting Ensemble	0.9800	0.0950	0.2600	0.5099	0.8100

3.1 Efficiency of different classifiers

Table 1 and Figure 2 shows the performance of different classifiers. The SVM achieved 0.9425 accuracy which is lower than the other models. XGBoost and LightGBM performed better with accuracies of 0.9644 and 0.9667. CNN gave the highest accuracy among single models reaching 0.9767 with low error values. The Voting Ensemble outperformed all models to predict anxiety after COVID-19.. It achieved 0.9800 accuracy the lowest error rates and the highest R^2 value 0.8100. This result shows that voting ensemble method improves both accuracy and stability compared to individual models. Figure 3 presents the ROC curves for all evaluated models in predicting post-COVID anxiety.

Table 2 shows the class wise performance of five classifiers (SVM, XGBoost, LightGBM, CNN and Voting Ensemble) across four classes (Agree, Neutral, Disagree and Strongly agree). Metrices are precision, recall, F1 score and support. For SVM precision ranged from 0.805 to 1.000 recall from 0.924 to 0.956 and F1-score from 0.874 to 0.970. XGBoost and LightGBM showed strong performance with F1-scores mostly above 0.91 while CNN achieved F1 scores between 0.934 and 0.973. The Voting Ensemble performed better than individual models with F1 scores of 0.975, 1.000, 0.993 and 0.957 for Agree, Neutral, Disagree and Strongly agree. This shows that ensemble methods improves accuracy and consistency class wise too.

3.2 Analysis of feature selection results

Table 3 presents a comparison of feature selection methods SHAP and ANOVA across four classes (Agree, Neutral, Disagree and Strongly agree) for predicting anxiety after COVID-19. SHAP outperforms ANOVA for all classes. SHAP

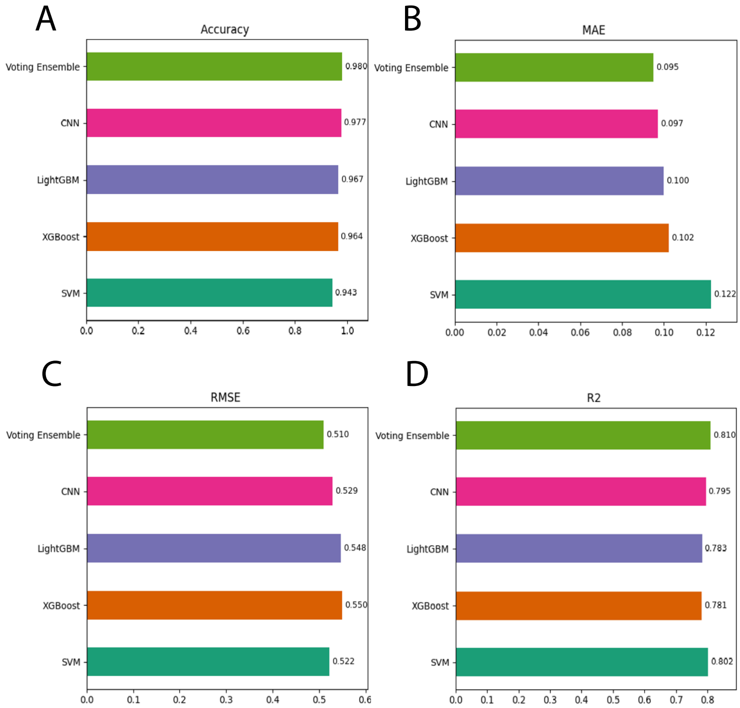

Fig. 2. *Comparative Performance Analysis of Machine Learning Models for Post-COVID-19 Anxiety Prediction*

achieves an AUC of 0.995 and accuracy of 0.985 for the Agree class, and an AUC of 0.998 with accuracy of 0.990 for the Neutral class whereas ANOVA scores 0.978 and 0.962 for Agree and 0.982 and 0.965 for Neutral class. These results shows that SHAP selected features provide better discrimination and overall classification performance than ANOVA.

3.3 Health factors linked to anxiety after recovery from COVID-19

The Figure 4 illustrates the SHAP summary plot. Drug addiction before COVID-19 had the highest impact and was followed by anxiety levels before the disease. Confidence levels before COVID also influenced outcomes. Post-COVID factors such as low energy, unhappiness and poor attentiveness were important. Age was a risk factor. Sleep quality and chest pain, before and after COVID-19 contributed significantly. Depression, dizziness and fainting had moderate effects. Vaccination dose status was protective and showed the importance of mental health before COVID-19.

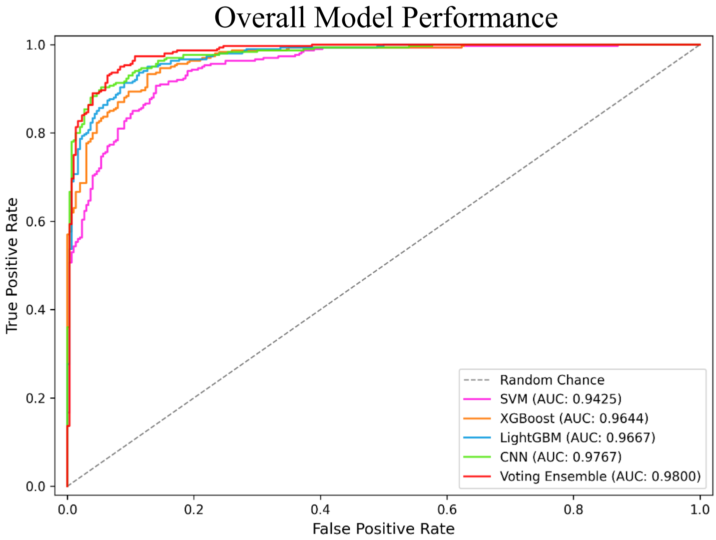

Fig. 3. *ROC curves comparing the performance of different machine learning models for predicting post-COVID anxiety.*

Table 2. Class wise model performance comparison

Model	**Class**	**PRE**	**Recall**	**F1**	**Support**
SVM	Agree	0.9700	0.9238	0.9463	210
	Neutral	0.9815	1.0000	0.9907	53
	Disagree	0.8049	0.9565	0.8742	69
	Strongly Agree	1.0000	0.9412	0.9697	68
XGBoost	Agree	1.0000	0.9367	0.9673	237
	Neutral	0.9833	1.0000	0.9916	59
	Disagree	1.0000	0.9870	0.9935	77
	Strongly Agree	0.8370	1.0000	0.9112	77
LightGBM	Agree	1.0000	0.9367	0.9673	237
	Neutral	1.0000	1.0000	1.0000	59
	Disagree	1.0000	1.0000	1.0000	77
	Strongly Agree	0.8370	1.0000	0.9112	77
CNN	Agree	0.9850	0.9500	0.9672	237
	Neutral	0.9830	0.9830	0.9830	59
	Disagree	0.9600	0.9870	0.9733	77
	Strongly Agree	0.9100	0.9600	0.9344	77
Voting Ensemble	Agree	0.9900	0.9600	0.9748	237
	Neutral	1.0000	1.0000	1.0000	59
	Disagree	0.9870	1.0000	0.9934	77
	Strongly Agree	0.9400	0.9740	0.9567	77

Table 3. Class Wise Feature Selection Performance Comparison for Anxiety

Method	Class	AUC	ACC	MCC	PRE	SEN	SPE	F1
SHAP	Agree	0.9950	0.9850	0.9700	0.9900	0.9800	0.9880	0.9850
	Neutral	0.9980	0.9900	0.9800	1.0000	0.9830	1.0000	0.9914
	Disagree	0.9960	0.9880	0.9750	0.9870	0.9870	0.9890	0.9870
	Strongly Agree	0.9930	0.9820	0.9620	0.9800	0.9740	0.9900	0.9770
ANOVA	Agree	0.9780	0.9620	0.9400	0.9700	0.9500	0.9650	0.9600
	Neutral	0.9820	0.9650	0.9480	0.9800	0.9500	0.9780	0.9650
	Disagree	0.9750	0.9600	0.9370	0.9550	0.9600	0.9610	0.9575
	Strongly Agree	0.9700	0.9550	0.9250	0.9450	0.9500	0.9600	0.9475

3.4 Comparison with existing methods

The table 4 compares existing methods with our proposed model. Abbaspour et al. achieve 84% accuracy while Gupta et al. and Islam et al. reach 93.23% and 93.84%. Our proposed model outperforms all with 98% accuracy, lower errors (MAE = 0.095, MSE = 0.260, RMSE = 0.5099) and a high R^2 of 0.810 showing more accurate and reliable predictions.

Table 4. Comparison With Existing Methods

Existing Methods	Accuracy
Abbaspour et al. [9]	84.00%
Gupta et al. [11]	93.23%
Islam et al. [5]	93.84%
Proposed Model	98.00%

4 Discussion

Our study shows that ensemble learning predicts post-COVID-19 health effects such as anxiety better than other methods. The voting ensembles exceptional performance (MAE = 0.095, RMSE = 0.5099, R^2 = 0.810) validates the effectiveness of combining diverse classifiers with different strengths and limitations. SHAP analysis shows that pre existing psychological conditions predict post-COVID complications better than demographics alone. his challenges traditional risk assessments that focus mainly on age and existing health conditions highlighting the need to include mental health screening in COVID-19 care. Our approach improves on previous studies by carefully handling class imbalance and selecting important features. The superior performance of SHAP over ANOVA demonstrates that model-agnostic explanation methods provide more clinically relevant feature rankings than traditional statistical approaches. The dataset

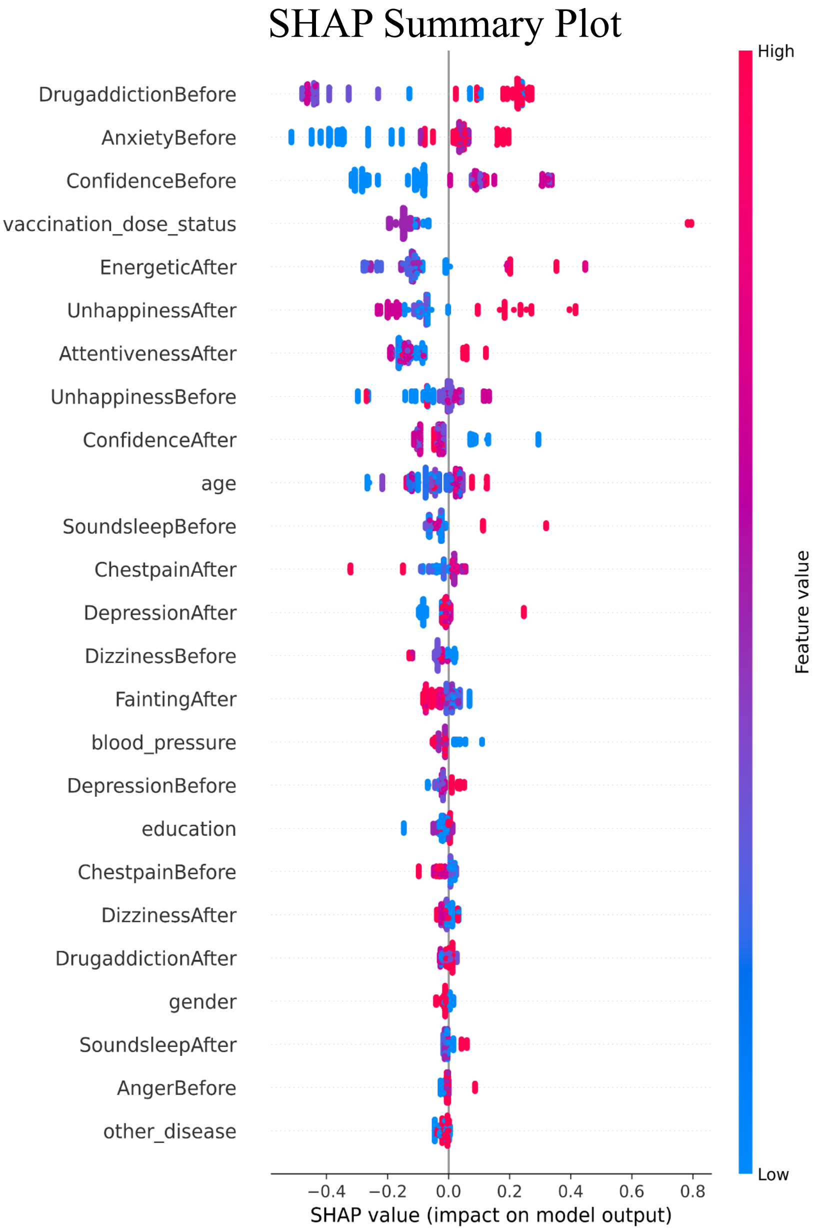

Fig. 4. *SHAP summary plot illustrating the impact of each feature on the voting ensemble model's predictions for post-COVID-19 anxiety.*

comprises 1,000 participants from a single country, which may limit the model's generalizability due to cultural and socioeconomic homogeneity. Future research using more diverse, multi-country cohorts is needed to strengthen external validity. Moreover, the cross-sectional design restricts our ability to examine changes in anxiety over time. Without follow-up data, the model can assess current risk but cannot capture temporal patterns or long-term psychological trajectories. Longitudinal studies would provide stronger causal insights and improve predictive robustness. Together, these findings and limitations highlight the need for broader empirical validation and expanded datasets to further strengthen the reliability and applicability of the proposed framework.

5 Conclusion

This study proposes a machine learning framework to predict post-COVID-19 health effects in recovered patients. Using a voting ensemble that achieves 98% accuracy outperforming individual models and previous studies. Using SHAP for feature analysis revealed key risk factors for post-COVID complications. Combined with SMOTE for class balancing our framework offers interpretable predictions and overcomes limitations of past studies. Although the model shows strong internal performance, it has not been tested on independent or multi-center datasets. Future work will focus on external validation using data from diverse regions to ensure broader applicability and robustness. The study relies solely on quantitative questionnaire data. Including qualitative perspectives such as clinician interviews, patient narratives or behavioral assessments could provide richer context and improve interpretability, representing an important direction for future research. This study sets a benchmark for post-COVID health prediction combining ensemble modeling with SHAP interpretability for clinically trusted insights. It highlights the importance of pre COVID psychological assessment and supports proactive risk stratification while guiding targeted interventions. Validation in real world settings could broaden its applicability to post-COVID syndromes. By focusing on anxiety after COVID-19, this study offers useful insights for early detection and mental health support for recovered patients.

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