Project Scope Statement

Body Signal Data

SUBMITTED BY:

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DATE:
Oct. 19 2023

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1. Project Summary

1.1 Project #	1.2 Project Description	1.3 Date Submitted	1.4 Project Priority
1	We're harnessing machine learning to analyze routine health data, aiming to classify individuals based on physiological signals related to smoking and drinking behaviors. Beyond traditional tobacco and alcohol biomarkers, we're exploring a wider range of signals. Our goal is to provide accurate identification of high-risk behaviors, enabling targeted interventions and using real-time feedback to promote positive change.	10/20/2023	Project II

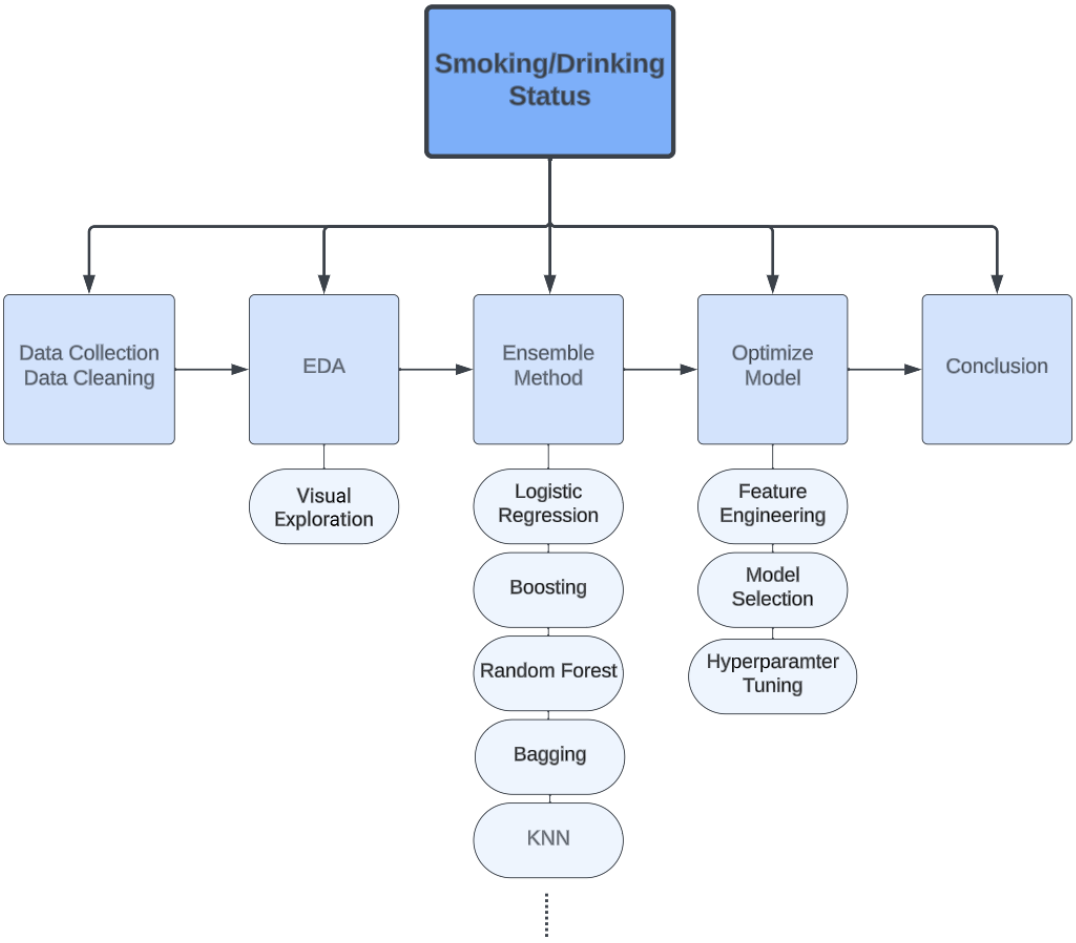
1.5 Step 1 Project Deliverable

Deliverable ID#	Description
1	Project Charter
2	Ensemble trained model with preliminary results of the training and testing.
3	Flask and Heroku application. (customer will choose whether to deploy it locally or on the cloud)
4	Final report of the project in addition to the cloud (heroku) deployed link

1.6 Step 2 List of Project Tasks

Task ID#	Task to be completed	Delivery Date	For Deliverable #
1	Submit Project Charter	09/16/2023	1
2	Generative Methods Based Analysis of the dataset (EDA visualization) ● Pair plots: Show pairwise relationships in a dataset. By using pair plots, we can immediately see the distributions of single variables and relationships between two variables. ● Scatter plots: Useful for spotting structured relationships between variables. ● Heatmaps: Useful for spotting correlations among multiple variables.	11/12/2023	2

3	Machine learning model deployment ● Perform the analysis by using traditional methods with generative and non-generative methods, and compare the results for different parameter sets. ● Tune the parameters of the ML algorithm to achieve better results. ● Report the evaluation metrics used and models' performance on the validation and test sets.	11/26/2023	3
4	Final report of the project ● Summary the insights and give the audience an understandable explanation. ● Answer the question in the introduction paragraph. ● Based on the conclusion and give the advice for the people who smoke or drink.	12/02/2023*	4



1.7 Step 3 Out of Scope

This project **will NOT accomplish or include** the following:

- Collection of new data or additional data sources beyond the provided dataset.
- Deployment of the final model to a production or operational environment.
- Building a full end-to-end pipeline for real-time predictions.
- Quantitative analysis of the downstream impacts of model predictions.
- Extensive error analysis or debugging of model limitations.

1.8 Step 4 Project Assumption

Project factors that will be considered to be true, real, or certain. Assumptions generally involve a certain degree of risk.

#	Assumption
1	The provided dataset is accurate and representative of the target population's health data related to smoking and drinking behaviors.

2	The machine learning models and algorithms chosen for the project are appropriate for the given dataset and can yield meaningful results.
3	Adequate resources, including computational resources and data processing capabilities, are available to complete the project within the specified timeline.

1.9 Step 5 Project Constraints

- Model accuracy should exceed 80% for both classifications.
- Model must be interpretable to understand predictive signals.
- Prediction speed should enable real-time use for APP.

1.10 Step 6 Updated Estimate

Estimate T&C hours required to complete project N/A	Enter total # of T&C hours N/A	If charge-back project, list total estimated T&C cost N/A	Enter N/A if not applicable.

1.11 Step 7 Approvals

Required For Project Class…	Role of Approver	Submitted for Approval on:	Approval Received on:
All classes	1. Client + Client Supervisor	Nakul R. Padalkar	09/16/2023
All classes	2. T&C Supervising Manager	Nakul R. Padalkar	11/12/2023
Class 3 + 4 only	4. VP for Technology & Communication	Nakul R. Padalkar	11/26/2023
Class 3 + 4 only	5. Project Review Board	Nakul R. Padalkar	12/02/2023

2. Introduction

Tobacco use and excessive alcohol consumption are major public health concerns globally, contributing to millions of preventable deaths each year. Being able to predict smoking and drinking behavior from physiological data could help public health agencies target interventions more effectively and contribute to personalized medicine. For example, public health agencies can allocate resources for smoking cessation or alcohol abuse programs to communities with higher prevalence, and healthcare providers can tailor their recommendations and treatment plans based on individual risk factors. This project seeks to develop machine learning models that can classify individuals as smoking status and drinkers/non-drinkers based on body signal data. The body signal data provides a wide range of biomarkers that may be predictive of smoking and drinking habits. However, these relationships have not been extensively studied using machine learning approaches. This project could gain new insights into factors like blood pressure, cholesterol, liver enzymes, etc. correlate with and potentially predict smoking and drinking behavior.

Overall, this is a classification problem aiming to categorize individuals based on their physiological profile. This paper attempts to address the following questions: Can physical indicators in routine health screening data effectively predict smoking and drinking status of individuals? Which signals show the strongest predictive relationships?

3. Analysis of the dataset and Trained Model

3.1 Exploratory Analysis and Visualization

Before moving into model training, it's essential to gain insights into our dataset through exploratory analysis. Our dataset does not have any missing value. The following graphs show the distribution of selected target variables for analysis and modeling: Smoke Status and Drink Status.

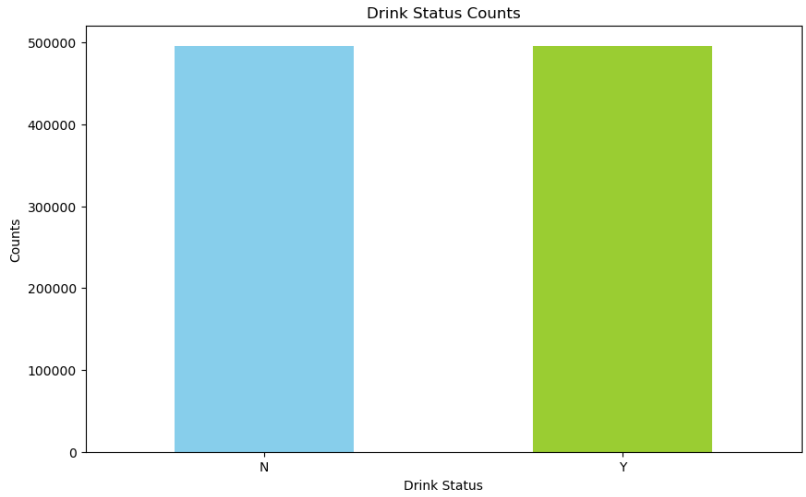


Figure 1 Distribution of the dependent variable (Drink Status)

Figure 1 illustrates the distribution of the dependent variable, Drink Status. `N` represents 'No', and `Y` represents 'Yes'. The distribution of Drink Status is intentionally balanced, with an equal representation of 'Yes' and 'No' to ensure a balanced dataset for analysis.

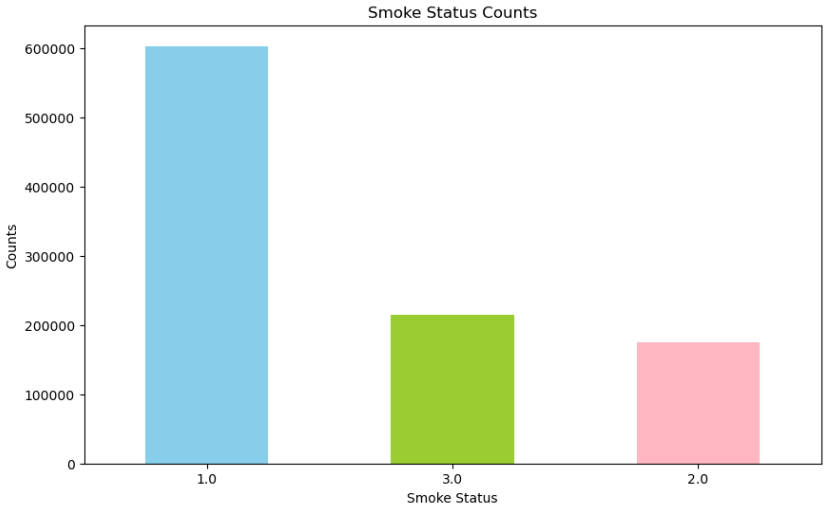


Figure 2 Distribution of the dependent variable (Smoke Status): 1 (never), 2(used to smoke but quit), 3(still smoke)

Figure 2 shows the distribution of the dependent variable, Smoke Status. `1` represents 'never smoke', `2` represents 'used to smoke but quit', and `3` represents 'still smoke'. The distribution of Smoke Status is imbalanced, with more than half of the records never smoking.

Table 1 & 2 Part of Data Summary

	age	height	weight	waistline	sight_left	sight_right	hear_left	hear_right	SBP	DBP
count	991346	991346	991346	991346	991346	991346	991346	991346	991346	991346
mean	47.614	162.241	63.284	81.233	0.981	0.978	1.031	1.030	122.432	76.053
std	14.181	9.283	12.514	11.850	0.606	0.605	0.175	0.172	14.543	9.889
min	20	130	25	8	0.1	0.1	1	1	67	32
25%	35	155	55	74.1	0.7	0.7	1	1	112	70
50%	45	160	60	81	1	1	1	1	120	76
75%	60	170	70	87.8	1.2	1.2	1	1	131	82
max	85	190	140	999	9.9	9.9	2	2	273	185

	HDL_chole	LDL_chole	triglyceride	hemoglobin	urine_protein	serum_creatinine	SGOT_AST	SGOT_ALT	gamma_GTP	SMK_stat_type_cd
count	991346	991346	991346	991346	991346	991346	991346	991346	991346	991346
mean	56.937	113.038	132.142	14.230	1.094	0.860	25.989	25.755	37.136	1.608
std	17.238	35.843	102.197	1.585	0.438	0.481	23.493	26.309	50.424	0.819
min	1	1	1	1	1	0.1	1	1	1	1
25%	46	89	73	13.2	1	0.7	19	15	16	1
50%	55	111	106	14.3	1	0.8	23	20	23	1
75%	66	135	159	15.4	1	1	28	29	39	2
max	8110	5119	9490	25	6	98	9999	7210	999	3

Table 1 & 2 above shows part of the summary of the variables including the two target variables, to provide a better idea of the data.

The below figure 3 is the heatmap for all columns including the categorical variables like Drink Status and Sex which have been converted to numerical variables. From the figure, we can observed
In Figure 3 below, we present a heatmap encompassing all columns, including categorical variables like Drink Status and Sex, which have been converted into numerical variables. From the figure, we observe several noteworthy correlations:

- Height and weight display a significant correlation of 0.72. We will calculate the BMI (Body Mass Index) to alleviate the inner correlation between height and weight.
- The correlation between height and sex is also substantial, standing at 0.72. This is expected, given the natural height differences between men and women.
- Diastolic blood pressure (DBP) and Systolic blood pressure (SBP) exhibit a high correlation of 0.74. This correlation implies a strong relationship between these two blood pressure measurements.
- Total cholesterol (tot_chole) and LDL cholesterol (LDL_chole) are significantly correlated, with a coefficient of 0.887. To address the high correlation between these variables, we should consider excluding one of these variables during model training to avoid issues related to redundancy and multicollinearity. Finally we removed the feature 'tot_chole', because this variable is able to be calculated from the other two variables based on a formula: HDL + LDL + 20% triglycerides = Total cholesterol; and 'tot_chole' has a higher variance.

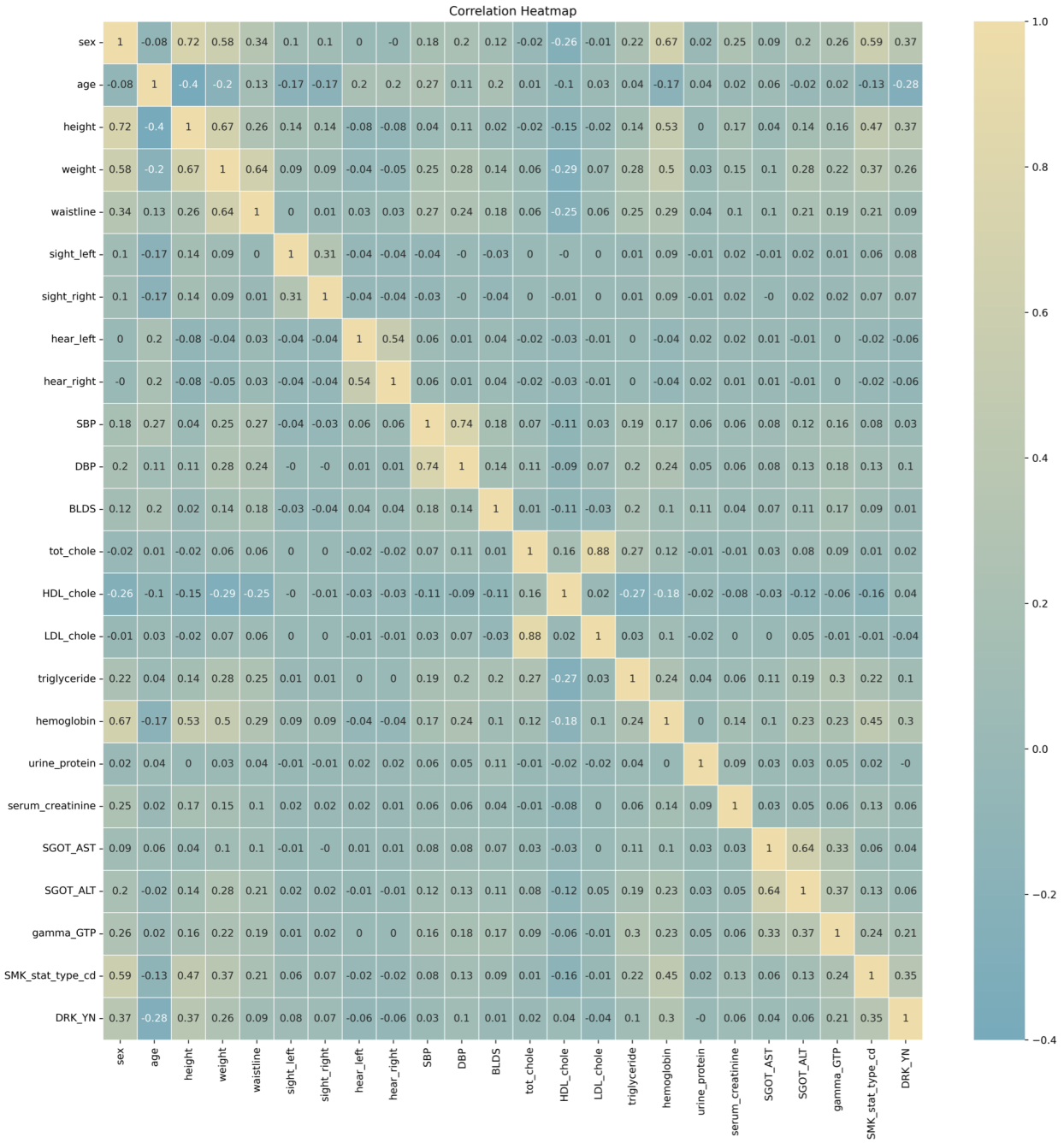


Figure 3 Correlation Matrix of all variables

3.2 Baseline Model

The dummy classifier is chosen as the baseline model. Dummy classifier makes predictions ignoring the input features, only based on the values of target variables, which makes it sensitive to the unbalanced dataset. If an advanced model fails to outperform the baseline, it indicates a failure to deal with unbalanced classes. The 'prior' strategy is used to generate predictions. It turns out that the classification accuracies of drinking status model and smoking status model are 49.5% and 32.5%, respectively. Considering that there are two classes for drinking status and three classes for smoking status. The

accuracy obtained by the dummy classifier is about the same as random guessing (50% and 33.3%, respectively), indicating that the dataset is not unbalanced.

4. Model Selection

To guide our model selection process for both target variables, smoke and drink status, we began with a baseline analysis. Following this preliminary classification, we evaluated several candidate models, including LogisticRegression, GaussianNB, KNeighborsClassifier, DecisionTreeClassifier, RandomForestClassifier, GradientBoostingClassifier, XGBClassifier, BaggingClassifier, SVM, QuadraticDiscriminantAnalysis, AdaBoostClassifier, and MLPClassifier.

Figures 4 and 5 below display the model results for smoke status and drink status, indicating that GradientBoostingClassifier, LogisticRegression, SVM, AdaBoostClassifier, and RandomForestClassifier exhibit the best performance with relatively high prediction accuracy on test data. Thus, we have selected these models as the level 0 models in the stacking process. Logistic regression is used as the level 1 combiner or metamodel to aggregate the results of the level 0 models.

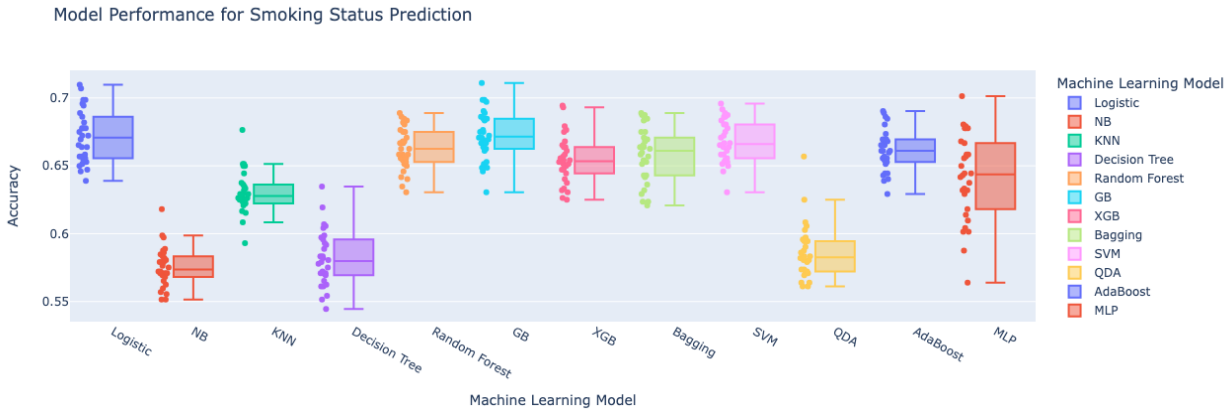


Figure 4 Machine Learning Model Result for Smoke Status

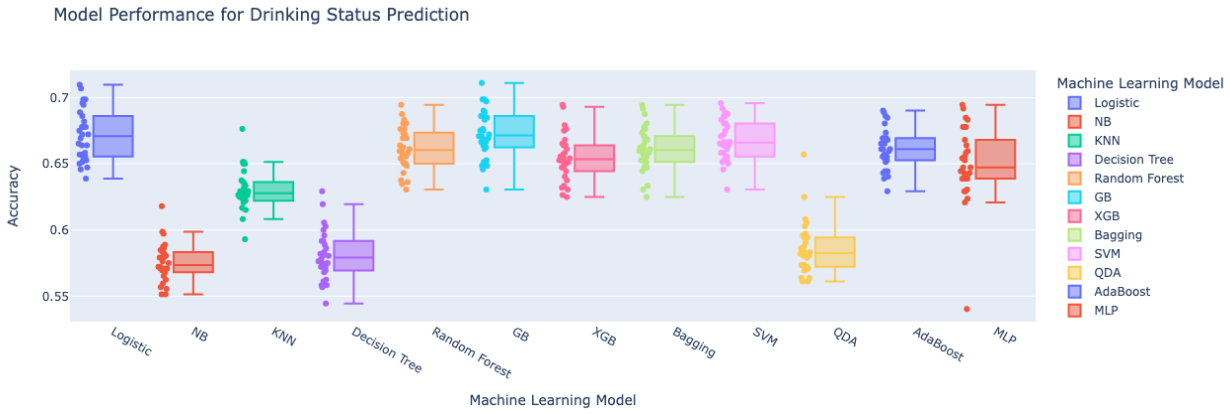


Figure 5 Machine Learning Model Result for Drink Status

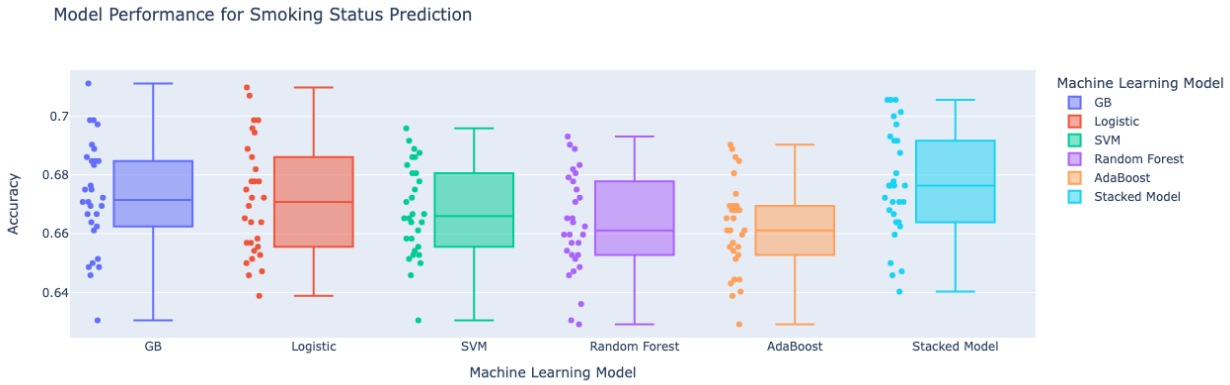


Figure 6 Machine Learning Best Models and Stacked Model Result for Smoke Status

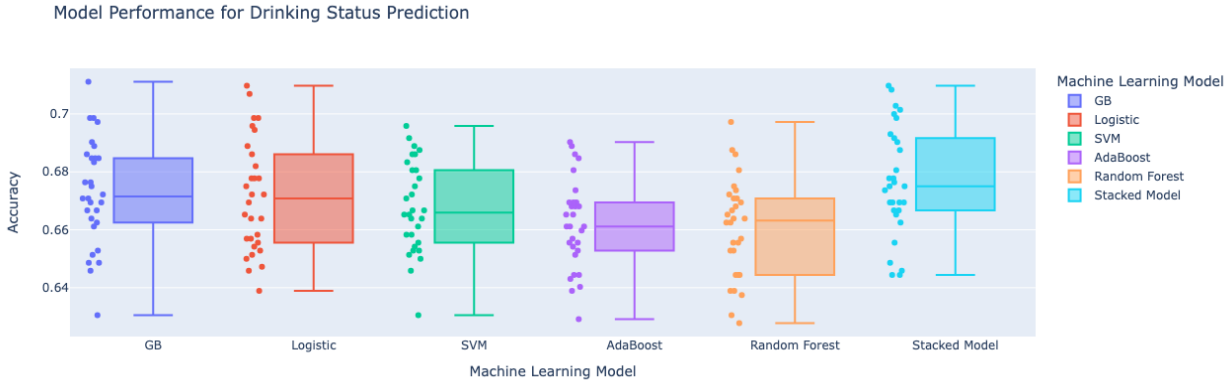


Figure 7 Machine Learning Best Models and Stacked Model Result for Drink Status

In addition to model selection, we have also chosen to implement a 10-fold cross-validation, repeated five times for each model. Figure 6 and Figure 7 above show the performance of the standalone and stacked models. Notably, the stacked model outperforms the individual candidate models, prompting us to focus on predicting smoke and drink status based on body signals using the stacked model. Additionally, to further improve the stacked models performance, we can fine-tune the hyperparameters to achieve even better results.

4.1 Model Performance Evaluation

Based on the stacked models, the prediction accuracy of the test dataset is 67.28% and 62.33% for drinking and smoking status models, respectively, which both outperform the baseline model.

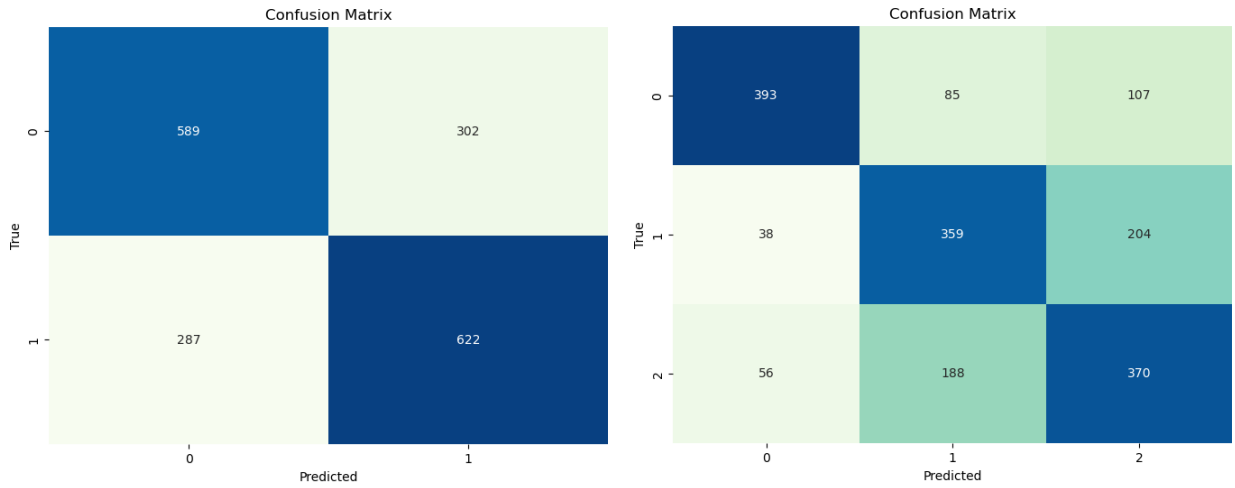


Figure 8 Confusion Matrix of Test Predictions for Drinking Status (left) and Smoking Status (right)

4.2 Feature Importance

For each of the selected best models, we analyze their feature importance. Among the top 5 important features of the drinking status prediction model, LDL cholesterol (HDL_chole) and age, followed by 'hemoglobin,' 'SGOT_ALT,' and 'gamma_GTP,' are the most significant contributors. These features prominently influenced four out of the five best base models.

In the case of the smoking status prediction model, 'gamma_GTP' is considered important by four out of five models, and age is deemed significant by three out of five models.

In summary, LDL cholesterol, gamma glutamyl transpeptidase (gamma_GTP), and age emerge as the primary features that play a pivotal role in predicting both drinking and smoking status.

Table 3 Top 5 Important Features for Drinking Status Prediction

Models	1	2	3	4	5
Logistic Regression	sex	hemoglobin	HDL_chole	SGOT_ALT	sight_left
GB	gamma_GTP	age	HDL_chole	SGOT_ALT	hemoglobin
SVM	gamma_GTP	age	SGOT_ALT	HDL_chole	triglyceride
Random Forest	gamma_GTP	HDL_chole	age	triglyceride	hemoglobin
AdaBoost	SGOT_ALT	HDL_chole	age	SGOT_AST	serum_creatinine

Table 4 Top 5 Important Features for Smoking Status Prediction

Models	1	2	3	4	5
Logistic Regression	hear_left	sight_left	SBP	bmi	HDL_chole
GB	sex	age	hemoglobin	gamma_GTP	bmi

SVM	age	gamma_GTP	waistline	HDL_chole	triglyceride
Random Forest	sex	hemoglobin	gamma_GTP	triglyceride	waistline
AdaBoost	age	SBP	BLDS	SGOT_ALT	gamma_GTP

5. Initial Deployment

5.1 Screen 1

We have selected Streamlit as a final deployment site. The site will display two 2 X 2 graphs. The first graph will display the dependent variable against the two most important features of the dataset. The second graph will display the drinking and smoking status with predictions from the feature vector given from the user input.

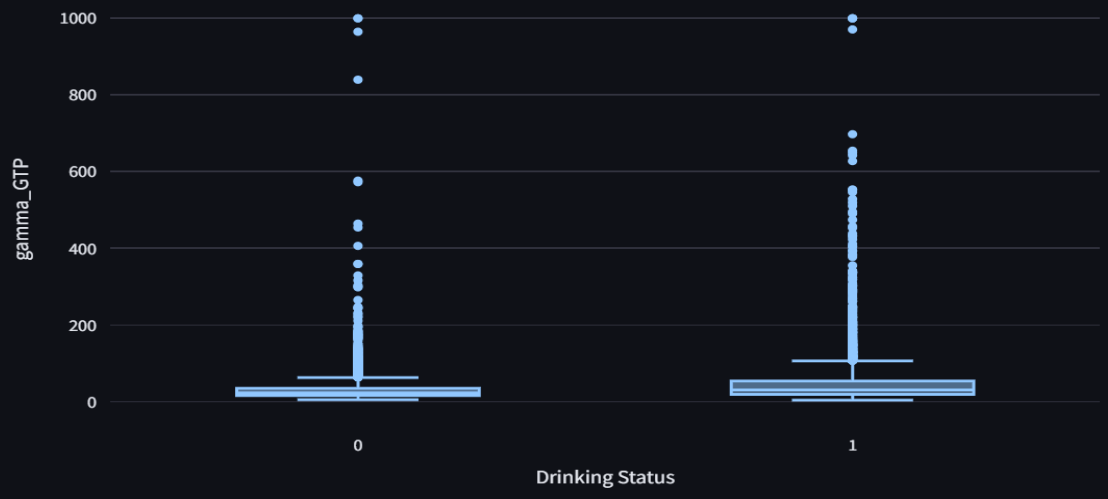
Smoking and Drinking Status Prediction App

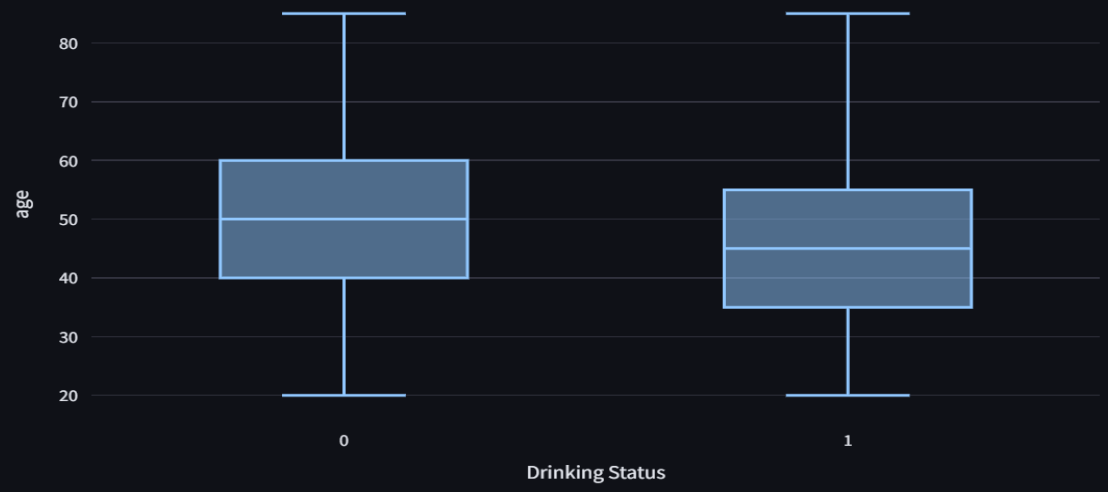
Boxplots for Important Features with Drinking and Smoking Status

Drinking Status | Smoking Status

Drink Status: 0 (No), 1(Yes)

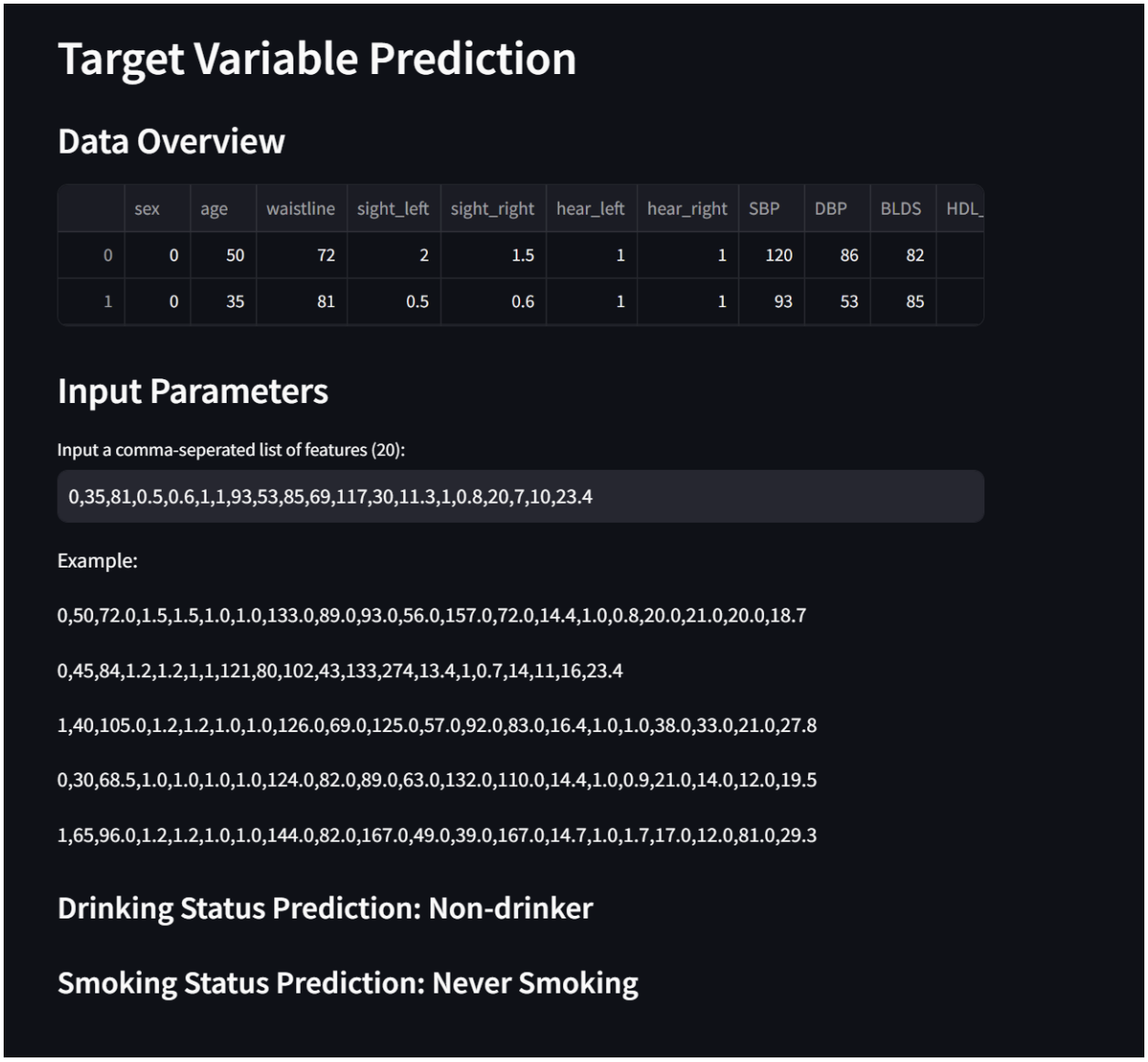
Box Plot of gamma_GTP vs drinking status





5.2 Screen 2

Figure below shows the updated image with the predicted drinking and smoking status. The feature vector for this prediction was 0, 35, 81, 0.5, 0.6 … (see figure). Here are five feature vectors that user can use for testing



5.3 Streamlit Application

5.3.1 The Streamlit Platform

Streamlit Cloud runs the user's applications in virtual containers, ensuring a dependable runtime environment. Streamlit refers to these containers as "Units." These Units can run applications created in Python, which is the primary language supported by Streamlit. For additional dependencies or

configurations, Streamlit Cloud allows the use of custom requirements and packages. Users can effortlessly scale their Streamlit apps by adjusting the number of Units or opting for different performance tiers available in Streamlit Cloud.

5.3.2 Application path

Users can use the App.py file and host it on Streamlit to test the model and the build. Please utilize the following five feature vectors to test the model. A table showing the variable and example value for each variable is also included below the input field. Users may choose to create any feature vectors to feed to the model.

5.3.3 Deployment, debugging, and updates

We used Streamlit Cloud's deployment feature to link a Github repository and leveraged it to deploy the model. Streamlit offers an integrated interface to view logs and troubleshoot issues. We adapted our model to ensure compatibility and optimal performance on the Streamlit platform.

Link: https://xuluw-machine-learning-projectapp-likerm.streamlit.app

6.Conclusion

The development of predictive models to ascertain smoke and drink statuses has been a comprehensive process, beginning with a rigorous baseline analysis and followed by the evaluation of a variety of machine learning classifiers. Our methodical approach has led to the selection of GradientBoostingClassifier, LogisticRegression, SVM, AdaBoostClassifier, and RandomForestClassifier as our primary models. These models have been effectively stacked with logistic regression serving as a meta-learner, thereby enhancing prediction accuracy to 67.28% for drinking status and 62.33% for smoking status—results that represent a tangible improvement over our baseline models.

The analytical examination of feature importance across the best-performing models has pinpointed LDL cholesterol, gamma glutamyl transpeptidase (gamma_GTP), and age as key factors in influencing the predictions for both target behaviors. This insight not only enriches our understanding of the underlying patterns in the data but also informs future efforts to refine the model or collect more pertinent data.

Deployment via Streamlit presents a user-friendly and efficient avenue to interact with the models. Streamlit Cloud's infrastructure has proven to be robust, facilitating seamless application testing and deployment. The inclusion of example feature vectors for testing ensures that the users can engage with the model conveniently, testing its robustness and accuracy in real-time scenarios.

By making the predictive tool accessible through a web interface, we've enabled a broader audience to benefit from our work, from healthcare professionals looking to identify at-risk individuals to researchers aiming to understand the determinants of health-related behaviors. Moreover, the ability to input custom feature vectors ensures that the tool remains flexible and relevant to diverse datasets.

In sum, the successful development, evaluation, and deployment of these predictive models for smoke and drink status are a testament to the power of machine learning in public health. The process exemplifies a harmonious blend of statistical rigor, practical utility, and user-centered design.