CSE445: Predicting Covid19 Vaccine Hesitancy in Bangladesh using Machine Learning Techniques

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Table of Contents

Abstract: The COVID-19 virus has sparked a global epidemic, halting many enterprises and restricting daily activities. Residents must be vaccinated in order to stop the virus from spreading in a small country like Bangladesh. The purpose of this study is to investigate and describe the general attitude of inhabitants of Bangladesh toward the vaccine, as well as any areas of hesitancy they may have. This study utilized a nationally representative cross-sectional survey. The study included 1134 participants from the general community who were 18 years of age or older. The survey assessed a range of sociodemographic and psychological variables (i.e., perceived COVID-19 risk). Vaccine hesitancy proportions were calculated and compared between groups with the aid of descriptive analysis. To get the adjusted OR, multiple logistic regression analyses were conducted. A comprehensive search method identified the key causes of willingness and hesitation with the COVID-19 vaccine. For analysis, regression models and test-train machine learning techniques were applied. The findings demonstrated that dominance analysis helped identify the primary barriers and promoters of vaccine usage and that respondent characteristics can be utilized to predict vaccination attitude.

1. Introduction:

In December 2019, the first case of COVID-19 caused by SARS-CoV-2 was discovered in Wuhan, China. COVID-19 has infected over 105 million people in 223 nations or territories by the first week of February 2021, resulting in over 2.3 million deaths worldwide.[1] Governments worldwide have shut down workplaces, quarantined citizens, and implemented a "work-from-home" strategy to battle this contagious sickness.[2][3][4] In March 2020, the World Health Organization proclaimed COVID-19 to be a pandemic, and many governments immediately began working on vaccines for COVID-19. At the end of November 2020, two American pharmaceutical companies announced the development of two COVID-19 vaccines with 90% to 95% efficacy.[5][6] Following this, a large number of other vaccinations that did not pose any health risks and were proven to be successful were produced and released by other nations.[7-10] Several nations, including the United States, the United Kingdom, and Canada, had approved 10 vaccines for full or early use by the end of 2020.[11] The vaccines were made available in the different countries almost immediately after they were licensed.

Nevertheless, a vaccination campaign can be bolstered or weakened by factors such as vaccine hesitancy. Vaccine hesitation is defined as a delay in accepting or refusing immunization despite the fact that the vaccination service is available.[12] In 2019, the World Health Organization (WHO) identified vaccination hesitancy as one of the top 10 threats to world health.[13] There has been a lot of attention given to the COVID-19 vaccine rollout because of reports of some vaccine recipients experiencing side effects, as well as conspiracy theories and misinformation spread on social media.[14] Therefore, the media's misleading coverage of the efficacy of certain vaccines has had a negative influence on the attitudes of potential vaccine recipients.[15][16] Because vaccine development was moving so quickly, there was an additional layer of nervousness that was compounded by this.[17] In addition to immediate effects, knowledge and awareness-related issues, religious, cultural, and sociocultural characteristics might also influence vaccine hesitancy.[12]

According to the findings of a study, the percentage of people throughout the world who are eager to become vaccinated could range anywhere from 55% to 90%.[18] However, the inclination or hesitancy to get vaccinated fluctuates over time.[12] The vaccination was not widely available when most of the prior studies were carried out; hence they were all done in wealthy countries. However, little is known regarding vaccine hesitancy in low- and middle-income countries (LMICs) population vaccination programs. Vaccines are generally accepted in low- and middle-income countries, such as Bangladesh.[19] A survey conducted in 2018 with 140 000 people in 140 countries found that 94% of people in South Asia thought vaccination was successful, and 95% thought vaccines were safe.[20] However, a separate survey conducted in Bangladesh, China, Ethiopia, Guatemala, and India indicated that more than fifty percent of respondents agreed or were neutral regarding the statement that "new vaccines entail greater risks than previous vaccines."[21]

Bangladesh has one of the largest COVID-19 impacts on its total health, economy, and community among LMICs. In Bangladesh, around 0.55 million COVID-19 cases have been confirmed by mid-February 2021, with about 10,000 individuals dying from the disease.[22] On 27 January 2021, Bangladesh's COVID-19 vaccine roll-out was begun, intending to immunize 138 million people,[23] little was known about this cohort's vaccine apprehension or willingness. As a result, the goals of our research were to (1) undertake a quick national assessment of COVID-19 vaccine hesitation in Bangladesh and (2) identify demographic subgroups with greater vaccine hesitancy rates.

2. Related work:

Many researchers have conducted experiments to detect covid-19 vaccine hesitancy using Machine Learning algorithms. Carrieri et al., for example, researched data collected by the Italian Ministry of Health about child immunization campaigns done in 6408 Italian municipalities in 2016 for seven vaccine-preventable diseases (pertussis, measles, Haemophilus influenzae type B, meningococcus, pneumococcus, mumps, and rubella)[24]. The research obtained Random Forest algorithm is the best model to make out-of-sample predictions with a high true positive rate and a low false-positive rate. Compared with the unpredictable baseline level, the accuracy with Random Forest improves by 24%. A higher VH risk is found in rural areas far from metropolitan cities and in almost all Southern regions, particularly Puglia, Calabria, and Sicilia.

A group of researchers surveyed adults (N= 2510) from February to March 2021 across five sites (Australia = 502, Germany = 516, Hong Kong= 445, UK= 512, USA= 535) using a cross-sectional design and stratified quota sampling for age, sex, and education[25]. The work aims to optimize vaccine hesitancy prediction in high-income countries using a machine learning approach. It was conducted using logistic regression to predict vaccination willingness; most of the included criteria that were identified from earlier research or clinical models of paranoia could be confirmed. The strongest conclusion was the specific mistrust's excellent predictive value, which properly identified 84 percent of people as vaccination reluctant or eager to get vaccinated.

In another work, Andrew Bell's colleagues used two data resources[26]. The first was Electronic Health Records collected by public clinics, namely the school-medicine centers in the Country, typically as a child is about to enter the first grade of primary school. The second data source used was publicly available census data which included the municipality population and the proportion of the population under 20 years of age. In this research, The best performing model is the gradient-boosted tress model was found to be 0.76 accuracies.

As observed, many remarkable performances have been obtained using machine learning techniques in order to detect vaccine hesitancy in pursuing diverse approaches, and many are still continuing. The key difference lies in this research that distinguishes it from the existing ones. The work aims to find the best performing classifier from the perspective of Among Bangladeshi people's vaccine hesitancy. As per our knowledge, research on such a purpose has not been conducted before.

3. Research Methodology

3.1 Data Acquisition

The initial raw dataset has been collected from the open science forum[27].

The dataset is a collection of information about various people and their views on the Covid-19 Vaccine. An effective survey was being conducted by the team in various regions of Bangladesh including Dhaka, Rajshahi, Khulna, Jamalpur, Barisal, etc. The dataset comprises a total of 3647 instances recorded over 38 attributes per instance.

Address	Address_Code	Age	Sex	Education	Employment1	Employment2	Monthly Income	Location	Marital Status	Diabetes	Hypertension	Chronic Kidney Disease	Chronic Respiratory Disease
Rajshahi	31	38.0	Female	11-12	Doctor/teacher	HCW	20001-50000	Semi-urban	Married	No	No	No	No
Rajshahi	31	36.0	Male	11-12	Doctor/teacher	HCW	20001-50000	Semi-urban	Married	No	No	No	No
Rajshahi	31	43.0	Female	6-10	Housewife	Housewife	<=10000	Rural	Married	No	No	No	No
Rajshahi	31	48.0	Male	1-5	Agriculture	Agriculture	10001-20000	Rural	Married	No	No	No	No
Rajshahi	31	30.0	Female	11-12	Day-labor	Day-labor	10001-20000	Semi-urban	Married	No	No	No	No

Perception_Covid19	Odds_infected	COVID19 Infection	Comply_Instruction	Mitigation_Measures	Vaccine Acceptance	Trust_HealthSystem	Trust_Media	Adverse_Vaccine	Payment
Infections are increasing day by day	Low	No	High	Low	Intend to vaccinate	High	Low	Completely free from side effects	Intend to pay
Infections are increasing day by day	Low	No	High	Moderate	Intend to vaccinate	High	Moderate	Completely free from side effects	Intend to pay
Infections are increasing day by day	Low	No	High	Moderate	Intend to vaccinate	High	Low	Completely free from side effects	Free
Infections are increasing day by day	Low	No	Moderate	Moderate	Intend to vaccinate	High	Moderate	Completely free from side effects	Free
Infections are increasing day by day	High	No	High	Moderate	Intend to vaccinate	High	Low	Completely free from side effects	Intend to pay

3.2. Data Pre-Processing

The dataset we have collected was not in a format that was suitable for machine learning algorithms to operate on. Massive data preprocessing has been done to ensure that machine learning algorithms can be effectively applied. Upon analyzing the raw dataset we gathered, we could identify several issues that needed to be handled first.

First of all, we needed to change the feature names to more understandable ones, as it was named in code words. We had to rename the feature names by reading the documentation of the raw dataset thoroughly.

Table 1 - Renaming the columns into meaningful names

PREVIOUS COLUMN NAME	NEW PROCESSED COLUMN NAME
ID1	ID
S1_address1	Address
S2_age1	Age
S3_sex1	Sex
S5_education1	Education
S6_employement1	Employment1
S6_employement2	Employment2
S7_monthly_f_income1	Monthly income
S8_location1	Location
S9_marital_status1	Marital status
S10_diabetis1	Diabetes
S10_htn1	Hypertension
S10_ckd1	Chronic kidney disease
S10_crd1	Chronic respiratory disease
S10_chd1	Chronic heart disease
S10_cancer1	Cancer
S10_others1	Other disease
S11_own_house1	Own house
S12_motor_cycle_cng1	Motor cycle
S12_rickshaw_van1	Rickshaw_van
S12_pickup_bus_car1	Pickup_bus_car
S13_television1	Television
S14_toilet1	Toilet facilities
S15_matarial_house1	House material
R1_perception_covid_191	Perception_covid19
R2_odds_of_you_infected_covid_191	Odds_infected
R3_you_affected_covid_191	Covid19 infection
R4_comply_instruction_government1	Comply_instruction
R5_mitigation_measures_taken_govenment1	Mitigation_measures
A1_vaccine_acceptance1	Vaccine acceptance
A2_trust_health_system1	Trust_healthsystem
A3_trust_information_regarding_media1	Trust_media
A4_adverse_effected_covid_191	Adverse_vaccine
F1_pay_for_vaccine1	Payment
F2_maximum_dose1	Maxdose willingness
Datafrom	Datafrom
Agegroup	Agegroup
Comorbidity	Comorbidity

Analyzing the dataset, we dropped the features - *ID1 and Datafrom* as these have no significance in the model training. In the raw dataset, these were just used to track the surveyee and surveyor.

Following this, the dataset was assessed for consistency. To do this, we identified the number of unique values for each feature. The features – *Perception_Covid19, Adverse_Vaccine, MaxDose Willingness* had unusually high values. Further analysis of these features showed that they had unclean string values. Thus these string values were cleaned and pre-processed. Table 2 shows the unique values for each of the features. Table 3 shows the processed values for *Adverse_Vaccine.*

Table 2 - Unique Values of Each Feature

FEATURE	UNIQUE VALUES
Address	52
Age	66
Sex	2
Education	5

Employment1	9
Employment2	7
Monthly income	5
Location	4
Marital status	3
Diabetes	2
Hypertension	2
Chronic kidney disease	2
Chronic respiratory disease	2
Chronic heart disease	2
Cancer	2
Other disease	2
Own house	2
Motor cycle	2
Rickshaw_van	2
Pickup_bus_car	2
Television	2
Toilet facilities	2
House material	3
Perception_covid19	8
Odds_infected	3
Covid19 infection	2
Comply_instruction	3
Mitigation_measures	3
Vaccine acceptance	3
Trust_healthsystem	3
Trust_media	3
Adverse_vaccine	11
Payment	2
Maxdose willingness	13
Agegroup	5
Comorbidity	2

Table 3 - Pre-processing of Adverse_Vaccine Column

Before Pre-processing	**Value_Counts**	**After Preprocessing**	**Value_Counts**
Completely free from side effects	2760	Completely free from side effects	2761
Safe and low free from side effects	534	Safe and low free from side effects	538
As a new vaccine, its side effects are not certain	219	As a new vaccine, its side effects are not certain	348
3 | As a new vaccine, its side effects are not certain	124		
2.safe and	4		
3.as a new	2		
1.complet	1		
3.as a new3.500-1000	1		
3.as anew	1		
3|as a new	1		

There were many null entries in the dataset, which needed to be fixed. Table 4 shows the number of null values in different features. It was observed that *Adverse_Vaccine, Odds_Infected, Mitigation_Measures* features had the highest null values. As these are all categorical features, the null values in every feature was replaced with the mode of that feature. This resulted in 0 null values for every feature. This was needed because as the null values were high, dropping them would decrease the size of the dataset significantly and hamper the accuracy.

Table 4 - Null value counts of different features

MaxDose Willingness	Value Counts
Adverse_Vaccine	1105
Age	2
Education	20
Monthly Income	29
Own House	2
Motor Cycle	6
Rickshaw_Van	6
Pickup_Bus_Car	6
Television	2
Toilet Facilities	2
House Material	10
Odds_infected	92
Comply_Instruction	4
Mitigation_Measures	95

3.3 Feature Selection

When it comes to predicting vaccine hesitancy (VH), not every feature available to us will have the same effect. Certain characteristics may be more critical than others, while others may be irrelevant to VH. As a result, it is critical to deal with just the most prominent features. During our pre-processing phase, we have already removed the feature Adverse_Vaccine. We can visualize correlations of the remaining features from plotting a heatmap.

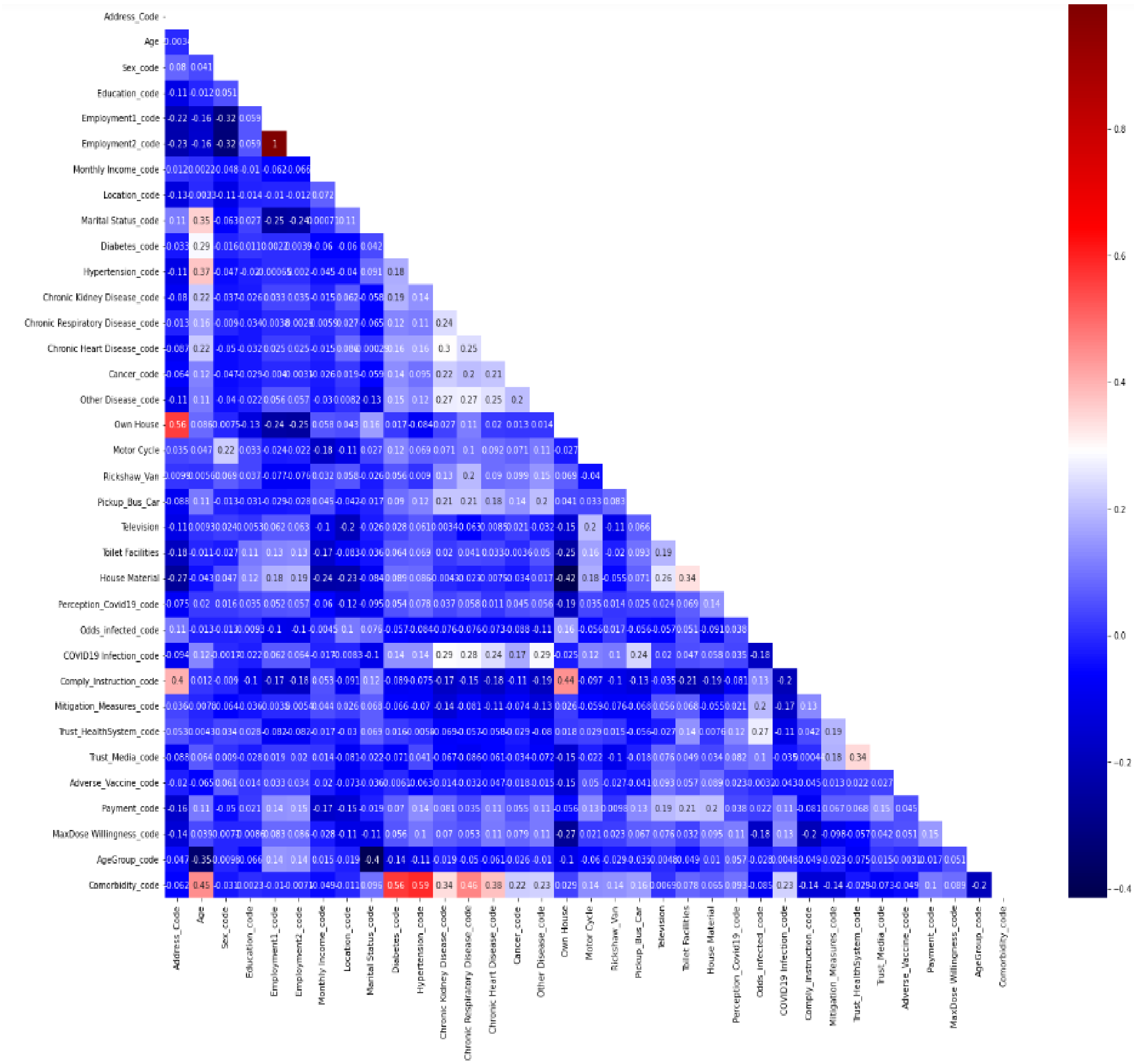


Figure 1 - Correlation Data of all the Features

Next, we measured the correlation between each pair of features to detect and accordingly drop the highly correlated ones. A high correlation between a pair of features indicates that the two features carry the same, and thus it is not required to have both of them. We used Pearson's correlation co-efficient[28]. We found Employment1 and Employment2 features are strongly correlated and exactly the same. So we kept only the Employment1 feature, and dropped Employment2.

3.4. Exploratory Data Analysis

The pre-processed dataset was examined, analyzed, and visualized, and the results gave out some interesting trends for vaccine hesitancy in Bangladesh.

The number of respondents based on different demographics was first visualized to understand the dataset.

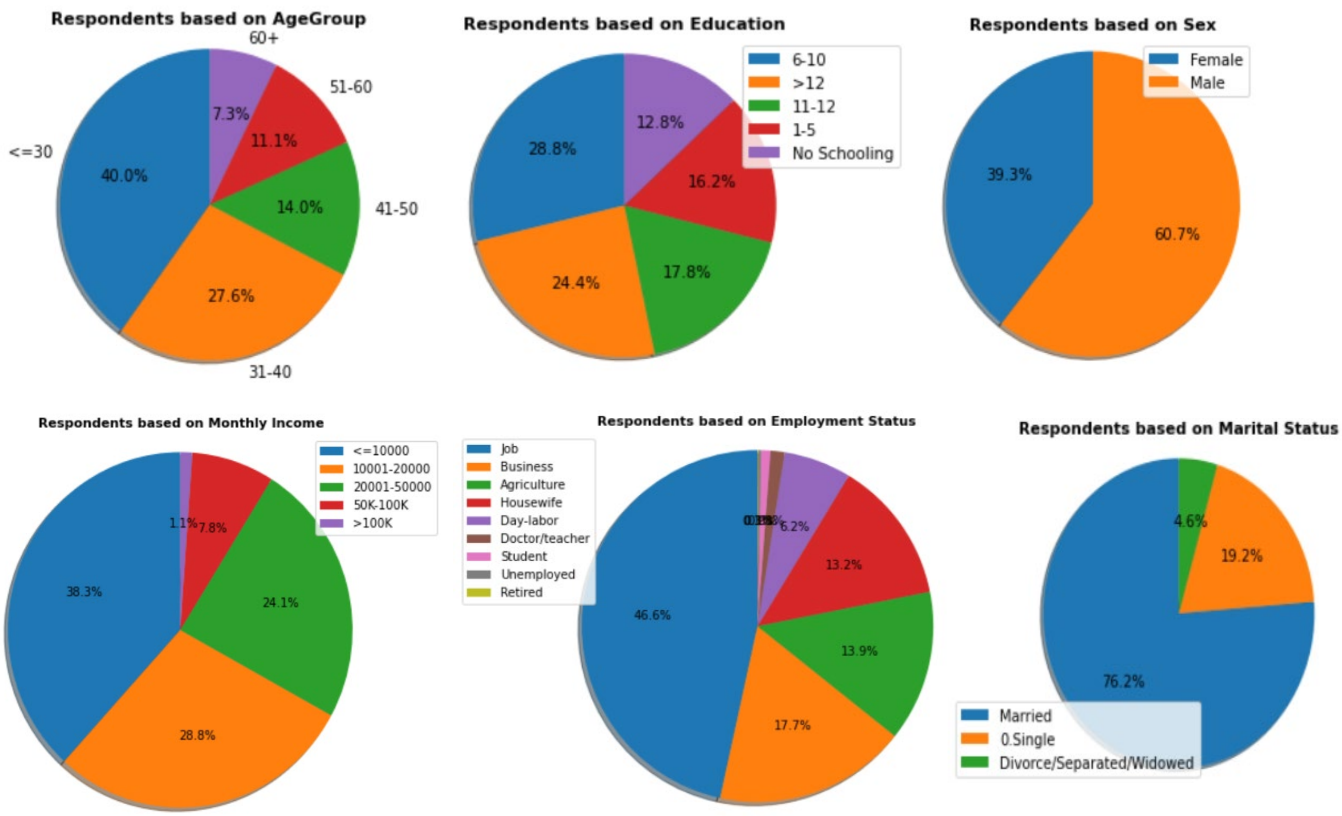


Fig2 : Percentage of Respondents based on Different Demographics

From *Figure 2*, the following statistics can be observed about the dataset:

- Most of the respondents are below 30 years of age (40%), followed by the 31-40 Age-Group (27.6%)
- In terms of education, the "Class 6 – Class 10" class had the highest response (28.8%) among the other classes. 12.8% of the respondents had completely no schooling, and 16.2% received education only up to Class 5. This observation is important since we want to understand the level of Vaccine Hesitancy in a low-income country like Bangladesh, where the education rate,

particularly in rural areas, is not much high – 64% of children in rural areas complete lower secondary education compared to 67% in urban areas. [1]

- Most of the respondents (38.3%) had a monthly income of less than BDT 10,000, compared to only 1.1% who had income over BDT 1 lac.
- Most of the respondents (48.6%) were in the Job Sector, followed by Business Sector (17.7%)
- Most of the respondents were married (76.2%)

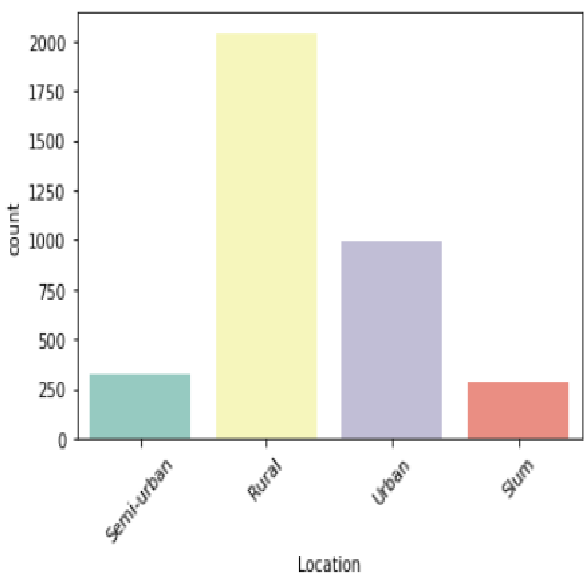


Figure 3 - Number of respondents from different Areas

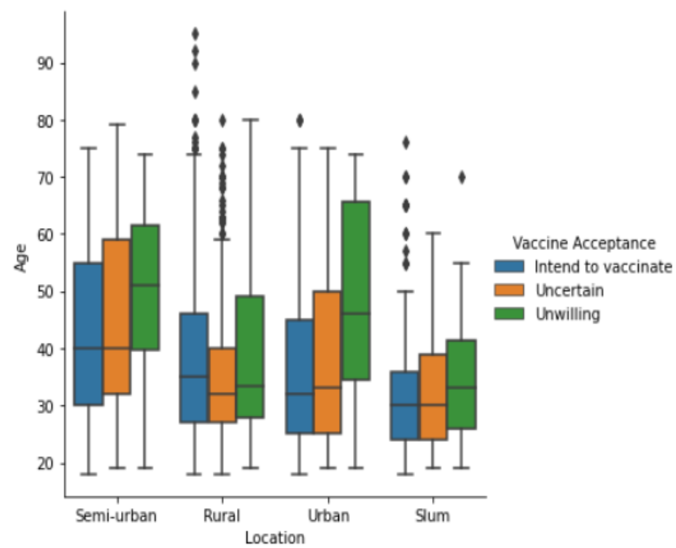


Figure 4 - Vaccine Acceptancy in different Areas based on Age

Figure 3 shows that the dataset contains mainly people from rural areas of Bangladesh. *Figure 4* shows the box plot of the Vaccine Acceptance Rate in different regions of Bangladesh (urban, semi-urban, rural, and slums) based on Age. Based on the Box Plot, the following statistics can be observed:

- In Urban Areas, the people who are willing to vaccinate are younger and have a lower median age than people who are unwilling to vaccinate. People willing to vaccinate have a lower quartile of 24 years of age and an upper quartile of 43 years of age. In contrast, People who are unwilling to vaccinate have a lower quartile of around 34 years of age and an upper quartile of around 66 years of age.

- In Semi-Urban Areas, the people who are willing to vaccinate have a lower median age(40) than people unwilling to vaccinate (51). People who are willing to vaccinate have a lower quartile of 30 years of age and an upper quartile of 56 years of age. In contrast, People who are unwilling to vaccinate have a lower quartile of around 40 years of age and an upper quartile of around 62 years of age.
- In Rural Areas, the people who are unwilling to vaccinate are almost of the same age group of the people who are willing to vaccinate. People who are willing to vaccinate have a lower quartile age of 27 years, a median age of 35, and an upper quartile age of 45 years. In contrast, People who are unwilling to vaccinate have a lower quartile of around 28 years of age, a median age of 33, and an upper quartile of around 48 years of age.
- The same observation of rural areas holds true in slum areas. People who are willing to vaccinate have a lower quartile age of 25 years, a median age of 30 years and upper quartile age of 35 years. In contrast, People who are unwilling to vaccinate have a lower quartile of around 28 years of age, median age of 33 and upper quartile of around 40 years of age.

Thus it can be concluded that in rural settings and slums, both younger and older people are equally not willing to vaccinate, whereas in urban and semi-urban settings elder people are less willing to vaccinate while younger people are more willing to vaccinate.

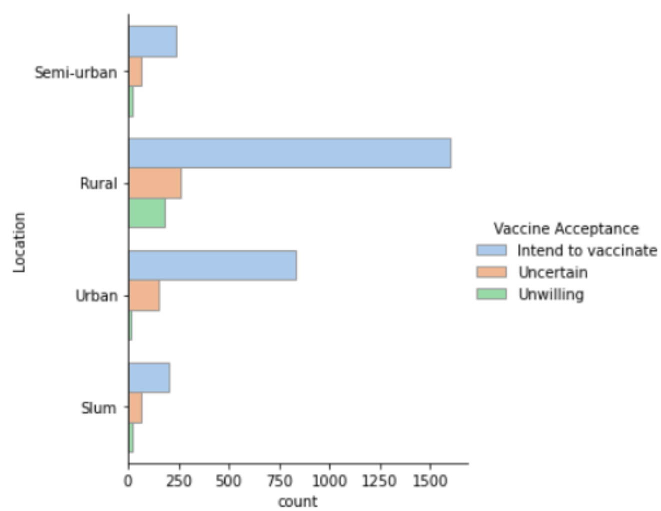


Figure 5 - Vaccine Acceptancy in different Areas of Bangladesh

Figure 5 shows that people from Rural areas are the most unwilling and uncertain about the Covid19 vaccination.

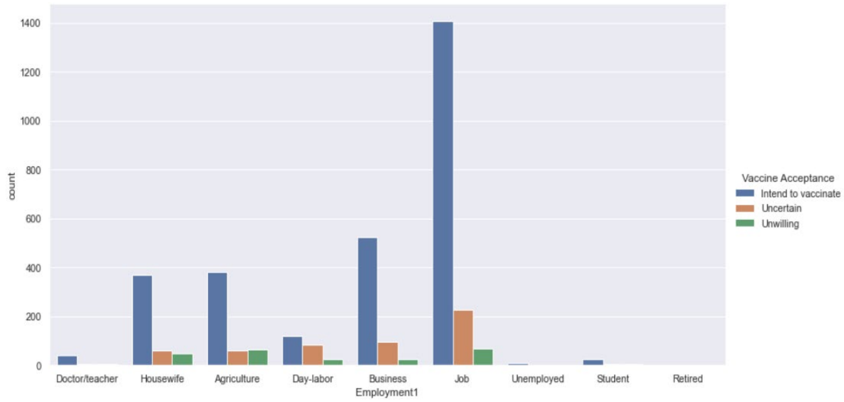
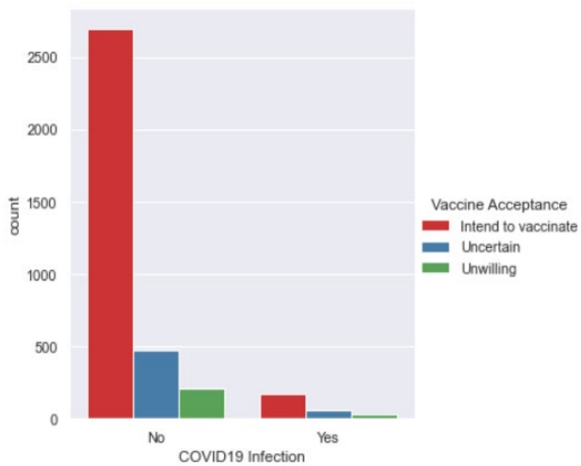
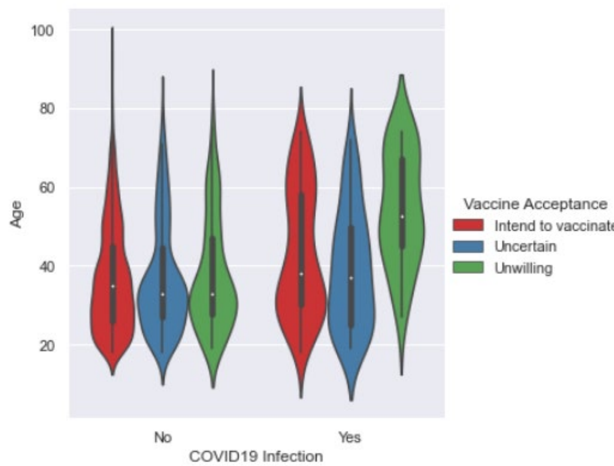
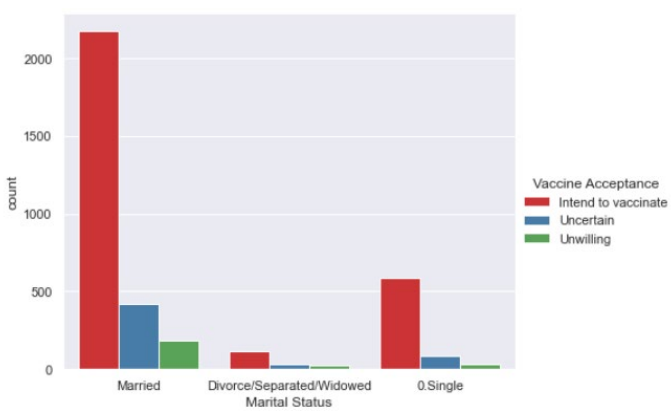


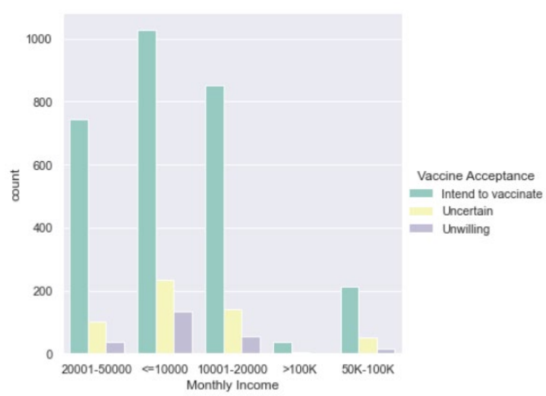
Figure 6 - Vaccine Acceptancy based on Employment Status

When taking Employment Status into account, the people who are unwilling to vaccinate are mostly housewives, farmers, day-laborers, and job holders. On the other hand the job holders and the businessmen are most uncertain about whether they would take the vaccine or not.









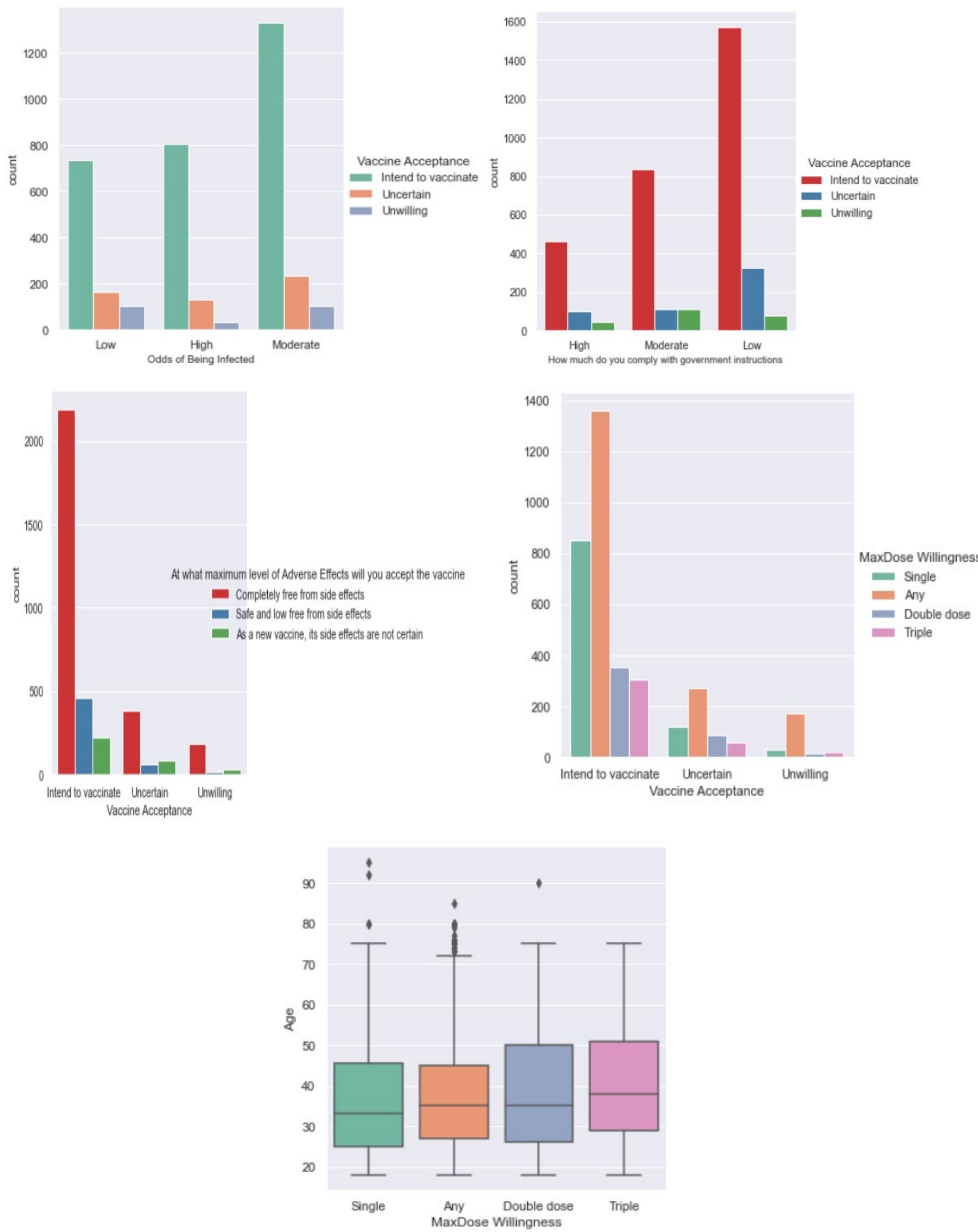


Fig 7 – Vaccine Acceptancy based on different demographics and criterions

The plots of various features (shown in Figure 7) give the following important information regarding the vaccine hesitancy and acceptance in Bangladesh:

1. If *Covid19 infection* is considered, the people whose families and themselves have never been affected by Covid19 are more unwilling and uncertain to vaccinate.
2. If *monthly income* is considered, people who have high income (50k-100k or greater than 100K) are have low vaccine hesitancy compare to lower income peoples. In fact, none of the people who earned greater than 100k BDT had any vaccine unwillingness or uncertainty, whereas the people who earned less than 10,000 BDT a month had the highest level of vaccine uncertainty and unwillingness.
3. If *odds of being infected* is considered, people who think they or their family members have high odds of infection have less vaccine hesitancy or unwillingness. In contrast, people who think they have low or moderate odds of getting infected have more vaccine unwillingness or uncertainty.
4. If *Adverse Effects* is considered, most of the people who intend to vaccinate said they will take the vaccine if it was completely free from side effects.
5. If *Maximum Dose Willingness* is considered, most of the people who will accept the vaccine said they will take any maximum dose, followed by maximum 1 dose. From all the classes (vaccine willingness, vaccine uncertainty and vaccine unwillingness), people are less willing to take double or triple dose of the Covid19 vaccine. Younger people are more likely to stick to single dose of the vaccine than double or triple dose, whereas elder people are more likely to take double or triple dose, if available.

4. Results

The dataset was trained with the four different classifiers. To determine which classifier perform the best, they were assessed against a variety of performance indicators. We evaluated the classifiers performance using four distinct metrics. They are: Accuracy, Precision, Recall, F1-Score.

Accuracy is the most intuitive performance measure and it is simply a ratio of correctly predicted observation to the total observations.

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

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

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

Recall is the ratio of correctly predicted positive observations to the all observations in actual class.

$$Recall = \frac{TP}{TP + FN}$$

F1 Score is the weighted average of Precision and Recall.

$$F1\ Score = \frac{2\ x\ Recall\ x\ Precision}{Recall + Precision}$$

4.1. ZeroR:

ZeroR is the simplest classification method which relies on the target and ignores all predictors. ZeroR classifier simply predicts the majority category (class). Although there is no predictability power in ZeroR, it is useful for determining a baseline performance as a benchmark for other classification methods. Table 5 shows the results of ZeroR

Table 5 - Results of ZeroR

	precision	recall	f1-score	support
0	0.78	1.00	0.88	286
1	0.00	0.00	0.00	54
2	0.00	0.00	0.00	25
accuracy			0.78	365
macro avg	0.26	0.33	0.29	365
weighted avg	0.61	0.78	0.69	365

4.2. K-Nearest Neighbor Classifier:

The k-nearest neighbor (KNN) algorithm is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. It's easy to implement and understand, but has a major drawback of becoming significantly slows as the size of that data in use grows.

```
X shape: (3647, 35)
y shape: (3647,)
K =  1 , Training Accuracy =  1.0  Test Accuracy =  0.7506849315068493 , Difference =  24.931506849315067 %
K =  5 , Training Accuracy =  0.8211456429006703  Test Accuracy =  0.7890410958904109 , Difference =  3.210454701025933 %
K =  10 , Training Accuracy =  0.805606337599025  Test Accuracy =  0.7972602739726027 , Difference =  0.8346063626422318 %
K =  15 , Training Accuracy =  0.8001218769043267  Test Accuracy =  0.8 , Difference =  0.012187690432663434 %
K =  20 , Training Accuracy =  0.7970749542961609  Test Accuracy =  0.7945205479452054 , Difference =  0.2554406350955496 %
K =  25 , Training Accuracy =  0.795551492992078  Test Accuracy =  0.7917808219178082 , Difference =  0.377067107426976 %
K =  30 , Training Accuracy =  0.7937233394271785  Test Accuracy =  0.7890410958904109 , Difference =  0.4682243536767605 %
K =  35 , Training Accuracy =  0.7949421084704449  Test Accuracy =  0.7890410958904109 , Difference =  0.5901012580033949 %
K =  40 , Training Accuracy =  0.7946374162096282  Test Accuracy =  0.8 , Difference =  0.53625837903718 %
K =  45 , Training Accuracy =  0.7958561852528946  Test Accuracy =  0.8 , Difference =  0.41438147471054565 %
K =  50 , Training Accuracy =  0.7949421084704449  Test Accuracy =  0.8 , Difference =  0.5057891529555159 %
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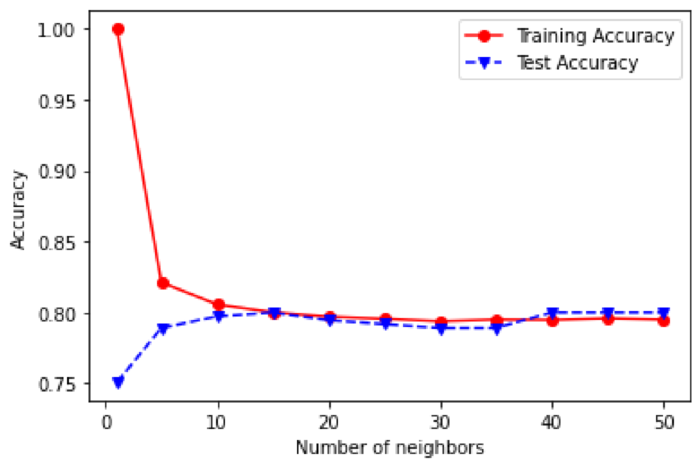


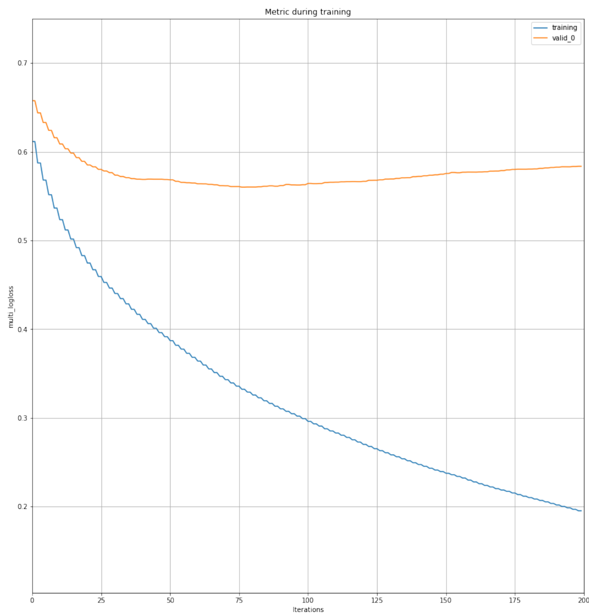
Figure 8 - Results of KNN

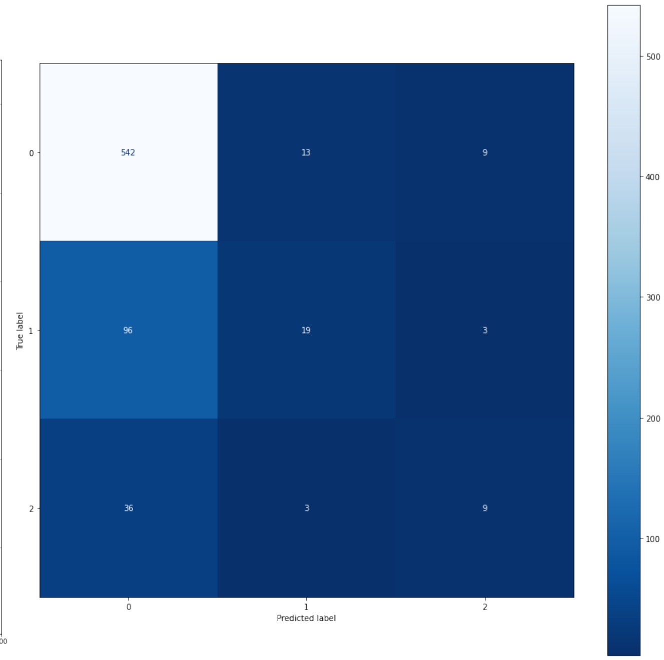
4.3. LightGBM:

LightGBM is a gradient boosting framework based on decision trees to increases the efficiency of the model and reduces memory usage. Gradient-based One Side Sampling Technique for LightGBM: Different data instances have varied roles in the computation of information gain.

Table 6 - Results of LightGBM

	precision	recall	f1-score	support
0	0.80	0.96	0.88	564
1	0.54	0.16	0.25	118
2	0.43	0.19	0.26	48
accuracy			0.78	730
macro avg	0.59	0.44	0.46	730
weighted avg	0.74	0.78	0.73	730





4.4 Decision Tree

The decision tree classifier creates the classification model by building a decision tree. Each node in the tree specifies a test on an attribute, each branch descending from that node corresponds to one of the possible values for that attribute.

Table 7 - Results of Decision Tree

	precision	recall	f1-score	support
0	0.82	0.97	0.89	286
1	0.50	0.13	0.21	54
2	0.50	0.20	0.29	25
accuracy			0.79	365
macro avg	0.61	0.43	0.46	365
weighted avg	0.75	0.79	0.74	365

5. Conclusion

The current study discovered differences in COVID-19 vaccine reluctance depending on the Bangladeshi general population's sociodemographic factors, health, and behavior. Preexisting indecision, cultural and religious beliefs, lack of conviction in the scientific enterprise of medicine and public health, particularly among the elderly, and lower levels of awareness were identified as contributing causes to vaccine hesitation. Additional research is needed to understand the complex interplay of numerous individual and social factors causing vaccine reluctance. To guarantee that

COVID-19 vaccinations are widely distributed, the government, public health experts, and advocates must be prepared to combat vaccine hesitancy and build vaccine awareness among potential recipients. To address these issues and support COVID-19 immunization programs, evidence-based educational and policy initiatives must be undertaken. The rates of willingness vary with vaccination appropriateness, but the frequent and ambiguous effects of vaccines may further diminish those rates. Once the issues highlighted in this study are addressed and the long-term favorable effects of the vaccines are clarified to the general community, the uptake of COVID-19 vaccines can be boosted.

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