Reduction of Antibiotic Resistance and Creating Public Awareness by Using Artificial Intelligence

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APPROVAL

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DECLARATION

We, hereby, declare that the work presented in this report is the outcome of the investigation performed by us under the supervision of **Bulbul Ahamed, Professor** and **Head,** Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. We reaffirm that no part of this thesis has been or is being submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Antibiotic resistance is a growing global threat that could potentially cause a future pandemic. Machine Learning (ML) is becoming more common in medical research and healthcare, improving clinical practices. One of the most important uses of ML is to fight Antimicrobial Resistance (AMR), as rising resistance to antibiotics and the difficulty of treating multidrug-resistant infections present serious challenges globally, with potentially life-threatening outcomes. In the era of increase in AMR, it is critical to identify antibiotic resistance early, raise public awareness about the issue, and implement comprehensive antibiotic stewardship programs. These steps will help limit the misuse of antibiotics and prevent the AMR problem from worsening. To develop an ML model, data from 224 patients in three public hospitals in Bangladesh were collected, resulting in a dataset of 1,119 instances. The Random Forest algorithm was used to evaluate antibiotic predictions based on patient prescriptions and clinical data, with training and testing. Additionally, a public dataset was used to assess people's knowledge, attitudes, and practices regarding antibiotics, processed using linear regression. The data included information such as gender, age, marital, education, occupation, monthly income, residence/area, religion in socio-demography. By applying the Random Forest algorithm (a supervised classifier), the model achieved an accuracy of 0.90, indicating strong predictive ability. In terms of public knowledge, linear regression analysis showed that 20.3% of participants had very weak knowledge, 22.9% weak, 18.1% moderate, 18.9% strong, and 19.8% very strong knowledge of antibiotics. Supervised ML tools have proven effective in predicting antibiotic resistance. This paper reviews how ML and Artificial Intelligence (AI) can be used to predict antibiotic resistance and discusses how these tools can help public improve antibiotic use practices.

Keywords:

Machine Learning, Artificial Intelligence, Supervised Machine Learning, Antibiotic Resistance, Random Forest Algorithm, Linear Regression

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ABR	Antibiotic Resistance
AMR	Anti-Microbial Resistance
ANOVA	Analysis of Variance
ARIS	Antibiotic Resistance Information System
AUROC	Area Under the Receiver Operating Characteristic
CI	Confidence Intervals
DT	Decision Tree
DMCH	Dhaka medical colleges and hospital
ES	Expert System
GUI	Graphical User Interface
GBM	Gradient Boosting Machine
ICU	Intensive Care Unit
IP	Image Processing Module
K-NN	K-Nearest Neighbors
LMIC	low- and middle-income countries
ML	Machine Learning
NLP	Natural Language Processing
NPV	Negative Predictive Value
NPV	Negative Predictive Value
OCR	Optical Character Recognition
PPV	Positive Predictive Value
RF	Random Forest
SVM	Support Vector Machine
SPSS	Statistical Package for Social Science
STAMH	Shaheed Tajuddin Ahmad Medical College Hospital
SSMCH	Shaheed Suhrawardy Medical College and Hospital
WHO	World Health Organization

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CHAPTER 1

INTRODUCTION

1.1 Background and significance of the study

Antibiotics are one of the most wonder discover of the 20th century (Davis & Davis, 2010) [4]. Alexander Fleming's discovery of penicillin in 1928 unshared in the modern area of antibiotics. Since antibiotics have saved the lives of many people with bacterial and fungal infections (BMJ Glob Health report, 2023) [19]. However, antimicrobial resistance (AMR) is growing global public health threat is the 21st century (WHO). It is estimated that antibiotics are chemical compounds that are using to kill or inhibit the growth of bacteria (Nagan, 2005). The overdose and inappropriate use of antibiotics, bacteria can insist on the mechanism to get stronger to fight back and prevail, referred as antibiotics resistance (Noor et al., 2023) [5]. On the other hand, antibiotics resistance refers to the ability of bacteria or other microorganisms to resist the effects of antibiotics that were previously effective against them. It is manifested as the ability of bacteria to withstand the destructive effective of chemical agents intended to eliminate them. Resistance to antibiotics is a threat Confronting health care system worldwide (Lalithabai et al., 2022)[24]. In 2019, the world health organization announced antibiotics resistance are one of the top 10 global public health threats facing humanity. It is estimated that bacterial AMR was directly responsible for 1.27 million global deaths in 2019 and contributed of 4.95 million deaths (World Health Organization, 2023) [23]. The UK government commissioned review on AMR in 2014 projected that if AMR is not controlled it world lead to significant impact on health with 10 million AMR related deaths annually and macroeconomic consequence with a cumulative economic loss of US$ 100 trillion by 2050(BMJ Glob Health report, 2023). In United States, more than 2.8 million people become infected with antibiotics resistance and more than 35,000 people die each year (AR threats report, 2019). It is estimated that all age deaths rate attributable to be highest in Western Sub-Saharan Africa, at 27.3 death per 100,000 people, and lowest in Australia, at 6.5 deaths per 100,000. South Asia experiences a high burden of antibiotics resistance with overall 76.8 deaths per 100,000 populations (Global Burden of Bacterial Antimicrobial Resistance Analysis report, 2019). It is estimated that, Bangladesh a developing country of Southeast Asia with a high degree of antibiotic resistance (Ahmad et al., 2019). In Bangladesh 90% of patients are resistance to Ciprofloxacin (one of the leading antibiotics), even 70% of deaths at ICU due to antimicrobial resistance (Islam, 2023). The morbidity rate of antibiotics resistance is 21.5% of heart, kidney and pediatric patients in BSMMU (TBS report, 2023). It is estimated that (27% rural and 40% urban) under 5 ages, 23% of 60 years and 35% of 0-15 years' people suffering from antibiotic resistance (SIAPS, 2015).AR carries a heavy social and economic burden. It is estimated to be responsible for 25000 deaths per year in the European Union and 700,000 deaths per year worldwide. By 2050, it is predicted that antimicrobial resistance could cause more death

than cancer. These circumstances not only involve human suffering, but also serious economic problems. It is estimated that, only in the European Union, antimicrobial resistance costs 1.5 billion euros per year in health costs and lost productivity. In addition, the World Bank has warned that, by 2050 antimicrobial resistant infections could cause economic damage comparable to the financial crisis of 2008(Sergio et al., 2019). Antibiotics resistance problem is challenging in low-income countries, because of high. Prevalence of infection irrational and inappropriate use of antibiotics (Vila and pal, 2010). Irrational use of antibiotics involves self-medication i.e. antibiotics purchased from pharmacies without prescription or leftover antibiotic from previous course of treatment (Grigoryan et al., 2006). It is estimated that more than 50% of antibiotics worldwide are purchased without prescription (Cars and Norbery, 2005). Now a day’ s antibiotic resistance is a serious global public health concern that is increasing day by day and cause increased the rate of morbidity and mortality and economic burden in this article, we propose a prescription policy framework on the base of AI. Them utilize forecast of bacterial infections and medication usage to assess the public with the goal of enhancing awareness regarding antibiotic consumption. Artificial Intelligence is the simulation of human intelligence process by machinery especially computer system. The current literature shows great interest in implementing machine learning techniques as clinical decision support tools for the prediction of antimicrobial resistance and the selection of appropriate empirical, antibiotic treatment. We assessed the effectiveness of ML trained models to predict and reduce AMR based only data available in the prescription and antibiotic susceptibility results together with simple patient demographics (age/sex/weight). Age, sex and weight have been reported in our studies as factor influencing AMR. This model aims to reduce the problem of antimicrobial resistance (AMR) using machine learning. The model is mainly intended for primary level doctors, nurses, who will discourage patients from unnecessary antibiotic use. The model is built on the subject doctors' prescriptions and their advice. Where information on a large number of patients, different types of problems and how much antibiotic use is needed to solve them will be given. The primary doctor/nurse will input the patient's description of the problem that matches this information into the model. The model will suggest the correct use of antibiotics from the database based on the problem and other information about the disease (based on previous information).

1.2 Objectives

- To develop a model for antibiotic detection, enabling users to accurately identify antibiotics and distinguish them from non-antibiotics.
- To provide a valuable tool for newly graduated doctors and nurses, helping them determine the appropriate antibiotic for specific diseases.
- To analyze prescription information in order to suggest the most suitable medication for a given disease, eliminating the need for a physical consultation with a doctor.
- To provide recommendations on whether an alternative medication can effectively treat the condition without using antibiotics.
- To guide users on the recommended duration of antibiotic courses and other relevant guidelines, promoting public awareness.
- To describe the knowledge, attitude, and practices regarding antibiotic use among the participants.
- To embed an expert system that validates the consistency of knowledge, attitude, practice and behavior results.
- To assess the knowledge of participants regarding antibiotic resistance.
- To discuss preventive measures for antibiotic resistance.
- To identify the socio-demographic characteristics of the participants.
- To explore the relationship between socio-demographic characteristics and knowledge about antibiotic use and resistance.

1.3 Visualization of our Model

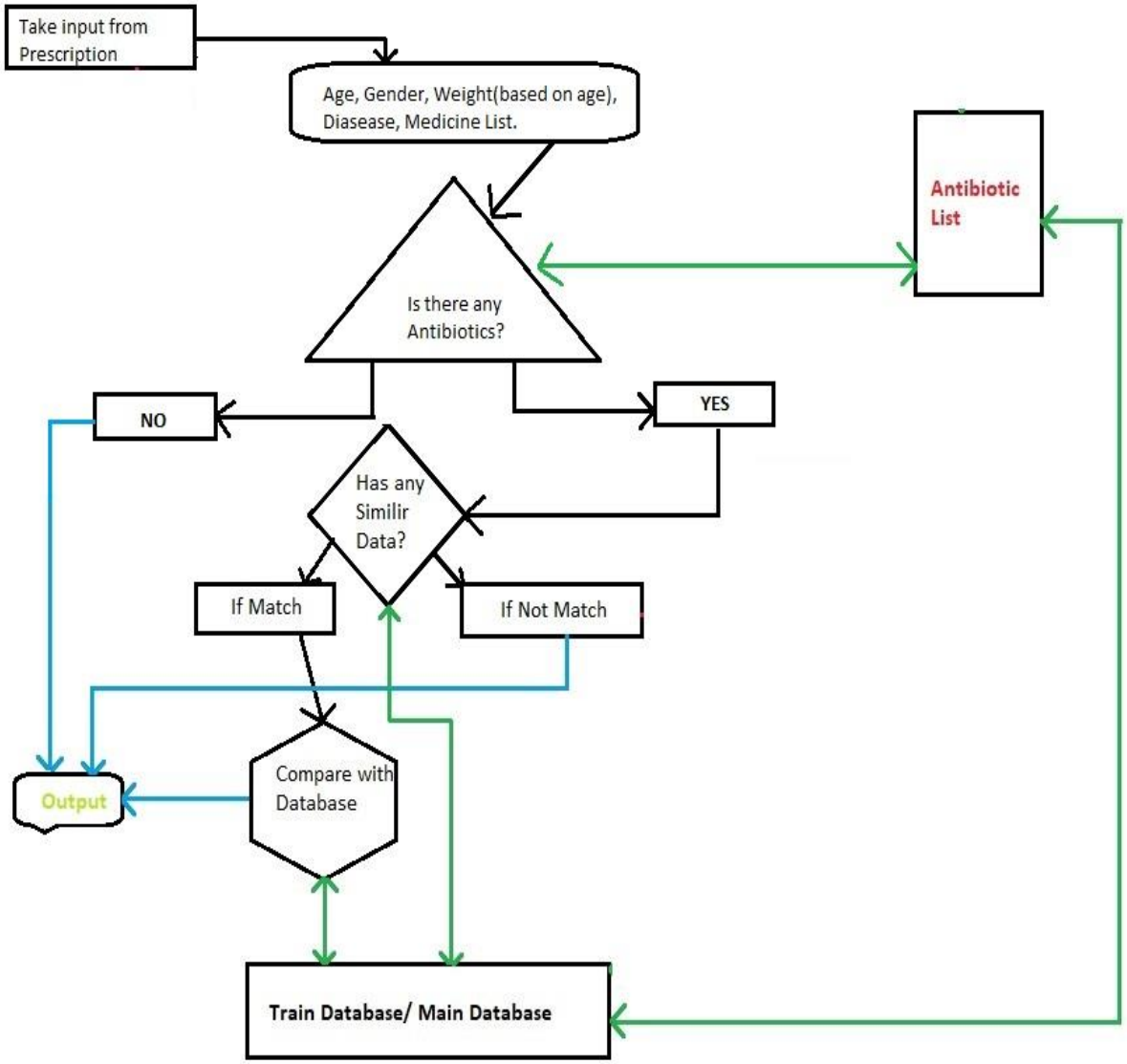


Figure 1.3.1 Visualization of Model

CHAPTER 2

Literature Review

2.1 Literature Review:

Antibiotic resistance is one of the most pressing public health challenges globally, with bacterial infections becoming harder to treat as antibiotics lose their efficacy. Artificial Intelligence (AI) is increasingly recognized as a powerful tool for both tackling antibiotic resistance and improving public awareness of this critical issue. The worldwide situation with respect to anti-microbial resistance remains a squeezing issue for open wellbeing, with a steady upward slant in resistance predominance over the past few decades. [3]

Anti-microbial resistance has ended up a worldwide challenge for human wellbeing, because it is connected to tall rates of mortality and dreariness. The primary anti-microbial resistance was detailed as before long as sulfonamides were presented in 1930; it anticipated the occurrence of anti-microbial resistance within the common environment within the pre-antibiotic period without supporting the presence of dangerous safe pathogens. (Muteeb et al., 2023) [2]. Artificial intelligence (AI) has demonstrated substantial competence in the field of AMR control in recent years. For example, artificial intelligence applications based on sequencing have been used to explore AMR. Furthermore, the collection of clinical data for the development of clinical decision support systems could assist clinicians in monitoring trends in antimicrobial resistance to promote antibiotics' sensible applications (Rabaan et al., 2022) [9].

This literature review will explore the current understanding of AI' s role in combating antibiotic resistance and raising awareness, highlighting relevant studies, methodologies, and findings in these areas [17]. In the computer sciences field, AI has a dynamic part to play in human intelligence stimulation systems and its research. The processes including speech recognition, visual perception, natural language processing, and decision making according to perceived data are stimulated using the technology The metadata from available health records and developments in processing performance are critical factors in the growth of AI systems [22].

We are created public healthcare databases use to government hospital prescription, are large collections of medical and health-related data it's often include information related to disease prevalence, treatment outcomes, drug prescriptions, and health conditions, including antibiotic trends. After scanning the prescription our model can store Patient all medical records and given essential result based on any kind of disease. One of the biggest concerns to global health is antibiotic resistance, which seriously jeopardizes the efficacy of contemporary medicine. If antibiotic-resistant diseases are not controlled, the World Health Organization (WHO) estimates that by 2050 they could result in over 10 million deaths per year (WHO, 2020) [28]. This problem is caused by bacteria that have evolved to be resistant

to antibiotic treatments, mainly as a result of over use and incorrect use of antibiotics. The over prescription and abuse of antibiotics are issues that are exacerbated by the human healthcare and agricultural sectors (Ventola, 2015) [13]. Innovative approaches are needed to address this, and artificial intelligence (AI) is becoming a vital weapon in the battle against antibiotic resistance.

Antibiotic resistance is being predicted, tracked, and mitigated with the help of Artificial intelligence more and more. It can anticipate patterns of bacterial resistance, optimize the prescription of antibiotics, and potentially find new antibiotics thanks to its enormous processing and analysis capacity (Chokshi et al., 2019) [23]. By giving real-time insights into the most effective antibiotic treatments for certain bacterial illnesses, artificial intelligence (AI) tools can assist clinicians in making better judgments. Artificial intelligence (AI) models are being used in healthcare settings to decrease needless prescriptions and increase treatment accuracy, which is slowing the spread of resistant germs (Fleming-Dutra et al., 2016). The effectiveness of AI in anticipating resistance has been shown in numerous research. (Nguyen et al. 2020) [37]. For example, employed deep learning algorithms to analyze genomic data in order to predict bacterial resistance. In a similar vein, Su et al.'s study from 2021 used patient data and bacterial genome sequences to build artificial intelligence models that could identify drugs that would not work, saving doctors' time when giving them. These models have demonstrated remarkable promise in hospital settings where tailored treatment can dramatically lower resistance risks, as seen by their excellent accuracy rates [6].

The potential of AI in identify prediction is one of the most noteworthy developments in the use of AI to tackle antibiotic resistance. It often takes a long time to reduce antibiotic resistance in the public due to the time-consuming nature and limited effectiveness of traditional awareness programs and drug research techniques. AI, however, can expedite this procedure. A novel antibiotic called Halicin was discovered by Stokes et al. (2020) by the application of machine learning algorithms to screen over 100 million chemical compounds. Halicin is effective against a variety of drug-resistant bacteria, such as, Escherichia coli, and, Mycobacterium tuberculosis. AI's ability to speed up the development of new Antibiotics is demonstrated by the quick identification and testing of such compounds [38].
Artificial Intelligence (AI) has the capability to analyze large prescription related databases and potentially uncover antibiotics that conventional methods would have missed. It is also capable of forecasting.

AI is revolutionizing how antibiotic resistance is monitored. By integrating data from hospitals and healthcare providers, AI algorithms can track and predict resistance patterns in real-time[29]. A notable example is the Resistance Open project, which uses AI to forecast the spread of resistant bacteria by analyzing patient data. This enables health officials to implement targeted strategies, such as stricter infection controls or awareness campaigns, in areas with rising resistance. AI is also being used to monitor antibiotic use and resistance in

livestock, a critical concern[42]. Algorithms can analyze prescription data to identify antibiotic misuse, supporting the enforcement of regulations that limit antibiotics as growth enhancers. These AI-driven surveillance tools hold great promise for reducing antibiotic overuse in both humans and animals, a key factor in addressing the global resistance crisis.

Raising public awareness about antibiotic resistance is crucial for its reduction. Research indicates that many individuals lack knowledge about the risks of antibiotic misuse and the importance of adhering to prescribed treatment regimens (Huttner et al., 2019) [9]. AI has proven to be a powerful tool in promoting public awareness through personalized health messages and educational campaigns. Using Natural Language Processing (NLP), AI can analyze social media, blogs, and public health data to identify knowledge gaps and tailor educational content to address these areas (Caplan et al., 2020) [14]. AI-powered catboats and virtual assistants are also being used to inform the public on the correct use of antibiotics, offering real-time, reliable information on when and how antibiotics should be used. These tools help to minimize self-medication and reduce antibiotic misuse in communities (Kim et al., 2021) [33]. Additionally, machine learning models can assess the effectiveness of public health initiatives by tracking changes in antibiotic usage patterns after educational campaigns have been distributed.

A notable example is the Antibiotic Resistance Information System (ARIS), which employs AI to monitor and assess the impact of public health campaigns across various platforms, such as social media and health websites. This system helps to improve campaigns by targeting high-risk groups, including elderly populations and those in rural areas, where antibiotic misuse is more prevalent (Wang et al., 2021) [27].

Despite the significant potential of AI in combating antibiotic resistance, several challenges remain. A major concern is the availability and quality of data. AI models rely on large amounts of high-quality data to generate accurate predictions, but such data is often lacking in low- and middle-income countries (LMICs), where antibiotic resistance is escalating. Without comprehensive global datasets, AI may struggle to predict resistance patterns effectively across different populations (Hernandez et al., 2019) [11]. Additionally, issues around data privacy and the ethical use of AI in healthcare arise. It is crucial that AI models safeguard patient privacy, particularly when working with sensitive health data. Moreover, AI systems could reinforce existing healthcare biases if they are trained on unrepresentative datasets. For example, AI models trained using data from high income countries may provide inaccurate predictions for LMICs, potentially leading to ineffective treatments and exacerbating health inequalities (Gianfrancesco et al., 2018) [18].

The writing proposes that AI has gigantic potential to diminish anti-microbial resistance through prescient analytics, personalized healthcare intercessions, and improved open

mindfulness campaigns. In any case, accomplishing significant decreases in resistance will require overcoming specialized, administrative, and moral obstructions. Future investigate ought to center on creating more generalized and straightforward AI models, making strides information sharing between teach, and coordination AI into existing anti-microbial stewardship programs.

All in all, we are able conclude that antimicrobial resistance is a genuine issue that's right now confronting in medication. The utilize of information recorded within the EHR and its investigation by ML strategies may progress clinical hone within the ICU. This would result both in individual benefits (wellbeing status of the quiet) and socio-economic benefits (administration of the wellbeing framework) [30].

Artificial Intelligence is swiftly emerging as a crucial asset in combating antibiotic resistance. AI provides a comprehensive approach by predicting resistance trends, optimizing antibiotic use, discovering new medications, and promoting public awareness. However, to unlock its full potential, challenges like data quality, inclusivity, and ethical issues must be overcome. Future research should prioritize creating AI models that are globally inclusive, representative of diverse populations, and uphold patient privacy. As AI advances, it holds tremendous potential to reduce antibiotic resistance and preserve the effectiveness of antibiotics for future generations.

CHAPTER 3

Methodology

3.1 Study design:

A descriptive cross-sectional survey was carried out with a random sample of 224 patient's data and 230 public data individuals from various randomly chosen locations. Supervised Learning Classification and ML algorithms (i.e., Decision Tree algorithm, random forest [RF],) were used to estimate the predictors of medicine. Participants completed a self-administered questionnaire that covered demographic characteristics, knowledge, attitudes, practices, behaviors related to antibiotic use and resistance

3.2 Study settings

For patient's data our selected place was government Dhaka medical colleges and hospital DMCH, STAMCH and SSMCH for public data our selected location was Sonargaon University, Sonargaon, Narayanganj, Munshiganj, and Dhaka.

3.3 Study period

The study was conducted during September 2023 to September 2024.

3.4 Descriptive Research Instrument

The investigators developed the questionnaire through a literature review and consisted of 38 closed-ended type questions in the form of multiple-choice answers. The questionnaire was made both in English and Bangla languages. A set of semi-structured and self-administrated questionnaire will be used for data collection. The questionnaire has five parts.

Part-I: The socio-demographic questionnaire was developed by the researcher for collecting the respondents' personal information. It consists of 8 items. Which are givenbelow (gender, age, marital status, level of education, occupation, monthly income religion, residence/ area). The instrument was validby three expert panels.

Part- II: The second part had 7 items to assess knowledge about antibiotics use and antimicrobial resistance.

Part- III: The third part had 8 items about the attitude towards antibiotics use and AMR. Attitudes' items have a 5-points Likert scale (1 strongly disagree to 5 strongly agree).

Part- IV: The fourth part assessed the participants practice towards antibiotics use and AMR, and each part had 7 questions in the form of a 5-points Likert scale (1 strongly disagree to 5 strongly agree).

Part- V: The fourth part assessed the participants' behavior towards antibiotics use and AMR, and each part had 8 questions in the form of a 5-points Likert scale (1 strongly disagree to 5 strongly agree).

During that phase, 38 individuals undertook the questionnaire to examine its validity and reliability and ensure clarity and understanding. Relevant inputs of the participant were taken into consideration, and the questionnaire was modified accordingly. Cronbach's α coefficient was used to test the questionnaire's internal consistency and taken when it was above (0.7). Responses from the pilot study were not included in the final study results.

3.5 Overall process of applying machine-learning/deep-learning models in AMR identification.

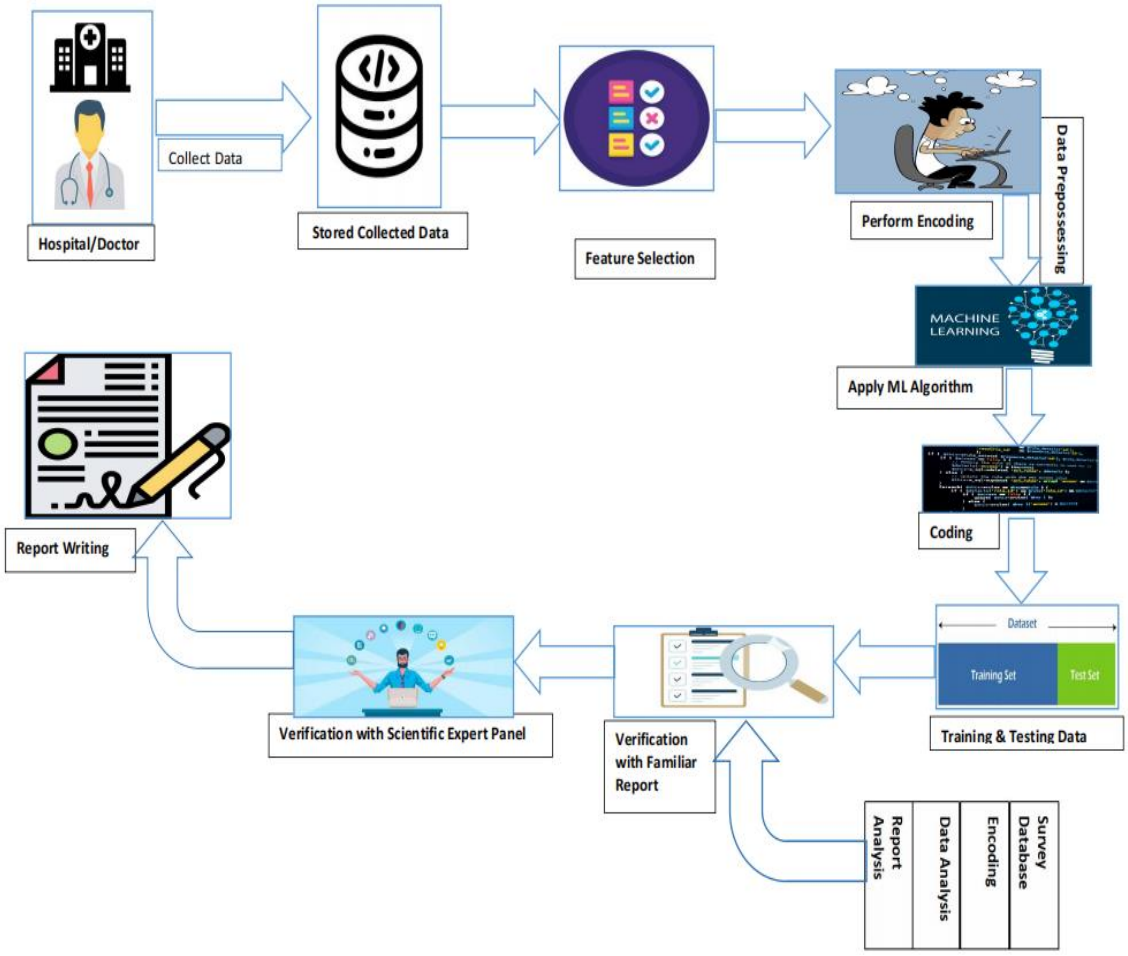


Figure 3.5.1 Overall process of applying machine-learning/deep-learning models

3.6 Data collection and collected method

We studied a diverse and large dataset collected from 3 medicals across five continents.
We have a dataset consisting of 224 subjects, with images from 3 distinct regions of interest: government medical colleges DMCH, STAMCH. For each subject, 3 regions of interest were selected for a specific disease, yielding the following input vectors:90 input vectors from DMCH,110 input vectors from STAMCH, 24 input vectors from SSMCH. And for survey the population was the public, such as family, friends, and relatives, as well as patients and students. All participant was selected from the available record at selected place and invited to participate in the study. Here, the study population is 227.

3.6.1 Preparational phase

A structured questionnaire was employed to collect responses from study participants over a three-month period, from July to September 2024. The research process began with the researcher meeting the research committee at Sonargaon University (SU) to seek approval and permissions from the university's authority. After receiving the necessary approvals, the researcher explained the study's purpose and benefits to the university authorities.

Upon obtaining permission from both the research committee and the university, the researcher introduced themselves to the participants prior to data collection. Respondents were thoroughly informed about the study's objectives and procedures. A consent form was provided alongside the questionnaire, outlining the details of the study. Each participant was made aware of their rights, including the right to refuse participation, the right to seek clarification, and the right to withdraw from the study at any time.

Participants who agreed to participate signed the consent form, after which data collection was conducted through a self-administered questionnaire. The researcher facilitated the process by reading the questionnaire to the subjects, clarifying details as needed until the participants fully understood the questions, and ensuring that sufficient time was given for each subject to respond. On average, each participant took approximately 20-30 minutes to complete the questionnaire. After completion, the researcher reviewed each questionnaire to ensure proper completion. Confidentiality and anonymity of the participants were maintained rigorously throughout the study.

The study was organized into three distinct phases:

Phase One: A general survey assessing participants' use of antibiotics and their understanding of antibiotic resistance.

Phase Two: An awareness campaign aimed at educating individuals about the risks associated with antibiotic misuse and its implications for resistance. This phase involved students from

Sonargaon University conducting informal discussions with participants, during which flyers highlighting key messages were distributed.

Phase Three: A follow-up questionnaire was administered to evaluate the effectiveness of the awareness campaign. During this phase, the students took turns presenting information, using the flyers as reference points to facilitate discussion and enhance understanding among participants.

Table 1. Click here to see the full summary of the patient dataset

I7

	A	B	C	D	E	F
1	Age(days)	Weight	Gender	Disease	Medicine	Antibiotics
2	10585	55	female	AWD	tab.azithromycin	yes
3	10585	55	female	AWD	tab.famotid	no
4	10585	55	female	AWD	inj.emistat	no
5	10585	55	female	AWD	tab.algin	no
6	29200	55	male	vertigo	tab.cinaron plus	no
7	29200	55	male	vertigo	cap.omeprazole	no
8	29200	55	male	vertigo	inj.emistat	no
9	29200	55	male	vertigo	tab.atova(10mg)	yes
10	22995	55	male	stroke	tab.clopid As	no
11	22995	55	male	stroke	tab.atova(10mg)	yes
12	22995	55	male	stroke	tab.comet XR(500mg)	no
13	22995	55	male	stroke	Tab.Empadus(10mg)	no
14	22995	55	male	stroke	Tab.cerevas(5mg)	no
15	22995	55	male	stroke	Tab.Furotil/cefuroxime(500mg)	yes
16	22995	55	male	stroke	Tab.Betaloc(25mg)	no
17	22995	55	male	stroke	tab.nitrin SR(2.6 mg)	yes
18	22995	55	male	stroke	Tab.Metacord MR(35mg)	no
19	22995	55	male	stroke	inj.Emistat(8mg)	no
20	27375	55	male	COPD	Tab.clarix(500mg)	no
21	27375	55	male	COPD	cap.omeprazole(20mg)	no
22	27375	55	male	COPD	tab.camlosant 5/20	no
23	27375	55	male	COPD	tab.Uromax D	no
24	27375	55	male	COPD	cap.dicaltrol(25mg)	no
25	27375	55	male	COPD	tab.Docopa(200mg)	no
26	27375	55	male	COPD	tab.Monas(10mg)	no
27	18250	55	male	TB	inj.ceftriaxone(1g)	yes
28	18250	55	male	TB	tab.clix(500mg)	yes
29	18250	55	male	TB	Tab.M-Kast(10mg)	no

Table 3.6.1.1 Patient's Dataset

3.6.2. Feature Selection and computation

In this research, the dataset contains features such as age**,** weight**,** gender**,** disease**,** medicine**,** and the use of antibiotics. The target variable is antibiotic**,** which indicates whether a medicine is antibiotic or not. The objective of the feature selection process is to identify the most relevant variables that contribute to predicting whether an antibiotic will be administered to a patient. The first step in the process is to handle missing data.

3.6.3 Data Preprocessing:

The data used in this study are derived from bacterial susceptibility records of patients from Dhaka Medical College, Shaheed Tajuddin Ahmed Medical College Hospital, and other healthcare facilities, totaling 1,119 entries. These records include 156 non-antibiotic types, 32 antibiotic types, and 97 different diseases. Given the complexity of the raw data, data mining could only commence following a thorough preprocessing stage, which involved tasks such as data filtering, detecting outliers, and standardizing the dataset. Unnecessary indicators were eliminated, and five key attributes were identified as potentially influencing antimicrobial resistance: patient's age, weight, gender, disease, medicine. Classification Label: Whether the medicine is an antibiotic or not was chosen as the classification label for this analysis. Anomaly Detection: Using the expertise of professionals and historical detection data, we identified any unreasonable or anomalous results within the original dataset. Since the data originates from reliable and systematic hospital testing institutions, there were relatively few anomalies. However, data with significant missing values were also classified as anomalies, and any records containing such values were directly removed. Standardization: To streamline further data processing, four key features were converted into numerical values, ensuring consistency in the quantification methods across the dataset.

Handle missing values. Encode categorical variables using label encoding to convert them into a format suitable for machine learning algorithms.

The results are shown in Table 1.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report

data = pd.read_csv('allPaitent.csv')

df = pd.DataFrame(data)

le_gender = LabelEncoder()
le_disease = LabelEncoder()
le_medicine = LabelEncoder()
le_antibiotic = LabelEncoder()

df['Gender'] = le_gender.fit_transform(df['Gender'])
df['Disease'] = le_disease.fit_transform(df['Disease'])
df['Medicine'] = le_medicine.fit_transform(df['Medicine'])
df['Antibiotic'] = le_antibiotic.fit_transform(df['Antibiotic'])

df.to_csv("Encoded_Data.csv")
```

Figure 3.6.3.1 Data Encoding

Age	Weight	Gender	Disease	Medicine	Antibiotics
29	55	0	5	560	1
29	55	0	5	612	0
29	55	0	5	256	0
29	55	0	5	549	0
80	55	1	94	580	0
80	55	1	94	70	0
80	55	1	94	256	0
80	55	1	94	559	1
63	55	1	84	587	0
63	55	1	84	559	1
63	55	1	84	590	0
63	55	1	84	26	0
63	55	1	84	31	0
63	55	1	84	27	1
63	55	1	84	25	0
63	55	1	84	659	1
63	55	1	84	29	0
63	55	1	84	199	0
75	55	1	8	32	0
75	55	1	8	80	0

Table 3.6.3.1 Encoding Dataset

3.7 Use of Machine Learning (ML) Algorithm

The Random Forest algorithm is a popular machine learning technique that creates a group of decision trees to solve classification problems. In this case, it is used to predict whether a medicine is an antibiotic (yes or no) based on the available data. The Random Forest method uses a process called bootstrapping, which means that each decision tree in the forest is trained on a random subset of the data. This helps create diverse trees and reduces the chance of the model overfitting, or performing well only on the training data but poorly on new data. The Random Forest algorithm was first introduced by Breiman in 2001. It is built on a technique called Bagging, where multiple decision trees are combined to make a final prediction. Here's a simplified breakdown of how it works:

From the original dataset, Random Forest uses the Bootstrap method to randomly select data points (with replacement) to create new training sets. This means each decision tree gets a slightly different set of data to train on. For each tree, instead of using all the available features (like age, gender, disease, etc.), Random Forest randomly selects a subset of these features. This ensures that the decision trees are diverse and don't all make the same splits. Each decision tree in the Random Forest is trained to predict whether a medicine is an antibiotic or not. The trees make decisions by splitting the data based on the features that best reduce uncertainty. Common measures for this are Gini impurity and entropy. After each tree makes its prediction,

Random Forest uses a voting method to combine the results. The category (antibiotic or non-antibiotic) with the most votes is chosen as the final prediction.

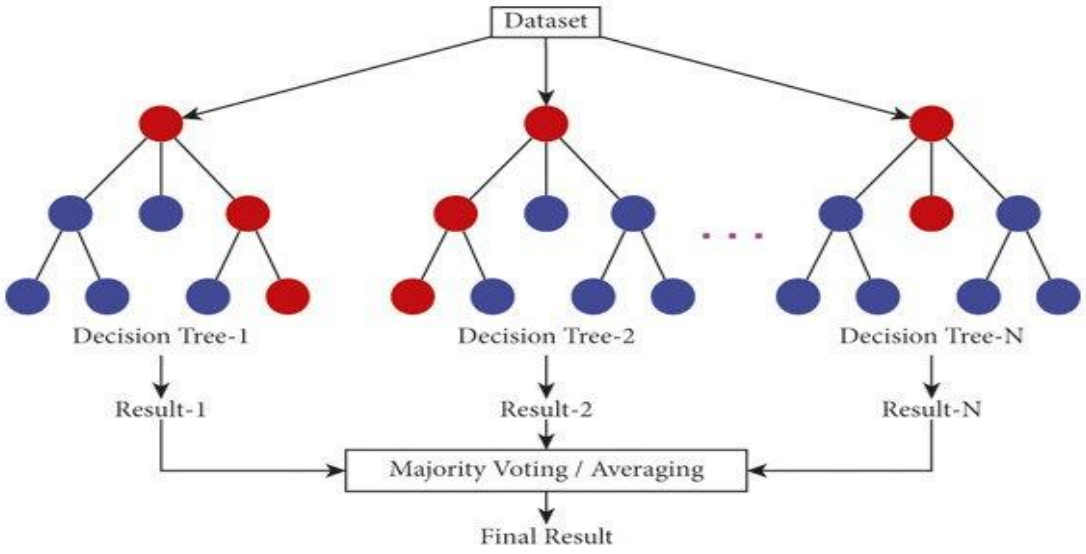


Figure 3.7.1 Random Forest Algorithm

3.7.1 The flow chart ML

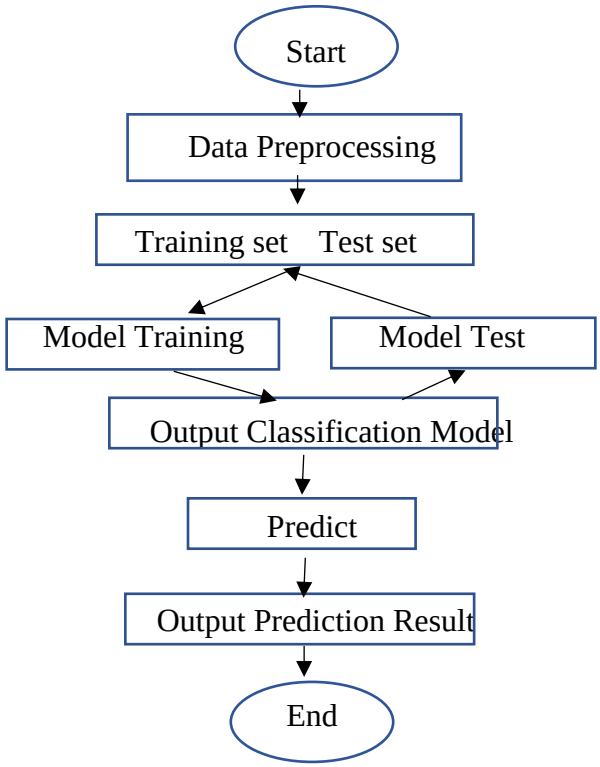


Figure 3.7.1.1 Flow chart of Random Forest

3.7.2 Model Performance Evaluation Indicators in this paper, F measure is used as the evaluation criterion of classification results. This method takes both precision (P) and recall (R) into account. P, R and F are calculated by the following formulas respectively.

Confusion Matrix

	Negative	Positive
Negative	187	1
Positive	23	13

Table 3.7.2.1 Confusion Matrix

	precision	recall	f1-score	support
0	0.94	0.95	0.94	188
1	0.71	0.67	0.69	36
accuracy			0.90	224
macro avg	0.82	0.81	0.81	224
weighted avg	0.90	0.90	0.90	224

Table 3.7.2.2 Classification Metrix

$$P=TP/ (TP+ FP)$$

$$R=TP/ (TP+FN)$$

$$F= (2P)/ (P+R)$$

Among them, TP is the sample number of positive classes, FP is the sample number of negative classes, FN is the number of samples with positive classes divided into negative classes, TP + FP is the sample number of actual classes, TP + FN is the sample number of due classes.

3.8 Training and Testing: The Learning Process:

Supervised machine learning algorithms rely on labeled examples to learn. Algorithms like linear and logistic regression, k-nearest neighbors (k-NN), support vector machine (SVM), decision tree (DT), random forest (RF), and gradient boosting machine (GBM) are some of the most commonly used. Neural networks and deep learning approaches are also becoming more prevalent. The performance of these models is often evaluated using the Area Under the Receiver Operating Characteristic (AUROC) curve, which measures the model's ability to differentiate between classes. Other performance metrics, such as accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), precision, recall, and F1 score, can all be derived from a confusion matrix.

Once the data preprocessing complete, the Random Forest algorithm is applied to the training set. The Random Forest algorithm creates multiple decision trees. Each tree is trained on a random subset of the training data (using bootstrapping). For each tree, a random subset of features (e.g., Gender, Disease, Medicine) is used to create splits that reduce uncertainty about whether the target variable (antibiotic = yes or no) is true. As multiple decision trees are built, each tree learns from different parts of the data, which helps capture a variety of patterns. The model is trained until all trees in the forest are complete. After training the model on the training data, it's time to evaluate how well it performs on the test data.
The trained Random Forest model is used to predict the target variable (antibiotic = yes or no) for the test data. Each tree in the forest gives its own prediction, and the final prediction is determined by majority voting — the category (yes or no) that gets the most votes from the trees is chosen. The predictions are compared with the actual values in the test set to measure the model's performance. Common evaluation metrics include:

The percentage of correct predictions out of all predictions made. The proportion of true positive predictions (correct antibiotic predictions) out of all positive predictions. The proportion of true positives identified out of all actual positives. The harmonic mean of precision and recall, useful when you want to balance both metrics. A table showing the number of true positives, false positives, true negatives, and false negatives, helping you understand the model's performance in greater detail.

To ensure that the model generalizes well**,** cross-validation is often used, especially when the dataset is limited. In cross-validation, the data is divided into multiple subsets, with one part used for testing and the rest for training. This process is repeated several times with different subsets, providing a comprehensive evaluation of the model. For example, in k-fold **cross-**validation**,** the data is split into *k* subsets, and the model is trained and tested *k* times, each time leaving out one subset for testing. Leave-one-out cross-validation is a more extreme form, where each example is used as a test case once, while the rest of the data is used for training. However, while cross-validation gives a thorough assessment of model performance, each iteration produces a different model, which means there is no final unified model unless one is retrained on the entire dataset.

3.9 Antibiotic prediction In this paper, a visual drug prediction platform is constructed. After login to the system, input the patient's relevant characteristic information and click the result button, the MIC prediction values of current bacteria for different antimicrobial agents will be displayed in the list below the page, as shown in Figure.



Figure 3.9.1 Application Dashboard

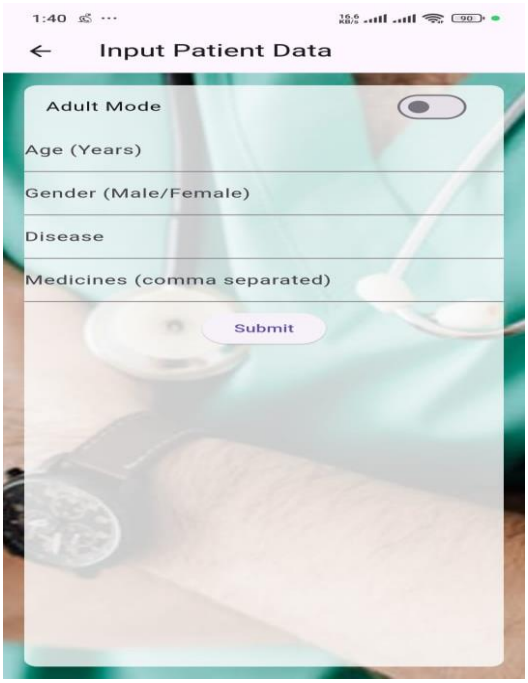


Figure 3.9.2 Application User Input

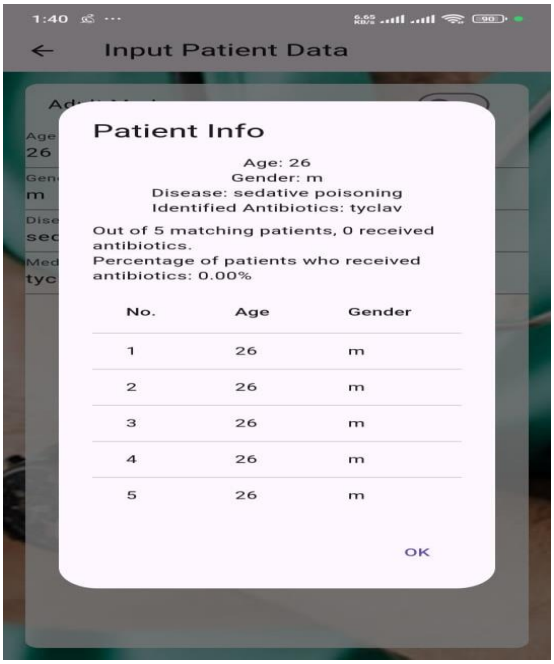


Figure 3.9.3 Antibiotic prediction

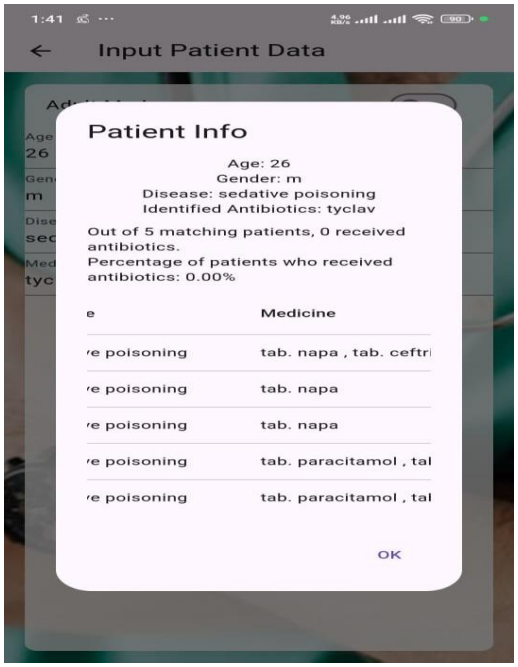


Figure 3.9.4 Alternative Medicine suggesstion

3.10 Descriptive Data Analysis

After finishing data collection, all data were checked, organized and edited, cleaned, coded, entered, and edited to consistency to minimum error. Data was analyzed by using Statistical Package for Social Science (SPSS) version 25. Descriptive statistics such as frequencies, percentages, range, means, and standard deviation used to analysis the socio- demographic characteristics. Result was presented through in the form of table and pie chart. Pearson's $\chi 2$-test was used to find the association between the level of antibiotics knowledge (good / poor) and sociodemographic variables. According to sociodemographic variables, the t-independent sample and ANOVA tests were used to find the differences in antibiotics' attitudes and practices.

Finally, the Pearson correlation test was used to test the relation between the total score of knowledge and mean scores of antibiotics attitude and practice. Data were reported as percentages and 95% confidence intervals (CI). The strength of the correlation between knowledge, attitude and practices of antibiotics describes as follow: 0.0-0.19 "very weak", 0.20-0.39 "weak", 0.40-0.59 "moderate", 0.60-0.79 "strong" and 0.80-1.0 "very strong". KAP's total scores were categorized into "good" and "poor" scores based on an 80% cut-off score. A significant level of $p<0.05$ was considered as a statistical significance.

3.10.1 Model Summary

This table presents the results of a Pearson correlation analysis examining the relationships between four key variables: Behavior, Knowledge, Attitude, and Practice. Pearson correlation measures the strength and direction of these associations. A correlation coefficient of 0.789 indicates a strong positive relationship between behavior and knowledge, suggesting that as knowledge increases, behavior improves significantly. The correlation between behavior and attitude is 0.935, showing a very strong association, implying that positive attitudes have a major impact on behavior. Similarly, behavior and practice have a correlation of 0.913, indicating that better practices align with improved behavior. Knowledge and attitude are also strongly correlated (0.803), meaning individuals with more knowledge tend to have more positive attitudes. The correlation between knowledge and practice is 0.876, further reinforcing the link between knowledge and good practices. Attitude and practice are very closely related as well, with a correlation of 0.908, suggesting that fostering positive attitudes can enhance practical outcomes. All correlations are statistically significant, with p-values less than 0.001, indicating that the relationships observed between these variables are not due to chance. This provides strong evidence of positive relationships between behavior, knowledge, attitude, and practice.

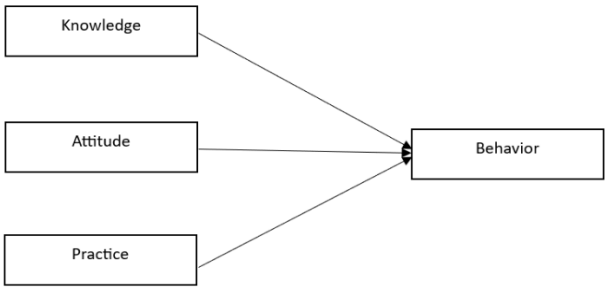


Figure 3.10.1.1 Hypothesis Formulation

Model Summary

		Behavior	Knowledge	Attitude	Practice
Pearson Correlation	Behavior	1	0.789	0.935	0.913
	Knowledge	0.789	1	0.803	0.876
	Attitude	0.935	0.803	1	0.908
	Practice	0.913	0.876	0.908	1
Sig. (1-tailed)	Behavior	.	<.001	<.001	<.001
	Knowledge	0	.	0	0
	Attitude	0	0	.	0
	Practice	0	0	0	.
N	Behavior	227	227	227	227
	Knowledge	227	227	227	227
	Attitude	227	227	227	227
	Practice	227	227	227	227

Table 3.10.1.1 Descriptive Model Summary

3.10.2 Regression analysis

This table provides the results of a **regression analysis** that examines the relationship between the dependent variable **Behavior** and the independent variables **Practice**, **Knowledge**, and **Attitude**. Here's a breakdown of the results:

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.948[a]	0.899	0.898	0.36631
a. Predictors: (Constant), Practice, Knowledge, Attitude				
b. Dependent Variable: Behaviour				

Table 3.10.2.1 Regression analysis

The value of **R = 0.948** indicates a **very strong positive correlation** between the independent variables (Practice, Knowledge, and Attitude) and the dependent variable (Behavior). This suggests that the combined effect of Practice, Knowledge, and Attitude can predict Behavior very accurately. The **R Square value = 0.899** means that **89.9% of the variance in Behavior** is explained by the combined predictors (Practice, Knowledge, and Attitude). This high percentage demonstrates that the model fits the data well, as a significant portion of the behavior can be accounted for by these three factors. The **Adjusted R Square = 0.898** is slightly lower than the R Square value, but it still shows that **89.8% of the variance in Behavior** is explained after adjusting for the number of predictors in the model. The adjusted value accounts for the potential inflation of R Square when multiple predictors are used, thus providing a more accurate representation of the model's explanatory power. The **standard error = 0.36631** represents the average distance that the observed values fall from the regression line. A lower standard error indicates that the data points are closer to the fitted regression line, meaning the model is making predictions with relatively high accuracy.

3.10.3 ANOVA Results for Regression Analysis

The following table summarizes the results of the **Analysis of Variance (ANOVA)** conducted for the regression model examining the relationship between the dependent variable **Behavior** and the independent variables **Practice**, **Knowledge**, and **Attitude**.

ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	266.706	3	88.902	662.543	<.001[b]
	Residual	29.923	223	0.134		
	Total	296.628	226			

a. Dependent Variable: Behavior

b. Predictors: (Constant), Practice, Knowledge, Attitude

Table 3.10.3.1 ANOVA Test Result

ANOVA Results the Regression Sum of Squares (266.706) indicates the amount of variance in Behavior that is explained by the predictors (Practice, Knowledge, and Attitude). The Residual Sum of Squares (29.923) reflects the unexplained variance, which represents the error after accounting for the predictors. The Total Sum of Squares (296.628) is the sum of the explained and unexplained variances, reflecting the overall variability in the dependent

variable. The Regression df (3) corresponds to the number of independent variables in the model. The Residual df (223) is calculated as the total number of observations (226) minus the number of predictors minus one, indicating the degrees of freedom associated with the error. The Total df (226) represents the total number of observations. The Mean Square for Regression (88.902) is obtained by dividing the regression sum of squares by its degrees of freedom. This value indicates the average variation explained by the model. The Mean Square for Residuals (0.134) reflects the average error variance, calculated by dividing the residual sum of squares by its degrees of freedom. The F-value of 662.543 indicates the overall significance of the regression model. It measures how much the regression model improves the prediction of the dependent variable (Behavior) compared to a model with no predictors. The p-value of < .001 indicates that the regression model is statistically significant. This finding suggests that there is less than a 0.1% probability that the observed relationship is due to chance. Thus, at least one of the predictors—Practice, Knowledge, or Attitude—contributes significantly to explaining the variance in Behavior.

3.10.4 Regression Coefficients

The following table presents the coefficients from the regression analysis conducted to assess the influence of Knowledge, Attitude, and Practice on the dependent variable Behavior. This analysis provides insights into how each predictor contributes to the overall model.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	0.544	0.085		6.415	<.001	0.712	0.377					
	Knowledge	0.164	0.042	0.168	1.54	<.001	0.146	0.018	0.789	0.103	0.033	0.233	4.301
	Attitude	0.786	0.066	0.608	11.981	<.001	0.657	0.916	0.935	0.626	0.255	0.176	5.69
	Practice	0.463	0.069	0.421	6.715	<.001	0.327	0.599	0.913	0.41	0.143	0.115	8.681

a. Dependent Variable: Behaviour

Table 3.10.4.1 Regression Coefficients Table

The constant (intercept) has an unstandardized coefficient (B) of 0.544, meaning that when all predictors (Knowledge, Attitude, and Practice) are zero, the predicted value of "Behavior" is 0.544. The t-value for the constant is 6.415, and the p-value is less than 0.001, making it statistically significant.

For Knowledge, the unstandardized coefficient (B) is 0.164, indicating that a one-unit increase in Knowledge is associated with a 0.164 unit increase in Behavior. The standardized coefficient (Beta) is 0.168, showing a relatively small standardized effect size. The t-value is 1.54, with a p-value less than 0.001, signifying that Knowledge has a significant effect, though its t-value is lower compared to other variables. The variance inflation factor (VIF) for Knowledge is 4.301, suggesting moderate multicollinearity, but it is below the threshold of concern.

For Attitude, the unstandardized coefficient (B) is 0.786, meaning a one-unit increase in Attitude results in a 0.786 unit increase in Behavior. The standardized coefficient (Beta) is 0.608, making Attitude the variable with the largest effect on Behavior. The t-value is 11.981, and the p-value is less than 0.001, making it highly significant, with the largest t-value among all variables. The VIF for Attitude is 5.69, which suggests some collinearity concerns as it is moderately high.

For Practice, the unstandardized coefficient (B) is 0.463, indicating that a one-unit increase in Practice increases Behavior by 0.463 units. The standardized coefficient (Beta) is 0.421, which shows a moderate effect size compared to the other variables. The t-value is 6.715, with a p-value less than 0.001, making it significant, though its effect is less than that of Attitude. The VIF for Practice is 8.681, a high value that indicates strong multicollinearity. High multicollinearity can reduce the reliability of this coefficient and make it hard to separate its effect from other predictors.

In conclusion, Attitude has the strongest impact on Behavior, as shown by its large Beta and t-values, followed by Practice and Knowledge. However, the high VIFs for Attitude and Practice indicate potential multicollinearity, which could affect the reliability of the model. If there is concern about multicollinearity, it may be addressed by removing or combining predictors, or using techniques like ridge regression.

CHAPTER 4

Results

This chapter provides an overview of the findings and results from the analysis are presented. The model presented in this paper is an automatic prescription reading system capable of running the whole analysis of an antibiotic resistance offline on mobile devices, from image acquisition to interpreted results. It helps ML throughout the whole analysis process, detect antibiotics from prescription, compare with database, showing result. The model can be summarized in three major components: first, a dedicated image processing module (IP) that reads and analyzes the prescription image; second, an expert system (ES) responsible for the interpretation of the data extracted by IP; third, a Graphical User Interface (GUI) that allows the execution of IP and ES on a smartphone, and user interaction. The image processing library of the program uses machine learning (ML) to identify the antibiotic medication, which is unusual for this type of application, and applies an innovative algorithm for the measurement of inhibitory diameters (detailed in Methods).

4.1 Predict Antibiotics: our model can identify antibiotcs based on our database, there are 32 antibiotics used in our database, which we collect from our prescription.

```python
import pandas as pd
import re
from sklearn.metrics import accuracy_score

def clean_medicine_name(medicine):
    medicine_cleaned = re.sub(r'[^a-zA-Z0-9\s]', '', medicine).strip().lower()
    return medicine_cleaned

csv_file_path = 'allPaitent.csv'
csv_data = pd.read_csv(csv_file_path)
csv_data['Medicine'] = csv_data['Medicine'].apply(clean_medicine_name)

input_medicine = input("Enter the name of the medicine for prediction: ")
input_medicine_cleaned = clean_medicine_name(input_medicine)

if input_medicine_cleaned in csv_data['Medicine'].values:
    antibiotic_status = csv_data[csv_data['Medicine'] == input_medicine_cleaned]['Antibiotics'].values[0]
    print(f"The medicine '{input_medicine}' is in the known list of medicines. Antibiotics: {antibiotic_status}")
else:
    matches = csv_data[csv_data['Medicine'].str.contains(input_medicine_cleaned, case=False)]
    if not matches.empty:
        print(f"Found partial match(es) for '{input_medicine}':")
        print(matches)
    else:
        print(f"The medicine '{input_medicine}' is not in the known list of medicines.")
```

Figure 4.1.1 Predict Antibiotics

```
    else:
        print(f"The medicine '{input_medicine}' is not in the known list of medicines.")

test_csv_file_path = 'allPaitent.csv'
test_data = pd.read_csv(test_csv_file_path)
test_data['Medicine'] = test_data['Medicine'].apply(clean_medicine_name)
actual_status = []
predicted_status = []

for index, row in test_data.iterrows():
    input_medicine_cleaned = row['Medicine']

    if input_medicine_cleaned in csv_data['Medicine'].values:
        antibiotic_status = csv_data[csv_data['Medicine'] == input_medicine_cleaned]['Antibiotics'].values[0]
        predicted_status.append(antibiotic_status)
    else:
        predicted_status.append('No')

    actual_status.append(row['Antibiotics'])
accuracy = accuracy_score(actual_status, predicted_status)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
Enter the name of the medicine for prediction:  inj.ceftriaxone(1g)
The medicine 'inj.ceftriaxone(1g)' is in the known list of medicines. Antibiotics: yes
```

Figure 4.1.2 Predict Antibiotics

4.2 Accuracy of Dataset:

```
import pandas as pd
import re
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

def clean_medicine_name(medicine):
    return re.sub(r'[^a-zA-Z0-9\s]', '', medicine).strip().lower()
csv_file_path = 'allPaitent.csv'
data = pd.read_csv(csv_file_path)
if 'Medicine' in data.columns:
    data['Medicine'] = data['Medicine'].apply(clean_medicine_name)
X = data.drop(columns=['Antibiotics'])
y = data['Antibiotics']
X = pd.get_dummies(X)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

TBC

```
Accuracy: 89.29%
```

Figure 4.2.1 Accuracy of Dataset

4.3 Confusion matrix of Dataset:

```
conf_matrix = confusion_matrix(y_test, y_pred, labels=model.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=conf_matrix, display_labels=model.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix")
plt.show()
```

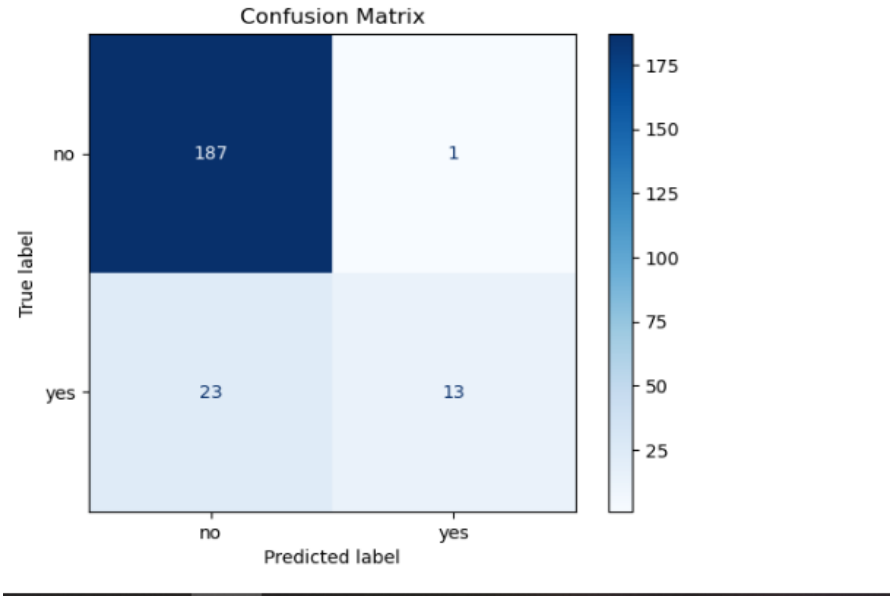


Figure 4.3.1 Confusion Matrix of Dataset

4.4 Identified the Antibiotics and showing suitable Medicine for Specific Disease.

Here our model identified antibiotics from image of prescription and also if it's not found age or others data as require it'll ask the user to enter those data, after getting all require data it'll analysis the data and showing all related patient information with highlight the antibiotics name.

4.4.1 A Python library built on "pytesseract" is a Python wrapper for Google's Tesseract-OCR Engine. It can read text from images and extract it as strings. and Pillow (PIL) is another python package it's used for Imaging Library (PIL) fork that adds support for opening, manipulating, and saving image files. "From PIL import Image, Image Filter, Image Enhance, ImageOps"

4.4.1.1: Image: The core module for working with images. Allows opening, saving, and performing basic image operations.

4.4.1.2: Image Filter: Provides various filters to apply to images, such as blurring, sharpening, and edge detection.

4.4.1.3: Image Enhance: Adjusts the sharpness, contrast, brightness, and color of images.

4.4.1.4: ImageOps: Provides operations such as mirroring, flipping, and grayscale conversion of images.

```
Identified Antibiotics: tyclav
Gender not found in the prescription. Please enter the gender (M/F): m
Disease not found in the prescription. Please enter the disease: sedative poisoning

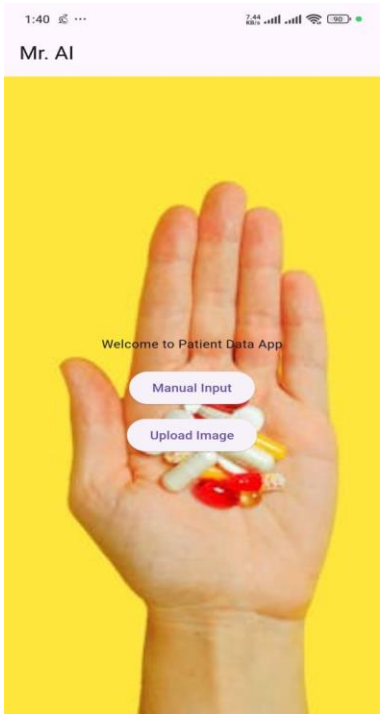
Patient Info: Age: 26, Gender: m, Disease: sedative poisoning

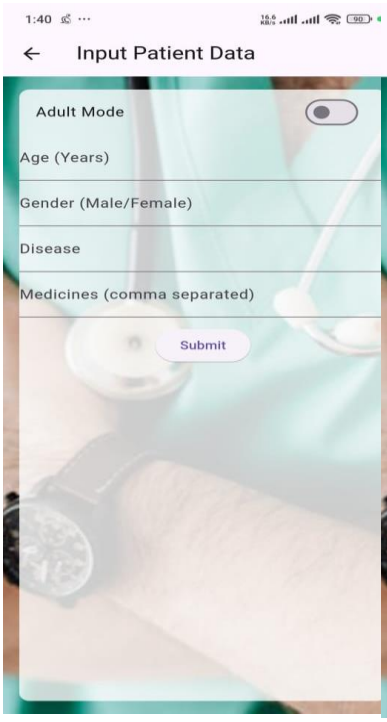
Out of 5 matching patients, 1 received antibiotics.
Percentage of patients who received antibiotics: 20.00%

Matching Patient Data:
+-------+-------+----------+--------------------+-----------------------------------------------+
|   No. |   Age | Gender   | Disease            | Medicine                                      |
|-------+-------+----------+--------------------+-----------------------------------------------|
|     1 |    26 | m        | sedative poisoning | tab. napa , tab. ceftriaxone                  |
|     2 |    26 | m        | sedative poisoning | tab. napa                                     |
|     3 |    26 | m        | sedative poisoning | tab. napa                                     |
|     4 |    26 | m        | sedative poisoning | tab. paracitamol , tab. napa extra, tab. algin |
|     5 |    26 | m        | sedative poisoning | tab. paracitamol , tab. sergel-20             |
+-------+-------+----------+--------------------+-----------------------------------------------+
```

Figure 4.4.1 Identified the Antibiotics and showing suitable Medicine for Specific Disease

4.5 Develop an Android Application based on our Model





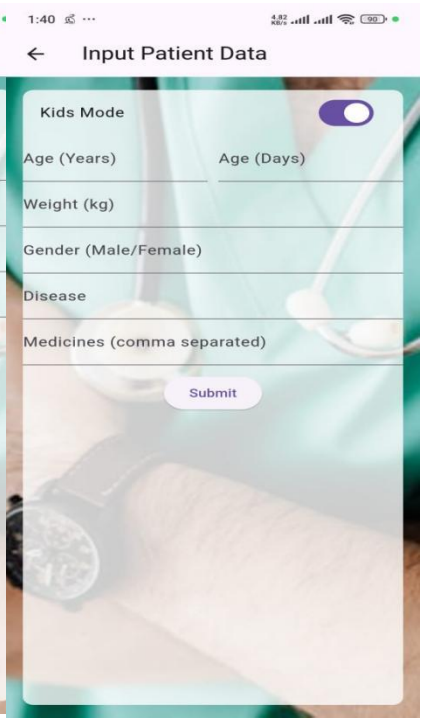


Figure 4.5.1 Home Page Figure 4.5.2 Adult Interface Figure 4.5.3 Kids Interface

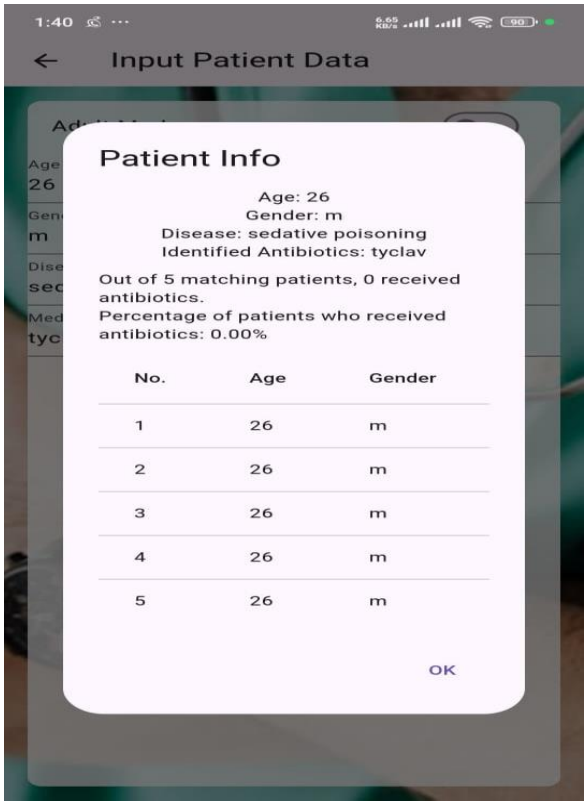


Figure 4.5.4 Result

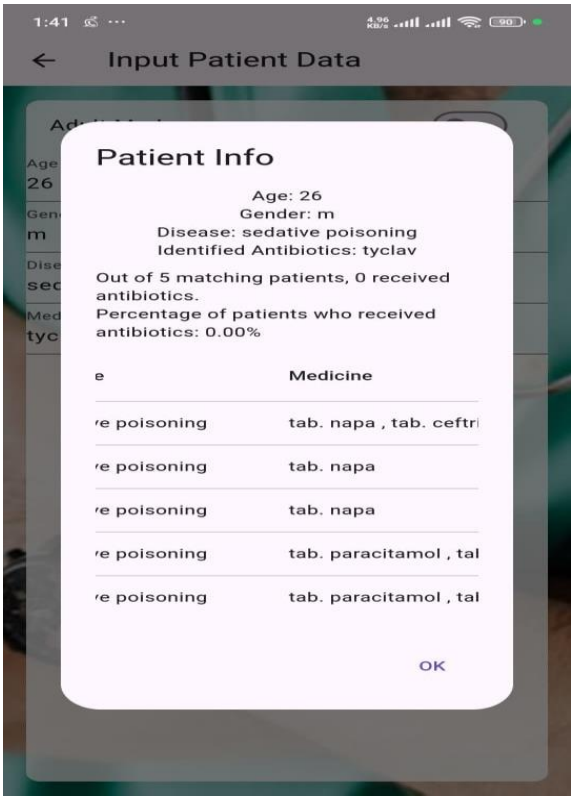


Figure 4.5.5 Result

4.6 Find which Antibiotics are mostly use in our database

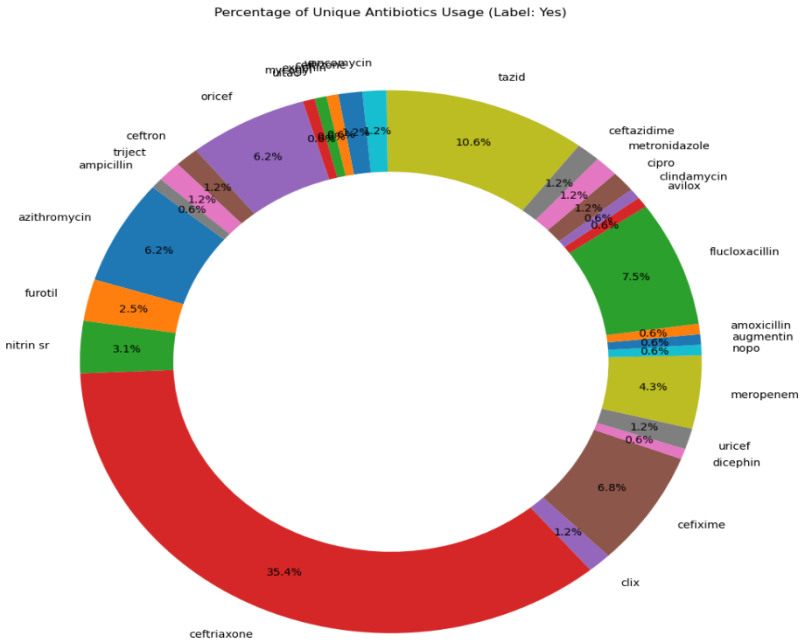


Figure 4.6.1 Find which Antibiotics are mostly use in our database

4.7 Assessment of Knowledge, attitude, practice and behavior: This Research Study was used a cross-sectional descriptive study designto assess the level of knowledge, attitude, practice and behavior regarding antibiotic use and resistance among general public Bangladesh.

4.7.1 The socio-demographic characteristics of the respondents

A total of 227 individuals participated in the study by completing the questionnaire from the selected location. In terms of gender distribution, the majority of respondents were male, accounting for 85.9%, while females represented 14.1%. The age range of the participants varied, with 17.2% aged 18-22 years, 47.1% aged 23-27 years, 18.9% aged 28-32 years, 4.0% aged 33-37 years, and 12.8% aged 38 years and above, yielding a mean age of 34.10 years (±5.430). Regarding marital status, 47.1% of respondents were unmarried, 51.5% were married, and 1.3% were divorced. Educational attainment among participants revealed that 1.3% were uneducated, 40.5% had completed primary education, 33.0% had secondary education, 16.3% had higher secondary education, 7.0% were graduates, and 1.8% held post-graduate degrees.

In terms of occupation, 3.1% were in government jobs, 64.8% were employed in non-government jobs, 5.3% were engaged in business, 24.2% were students, and 2.6% were retired. The monthly income of respondents was categorized as follows: 42.7% earned BDT 15,000 and under, 31.4% earned between BDT 15,001 and 25,000, 14.1% earned between BDT 25,001 and 35,000, 5.7% earned between BDT 35,001 and 45,000, and 6.2% earned BDT 45,000 and above. The religious affiliation of the respondents indicated that 83.7% identified as Muslim, 15.4% as Hindu, and 0.9% belonged to other religions. Geographically, respondents were distributed across various locations, with 24.2% from Dhanmondi, 8.4% from Panthapath, 25.6% from Farmgate, 35.2% from Sonargaon, and 6.6% from Munsiganj. These characteristics provide a comprehensive overview of the demographic profile of the study participants, essential for contextualizing the research findings.

Sociodemographic characteristics, total respondents (n=227).

Variable	Responses	N	N %
Gender	Male	195	85.9%
	Female	32	14.1%
	Others	0	0.0%
Age	18-22 years	39	17.2%
	23-27 years	107	47.1%
	28-32 years	43	18.9%
	33-37 years	9	4.0%
	38 above	29	12.8%
Marital	Unmarried	107	47.1%
	Married	117	51.5%
	Divorce	3	1.3%

Education	Uneducated	3	1.3%
	Primary	92	40.5%
	S.S.C	75	33.0%
	H.S.C	37	16.3%
	Graduation	16	7.0%
	M.sc	4	1.8%
Occupation	Government	7	3.1%
	Non-government	147	64.8%
	Business	12	5.3%
	Student	55	24.2%
	Retired	6	2.6%
Income	<=15000	97	42.7%
	15001-25000	71	31.3%
	25001-35000	32	14.1%
	35001-45000	13	5.7%
	>=45000	14	6.2%
Religion	Muslim	190	83.7%
	Hindu	35	15.4%
	others	2	0.9%
Area	Dhanmondi	55	24.2%
	Panthapath	19	8.4%
	Farmgate	58	25.6%
	Sonargaon	80	35.2%
	Munsiganj	15	6.6%

Table 4.7.1.1The socio-demographic characteristics of the respondents

4.7.2 Knowledge Towards Antibiotic Use

Figure 1 illustrates the respondents' knowledge regarding antibiotic use through their responses to various knowledge-related questions. The analysis revealed that 23.3% of respondents strongly agreed, while 26.9% disagreed, 2% remained neutral, 13.7% agreed, and 30.0% strongly agreed that antibiotics are a type of medicine. Furthermore, regarding the statement that antibiotics should be used only as per the advice of a registered physician, 36.6% strongly agreed, 12.8% disagreed, 4.4% were neutral, 14.5% agreed, and 31.4% strongly agreed. When asked whether antibiotics should be discontinued if a patient feels better, responses showed that 15.9% strongly agreed, 22.9% disagreed, 5.7% were neutral, 25.1% agreed, and 30.4% strongly agreed. Additionally, 29.1% strongly agreed, 22.0% disagreed, 6.2% were neutral,

16.3% agreed, and 26.4% strongly agreed that unnecessary use of antibiotics increases the risk of illness or disease. Regarding antibiotic resistance, 17.2% strongly agreed, 28.2% disagreed, 12.8% were neutral, 15.9% agreed, and 26.0% strongly agreed that antibiotic resistance occurs when bacteria lose their sensitivity to antibiotics. Conversely, 16.3% strongly agreed, 29.5% disagreed, 11.9% were neutral, 19.8% agreed, and 22.5% strongly agreed that antibiotic resistance is not a serious problem. Lastly, concerning the potential side effects of antibiotics, 15.9% strongly agreed, 26.4% disagreed, 10.6% were neutral, 29.5% agreed, and 17.6% strongly agreed that antibiotics often cause side effects such as diarrhea and other issues. These findings highlight varying levels of knowledge about antibiotic use among the respondents, indicating areas where further education may be necessary.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
k9	23.3%	26.9%	6.2%	13.7%	30.0%
k10	36.6%	12.8%	4.4%	14.5%	31.7%
k11	15.9%	22.9%	5.7%	25.1%	30.4%
k12	29.1%	22.0%	6.2%	16.3%	26.4%
k13	17.2%	28.2%	12.8%	15.9%	26.0%
k14	16.3%	29.5%	11.9%	19.8%	22.5%
k15	15.9%	26.4%	10.6%	29.5%	17.6%

Table 4.7.2.1 Knowledge Towards Antibiotic Use

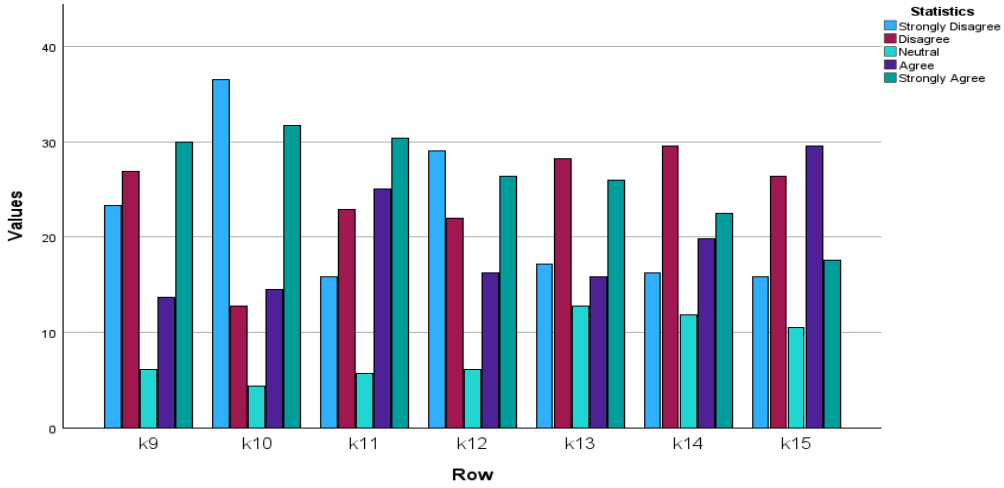


Figure 4.7.2.1 Knowledge Towards Antibiotic Use

k9. Antibiotic is a type of medicine.

k10. Antibiotic should be used as per the advice of a registered physician.

k11. If the patient feels better, antibiotic should be discontinued.

k12. Unnecessary used of antibiotic increase the risk of illness/disease.

k13. Antibiotics resistance is happening when a bacterium lost its sensitivity to an antibiotic.

k14. Antibiotics resistance is not a serious problem.

k15. Antibiotics often cause side effects such as diarrhea and others.

4.7.3 Distribution of Level of Knowledge Among the Participants

Table 4 presents the distribution of knowledge levels among participants regarding antibiotic use and resistance. The scoring system for knowledge was based on 34 indicators, with a maximum and minimum possible score ranging from 0 to 100. The results revealed that a significant proportion of participants exhibited varying levels of knowledge. Specifically, 20.3% of participants were classified as having very weak knowledge, while 22.9% were categorized as having weak knowledge. Furthermore, 18.1% demonstrated moderate knowledge, 18.9% were identified as having strong knowledge, and 19.8% were classified as possessing very strong knowledge. These findings indicate a diverse understanding of antibiotic use and resistance among the participants, highlighting the need for targeted educational interventions to improve overall knowledge levels in this area

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	very weak	46	20.3	20.3	20.3
	weak	52	22.9	22.9	43.2
	moderate	41	18.1	18.1	61.2
	strong	43	18.9	18.9	80.2
	very strong	45	19.8	19.8	100.0
	Total	227	100.0	100.0	

Table 4.7.3.1 Distribution of Level of Knowledge Among the Participants

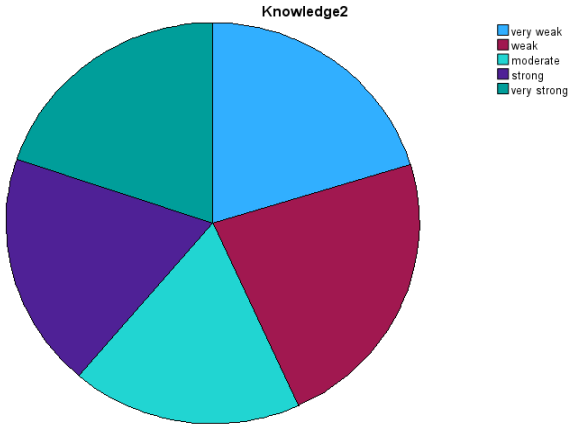


Figure 4.7.3.2 Distribution of Level of Knowledge Among the Participants

4.7.3.0 Association between knowledge of antibiotics use and demographic variable

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Education	uneducated	Count	1	0	2	0	0	3	106.897	<0.001
		% within Educat	33.30%	0.00%	66.70%	0.00%	0.00%	100.00%		
		% within Knowlv	2.20%	0.00%	4.90%	0.00%	0.00%	1.30%		
		% of Total	0.40%	0.00%	0.90%	0.00%	0.00%	1.30%		
	primary	Count	30	38	11	1	12	92		
		% within Educat	32.60%	41.30%	12.00%	1.10%	13.00%	100.00%		
		% within Knowlv	65.20%	73.10%	26.80%	2.30%	26.70%	40.50%		
		% of Total	13.20%	16.70%	4.80%	0.40%	5.30%	40.50%		
	ssc	Count	14	13	17	15	16	75		
		% within Educat	18.70%	17.30%	22.70%	20.00%	21.30%	100.00%		
		% within Knowlv	30.40%	25.00%	41.50%	34.90%	35.60%	33.00%		
		% of Total	6.20%	5.70%	7.50%	6.60%	7.00%	33.00%		
	hsc	Count	0	0	11	17	9	37		
		% within Educat	0.00%	0.00%	29.70%	45.90%	24.30%	100.00%		
		% within Knowlv	0.00%	0.00%	26.80%	39.50%	20.00%	16.30%		
		% of Total	0.00%	0.00%	4.80%	7.50%	4.00%	16.30%		
	graguation	Count	1	1	0	7	7	16		
		% within Educat	6.30%	6.30%	0.00%	43.80%	43.80%	100.00%		
		% within Knowlv	2.20%	1.90%	0.00%	16.30%	15.60%	7.00%		
		% of Total	0.40%	0.40%	0.00%	3.10%	3.10%	7.00%		
	msc	Count	0	0	0	3	1	4		
		% within Educat	0.00%	0.00%	0.00%	75.00%	25.00%	100.00%		
		% within Knowlv	0.00%	0.00%	0.00%	7.00%	2.20%	1.80%		
		% of Total	0.00%	0.00%	0.00%	1.30%	0.40%	1.80%		
Total		Count	46	52	41	43	45	227		
		% within Educat	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		

Table 4.7.3.2 Education of Participants in Knowledge

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Merital	Unmarried	Count	30	28	24	11	14	107	24.146	0.002
		% within Merital	28.00%	26.20%	22.40%	10.30%	13.10%	100.00%		
		% within Knowlv	65.20%	53.80%	58.50%	25.60%	31.10%	47.10%		
		% of Total	13.20%	12.30%	10.60%	4.80%	6.20%	47.10%		
	Married	Count	16	23	16	32	30	117		
		% within Merital	13.70%	19.70%	13.70%	27.40%	25.60%	100.00%		
		% within Knowlv	34.80%	44.20%	39.00%	74.40%	66.70%	51.50%		
		% of Total	7.00%	10.10%	7.00%	14.10%	13.20%	51.50%		
	Divorce	Count	0	1	1	0	1	3		
		% within Merital	0.00%	33.30%	33.30%	0.00%	33.30%	100.00%		
		% within Knowlv	0.00%	1.90%	2.40%	0.00%	2.20%	1.30%		
		% of Total	0.00%	0.40%	0.40%	0.00%	0.40%	1.30%		
Total		Count	46	52	41	43	45	227		
		% within Merital	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		

Table 4.7.3.3 Marital Status of Participants in Knowledge

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Occupation	gov	Count	2	4	1	0	0	7	40.651	<0.001
		% within Occupa	28.60%	57.10%	14.30%	0.00%	0.00%	100.00%		
		% within Knowlv	4.30%	7.70%	2.40%	0.00%	0.00%	3.10%		
		% of Total	0.90%	1.80%	0.40%	0.00%	0.00%	3.10%		
	non gov	Count	21	30	28	32	36	147		
		% within Occupa	14.30%	20.40%	19.00%	21.80%	24.50%	100.00%		
		% within Knowlv	45.70%	57.70%	68.30%	74.40%	80.00%	64.80%		
		% of Total	9.30%	13.20%	12.30%	14.10%	15.90%	64.80%		
	buisness	Count	2	1	2	2	5	12		
		% within Occupa	16.70%	8.30%	16.70%	16.70%	41.70%	100.00%		
		% within Knowlv	4.30%	1.90%	4.90%	4.70%	11.10%	5.30%		
		% of Total	0.90%	0.40%	0.90%	0.90%	2.20%	5.30%		
	student	Count	21	17	7	7	3	55		
		% within Occupa	38.20%	30.90%	12.70%	12.70%	5.50%	100.00%		
		% within Knowlv	45.70%	32.70%	17.10%	16.30%	6.70%	24.20%		
		% of Total	9.30%	7.50%	3.10%	3.10%	1.30%	24.20%		
	retired	Count	0	0	3	2	1	6		
		% within Occupa	0.00%	0.00%	50.00%	33.30%	16.70%	100.00%		
		% within Knowlv	0.00%	0.00%	7.30%	4.70%	2.20%	2.60%		
		% of Total	0.00%	0.00%	1.30%	0.90%	0.40%	2.60%		
Total		Count	46	52	41	43	45	227		
		% within Occupa	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		

Table 4.7.3.4 Occupation of Participants in Knowledge

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
religion	Muslim	Count	41	43	31	40	35	190	14.719	0.065
		% within religior	21.60%	22.60%	16.30%	21.10%	18.40%	100.00%		
		% within Knowlv	89.10%	82.70%	75.60%	93.00%	77.80%	83.70%		
		% of Total	18.10%	18.90%	13.70%	17.60%	15.40%	83.70%		
	Hindu	Count	5	9	8	3	10	35		
		% within religior	14.30%	25.70%	22.90%	8.60%	28.60%	100.00%		
		% within Knowlv	10.90%	17.30%	19.50%	7.00%	22.20%	15.40%		
		% of Total	2.20%	4.00%	3.50%	1.30%	4.40%	15.40%		
	others	Count	0	0	2	0	0	2		
		% within religior	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%		
		% within Knowlv	0.00%	0.00%	4.90%	0.00%	0.00%	0.90%		
		% of Total	0.00%	0.00%	0.90%	0.00%	0.00%	0.90%		
Total		Count	46	52	41	43	45	227		
		% within religior	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		

Table 4.7.3.5 Religion of Participants in Knowledge

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Gender	Male	Count	39	47	34	37	38	195	1.29	0.863
		% within Gender	20.00%	24.10%	17.40%	19.00%	19.50%	100.00%		
		% within Knowle	84.80%	90.40%	82.90%	86.00%	84.40%	85.90%		
		% of Total	17.20%	20.70%	15.00%	16.30%	16.70%	85.90%		
	Female	Count	7	5	7	6	7	32		
		% within Gender	21.90%	15.60%	21.90%	18.80%	21.90%	100.00%		
		% within Knowle	15.20%	9.60%	17.10%	14.00%	15.60%	14.10%		
		% of Total	3.10%	2.20%	3.10%	2.60%	3.10%	14.10%		
Total		Count	46	52	41	43	45	227		
		% within Gender	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		

Table 4.7.3.6 Gender of Participants in Knowledge

			Knowledge					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
area	Dhanmondi	% within area	32.70%	45.50%	21.80%	0.00%	0.00%	100.00%	149.651	<0.001
		% within Knowlv	39.10%	48.10%	29.30%	0.00%	0.00%	24.20%		
		% of Total	7.90%	11.00%	5.30%	0.00%	0.00%	24.20%		
	Panthapath	Count	4	2	4	6	3	19		
		% within area	21.10%	10.50%	21.10%	31.60%	15.80%	100.00%		
		% within Knowlv	8.70%	3.80%	9.80%	14.00%	6.70%	8.40%		
		% of Total	1.80%	0.90%	1.80%	2.60%	1.30%	8.40%		
	Farmgate	Count	22	23	7	0	6	58		
		% within area	37.90%	39.70%	12.10%	0.00%	10.30%	100.00%		
		% within Knowlv	47.80%	44.20%	17.10%	0.00%	13.30%	25.60%		
		% of Total	9.70%	10.10%	3.10%	0.00%	2.60%	25.60%		
	Sonargaon	Count	0	0	16	30	34	80		
		% within area	0.00%	0.00%	20.00%	37.50%	42.50%	100.00%		
		% within Knowlv	0.00%	0.00%	39.00%	69.80%	75.60%	35.20%		
		% of Total	0.00%	0.00%	7.00%	13.20%	15.00%	35.20%		
	Munsiganj	Count	2	2	2	7	2	15		
		% within area	13.30%	13.30%	13.30%	46.70%	13.30%	100.00%		
		% within Knowlv	4.30%	3.80%	4.90%	16.30%	4.40%	6.60%		
		% of Total	0.90%	0.90%	0.90%	3.10%	0.90%	6.60%		
Total		Count	46	52	41	43	45	227		
		% within area	20.30%	22.90%	18.10%	18.90%	19.80%	100.00%		
		% within Knowlv	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		

Table 4.7.3.7 Area of Participants in Knowledge

4.7.4 Attitudes Towards Antibiotic Use

The overall score reflecting respondents' attitudes towards antibiotic use was 76.8%. Figure 3 illustrates the various attitudes of participants regarding antibiotics. Notably, 22.9% of respondents strongly disagreed, 27.3% disagreed, 6.2% remained neutral, 14.1% agreed, and 29.5% strongly agreed with the statement, "The price of antibiotics is too high, so they can't afford it." In terms of adherence to treatment, 36.6% strongly disagreed, 14.5% disagreed, 4.8% were neutral, 14.1% agreed, and 30.0% strongly agreed that they always complete the prescribed course of antibiotics. When asked whether they believed antibiotics could cure their illness faster, 29.5% strongly disagreed, 24.7% disagreed, 5.7% were neutral, 23.3% agreed, and 16.7% strongly agreed. Additionally, regarding seeking medical advice, 30.8% strongly disagreed, 22.0% disagreed, 7.0% were neutral, 15.4% agreed, and 24.7% strongly agreed that if they fell ill, they would ask for symptoms. Awareness of antibiotics was also assessed, with 17.2% strongly disagreeing, 29.5% disagreeing, 12.8% neutral, 15.0% agreeing, and 25.6% strongly agreeing that they know which medicines are antibiotics when taking medication. Furthermore, 20.7% strongly disagreed, 19.8% disagreed, 11.5% were neutral, 29.5% agreed, and 18.5% strongly agreed that they normally check the expiry date of antibiotics before use. Concerning emergency preparedness, 17.6% strongly disagreed, 27.3% disagreed, 9.7% were neutral, 27.8% agreed, and 17.6% strongly agreed that they always keep antibiotic stocks at home. Lastly, regarding sharing medications, 24.2% strongly disagreed, 27.8% disagreed, 6.2% were neutral, 14.1% agreed, and 27.8% strongly agreed that if a family member was sick, they would give them their antibiotics. These findings underscore the varied attitudes towards antibiotic use among respondents, indicating areas where further education and awareness are needed.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
A16	22.9%	27.3%	6.2%	14.1%	29.5%
A17	36.6%	14.5%	4.8%	14.1%	30.0%
A18	29.5%	24.7%	5.7%	23.3%	16.7%
A19	30.8%	22.0%	7.0%	15.4%	24.7%
A20	17.2%	29.5%	12.8%	15.0%	25.6%
A21	20.7%	19.8%	11.5%	29.5%	18.5%
A22	17.6%	27.3%	9.7%	27.8%	17.6%
A23	24.2%	27.8%	6.2%	14.1%	27.8%

Table 4.7.4 .1 Attitudes Towards Antibiotic Use

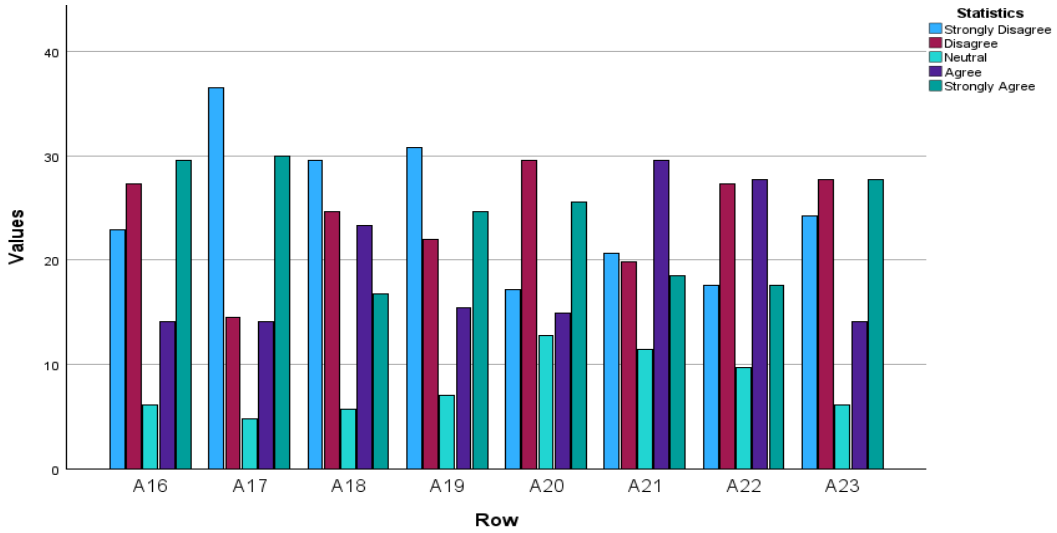


Figure 4.7.4.1 Attitudes Towards Antibiotic Use

A16. The Price of Antibiotic is too high so I can't afford it.

A17. I always complete the course of treatment with antibiotics.

A18. I believe antibiotics cure my illness faster.

A19. If the fall my illness, I ask for a symptom.

A20. I know which medicines are the antibiotics when I take medicine.

A21. I'll normally look at the expire date of antibiotics before taking it.

A22. I always keep antibiotic stocks at home in case of emergency.

23. If my family member is sick, I will give my antibiotics to them.

4.7.5 Distribution of Attitude Levels Among Participants

Table presents the distribution of attitudes among participants based on 34 indicators related to antibiotic use and resistance, with scores ranging from 0 to 100. The results indicate that a significant portion of participants exhibited varying levels of attitudes towards antibiotics. Specifically, 24.2% were classified as having very weak attitudes, while 16.3% exhibited weak attitudes. Additionally, 18.9% were categorized as having moderate attitudes, and 20.3% demonstrated strong attitudes. Finally, another 20.3% of participants were classified as having very strong attitudes. These findings reveal a diverse range of attitudes towards antibiotics among the respondents, suggesting the need for targeted educational interventions to improve understanding and responsible use.

Attitude

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	very weak	55	24.2	24.2	24.2
	weak	37	16.3	16.3	40.5
	moderate	43	18.9	18.9	59.5
	strong	46	20.3	20.3	79.7
	very strong	46	20.3	20.3	100.0
	Total	227	100.0	100.0	

Table 4.7.5.1 Distribution of Attitude Levels Among Participants

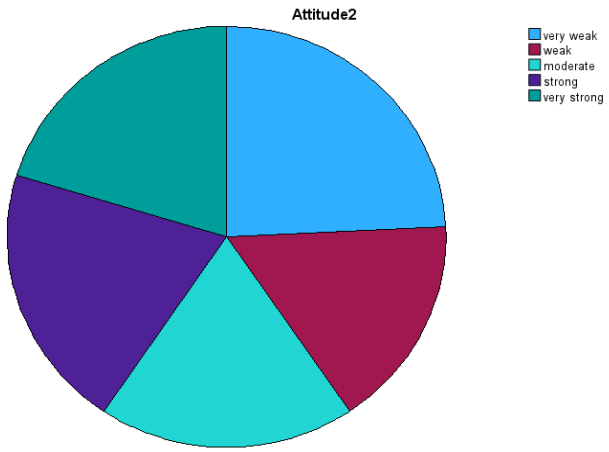


Figure 4.7.5.1 Distribution of Attitude Levels Among Participants

Association between Attitude of antibiotics use and demographic variables

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Gender	Male	Count	50	29	40	54	22	195	7.41%	11.60%
		% within Gender	25.60%	14.90%	20.50%	27.70%	11.30%	100.00%		
		% within Attitude11	90.90%	78.40%	85.10%	81.80%	100.00%	85.90%		
		% of Total	22.00%	12.80%	17.60%	23.80%	9.70%	85.90%		
	Female	Count	5	8	7	12	0	32		
		% within Gender	15.60%	25.00%	21.90%	37.50%	0.00%	100.00%		
		% within Attitude11	9.10%	21.60%	14.90%	18.20%	0.00%	14.10%		
		% of Total	2.20%	3.50%	3.10%	5.30%	0.00%	14.10%		
Total		Count	55	37	47	66	22	227		
		% within Gender	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		

Table 4.7.5.2 Gender of Participants in Attitude

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Merital	Unmarried	Count	34	17	24	28	4	107	19.031	0.016
		% within Merital	31.80%	15.90%	22.40%	26.20%	3.70%	100.00%		
		% within Attitude11	61.80%	45.90%	51.10%	42.40%	18.20%	47.10%		
		% of Total	15.00%	7.50%	10.60%	12.30%	1.80%	47.10%		
	Married	Count	20	20	21	38	18	117		
		% within Merital	17.10%	17.10%	17.90%	32.50%	15.40%	100.00%		
		% within Attitude11	36.40%	54.10%	44.70%	57.60%	81.80%	51.50%		
		% of Total	8.80%	8.80%	9.30%	16.70%	7.90%	51.50%		
	Divorce	Count	1	0	2	0	0	3		
		% within Merital	33.30%	0.00%	66.70%	0.00%	0.00%	100.00%		
		% within Attitude11	1.80%	0.00%	4.30%	0.00%	0.00%	1.30%		
		% of Total	0.40%	0.00%	0.90%	0.00%	0.00%	1.30%		
Total		Count	55	37	47	66	22	227		
		% within Merital	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		

Table 4.7.5.3 Marital Status of Participants in Attitude

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Occupation	gov	Count	2	4	0	1	0	7	40.84%	<0.001
		% within Occupation	28.60%	57.10%	0.00%	14.30%	0.00%	100.00%		
		% within Attitude11	3.60%	10.80%	0.00%	1.50%	0.00%	3.10%		
		% of Total	0.90%	1.80%	0.00%	0.40%	0.00%	3.10%		
	non gov	Count	28	20	29	48	22	147		
		% within Occupation	19.00%	13.60%	19.70%	32.70%	15.00%	100.00%		
		% within Attitude11	50.90%	54.10%	61.70%	72.70%	100.00%	64.80%		
		% of Total	12.30%	8.80%	12.80%	21.10%	9.70%	64.80%		
	buisness	Count	3	2	5	2	0	12		
		% within Occupation	25.00%	16.70%	41.70%	16.70%	0.00%	100.00%		
		% within Attitude11	5.50%	5.40%	10.60%	3.00%	0.00%	5.30%		
		% of Total	1.30%	0.90%	2.20%	0.90%	0.00%	5.30%		
	student	Count	22	11	11	11	0	55		
		% within Occupation	40.00%	20.00%	20.00%	20.00%	0.00%	100.00%		
		% within Attitude11	40.00%	29.70%	23.40%	16.70%	0.00%	24.20%		
		% of Total	9.70%	4.80%	4.80%	4.80%	0.00%	24.20%		
	retired	Count	0	0	2	4	0	6		
		% within Occupation	0.00%	0.00%	33.30%	66.70%	0.00%	100.00%		
		% within Attitude11	0.00%	0.00%	4.30%	6.10%	0.00%	2.60%		
		% of Total	0.00%	0.00%	0.90%	1.80%	0.00%	2.60%		
Total		Count	55	37	47	66	22	227		
		% within Occupation	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		

Table 4.7.5.4 Occupation of Participants in Attitude

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
Education	uneducated	Count	1	0	2	0	0	3	85.58%	<0.001
		% within Education	33.30%	0.00%	66.70%	0.00%	0.00%	100.00%		
		% within Attitude11	1.80%	0.00%	4.30%	0.00%	0.00%	1.30%		
		% of Total	0.40%	0.00%	0.90%	0.00%	0.00%	1.30%		
	primary	Count	35	24	21	9	3	92		
		% within Education	38.00%	26.10%	22.80%	9.80%	3.30%	100.00%		
		% within Attitude11	63.60%	64.90%	44.70%	13.60%	13.60%	40.50%		
		% of Total	15.40%	10.60%	9.30%	4.00%	1.30%	40.50%		
	ssc	Count	19	11	13	21	11	75		
		% within Education	25.30%	14.70%	17.30%	28.00%	14.70%	100.00%		
		% within Attitude11	34.50%	29.70%	27.70%	31.80%	50.00%	33.00%		
		% of Total	8.40%	4.80%	5.70%	9.30%	4.80%	33.00%		
	hsc	Count	0	1	8	21	7	37		
		% within Education	0.00%	2.70%	21.60%	56.80%	18.90%	100.00%		
		% within Attitude11	0.00%	2.70%	17.00%	31.80%	31.80%	16.30%		
		% of Total	0.00%	0.40%	3.50%	9.30%	3.10%	16.30%		
	graguation	Count	0	1	3	11	1	16		
		% within Education	0.00%	6.30%	18.80%	68.80%	6.30%	100.00%		
		% within Attitude11	0.00%	2.70%	6.40%	16.70%	4.50%	7.00%		
		% of Total	0.00%	0.40%	1.30%	4.80%	0.40%	7.00%		
	msc	Count	0	0	0	4	0	4		
		% within Education	0.00%	0.00%	0.00%	100.00%	0.00%	100.00%		
		% within Attitude11	0.00%	0.00%	0.00%	6.10%	0.00%	1.80%		
		% of Total	0.00%	0.00%	0.00%	1.80%	0.00%	1.80%		
Total		Count	55	37	47	66	22	227		
		% within Education	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		

Table 4.7.5.5 Education of Participants in Attitude

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
religion	Muslim	Count	47	30	34	58	21	190	13.35%	10.00%
		% within religion	24.70%	15.80%	17.90%	30.50%	11.10%	100.00%		
		% within Attitude11	85.50%	81.10%	72.30%	87.90%	95.50%	83.70%		
		% of Total	20.70%	13.20%	15.00%	25.60%	9.30%	83.70%		
	Hindu	Count	8	7	11	8	1	35		
		% within religion	22.90%	20.00%	31.40%	22.90%	2.90%	100.00%		
		% within Attitude11	14.50%	18.90%	23.40%	12.10%	4.50%	15.40%		
		% of Total	3.50%	3.10%	4.80%	3.50%	0.40%	15.40%		
	others	Count	0	0	2	0	0	2		
		% within religion	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%		
		% within Attitude11	0.00%	0.00%	4.30%	0.00%	0.00%	0.90%		
		% of Total	0.00%	0.00%	0.90%	0.00%	0.00%	0.90%		
Total		Count	55	37	47	66	22	227		
		% within religion	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		

Table 4.7.5.6 Religion of Participants in Attitude

			Attitude					Total	X2	p-value
			very weak	weak	moderate	strong	very strong			
area	Dhanmondi	Count	25	16	12	2	0	55	154.60%	<0.001
		% within area	45.50%	29.10%	21.80%	3.60%	0.00%	100.00%		
		% within Attitude11	45.50%	43.20%	25.50%	3.00%	0.00%	24.20%		
		% of Total	11.00%	7.00%	5.30%	0.90%	0.00%	24.20%		
	Panthapath	Count	3	2	4	10	0	19		
		% within area	15.80%	10.50%	21.10%	52.60%	0.00%	100.00%		
		% within Attitude11	5.50%	5.40%	8.50%	15.20%	0.00%	8.40%		
		% of Total	1.30%	0.90%	1.80%	4.40%	0.00%	8.40%		
	Farmgate	Count	23	16	18	1	0	58		
		% within area	39.70%	27.60%	31.00%	1.70%	0.00%	100.00%		
		% within Attitude11	41.80%	43.20%	38.30%	1.50%	0.00%	25.60%		
		% of Total	10.10%	7.00%	7.90%	0.40%	0.00%	25.60%		
	Sonargaon	Count	1	2	11	44	22	80		
		% within area	1.30%	2.50%	13.80%	55.00%	27.50%	100.00%		
		% within Attitude11	1.80%	5.40%	23.40%	66.70%	100.00%	35.20%		
		% of Total	0.40%	0.90%	4.80%	19.40%	9.70%	35.20%		
	Munsiganj	Count	3	1	2	9	0	15		
		% within area	20.00%	6.70%	13.30%	60.00%	0.00%	100.00%		
		% within Attitude11	5.50%	2.70%	4.30%	13.60%	0.00%	6.60%		
		% of Total	1.30%	0.40%	0.90%	4.00%	0.00%	6.60%		
Total		Count	55	37	47	66	22	227		
		% within area	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		
		% within Attitude11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	24.20%	16.30%	20.70%	29.10%	9.70%	100.00%		

Table 4.7.5.7 Area of Participants in Attitude

4.7.6 Practices Towards Antibiotic Use

The overall score related to respondents' practices regarding antibiotic use was 85.6%. Figure 4 illustrates the participants' practices towards antibiotics. A notable 22.9% of respondents strongly disagreed, and 17.6% disagreed with participating in antibiotic awareness initiatives aimed at promoting optimal use. In contrast, 36.6% remained neutral, while only 13.7% agreed, and 8.4% strongly agreed to participate in such initiatives. Regarding adherence to antibiotic treatment, 11.5% strongly disagreed, 30.8% disagreed, 19.4% remained neutral, 17.2% agreed, and 21.1% strongly agreed that they complete the full course of antibiotics. When it comes to recognizing the need for antibiotics, 23.3% strongly disagreed, and 27.8% disagreed, while 6.2% remained neutral; 14.5% agreed, and 28.2% strongly agreed that they typically know when antibiotics are necessary. Additionally, 35.7% strongly disagreed, and 13.2% disagreed with having taken measures to prevent antibiotic resistance, while 30.4% strongly agreed they contribute to the development of resistance. Furthermore, 18.9% strongly disagreed, and 27.3% disagreed that antibiotics are effective for treating viral infections, with 29.5% strongly agreeing to the contrary. Lastly, regarding participation in antibiotic awareness, 22.9% strongly disagreed, 27.8% disagreed, and 12.8% remained neutral, while 16.7% agreed and 23.8% strongly agreed. In the context of using antibiotics for coughs or sore throats, 18.1% strongly disagreed, 26.9% disagreed, and 9.7% remained neutral, with 29.1% agreeing and 16.3% strongly agreeing. These results indicate a mix of awareness and practices among respondents, highlighting areas for improvement in antibiotic stewardship.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
P24	17.6%	36.6%	13.7%	23.8%	8.4%
P25	11.5%	30.8%	19.4%	17.2%	21.1%
P26	23.3%	27.8%	6.2%	14.5%	28.2%
P27	35.7%	13.2%	5.3%	15.4%	30.4%
P28	30.0%	22.0%	7.0%	15.4%	25.6%
P29	18.9%	27.8%	12.8%	16.7%	23.8%
P30	18.1%	26.9%	9.7%	29.1%	16.3%

Table 4.7.6.1 Practices Towards Antibiotic Use

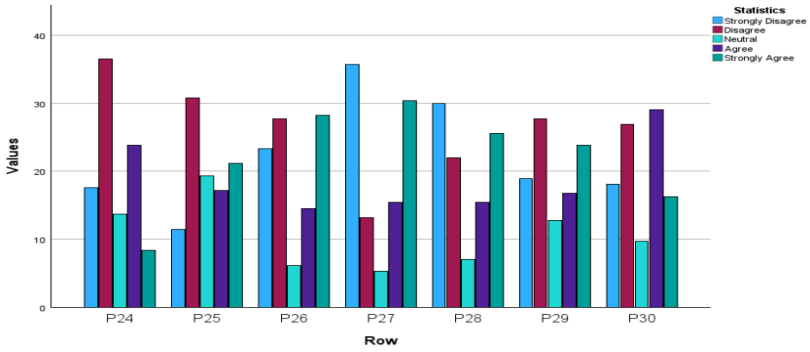


Figure 4.7.6.1 Practices Towards Antibiotic Use

P24. I participate in antibiotic awareness to promote the optimal use of antibiotics.

P25. I finish the full course of antibiotic treatment.

P26. I usually know when I need antibiotic.

P27. I have taken measures to prevent resistance.

P28. When I take antibiotics, I contribute to the development of antibiotic resistance.

P29. Antibiotics are effective in the treatment of viral infections.

P30. Do you prefer take to antibiotics when you have cough or sore throat?

4.7.7 Distribution of Level of Practice Among Participants

Table 4 presents the distribution of practice levels among participants, based on 34 indicators related to antibiotic use and resistance, with a scoring range of 0 to 100. The findings reveal that a significant proportion of participants, 20.3%, were classified as having very weak practices, while 19.4% exhibited weak practices. A notable 20.3% of participants demonstrated moderate practices, and 24.2% were classified as having strong practices. Lastly, 15.9% of participants were categorized as having very strong practices. These results highlight a diverse range of practices among the respondents, indicating areas that may require targeted educational interventions to enhance antibiotic use and resistance awareness.

Practice

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	very weak	46	20.3	20.3	20.3
	weak	44	19.4	19.4	39.6
	moderate	46	20.3	20.3	59.9
	strong	55	24.2	24.2	84.1
	very strong	36	15.9	15.9	100.0
	Total	227	100.0	100.0	

Table 4.7.7.1 Distribution of Level of Practice Among Participants

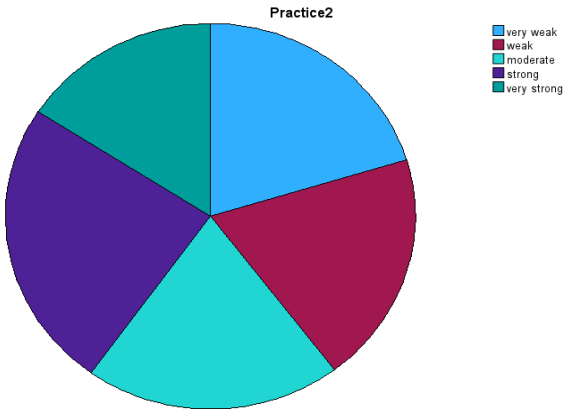


Figure 4.7.7.1 Distribution of Level of Practice Among Participants

Association between Practice of antibiotics use and demographic variables

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
Gender	Male	Count	40	39	36	49	31	195	2.995	0.559
		% within Gender	20.50%	20.00%	18.50%	25.10%	15.90%	100.00%		
		% within Practice2	87.00%	88.60%	78.30%	89.10%	86.10%	85.90%		
		% of Total	17.60%	17.20%	15.90%	21.60%	13.70%	85.90%		
	Female	Count	6	5	10	6	5	32		
		% within Gender	18.80%	15.60%	31.30%	18.80%	15.60%	100.00%		
		% within Practice2	13.00%	11.40%	21.70%	10.90%	13.90%	14.10%		
		% of Total	2.60%	2.20%	4.40%	2.60%	2.20%	14.10%		
Total		Count	46	44	46	55	36	227		
		% within Gender	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		

Table 4.7.7.2 Gender of Participants in Practice

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
Merital	Unmarried	Count	27	23	25	20	12	107	15.512	0.05
		% within Merital	25.20%	21.50%	23.40%	18.70%	11.20%	100.00%		
		% within Practice2	58.70%	52.30%	54.30%	36.40%	33.30%	47.10%		
		% of Total	11.90%	10.10%	11.00%	8.80%	5.30%	47.10%		
	Married	Count	19	20	19	35	24	117		
		% within Merital	16.20%	17.10%	16.20%	29.90%	20.50%	100.00%		
		% within Practice2	41.30%	45.50%	41.30%	63.60%	66.70%	51.50%		
		% of Total	8.40%	8.80%	8.40%	15.40%	10.60%	51.50%		
	Divorce	Count	0	1	2	0	0	3		
		% within Merital	0.00%	33.30%	66.70%	0.00%	0.00%	100.00%		
		% within Practice2	0.00%	2.30%	4.30%	0.00%	0.00%	1.30%		
		% of Total	0.00%	0.40%	0.90%	0.00%	0.00%	1.30%		
Total		Count	46	44	46	55	36	227		
		% within Merital	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		

Table 4.7.7.3 Material of Participants in Practice

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
Education	uneducated	Count	0	1	2	0	0	3	96.031	<0.001
		% within Education	0.00%	33.30%	66.70%	0.00%	0.00%	100.00%		
		% within Practice2	0.00%	2.30%	4.30%	0.00%	0.00%	1.30%		
		% of Total	0.00%	0.40%	0.90%	0.00%	0.00%	1.30%		
	primary	Count	31	32	18	7	4	92		
		% within Education	33.70%	34.80%	19.60%	7.60%	4.30%	100.00%		
		% within Practice2	67.40%	72.70%	39.10%	12.70%	11.10%	40.50%		
		% of Total	13.70%	14.10%	7.90%	3.10%	1.80%	40.50%		
	ssc	Count	14	10	18	22	11	75		
		% within Education	18.70%	13.30%	24.00%	29.30%	14.70%	100.00%		
		% within Practice2	30.40%	22.70%	39.10%	40.00%	30.60%	33.00%		
		% of Total	6.20%	4.40%	7.90%	9.70%	4.80%	33.00%		
	hsc	Count	0	0	7	18	12	37		
		% within Education	0.00%	0.00%	18.90%	48.60%	32.40%	100.00%		
		% within Practice2	0.00%	0.00%	15.20%	32.70%	33.30%	16.30%		
		% of Total	0.00%	0.00%	3.10%	7.90%	5.30%	16.30%		
	graguation	Count	1	1	1	6	7	16		
		% within Education	6.30%	6.30%	6.30%	37.50%	43.80%	100.00%		
		% within Practice2	2.20%	2.30%	2.20%	10.90%	19.40%	7.00%		
		% of Total	0.40%	0.40%	0.40%	2.60%	3.10%	7.00%		
	msc	Count	0	0	0	2	2	4		
		% within Education	0.00%	0.00%	0.00%	50.00%	50.00%	100.00%		
		% within Practice2	0.00%	0.00%	0.00%	3.60%	5.60%	1.80%		
		% of Total	0.00%	0.00%	0.00%	0.90%	0.90%	1.80%		
Total		Count	46	44	46	55	36	227		
		% within Education	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		

Table 4.7.7.4 Education of Participants in Practice

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
Occupation	gov	Count	4	1	2	0	0	7	40.295	<0.001
		% within Occupation	57.10%	14.30%	28.60%	0.00%	0.00%	100.00%		
		% within Practice2	8.70%	2.30%	4.30%	0.00%	0.00%	3.10%		
		% of Total	1.80%	0.40%	0.90%	0.00%	0.00%	3.10%		
	non gov	Count	23	20	30	47	27	147		
		% within Occupation	15.60%	13.60%	20.40%	32.00%	18.40%	100.00%		
		% within Practice2	50.00%	45.50%	65.20%	85.50%	75.00%	64.80%		
		% of Total	10.10%	8.80%	13.20%	20.70%	11.90%	64.80%		
	buisness	Count	3	3	3	1	2	12		
		% within Occupation	25.00%	25.00%	25.00%	8.30%	16.70%	100.00%		
		% within Practice2	6.50%	6.80%	6.50%	1.80%	5.60%	5.30%		
		% of Total	1.30%	1.30%	1.30%	0.40%	0.90%	5.30%		
	student	Count	16	20	8	5	6	55		
		% within Occupation	29.10%	36.40%	14.50%	9.10%	10.90%	100.00%		
		% within Practice2	34.80%	45.50%	17.40%	9.10%	16.70%	24.20%		
		% of Total	7.00%	8.80%	3.50%	2.20%	2.60%	24.20%		
	retired	Count	0	0	3	2	1	6		
		% within Occupation	0.00%	0.00%	50.00%	33.30%	16.70%	100.00%		
		% within Practice2	0.00%	0.00%	6.50%	3.60%	2.80%	2.60%		
		% of Total	0.00%	0.00%	1.30%	0.90%	0.40%	2.60%		
Total		Count	46	44	46	55	36	227		
		% within Occupation	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		

Table 4.7.7.5 Occupation of Participants in Practice

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
religion	Muslim	Count	38	37	33	50	32	190	13.258	0.103
		% within religion	20.00%	19.50%	17.40%	26.30%	16.80%	100.00%		
		% within Practice2	82.60%	84.10%	71.70%	90.90%	88.90%	83.70%		
		% of Total	16.70%	16.30%	14.50%	22.00%	14.10%	83.70%		
	Hindu	Count	8	7	11	5	4	35		
		% within religion	22.90%	20.00%	31.40%	14.30%	11.40%	100.00%		
		% within Practice2	17.40%	15.90%	23.90%	9.10%	11.10%	15.40%		
		% of Total	3.50%	3.10%	4.80%	2.20%	1.80%	15.40%		
	others	Count	0	0	2	0	0	2		
		% within religion	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%		
		% within Practice2	0.00%	0.00%	4.30%	0.00%	0.00%	0.90%		
		% of Total	0.00%	0.00%	0.90%	0.00%	0.00%	0.90%		
Total		Count	46	44	46	55	36	227		
		% within religion	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		

Table 4.7.7.6 Religion of Participants in Practice

			Practice					Total	x2	P Value
			very weak	weak	moderate	strong	very strong			
area	Dhanmondi	Count	23	19	13	0	0	55	172.362	<0.001
		% within area	41.80%	34.50%	23.60%	0.00%	0.00%	100.00%		
		% within Practice2	50.00%	43.20%	28.30%	0.00%	0.00%	24.20%		
		% of Total	10.10%	8.40%	5.70%	0.00%	0.00%	24.20%		
	Panthapath	Count	1	2	5	6	5	19		
		% within area	5.30%	10.50%	26.30%	31.60%	26.30%	100.00%		
		% within Practice2	2.20%	4.50%	10.90%	10.90%	13.90%	8.40%		
		% of Total	0.40%	0.90%	2.20%	2.60%	2.20%	8.40%		
	Farmgate	Count	19	22	17	0	0	58		
		% within area	32.80%	37.90%	29.30%	0.00%	0.00%	100.00%		
		% within Practice2	41.30%	50.00%	37.00%	0.00%	0.00%	25.60%		
		% of Total	8.40%	9.70%	7.50%	0.00%	0.00%	25.60%		
	Sonargaon	Count	0	0	9	44	27	80		
		% within area	0.00%	0.00%	11.30%	55.00%	33.80%	100.00%		
		% within Practice2	0.00%	0.00%	19.60%	80.00%	75.00%	35.20%		
		% of Total	0.00%	0.00%	4.00%	19.40%	11.90%	35.20%		
	Munsiganj	Count	3	1	2	5	4	15		
		% within area	20.00%	6.70%	13.30%	33.30%	26.70%	100.00%		
		% within Practice2	6.50%	2.30%	4.30%	9.10%	11.10%	6.60%		
		% of Total	1.30%	0.40%	0.90%	2.20%	1.80%	6.60%		
Total		Count	46	44	46	55	36	227		
		% within area	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		
		% within Practice2	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	19.40%	20.30%	24.20%	15.90%	100.00%		

Table 4.7.7.7 Area of Participants in Practice

4.7.8 Behavior towards antibiotics use:

The overall respondents' score in relation to practice was 85.6%.

Figure 4 shows the participants' practice towards antibiotics use. Of all the respondents, 31.7% strongly disagree, 23.8% disagree, 5.7% neutral, 22.9% agree, and 15.9% strongly agree that antibiotic remaining can be used again far similar symptoms without a doctor instruction. Of all the respondents, 29.1% strongly disagree, 20.7% disagree, 6.2% neutral, 17.2% agree, and 26.9% strongly agree that taking low dose of antibiotics is better that not taking any dose. Of all the respondents, 18.9% strongly disagree, 27.8% disagree, 12.3% neutral, 16.3% agree, and 24.7% strongly agree that they take the antibiotic directly from the pharmacists without a prescription from doctor. Of all the respondents, 17.2% strongly disagree, 26.9% disagree, 9.7% neutral, 28.6% agree, and 17.6% strongly agree that the symptoms do not improve after taking antibiotic stop taking it by self. Of all the respondents, 24.2% strongly disagree, 26.4% disagree, 7.0% neutral, 14.1% agree, and 28.2% strongly agree that would they take antibiotics before meals? Of all the respondents, 36.1% strongly disagree, 12.8% disagree, 4.4% neutral, 16.3% agree, and 30.4% strongly agree that do you keep antibiotic syrup in the refrigerator? Of all the respondents, 31.3% strongly disagree, 20.3% disagree, 7.0% neutral, 15.9% agree, and 25.6% strongly agree that B37. Do you store antibiotics in a place with exposure to the sun? Of all the respondents, 19.4% strongly disagree, 27.3% disagree, 12.8% neutral, 15.9% agree, and 24.7% strongly agree that B38. Return for more antibiotics after finishing the prescription.

	B31	B32	B33	B34	B35	B36	B37	B38
Strongly Disagree	31.7%	29.1%	18.9%	17.2%	24.2%	36.1%	31.3%	19.4%
Disagree	23.8%	20.7%	27.8%	26.9%	26.4%	12.8%	20.3%	27.3%
Neutral	5.7%	6.2%	12.3%	9.7%	7.0%	4.4%	7.0%	12.8%
Agree	22.9%	17.2%	16.3%	28.6%	14.1%	16.3%	15.9%	15.9%
Strongly Agree	15.9%	26.9%	24.7%	17.6%	28.2%	30.4%	25.6%	24.7%

Table 4.7.8.1 Behavior towards antibiotics use

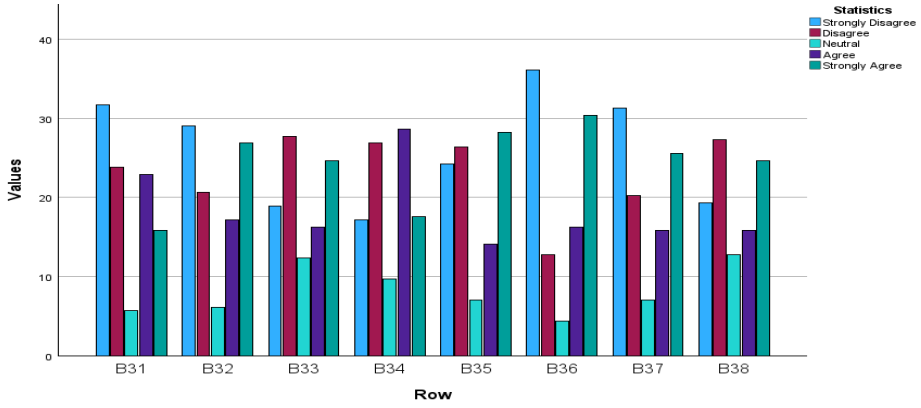


Figure 4.7.8.1 Behavior towards antibiotics use

B31. Antibiotic remaining can be used again far similar symptoms without a doctor instruction.

B32. Taking low dose of antibiotics is better that not taking any dose.

B33. I take the antibiotic directly from the pharmacists without a prescription from doctor.

B34. If the symptoms do not improve after taking antibiotic stop taking it by self.

B35. Would you take antibiotics before meals?

B36. Do you keep antibiotic syrup in the refrigerator**?**

B37. Do you store antibiotics in a place with exposure to the sun?

B38. Return for more antibiotics after finishing the prescription.

4.7.9 Distribution of level of Behavior among the participants

Table 4 showed the level of practice of participants. On the based on 34 indicators of antibiotic use and resistance as considered in this study were (0-100). Most of the participants (20.3%) were classified as having very weak knowledge, (22.0%) weak knowledge, (17.6 %) moderate, (19.8 %) strong and (20.3%) very strong participants were classified as having average attitude.

Behavior

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	very weak	46	20.3	20.3	20.3
	weak	50	22.0	22.0	42.3
	moderate	40	17.6	17.6	59.9
	strong	45	19.8	19.8	79.7
	very strong	46	20.3	20.3	100.0
	Total	227	100.0	100.0	

Table 4.7.9.1 Distribution of level of Behavior among the participants

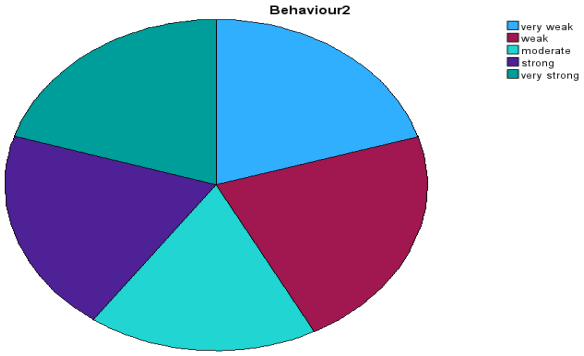


Figure 4.7.9.1 Distribution of level of Behavior among the participants

Association between Behavior of antibiotics use and demographic variables

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
Occupation	gov	Count	1	3	3	0	0	7	49.024	<0.001
		% within Occupation	14.30%	42.90%	42.90%	0.00%	0.00%	100.00%		
		% within Behaviour11	2.20%	6.00%	7.50%	0.00%	0.00%	3.10%		
		% of Total	0.40%	1.30%	1.30%	0.00%	0.00%	3.10%		
	non gov	Count	23	25	28	35	36	147		
		% within Occupation	15.60%	17.00%	19.00%	23.80%	24.50%	100.00%		
		% within Behaviour11	50.00%	50.00%	70.00%	64.80%	97.30%	64.80%		
		% of Total	10.10%	11.00%	12.30%	15.40%	15.90%	64.80%		
	buisness	Count	2	6	1	3	0	12		
		% within Occupation	16.70%	50.00%	8.30%	25.00%	0.00%	100.00%		
		% within Behaviour11	4.30%	12.00%	2.50%	5.60%	0.00%	5.30%		
		% of Total	0.90%	2.60%	0.40%	1.30%	0.00%	5.30%		
	student	Count	20	16	6	12	1	55		
		% within Occupation	36.40%	29.10%	10.90%	21.80%	1.80%	100.00%		
		% within Behaviour11	43.50%	32.00%	15.00%	22.20%	2.70%	24.20%		
		% of Total	8.80%	7.00%	2.60%	5.30%	0.40%	24.20%		
	retired	Count	0	0	2	4	0	6		
		% within Occupation	0.00%	0.00%	33.30%	66.70%	0.00%	100.00%		
		% within Behaviour11	0.00%	0.00%	5.00%	7.40%	0.00%	2.60%		
		% of Total	0.00%	0.00%	0.90%	1.80%	0.00%	2.60%		
Total		Count	46	50	40	54	37	227		
		% within Occupation	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.2 Occupation of Participants in Behavior

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
Gender	Male	Count	40	43	34	42	36	195	6.98	0.137
		% within Gender	20.50%	22.10%	17.40%	21.50%	18.50%	100.00%		
		% within Behaviour11	87.00%	86.00%	85.00%	77.80%	97.30%	85.90%		
		% of Total	17.60%	18.90%	15.00%	18.50%	15.90%	85.90%		
	Female	Count	6	7	6	12	1	32		
		% within Gender	18.80%	21.90%	18.80%	37.50%	3.10%	100.00%		
		% within Behaviour11	13.00%	14.00%	15.00%	22.20%	2.70%	14.10%		
		% of Total	2.60%	3.10%	2.60%	5.30%	0.40%	14.10%		
Total		Count	46	50	40	54	37	227		
		% within Gender	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.3 Gender of Participants in Behavior

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
religion	Muslim	Count	37	41	30	49	33	190	13.352	0.1
		% within religion	19.50%	21.60%	15.80%	25.80%	17.40%	100.00%		
		% within Behaviour11	80.40%	82.00%	75.00%	90.70%	89.20%	83.70%		
		% of Total	16.30%	18.10%	13.20%	21.60%	14.50%	83.70%		
	Hindu	Count	9	9	8	5	4	35		
		% within religion	25.70%	25.70%	22.90%	14.30%	11.40%	100.00%		
		% within Behaviour11	19.60%	18.00%	20.00%	9.30%	10.80%	15.40%		
		% of Total	4.00%	4.00%	3.50%	2.20%	1.80%	15.40%		
	others	Count	0	0	2	0	0	2		
		% within religion	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%		
		% within Behaviour11	0.00%	0.00%	5.00%	0.00%	0.00%	0.90%		
		% of Total	0.00%	0.00%	0.90%	0.00%	0.00%	0.90%		
Total		Count	46	50	40	54	37	227		
		% within religion	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.4 Religion of Participants in Behavior

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
Merital	Unmarried	Count	31	21	19	25	11	107	17.459	0.26
		% within Merital	29.00%	19.60%	17.80%	23.40%	10.30%	100.00%		
		% within Behaviour11	67.40%	42.00%	47.50%	46.30%	29.70%	47.10%		
		% of Total	13.70%	9.30%	8.40%	11.00%	4.80%	47.10%		
	Married	Count	15	27	20	29	26	117		
		% within Merital	12.80%	23.10%	17.10%	24.80%	22.20%	100.00%		
		% within Behaviour11	32.60%	54.00%	50.00%	53.70%	70.30%	51.50%		
		% of Total	6.60%	11.90%	8.80%	12.80%	11.50%	51.50%		
	Divorce	Count	0	2	1	0	0	3		
		% within Merital	0.00%	66.70%	33.30%	0.00%	0.00%	100.00%		
		% within Behaviour11	0.00%	4.00%	2.50%	0.00%	0.00%	1.30%		
		% of Total	0.00%	0.90%	0.40%	0.00%	0.00%	1.30%		
Total		Count	46	50	40	54	37	227		
		% within Merital	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.5 Material of Participants in Behavior

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
Education	uneducated	Count	1	0	2	0	0	3	87.522	<0.001
		% within Education	33.30%	0.00%	66.70%	0.00%	0.00%	100.00%		
		% within Behaviour11	2.20%	0.00%	5.00%	0.00%	0.00%	1.30%		
		% of Total	0.40%	0.00%	0.90%	0.00%	0.00%	1.30%		
	primary	Count	32	34	13	4	9	92		
		% within Education	34.80%	37.00%	14.10%	4.30%	9.80%	100.00%		
		% within Behaviour11	69.60%	68.00%	32.50%	7.40%	24.30%	40.50%		
		% of Total	14.10%	15.00%	5.70%	1.80%	4.00%	40.50%		
	ssc	Count	13	14	13	21	14	75		
		% within Education	17.30%	18.70%	17.30%	28.00%	18.70%	100.00%		
		% within Behaviour11	28.30%	28.00%	32.50%	38.90%	37.80%	33.00%		
		% of Total	5.70%	6.20%	5.70%	9.30%	6.20%	33.00%		
	hsc	Count	0	0	9	18	10	37		
		% within Education	0.00%	0.00%	24.30%	48.60%	27.00%	100.00%		
		% within Behaviour11	0.00%	0.00%	22.50%	33.30%	27.00%	16.30%		
		% of Total	0.00%	0.00%	4.00%	7.90%	4.40%	16.30%		
	graguation	Count	0	2	2	9	3	16		
		% within Education	0.00%	12.50%	12.50%	56.30%	18.80%	100.00%		
		% within Behaviour11	0.00%	4.00%	5.00%	16.70%	8.10%	7.00%		
		% of Total	0.00%	0.90%	0.90%	4.00%	1.30%	7.00%		
	msc	Count	0	0	1	2	1	4		
		% within Education	0.00%	0.00%	25.00%	50.00%	25.00%	100.00%		
		% within Behaviour11	0.00%	0.00%	2.50%	3.70%	2.70%	1.80%		
		% of Total	0.00%	0.00%	0.40%	0.90%	0.40%	1.80%		
Total		Count	46	50	40	54	37	227		
		% within Education	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.6 Education of Participants in Behavior

			Behavior11					Total	X2	P Value
			very weak	weak	moderate	strong	very strong			
area	Dhanmondi	Count	24	19	12	0	0	55	190.566	<0.001
		% within area	43.60%	34.50%	21.80%	0.00%	0.00%	100.00%		
		% within Behaviour11	52.20%	38.00%	30.00%	0.00%	0.00%	24.20%		
		% of Total	10.60%	8.40%	5.30%	0.00%	0.00%	24.20%		
	Panthapath	Count	2	1	4	11	1	19		
		% within area	10.50%	5.30%	21.10%	57.90%	5.30%	100.00%		
		% within Behaviour11	4.30%	2.00%	10.00%	20.40%	2.70%	8.40%		
		% of Total	0.90%	0.40%	1.80%	4.80%	0.40%	8.40%		
	Farmgate	Count	18	28	10	1	1	58		
		% within area	31.00%	48.30%	17.20%	1.70%	1.70%	100.00%		
		% within Behaviour11	39.10%	56.00%	25.00%	1.90%	2.70%	25.60%		
		% of Total	7.90%	12.30%	4.40%	0.40%	0.40%	25.60%		
	Sonargaon	Count	0	1	12	32	35	80		
		% within area	0.00%	1.30%	15.00%	40.00%	43.80%	100.00%		
		% within Behaviour11	0.00%	2.00%	30.00%	59.30%	94.60%	35.20%		
		% of Total	0.00%	0.40%	5.30%	14.10%	15.40%	35.20%		
	Munsiganj	Count	2	1	2	10	0	15		
		% within area	13.30%	6.70%	13.30%	66.70%	0.00%	100.00%		
		% within Behaviour11	4.30%	2.00%	5.00%	18.50%	0.00%	6.60%		
		% of Total	0.90%	0.40%	0.90%	4.40%	0.00%	6.60%		
Total		Count	46	50	40	54	37	227		
		% within area	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		
		% within Behaviour11	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%		
		% of Total	20.30%	22.00%	17.60%	23.80%	16.30%	100.00%		

Table 4.7.9.7 Area of Participants in Behavior

CHAPTER 5

Discussion

Antibiotic resistance (ABR) poses a significant public health challenge worldwide, In this study we try to understand public knowledge, attitudes, practices, and behaviors regarding antibiotics for effective intervention strategies. This research highlights the varied levels of awareness within the public, which can profoundly affect their behaviors related to antibiotic usage and resistance. The findings reveal that a large portion of the population lacks sufficient knowledge about antibiotic resistance, with many participants confused about appropriate antibiotic use, particularly regarding misconceptions about their effectiveness against infections. This knowledge gap is alarming, as misinformation can lead to inappropriate self-medication and the overuse of antibiotics. Therefore, educational campaigns focused on enhancing awareness about antibiotic resistance and promoting correct antibiotic use are crucial. By improving public understanding, we can encourage a more responsible approach to antibiotic consumption.

The study also reveals that many individuals still partake in practices that contribute to antibiotic resistance, such as saving leftover antibiotics for future use, sharing antibiotics with others, and not completing prescribed courses. These behaviors highlight the pressing need for clearer guidelines and education regarding proper antibiotic usage. Healthcare professionals play a crucial role in reinforcing correct practices through effective communication with patients, emphasizing the importance of adhering to prescribed treatments. Moreover, the behavior surrounding antibiotic use is influenced by knowledge, attitudes, and practices. Individuals with a greater awareness of antibiotic resistance are more likely to consult healthcare providers before taking antibiotics, while those with limited knowledge may resort to self-medication or seek antibiotics without a prescription. This underscores the need for public health initiatives that foster communication between healthcare providers and patients, ensuring that individuals understand when antibiotics are necessary and when they are not.

To enhance public knowledge and behavior regarding antibiotic use, machine learning (ML) offers promising solutions. We have developed a smart system that incorporates ML, Optical Character Recognition (OCR), and an easy-to-use interface to improve antibiotic identification. The system can extract patient prescription data from images or manual entries and compare it against a comprehensive database of antibiotics, aiding healthcare providers in determining the necessity of antibiotics using a Random Forest ML model applicable to all patient cases. A key advantage of this system is its ability to automatically detect antibiotics in prescriptions and provide guidance on their necessity, addressing the critical issue of antibiotic misuse that contributes to antimicrobial resistance (AMR). The implementation of OCR technology allows patients to upload prescription images rather than manually entering data, which saves time and minimizes errors, especially in busy healthcare environments.

Although the study faced challenges in managing complex patient data and ensuring the accuracy of the ML models, improvements in data processing and labeling helped resolve these issues. The potential impact of this system is substantial, as it offers a solution to antibiotic overprescription and enhances patient care through accurate predictions. Looking forward,

expanding the database to include a wider range of diseases and medications could further improve the system’s accuracy and applicability. Moreover, employing advanced ML models, such as neural networks, and integrating cloud technology would enhance the system's robustness, allowing it to access up-to-date antibiotic databases. By addressing these areas for improvement, this innovative system could become an invaluable tool in the ongoing battle against AMR, supporting better decision-making and ultimately contributing to the optimization of antibiotic use in healthcare settings.

CHAPTER 6

Conclusion, Limitations, Recommendation

6.1 Conclusion

Recent research has highlighted the growing interest in using machine learning (ML) to predict antimicrobial resistance (AMR), yielding promising outcomes. This review analyzed existing studies on AMR prediction through ML algorithms and their potential to enhance antimicrobial stewardship. ML models have shown promise in accurately predicting multidrug resistance, supporting more personalized antibiotic prescribing, and aiding the development of clinical decision support tools. Although artificial intelligence (AI) is expected to increasingly assist in healthcare decision-making, human oversight remains crucial to ensure patient-specific care. Given the complexity of clinical decision-making, ML-based approaches must be proven effective in real-world practice before their integration into routine clinical workflows. our model provides a powerful tool in the fight against antibiotic-resistant bacteria by leveraging vast datasets to predict resistance patterns and guide treatment decisions. By supporting targeted antibiotic use, this approach minimizes over prescription, helps prevent the emergence of resistant strains, and improves patient outcomes. However, the long-term success of combating antibiotic resistance hinges on collaborative efforts among healthcare professionals, policymakers, and the public. Through ongoing research, education, and responsible antibiotic use, we can make significant strides in reducing the spread of resistance and safeguarding global health.

6.2 Limitations

The model has several limitations that impact its utility and accuracy. First, it is restricted to predicting only the diseases and medications present in the existing database, which limits its applicability to unlisted conditions or treatments. The system does not prescribe actual medications; it merely identifies antibiotics based on historical data. Furthermore, it lacks a search functionality, confining user interaction to predefined input fields.

Additionally, the model is built on a limited dataset of 224 patient records, raising concerns about the reliability of predictions, particularly for rare cases. Its internal design is for testing purposes only and is not intended for public or clinical use. The current Android application version also faces stability issues, necessitating updates for improved performance.

Notably, the model does not consider antibiotic resistance levels and lacks direct consultation with medical professionals, relying solely on data collected from government hospitals. Therefore, the results may vary if data were obtained from a more diverse range of healthcare facilities. Importantly, this model should not be viewed as a substitute for professional medical advice or treatment decisions.

6.3 Recommendation

To enhance the effectiveness of the model, it is crucial to expand data collection by gathering patient data from a broader range of both government and non-government hospitals, thereby improving the diversity and robustness of the dataset. Emphasizing the collection of specific disease data will facilitate more targeted analyses and improve predictive accuracy. Collaboration with disease specialists is recommended to validate data and ensure that model predictions align with clinical practices. Additionally, enhancing data analysis systems through advanced analytics tools will provide deeper insights and improve decision-making. The model should utilize optimal datasets for training, focusing on representative and comprehensive data to strengthen its predictive capabilities. Incorporating advanced algorithms and state-of-the-art machine learning techniques can significantly improve accuracy and performance. Furthermore, developing a robust Android application that prioritizes user experience and functionality will enhance its overall effectiveness. It is also essential to implement features for accurate antibiotic prediction and comprehensive usage guidelines, which will support user understanding and adherence to medical practices. Finally, the model should be modified to include predictions of antibiotic resistance levels, providing critical information for informed decision-making regarding antibiotic prescriptions.

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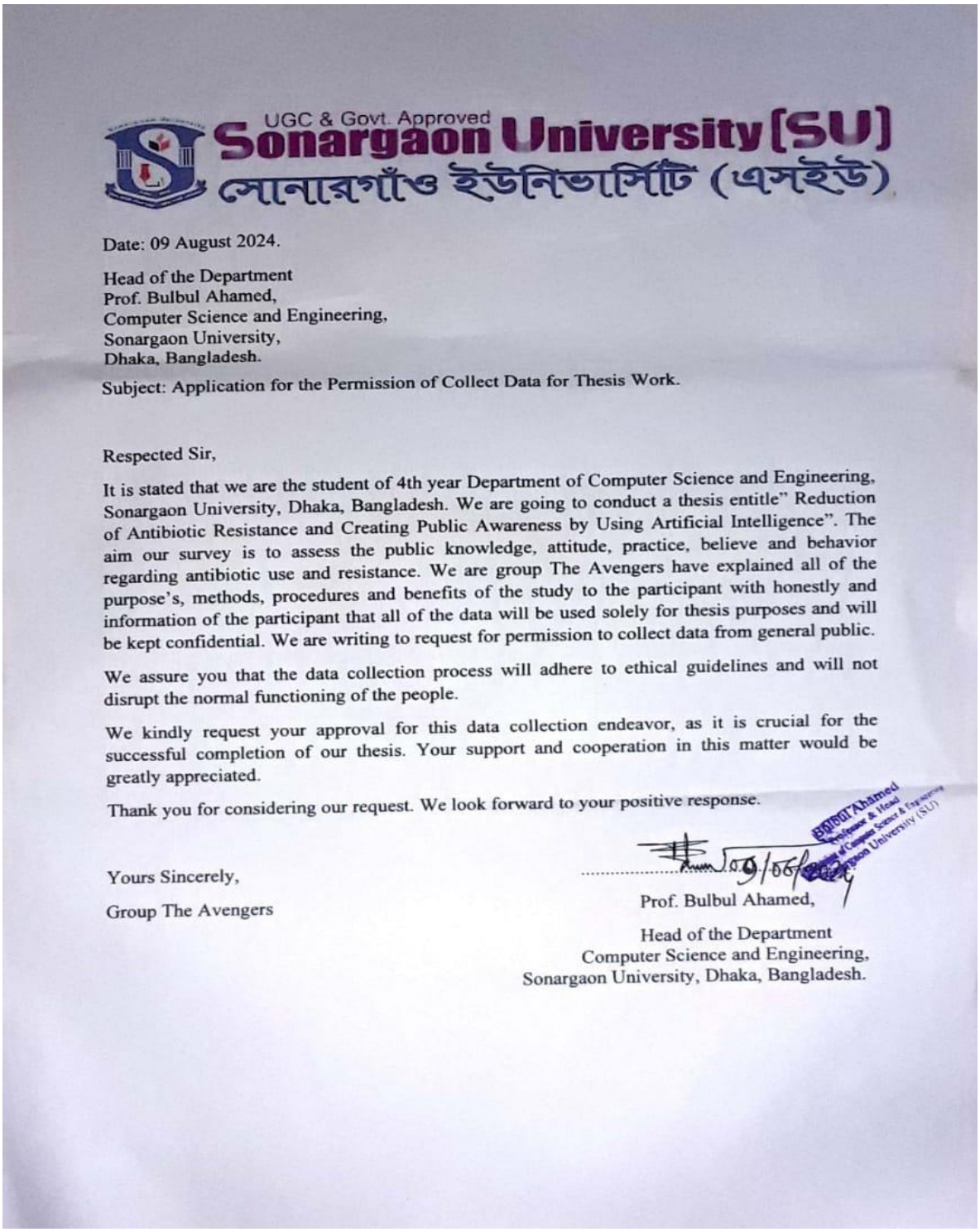
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APPENDIX

Permission Letter, Questionnaires, Study Timeline

Permission Letter



UGC & Govt. Approved
Sonargaon University (SU)
সোনারগাঁও ইউনিভার্সিটি (এসইউ)

Date: 09 August 2024.

Head of the Department
Prof. Bulbul Ahamed,
Computer Science and Engineering,
Sonargaon University,
Dhaka, Bangladesh.

Subject: Application for the Permission of Collect Data for Thesis Work.

Respected Sir,

It is stated that we are the student of 4th year Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. We are going to conduct a thesis entitle" Reduction of Antibiotic Resistance and Creating Public Awareness by Using Artificial Intelligence". The aim our survey is to assess the public knowledge, attitude, practice, believe and behavior regarding antibiotic use and resistance. We are group The Avengers have explained all of the purpose's, methods, procedures and benefits of the study to the participant with honestly and information of the participant that all of the data will be used solely for thesis purposes and will be kept confidential. We are writing to request for permission to collect data from general public.

We assure you that the data collection process will adhere to ethical guidelines and will not disrupt the normal functioning of the people.

We kindly request your approval for this data collection endeavor, as it is crucial for the successful completion of our thesis. Your support and cooperation in this matter would be greatly appreciated.

Thank you for considering our request. We look forward to your positive response.

Yours Sincerely,

Group The Avengers

.....

Prof. Bulbul Ahamed,

Head of the Department
Computer Science and Engineering,
Sonargaon University, Dhaka, Bangladesh.

Questionnaires

Survey Information Sheet

Name of the researcher: Group **The Avengers**

Title of the Research: Reduction of Antibiotic Resistance and Creating Public Awareness by Using Artificial Intelligence

Survey Purpose: The aim of the study is to assess the public knowledge, attitude, practice, believe and behavior regarding antibiotic use and resistance.

Research conducting process: Permission was taken from our honorable the supervision of **Prof. Bulbul Ahamed,** Head of the Department of Computer Science and Engineering, Sonargaon University, Dhaka, Bangladesh. The researcher will meet and introduced himself to the participants and will explain to the participants about the study objectives, their rights and benefits of the study and will be asked them to participate in the study. Data will be collected from respondent through self-administered questionnaire. Confidentiality and anonymity will be maintained strictly.

Your right as a participant in these researching activities: Participation into this research depends on you. You have the right to withdraw any time from this research.

Potential Risk: You will not be confronted with physical, psychological or social risks.

The Effective Usefulness: The study findings will provide a sound knowledge about antibiotic use and resistance directly or indirectly to increase public knowledge.

Confidentiality: All of the data and information will be stored in a way, which will not be disclosed to anyone else except the researcher only.

Contact Information: Group-The Avengers will conduct this research and you can ask any question to him regarding this research, if you have any query or any complain then you can directly contact with our team leader Md Omar Faruque (Email: faruk.cse.su@gmail.com).

Signing of Consent Paper: This research is clearly explained to me and I understood the information given here. I agree to participate in this research. I am expressing my contentment's on the discussion with the researcher associated in this research. I have understood that to participate in this research is voluntary and any obligation.

I can abstain myself from this research. I have read all the above-mentioned conditions are told before me and I am expressing my self-complacent and consent to participate in this research.

…… …….

Investigator Participant's signature

……..

Phone number:

…….. …...…….

Email: Participant's full name

Date: Date:

Consent From for participants

Research Title:" Reduction of Antibiotic Resistance and Creating Public Awareness by Using Artificial Intelligence"

Before I sign below, I acknowledge that I have been informed and explained about purpose, methods, procedures and benefits of the study by the researcher, and I understand all of that explanation. I agree to be as a participant of this study.

We are the researcher of group The **Avengers** have explained all of the purpose's methods, procedures and benefits of the study to the participant with honestly and information of the participant that all of the data will be used for purpose of the research study.

…… …….

Investigator signature

Participant's

Group …….

……..

Phone number

…….. ..……..

Email:

Participant's full name

Date:

Date:

Please take a few minutes to complete this survey. We request your kind cooperation and honest answers in filling out this questionnaire. All your information will remain ***confidential & won't be used for any purpose other*** than the research only.

INSTRUCTION: Please read the following questions carefully and provide most suitable information by placing a **TICK** in the boxes provided.

Section-A

1) **Gender:**

Male	Female	Others

2) **Age:**

18-22 Years	23-27 Years	28-32 Years	33-37 Years	38 Years or above

3) **Marital:**

Single	Married	Divorced

4) **Education:**

Intermediate or below	Undergraduate	Graduate	Professional	Others

5) **Occupation:**

Government Sector	Private Sector	Self-Employed	Student	Retired

6) **Monthly Income:**

Below 15,000 Tk	15,001-25,000 Tk	25,001-35,000 Tk	35,001-45,000 TK	Above 45,000TK

7) **Residence/Area:**

8) **Religion:**

Muslim	Hindu	Others

Section-B

Knowledge Related questionnaires:

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
9. Antibiotic is a type of medicine.					
10. Antibiotic should be used as per the advice of a registered physician.					
11. If the patient feels better, antibiotic should be discontinued.					
12. Unnecessary used of antibiotic increase the risk of illness/disease.					
13. Antibiotics resistance are happening when a bacterium lost its sensitivity to an antibiotic.					
14. Antibiotics resistance is not a serious problem.					
15. Antibiotics often cause side effects such as diarrhea and others.					

Attitude Related Questionnaires:

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
16. The Price of Antibiotic is too high so I can't afford it.					
17. I Always complete the course of treatment with antibiotics.					
18. I believe antibiotics cure my illness faster.					
19. If the fall my illness, I ask for an antibiotics prescription to prevent my symptoms.					
20. I know which medicines are the antibiotics when I take medicine.					
21. I'll normally look at the expire date of antibiotics before taking it.					

22. I always keep antibiotic stocks at home in case of emergency.					
23. If my family member is sick, I usually will give my antibiotics to them.					

Practice Related questionnaires:

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
23. I participate in antibiotic awareness campaigns to promote the optimal use of antibiotics.					
25. I finish the full course of antibiotic treatment.					
26. I usually know when I need antibiotic.					
27. I have taken measures to prevent antibiotic resistance.					
28. When I take antibiotics, I contribute to the development of antibiotic resistance.					
29. Antibiotics are effective in the treatment of viral infections.					
30. Do you prefer take to antibiotics when you have cough or sore throat?					

Believe & behavior Related questionnaires:

Items	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
31. Antibiotic remaining can be used again far similar symptoms without a doctor instruction.					
32. Taking low dose of antibiotics is better that not taking any dose.					
33. I take the antibiotic directly from the pharmacists without a prescription from doctor.					
34. If the symptoms do not improve after taking antibiotic stop taking it by self.					
35. Would you take antibiotics before meals?					
36. Do you keep antibiotic syrup in the refrigerator**?**					
37. Do you store antibiotics in a place with exposure to the sun?					
38. Return for more antibiotics after finishing the prescription.					

Thanks for your cooperation

Study Timeline

Time Schedule	Oct /23	Nov /23	Dec /23	Jan /24	Feb /24	Mar /24	Apr /24	May /24	June /24	July /24	Aug /24	Sept /24	Oct /24
Title Selection													
Research Group Formation													
Literature Review													
Questionnaire Development													
Proposal Writing													
Proposal Preparation													
Proposal Defense													
Proposal Submission													
Data Collection													
Data Analysis													
Report Writing													
Final Defense													
Paper Submission													