ACKNOWLEDGEMENT

We extremely thankful **to Dr.P.Narayana**, the Founder Chairman of Narayana Group for his good initiation starting technical institution in Gudur like rural area for helping economically poor
students.

We also thankful to **Mr.K.Puneeth**, the **Chairman** of **Narayana Group** for providing the infrastructural facilities to work in, without this the work would not have been possible.

We would like to express our deep sense of gratitude to **Dr. V. Ravi Prasad, Principal, Narayana Engineering College, Gudur** for his continuous effort in creating a competitive
environment in our college and encouraging throughout this course.

We would like to convey our heartfelt thanks to **Dr.P.Venkateswara Rao, Professor**& HOD of Computer Science and Engineering for giving the opportunity to embark up on this topic and for his continues encouragement throughout the preparation of the project.

We would like to thank our Project Coordinator **Mr.E.Ramesh Reddy, Assoc.Professor** Department of Computer Science and Engineering for giving the opportunity to for his continues encouragement throughout the preparation of the project.

We would like to thank our Guide **Mr.R.Sivaiah Asst, Professor** for their valuable guidance, constant assistance, support, endurance and constructive suggestions for the betterment of the project.

We also wish to thank all the Staff members of the Department of Computer Science & Engineering for helping us directly or indirectly in completing this project successfully.

Finally we are thankful to our parents and friends for their continued moral and material support throughout the course and in helping us to finalize the report.

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B. Mary Madhuri (21F11A0505)

T.NagaBhavitha(21F11A0556)

DECLARATION

We hereby declare that the project entitled **EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR PATIENT SAFETY BY USING AN APPLICATION PHARMACOVILIGENCE** has been done by us under the guidance **Mr.R.Sivaiah Asst, Professor** Department of Computer Science & Engineering. This project work has been submitted to **NARAYANA ENGINEERING COLLEGE, GUDUR** as a part of partial fulfillment of the requirements for the award of degree of **Bachelor of Technology**.

We also declare that this project report has not been submitted at any time to another institute or University for the award of any degree.

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Place: Gudur

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ABSTRACT

Explainable AI (XAI) is a methodology that complements the black box of artificial intelligence, and its necessity has recently been highlighted in various fields. The purpose of this research is to identify studies in the field of pharmacovigilance using XAI. Though there have been many previous attempts to select papers, with a total of 781 papers being confirmed, only 25 of them manually met the selection criteria. This study presents an intuitive review of the potential of XAI technologies in the field of pharmacovigilance. In the included studies, clinical data, registry data, and knowledge data were used to investigate drug treatment, side effects, and interaction studies based on tree models, neural network models, and graph models. Finally, key challenges for several research issues for the use of XAI in pharmacovigilance were identified. Although artificial intelligence (AI) is actively used in drug surveillance and patient safety, gathering adverse drug reaction information, extracting drug-drug interactions, and predicting effects, XAI is not normally utilized. Therefore, the potential challenges involved in its use alongside future prospects should be continuously discussed.

LIST OF FIGURES

CHAPTER-1

INTRODUCTION

1.1 About Machine Learning

Machine learning (ML) is the study of computer algorithms that improve automatically through experience. It is seen as a subset of artificial intelligence. Machine learning algorithms build a mathematical model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or infeasible to develop conventional algorithms to perform the needed tasks.

Machine learning is closely related to computational statistics, which focuses on making predictions using computers. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

Machine learning involves computers discovering how they can perform tasks without being explicitly programmed to do so. It involves computers learning from data provided so that they carry out certain tasks. For simple tasks assigned to computers, it is possible to program algorithms telling the machine how to execute all steps required to solve the problem at hand; on the computer's part, no learning is needed. For more advanced tasks, it can be challenging for a human to manually create the needed algorithms. In practice, it can turn out to be more effective to help the machine develop its own algorithm, rather than have human programmers specify every needed step.

The discipline of machine learning employs various approaches to help computers learn to accomplish tasks where no fully satisfactory algorithm is available. In cases where vast numbers of potential answers exist, one approach is to label some of the correct answers as valid. This can then be used as training data for the computer to improve the algorithm(s) it uses to determine correct answers. For example, to train a system for the task of digital character recognition, the MNIST dataset has often been used.

Machine learning approaches

Early classifications for machine learning approaches sometimes divided them into three broad categories, depending on the nature of the "signal" or "feedback" available to the learning system. These were:

Supervised learning: The computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs.

Unsupervised learning: No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning).

Reinforcement learning: A computer program interacts with a dynamic environment in which it must perform a certain goal (such as driving a vehicle or playing a game against an opponent) As it navigates its problem space, the program is provided feedback that's analogous to rewards, which it tries to maximise.

Other approaches or processes have since developed that don't fit neatly into this three-fold categorisation, and sometimes more than one is used by the same machine learning system. For example topic modeling, dimensionality reduction or meta learning. [8] As of 2020, deep learning has become the dominant approach for much ongoing work in the field of machine learning.

1.2 About the Project

The World Health Organization defines pharmacovigilance (PV) as the science and activities related to the detection, assessment, understanding, and prevention of adverse effects or other drug-related problems. Recent artificial intelligence-based technologies can be an efficient complement to traditional PV methods, which can be costly and time-consuming and can result in adverse drug reactions (ADRs) that go unreported to healthcare professionals. Artificial intelligence (AI) can improve PV, but its use in PV is still in the early stages of research. Various machine learning (ML) techniques, together with natural language . processing and data mining, can be applied to electronic health records, claims databases and social media data to improve the characterization of known drug side effects and reactions, and to detect new signals.

AI-based technologies have been criticized for their inexplicable algorithms, despite their high predictive power. In critical decision areas such as healthcare, the reasoning behind a decision is as important as the decision itself, which is why there is growing interest in and research and development around Explainable Artificial Intelligence (XAI). XAI was developed to improve the transparency of AI systems and generate explanations for them, and seeks to increase trust and understanding by assessing the strengths and limitations of existing models. Approaches that extract information from a model’s decision-making process, such as post-hoc explanations, can provide useful information for practitioners and users interested in case by- case explanations rather than the internal workings of a model. XAI increases the explain ability and transparency of AI algorithms by making it possible to interpret the variables that influence decisions, complex internal features, and learned decision paths within a decision process. I.R. Ward et al. successfully quantified the importance of features using an XAI algorithm, further demonstrating the potential contribution of XAI to PV monitoring. The importance of PV in medicine is relevant to all species affected by medical interventions, and ensuring medical safety requires attention and research into approaches such as drug safety reporting and the exchange of reliable and timely information on PV activities. The global pharma covigilance and drug safety software market size was valued at USD 6.9 billion in 2021 and is estimated to expand at a compound annual growth rate (CAGR) of 10.5% between 2022 and 2030 (Source: www.grandviewresearch.com). The aim of this study was to review the literature on the use of XAI in PV by identifying publications related to ML/AI and drugs and the rationale for the reported findings. From the perspective of AI and XAI usage, these studies were analyzed, and the findings were summarized, in which the use of XAI in the field of PV is referred to as "PV XAI". The main contributions are highlighted and discussed below:

- This study is clearly an early attempt to review XAI research in PV. Unlike other fields, we found that XAI research in PV is at an early stage of development, limited to a few articles and some methodologies.
- Nevertheless, we have identified the positive potential of PV XAI for drug therapy, ADRs, poly pharmacy and drug repurposing.
- While safety issues in real-world healthcare settings may limit the growth of the field, we expect PV XAI research to expand as it has in other areas, and we encourage collaboration and ongoing research discussions with experts in the field.

CHAPTER-2

LITERATURE SURVEY

2.1 LITERATURE SURVEY

In this study, the trend of XAI in the field of PV was examined. However, the trend was also explored broadly to more diverse aspects, including interpretable artificial intelligence. Although there is a clear difference between Explainable AI (knowledge about what different nodes represent and their importance to model performance) and Interpretable AI (ability to determine cause and effect in a machine learning model), based on the same aim, they were comprehensively reviewed.

There has been a surge in XAI studies in drug-related applications since 2019, with relatively few studies from 2013 to 2018. The limited number of publications indicates a demand for more research on XAI in PV applications. The selection of appropriate search terms for the exploration of XAI-related research in PV was not easy; we started manually with broad keywords. The following five searches were performed: pharmacovigilance XAI (47), pharmacovigilance "explainable artificial intelligence" pharmacovigilance explainable AI , pharmacovigilance explainable ML and pharmacovigilance explainable machine learning. These search terms were used in a Google Scholar search on 22 June 2022, and the numbers in parentheses are the number of articles returned from each search. Retrieved articles were first screened for titles and abstracts to exclude duplicates, then articles were added through a first full-text review for relevance and a second full-text review based on a selective methodology, resulting in a final selection of 25 unique publication. PV involves the collection and analysis of data from patient records or other sources to identify causal relationships between medicines and adverse drug reactions. While the potential for monitoring and preventing adverse drug reactions through clinical data is great, exploiting it can be time-consuming because clinical data is highly heterogeneous in structure and domain, and is often managed in multiple files. In addition, specific expertise is required to make sense of clinical information and often requires an understanding of appropriate related prescriptions, which in most cases requires a long preparation time with clinical researchers. PV involves the collection and analysis of data from patient records or other sources to identify causal relationships between medicines and adverse drug reactions.

CHAPTER-3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

- In pharmacovigilance, this means developing models that can explain how they arrive at predictions or decisions regarding drug safety and adverse effects.
- AI models can be used to predict and prevent potential risks associated with medications.
- pharmacovigilance workflows, XAI can help prioritize alerts or signals related to drug safety.
- XAI approaches align with regulatory requirements for transparency and accountability in healthcare AI applications

3.1.1 DISADVANTAGES OF EXISTING SYSTEM

- Biased data or incomplete information may lead to skewed explanations or inaccurate risk assessments.
- Misinterpretation of explanations or lack of clarity in presented information can hinder effective decision-making in pharmacovigilance tasks.

3.2 PROPOSED SYSTEM

- Develop and implement XAI techniques that provide detailed and actionable explanations for model predictions in pharmacovigilance.
- Design interactive interfaces that allow users to explore and interact with XAIgenerated explanations.
- Explore the use of hybrid models that combine the strengths of interpretable models (e.g., decision trees, rule-based systems) with the predictive power of complex machine learning algorithms (e.g., deep learning).
- This hybrid approach aims to maintain high accuracy while ensuring transparency and explainability.

3.2.1 ADVANTAGES OF PROPOSED SYSTEM

- To improve transparency
- This allows for accurate risk assessments while maintaining the ability to explain the reasoning behind predictions.

3.3 FEASIBILITY STUDY

3.3.1 Technical Feasibility

According to Roger S. Pressman, Technical Feasibility is the assessment of the technical resources of the organization. The organization needs IBM compatible machines with a graphical web browser connected to the Internet and Intranet. The system is developed for platform Independent environment. Java Server Pages, JavaScript, HTML, SQL server and

WebLogic Server are used to develop the system. The technical feasibility has been carried out. The system is technically feasible for development and can be developed with the existing facility.

3.3.2 Economic Feasibility

Economic Feasibility or Cost-benefit is an assessment of the economic justification for a computer based project. As hardware was installed from the beginning & for lots of purposes thus the cost on project of hardware is low. Since the system is a network based, any number of employees connected to the LAN within that organization can use this tool from at anytime. The Virtual Private Network is to be developed using the existing resources of the organization. So the project is economically feasible.

3.3.3 Operational Feasibility

This system is being automated on the request of the technical department of our company. This new system meets their requirement and covers all aspects required much better than the old manual system. Most of the people involved in this branch are computer literate and do not need much training if this system is implemented.

Hence it is operationally feasible.

3.4 SOFTWARE REQUIREMENT SPECIFICATION

3.4.1 Functional Requirements

The main purpose of functional requirements within the requirement specification document is to define all the activities or operations that take place in the system. But the general functional requirements arrived at the end of the interaction with the users are listed bellow

This project provides:

1. Authentication of user whenever he/she logs in to the system
2. System shut down in case of a cyber-attack
3. A verification email is sent to user whenever he/she register for the first time on some software system

3.4.2 Non-functional requirements

The major non-functional Requirements of the system are as follows

Usability

The system is designed with completely automated process hence there is no or less user intervention.

Reliability

The system is more reliable because of the qualities that are inherited from the chosen platform java. The code built by using java is more reliable.

Performance

This system is developing in the high level languages and using the advanced frontend and back-end technologies it will give response to the end user on client system with in very less time.

Supportability

The system is designed to be the cross platform supportable. The system is supported on a wide range of hardware and any software platform, which is having JVM, built into the system.

Implementation

The system is implemented in web environment using struts framework. The apache tomcat is used as the web server and windows xp professional is used as the platform.

Interface the user interface is based on Struts provides HTML Tag

3.5 SOFTWARE AND HARDWARE REQUIREMENTS

3.5.1 Software Requirements

Operating System	:	Windows 10 64 bit
Programming language	:	Python
Front End	:	HTML, CSS
Back End	:	MySQL 5.0
Framework	:	Django
Server	:	Xampp

3.5.2 Hardware Requirements

Processor	:	I3
RAM	:	4 GB
Hard Disk	:	500 GB

CHAPTER-4
DESIGN PROCESS

4.1 INTRODUCTION

The most creative and challenging phase of the life cycle is system and design. The term design describes a final system and the process by which it is developed. It refer to the technical specifications that will be applied in implementation the candidate system. The design may be defined as “the process of applying various techniques and principles for the purpose of defining a device, a process or a system in sufficient details to permit its physical realization”.

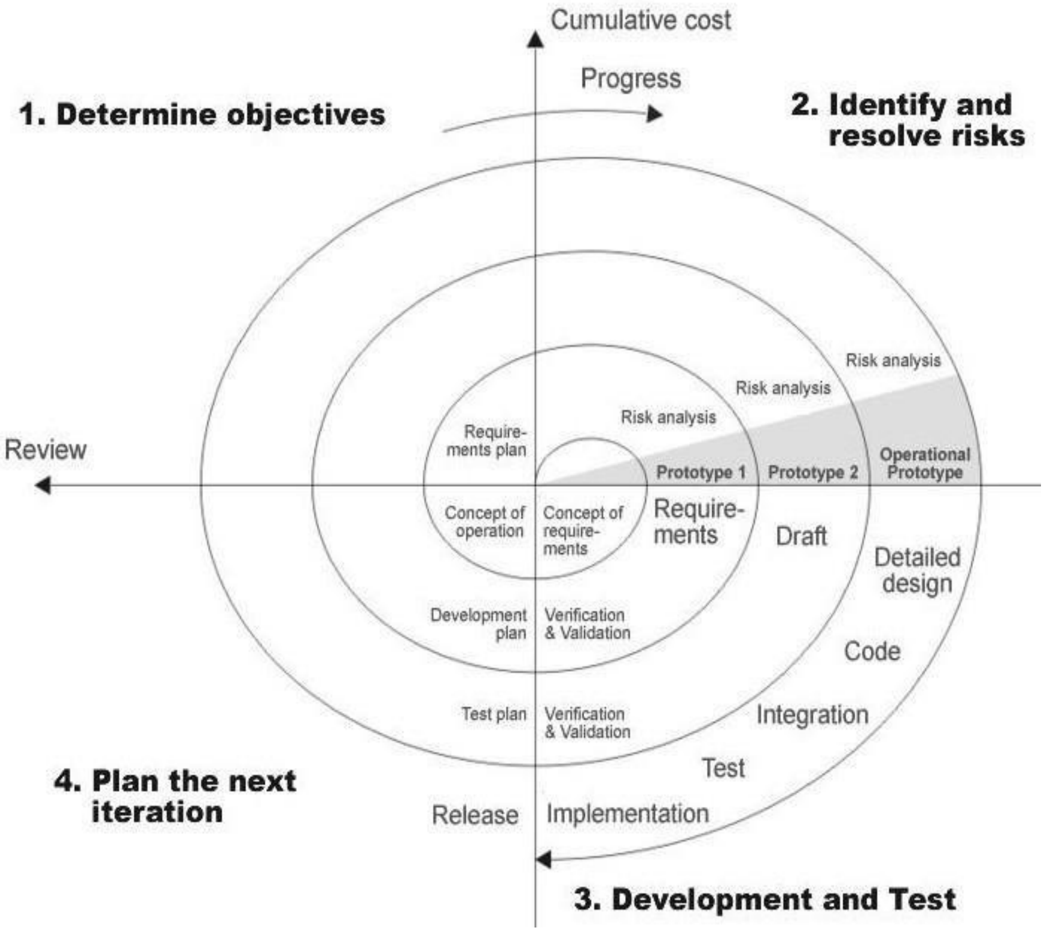
The design’s goal is how the output is to be produced and in what format samples of the output and input are also presented. Second input data and database files have to be designed to meet the requirements of the proposed output. The processing phase is handled through the program construction and testing. Finally details related to justification of the system and an estimate of the impact of the candidate system on the users and the organization are documented and evaluated by management as a step toward implementation.

The importance of software design can be stated in a single word **“Quality”.** Design provides us with representation of software that can be assessed for quality. Design is the only way that we can accurately translate a customer’s requirements into a finished software product or system without design we risk building an unstable system, that might fail it small changes are made or may be difficult to test, or one who’s quality can’t be tested. So it is an essential phase in the development of a software product.

4.1.1 SDLC METHODOLOGY

The document ply vital role in the development of life cycle (SDLC) as it describes the complete requirement of the system. It means for use by developers and will be the basic during testing phase. Any changes made to the requirements in the future will have to go through formal change approval process.

SPIRAL MODEL was defined by Barry Boehm in his 1988 article, “A spiral model of Software Development and Enhancement.



Stages in SDLC

- Requirement Gathering
- Analysis
- Designing
- Coding
- Testing
- Maintenance

4.2 SYSTEM ARCHITECTURE

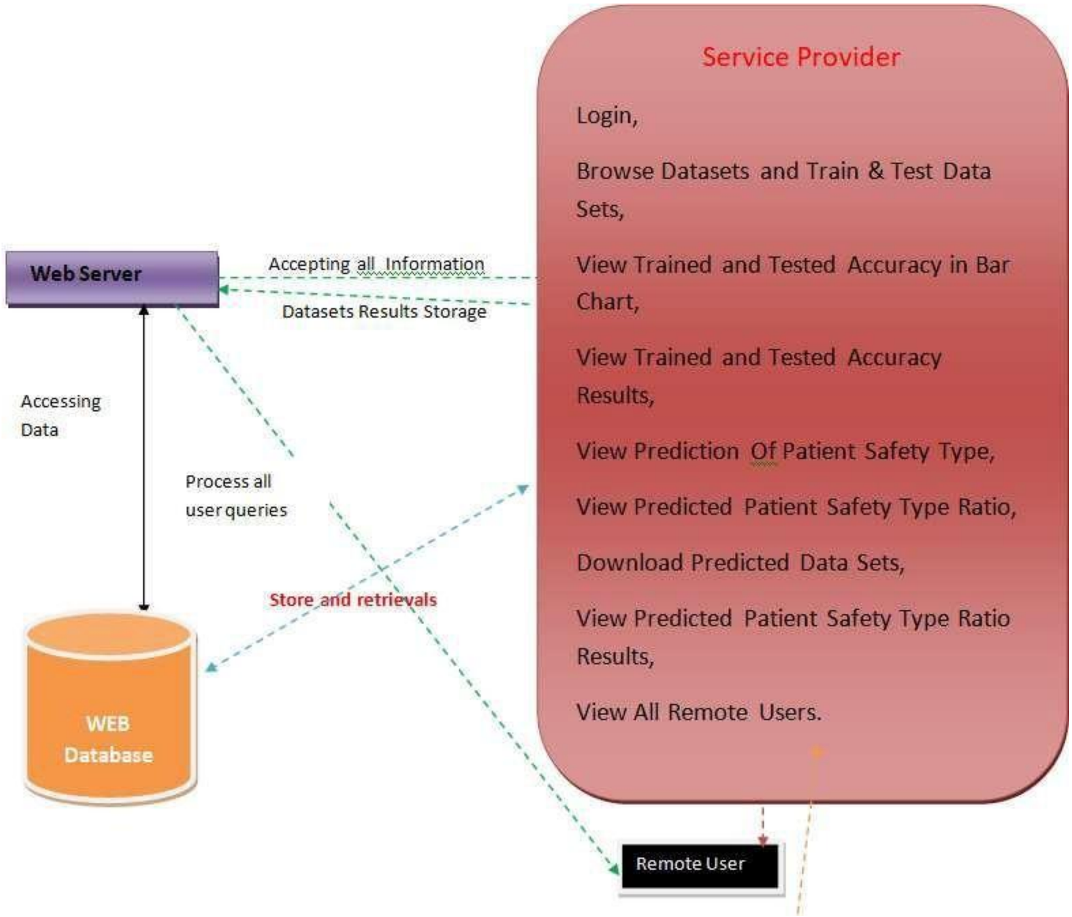


Fig. 4.1: System Overview

4.3INPUT & OUTPOUT REPRESENTETION

Input design:

Input design includes data mediums used for inputting data and validations that are to be done during data entry. Different messages regarding data are given to guide users during data entry. Validation checks are done for each input.

Data entry screens are designed so that the system interacts with the user in providing an effective dialogue. Fields in the screen are logically arranged to help the user.

The design is the process of converting the user-originated inputs into a computebased format. The goal of the input design is to make the data entry easier, logical and free from error. Errors in the input data are controlled by input design.

The application has been developed in a user-friendly manner. The windows have been designed in such a way that during the processing the cursor is placed in the position where the data must be entered. If any of the data going into the system is wrong then the process and output will magnify these errors.

The decisions made during design of input are:

1) To achieve the highest possible level of accuracy.

2) To provide a list of possible choices and help while accepting the input for an important field wherever possible outputs from computer system are required primarily to communicate the results of processing to the users. They are also used to provide a permanent copy of these results for later consultation/verification.

Output Design:

Output refers to the results and information that are generated by the system. Output is the main reason for developing the system and based on this, the usefulness and applicability of system are evaluated.

Outputs from computer systems are required primarily to communicate the results of processing to users. Efficiently designed outputs enhance the understandability of the information.

According to the requirements of the system, various types of outputs are considered and designed as follows.

Internal outputs, whose destination is within the organization and which require careful design because they are the user's main interface with the computer.

Interactive outputs, in which the user communication with the Computer is essential.

4.4 UML DIAGRAMS

The overall logical structure of a database can be expressed graphically by an **E-R diagram.** The relative simplicity and pictorial clarity of this diagramming technique may well account in large part for the widespread use of the E-R model. Such a diagram consists of the following major components.

Rectangles: Represent Entity Sets.

Ellipses: Represent attributes.

Diamonds: Represent relationship sets

Lines: Link attributes to entity sets and entity sets

4.5Building blocks of the UML

The vocabulary of the UML encompasses three kinds of building blocks.

1. Things.
2. Relationships.
3. Diagrams.

Things in the UML

Things are the abstractions that are first-class citizen in a model.

There are four kinds of things in the UML.

1. Structure things.
2. Behavioral things.
3. Grouping things.
4. Annotational things.

These things are the basic object-oriented building blocks of the UML. You use them to write well-formed models.

Relationships in the UML

Thingscan be connected to logically are physically with the help of relationship in object oriented modeling.These are four kinds of relationships in the UML.

1. Dependency.
2. Association.
3. Generalization.
4. Realization.

Diagrams in the UML

A diagram is a graphical representation of a set of elements. These are nine kinds of diagrams in the UML.

1. Class diagram.	6. Activity diagram.
2. Object diagram	7. Component diagram.
3. Usecase diagram.	8. State chart diagram.
4. Sequence diagram.	9. Deployment diagram.

5. Collaboration diagram

USECASE DIAGRAM

Use case diagram shows a set of usecases and actors (a special kind of class) and their relationship. Usecase diagrams address the static usecase view of a system.

These diagrams are especially important in organizing and modeling the behavioral of a system both sequence and collaboration diagrams are kind of interaction diagram.

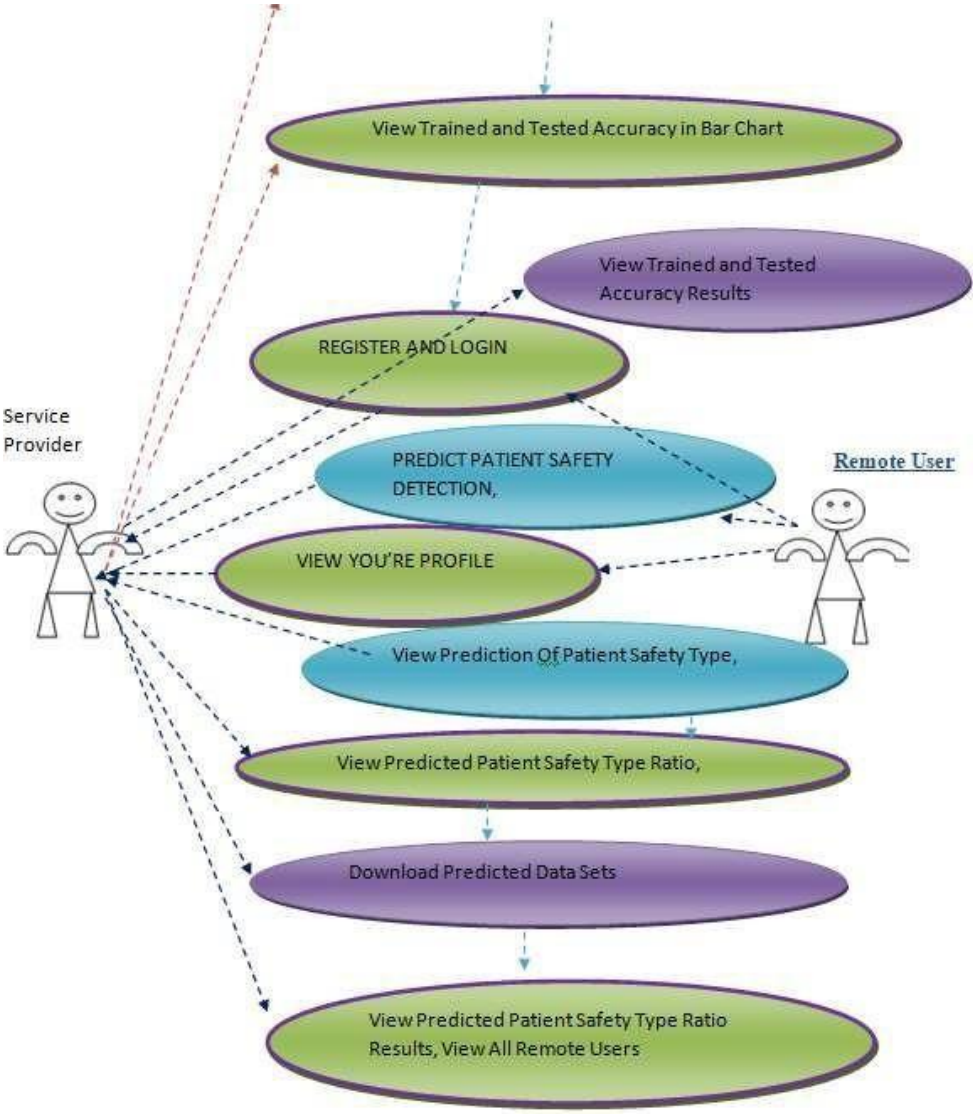


Fig. 4.42: Use-case Diagram

CLASS DIAGRAM:

Class diagrams area unit the foremost common diagrams employed in UML. Category diagram consists of categories, interfaces, associations and collaboration. Category diagrams primarily represent the thing directed read of a system that is static in nature. Active category is employed in a very category diagram to represent the concurrency of the system.

Class diagram represents the thing orientation of a system. Therefore it's usually used for development purpose. This can be the foremost wide used diagram at the time of system construction.

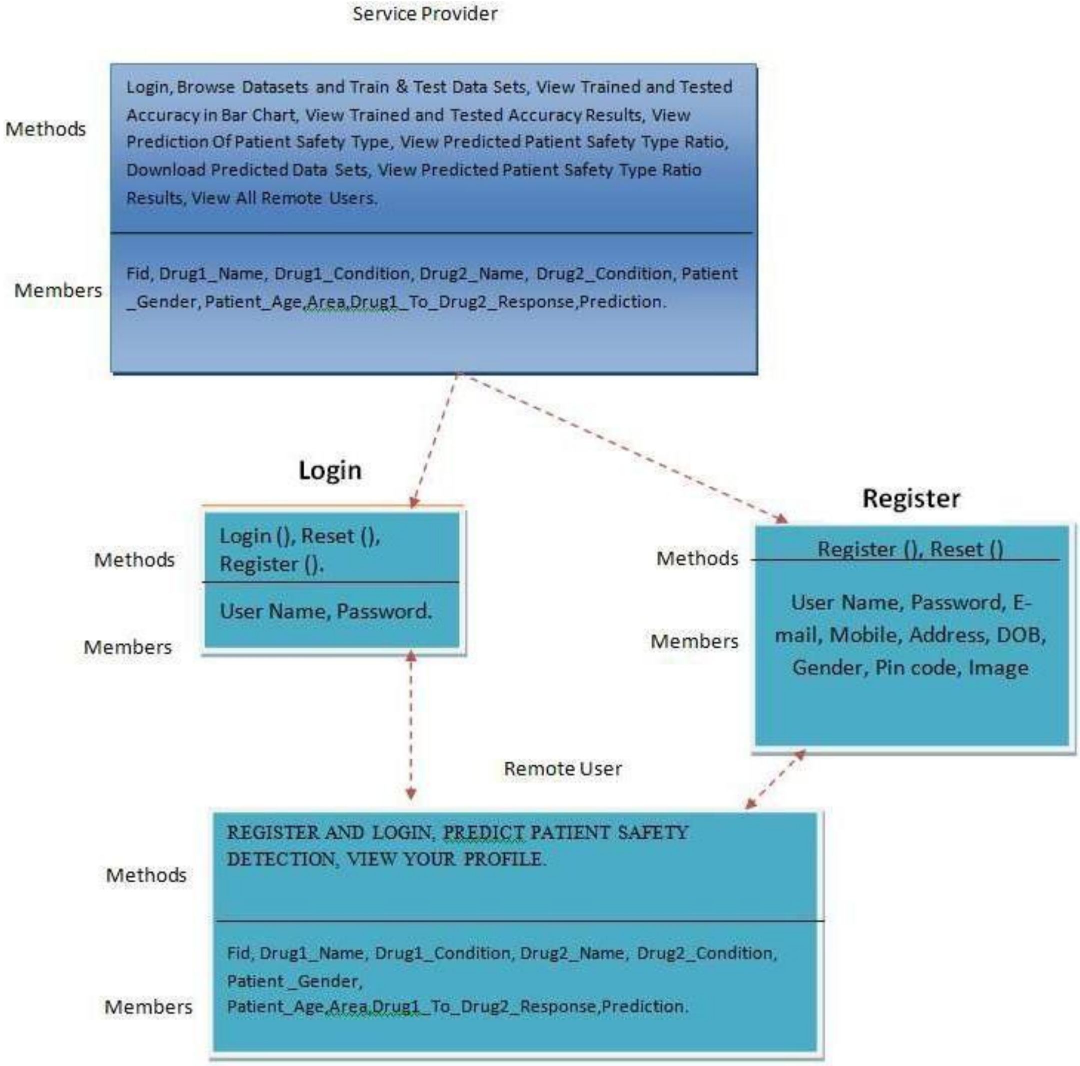


Fig. 4.43: Class Diagram

SEQUENCE DIAGRAM

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

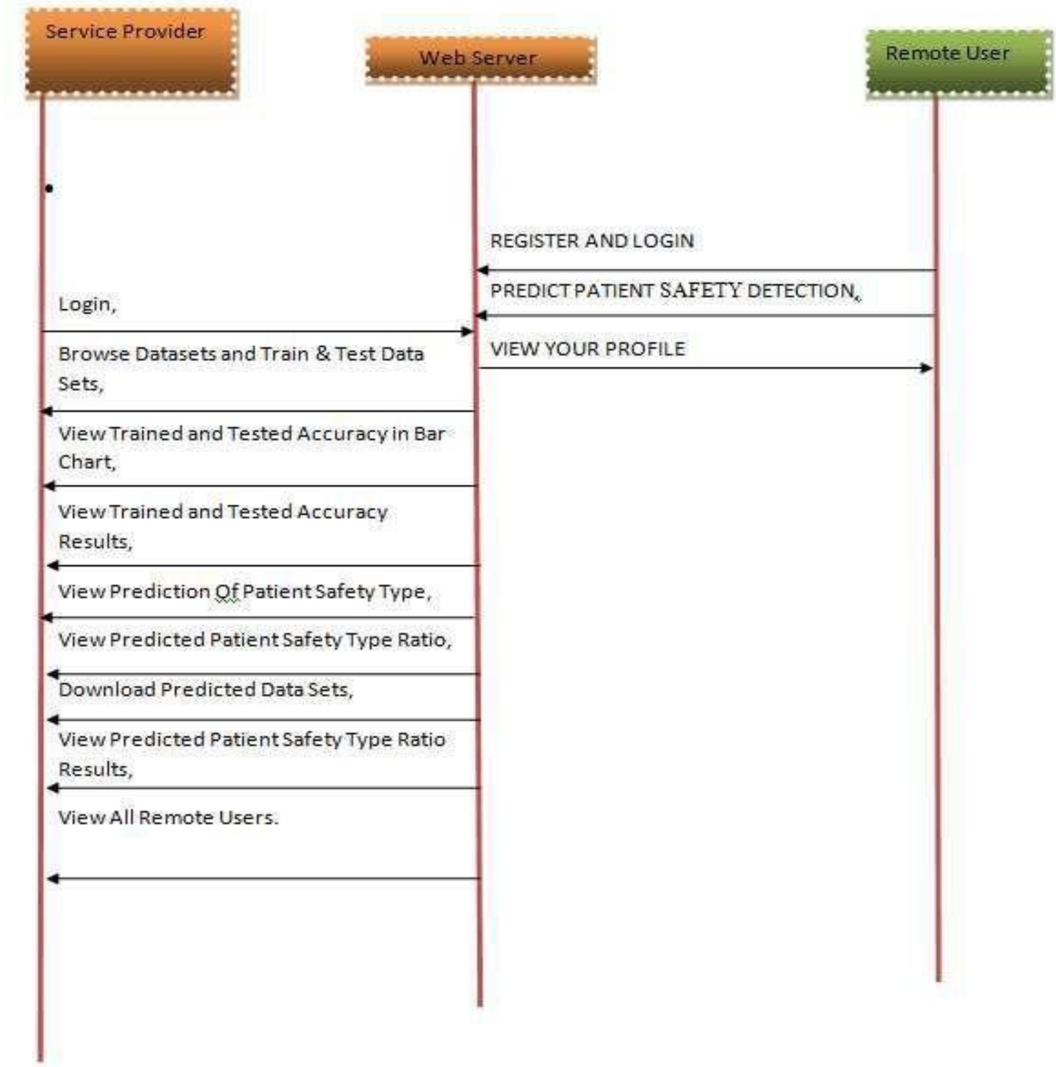
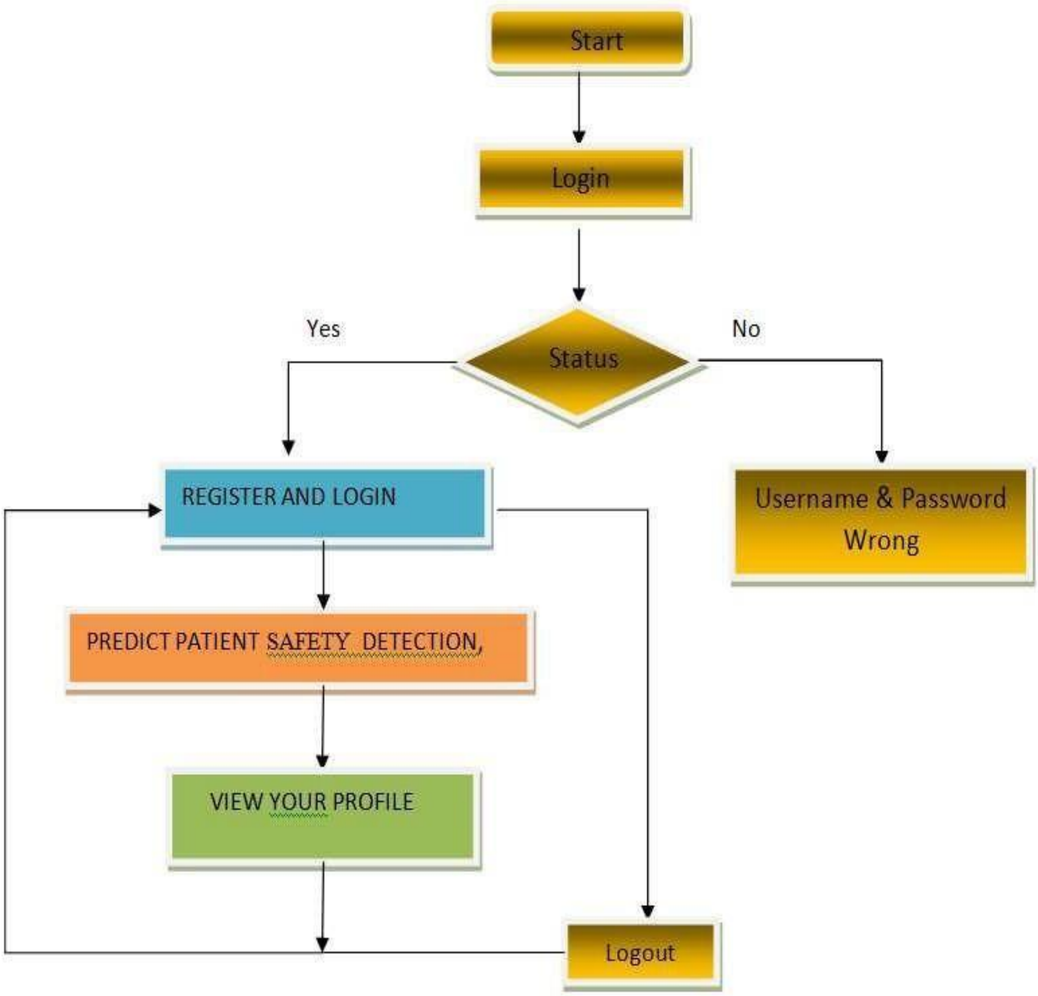


Fig. 4.4.4: Sequence Diagram

ACTIVITY DIAGRAM

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control



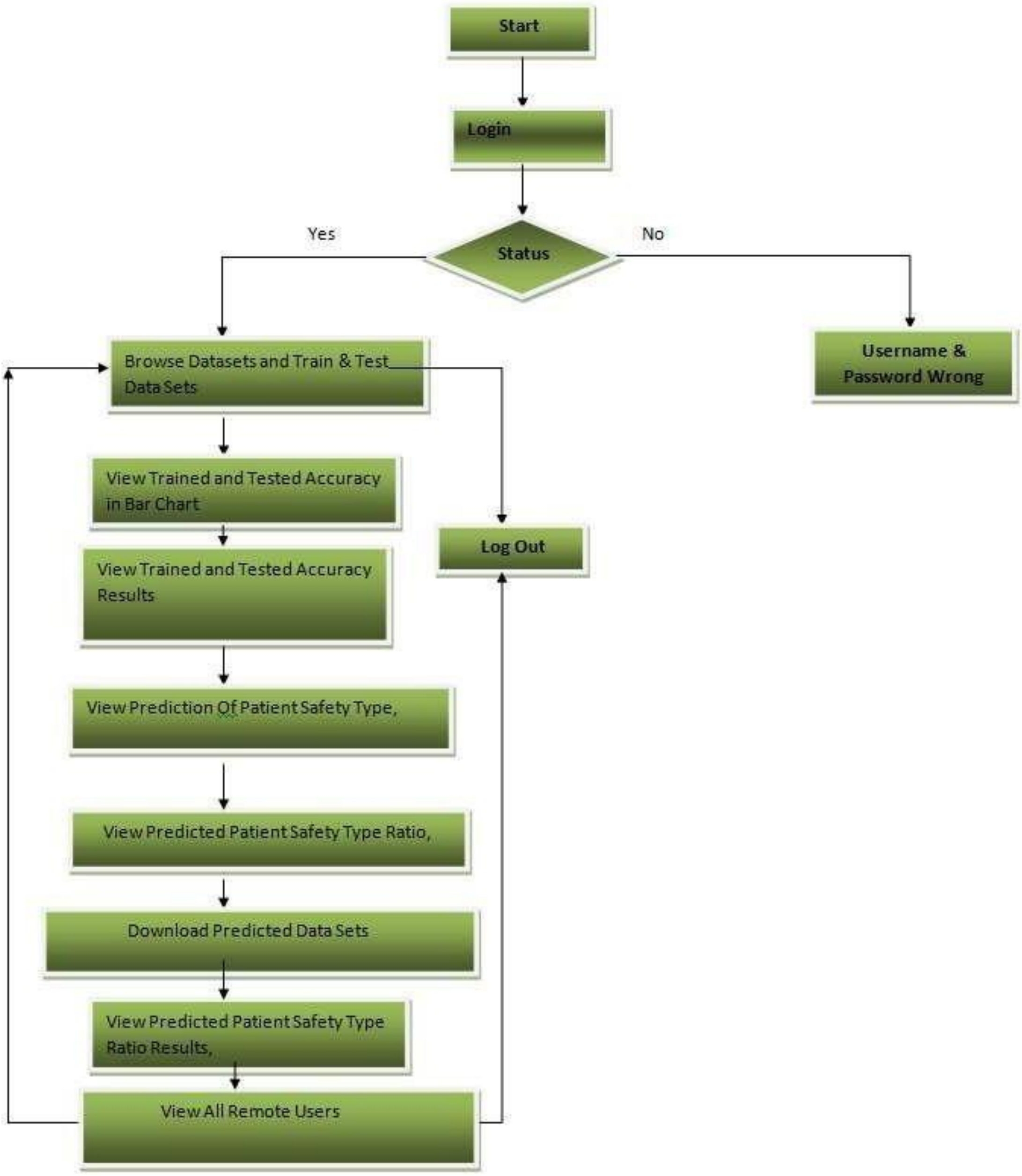


Fig. 4.4.5: Activity Diagram

CHAPTER-5

METHODOLOGY

5.1 MODULE DESCRIPTION:

Service Provider

- In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Browse Datasets and Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results, View Prediction Of Patient Safety Type, View Predicted Patient Safety Type Ratio,Download Predicted Data Sets, View Predicted Patient Safety Type Ratio Results, View All Remote Users

Train and Test Model

- In this module, the service provider split the Used dataset into train and test data of ratio 70 % and 30 % respectively. The 70% of the data is consider as train data which is used to train the model and 30% of the data is consider as test which is used to test the model

Remote User

- ü In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT PATIENT SAFETY DETECTION, VIEW YOUR PROFILE.

Classification

- In this module, user enter data and classify them using tested machine learning models.

5.2 Algorithm

Support Vector Machine

- In machine learning, support-vector machines (SVMs, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data for classification and regression analysis. An SVM training algorithm builds a model that assigns new examples to one category or the other, making it a non-probabilistic binary linear classifier.

Gradient Boosting Classifier

- Gradient Boosting is a powerful boosting algorithm that combines several weak learners into strong learners, in which each new model is trained to minimize the loss function such as mean squared error or cross-entropy of the previous model using gradient descent. In each iteration, the algorithm computes the gradient of the loss function with respect to the predictions of the current ensemble and then trains a new weak model to minimize this gradient. The predictions of the new model are then added to the ensemble, and the process is repeated until a stopping criterion is met.

Random forest

- It generates multi decision trees from which each decision tree uses a part of data sample and predicts the result.
- Then the result which was achieved by maximum number of trees is considered as the final prediction.
- Random forest is a Supervised Learning algorithm which uses ensemble learning method for classification and regression. Random forest is a bagging technique and the trees in random forests run in parallel without any interactions.
- A Random Forest operates by constructing several decision trees during training time and outputting the mean of the classes as the prediction of all the trees.

Decision Tree

- Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems.
- It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.
- It is a graphical representation for all the possible solutions to a problem/decision based on given conditions.

Logistic Regression

- Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables.
- Logistic regression predicts the output of a categorical dependent variable. Therefore the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, **it gives the probabilistic values which lie between 0 and 1.**

5.3 TEST CASES

TC. No	Test Case	Input	Expected Output	Observed Output	Result
1	Login	Enter Wrong User Name and Password	Invalid Login Details	User name and Password are invalid	Pass
2	Login	Enter User Name and Password	Login Successful	Login Successful	Pass
3	Mobile Number	Enter Alphanumeric characters	Mobile number must be digits only	Mobile number in 10 digits only	Fail
4	Upload file	Browse file	file uploaded successfully	file Uploaded successful	**Pass**

CHAPTER-6
RESULTS & DISSCUSSIONS

RESULTS & DISSCUSSIONS

Code:

```
from django.db.models import Count, Avg from django.shortcuts import render, redirect from django.db.models import Count from django.db.models import Q import datetime import xlwt from django.http import HttpResponse
import pandas as pd from sklearn.feature_extraction.text import CountVectorizer from sklearn.metrics import accuracy_score, confusion_matrix, classification_report from sklearn.metrics import accuracy_score from sklearn.tree import DecisionTreeClassifier
# Create your views here.
from Remote_User.models import
ClientRegister_Model,predict_safety,detection_ratio,detection_a ccuracy
def serviceproviderlogin(request): if request.method == "POST": admin = request.POST.get('username') password = request.POST.get('password') if admin == "Admin" and password =="Admin": detection_accuracy.objects.all().delete() return redirect('View_Remote_Users')
return render(request,'SProvider/serviceproviderlogin.html')
def
View_Prediction_Of_Patient_Safety_Detection_Ratio(request):
detection_ratio.objects.all().delete() ratio = "" kword = 'No Safety' print(kword) obj = predict_safety.objects.all().filter(Q(Prediction=kword)) obj1 = predict_safety.objects.all()
count = obj.count(); count1 = obj1.count(); ratio = (count / count1) * 100 if ratio != 0:
detection_ratio.objects.create(names=kword, ratio=ratio)
ratio12 = "" kword12 = 'Safety' print(kword12)
obj12 =
predict_safety.objects.all().filter(Q(Prediction=kword12)) obj112 = predict_safety.objects.all() count12 = obj12.count(); count112 = obj112.count(); ratio12 = (count12 / count112) * 100 if ratio12 != 0:
detection_ratio.objects.create(names=kword12,
ratio=ratio12)
obj = detection_ratio.objects.all() return render(request,
'SProvider/View_Prediction_Of_Patient_Safety_Detection_Rati o.html', {'objs': obj})
def View_Remote_Users(request):
obj=ClientRegister_Model.objects.all() return
```

```
render(request,'SProvider/View_Remote_Users.html',{'objects': obj})
def charts(request,chart_type):
chart1 =
detection_ratio.objects.values('names').annotate(dcount=Avg('r atio'))
return render(request,"SProvider/charts.html", {'form':chart1, 'chart_type':chart_type})
def charts1(request,chart_type):
chart1 = detection_accuracy.objects.values('names').annotate(dcount=Av g('ratio'))
return render(request,"SProvider/charts1.html",
{'form':chart1, 'chart_type':chart_type})
def View_Prediction_Of_Patient_Safety_Detection(request):
obj =predict_safety.objects.all() return render(request,
'SProvider/View_Prediction_Of_Patient_Safety_Detection.html',
{'list_objects': obj})
def likeschart(request,like_chart):
charts
=detection_accuracy.objects.values('names').annotate(dcount=A vg('ratio'))
return render(request,"SProvider/likeschart.html",
{'form':charts, 'like_chart':like_chart})
def Download_Predicted_DataSets(request):
response = HttpResponse(content_type='application/ms-excel')
# decide file name response['Content-Disposition'] = 'attachment;
filename="Predicted_Datasets.xls"'
# creating workbook wb = xlwt.Workbook(encoding='utf-8')
# adding sheet ws = wb.add_sheet("sheet1") # Sheet header, first row row_num = 0
font_style = xlwt.XFStyle() # headers are bold font_style.font.bold = True # writer = csv.writer(response) obj = predict_safety.objects.all() data = obj # dummy method to fetch data. for my_row in data:
row_num = row_num + 1
ws.write(row_num, 0, my_row.Fid, font_style) ws.write(row_num, 1, my_row.Drug1_Name, font_style) ws.write(row_num, 2, my_row.Drug1_Condition, font_style) ws.write(row_num, 3, my_row.Drug2_Name, font_style) ws.write(row_num, 4, my_row.Drug2_Condition, font_style) ws.write(row_num, 5, my_row.Patient_Gender, font_style) ws.write(row_num, 6, my_row.Patient_Age, font_style) ws.write(row_num, 7,
```

```
my_row.Area, font_style) ws.write(row_num, 8, my_row.Drug1_To_Drug2_Response,
font_style) ws.write(row_num, 9, my_row.Prediction, font_style)
wb.save(response) return response def train_model(request):
detection_accuracy.objects.all().delete()
df = pd.read_csv('Datasets.csv')
def apply_response(Label):
if (Label == 0):
return 0 # Safety
elif (Label == 1):
return 1 # No Safety
df['results'] = df['Safety_Label'].apply(apply_response)
X = df['Fid'] y = df['results']
print("FID") print(X) print("Results") print(y)
cv = CountVectorizer() X = cv.fit_transform(X)
models = [] from sklearn.model_selection import train_test_split X_train, X_test, y_train,
y_test = train_test_split(X, y, test_size=0.20)
X_train.shape, X_test.shape, y_train.shape
print("Deep Neural Network (DNN)")
from sklearn.neural_network import MLPClassifier mlpc = MLPClassifier().fit(X_train,
y_train) y_pred = mlpc.predict(X_test) print("ACCURACY")
print(accuracy_score(y_test, y_pred) * 100) print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, y_pred)) models.append(('MLPClassifier', mlpc))
detection_accuracy.objects.create(names="Deep Neural
Network (DNN)", ratio=accuracy_score(y_test, y_pred) *
100)
# SVM Model
print("SVM") from sklearn import svm lin_clf = svm.LinearSVC() lin_clf.fit(X_train,
y_train) predict_svm = lin_clf.predict(X_test) svm_acc = accuracy_score(y_test,
predict_svm) * 100 print(svm_acc)
print("CLASSIFICATION REPORT")
print(classification_report(y_test, predict_svm))
print("CONFUSION MATRIX")
```

```
print(confusion_matrix(y_test, predict_svm)) models.append(('svm', lin_clf))
detection_accuracy.objects.create(names="SVM",
ratio=svm_acc)
print("Logistic Regression")
from sklearn.linear_model import LogisticRegression reg =
LogisticRegression(random_state=0,
solver='lbfgs').fit(X_train, y_train)
y_pred = reg.predict(X_test) print("ACCURACY")
print(accuracy_score(y_test, y_pred) * 100) print("CLASSIFICATION REPORT")
print(classification_report(y_test, y_pred))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, y_pred)) models.append(('logistic', reg))
detection_accuracy.objects.create(names="Logistic
Regression", ratio=accuracy_score(y_test, y_pred) * 100) print("Gradient Boosting
Classifier")
from sklearn.ensemble import GradientBoostingClassifier clf =
GradientBoostingClassifier(n_estimators=100,
learning_rate=1.0, max_depth=1, random_state=0).fit( X_train, y_train)
clfpredict = clf.predict(X_test) print("ACCURACY")
print(accuracy_score(y_test, clfpredict) * 100) print("CLASSIFICATION REPORT")
print(classification_report(y_test, clfpredict))
print("CONFUSION MATRIX")
print(confusion_matrix(y_test, clfpredict)) models.append(('GradientBoostingClassifier',
clf)) detection_accuracy.objects.create(names="Gradient Boosting Classifier",
ratio=accuracy_score(y_test, clfpredict) *
100)
csv_format = 'Results.csv' df.to_csv(csv_format, index=False) df.to_markdown
obj = detection_accuracy.objects.all() return render(request,'SProvider/train_model.html',
{'objs': obj})
```


Home Page
127.0.0.1:8000
Explainable Artificial Intelligence for Patient Safety A Review of Application in Pharmacovigilance
Home| Remote User | Service Provider
PATIENT SAFETY &
QUALITY IS OUR KEY PRIORITY
Machine learning, pharmacovigilance, explainable artificial intelligence..
Search
ENG
INTL
19:35
24-03-2025

FIG6.1:

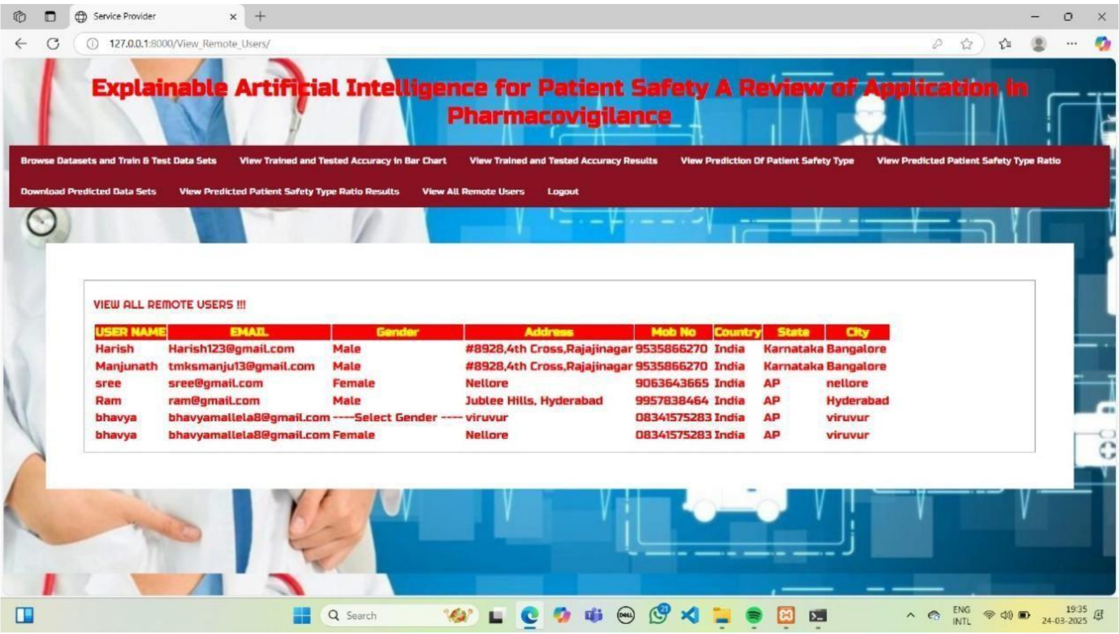

Service Provider
127.0.0.1:8000/View_Remote_Users/
Explainable Artificial Intelligence for Patient Safety A Review of Application in Pharmacovigilance
Browse Datasets and Train & Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
View Prediction Of Patient Safety Type
View Predicted Patient Safety Type Ratio
Download Predicted Data Sets
View Predicted Patient Safety Type Ratio Results
View All Remote Users
Logout
VIEW ALL REMOTE USERS !!!
USER NAME EMAIL Gender Address Mob No Country State City
Harish Harish123@gmail.com Male #8928,4th Cross,Rajajinagar 9535866270 India Karnataka Bangalore
Manjunath tmksmanju13@gmail.com Male #8928,4th Cross,Rajajinagar 9535866270 India Karnataka Bangalore
sree sree@gmail.com Female Nellore 9063643665 India AP nellore
Ram ram@gmail.com Male Jublee Hills, Hyderabad 9957838464 India AP Hyderabad
bhavya bhavyamallela8@gmail.com ----Select Gender ---- viruvur 08341575283 India AP viruvur
bhavya bhavyamallela8@gmail.com Female Nellore 08341575283 India AP viruvur
Search
ENG
INTL
19:35
24-03-2025

FIG 6.2:

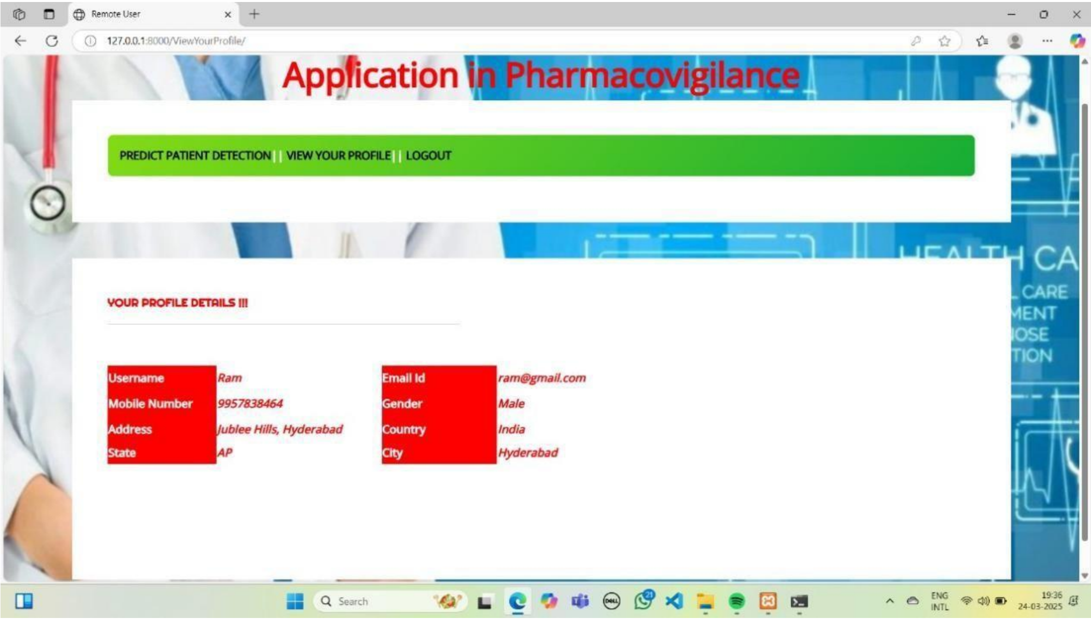

Remote User
127.0.0.1:8000/ViewYourProfile/
Application in Pharmacovigilance
PREDICT PATIENT DETECTION || VIEW YOUR PROFILE || LOGOUT
YOUR PROFILE DETAILS !!!
Username
Ram
Mobile Number
9957838464
Address
Jublee Hills, Hyderabad
State
AP
Email Id
ram@gmail.com
Gender
Male
Country
India
City
Hyderabad

FIG 6.3:

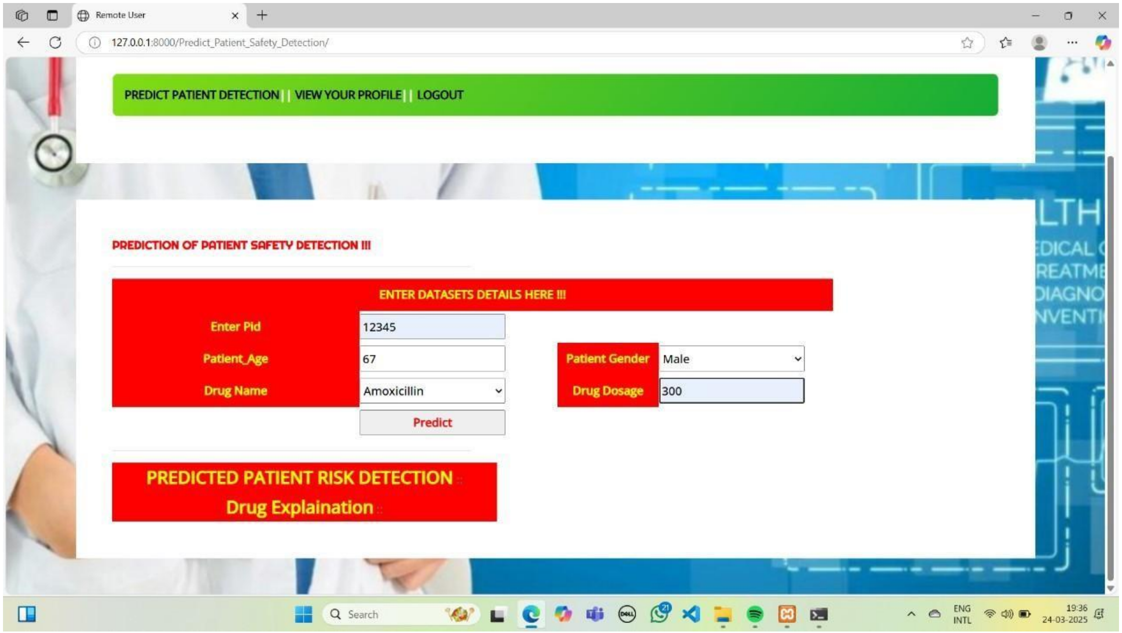

Remote User
127.0.0.1:8000/Predict_Patient_Safety_Detection/
PREDICT PATIENT DETECTION || VIEW YOUR PROFILE || LOGOUT
PREDICTION OF PATIENT SAFETY DETECTION !!!
ENTER DATASETS DETAILS HERE !!!
Enter Pid
12345
Patient_Age
67
Drug Name
Amoxicillin
Patient Gender
Male
Drug Dosage
300
Predict
PREDICTED PATIENT RISK DETECTION
Drug Explaination

FIG 6.4:

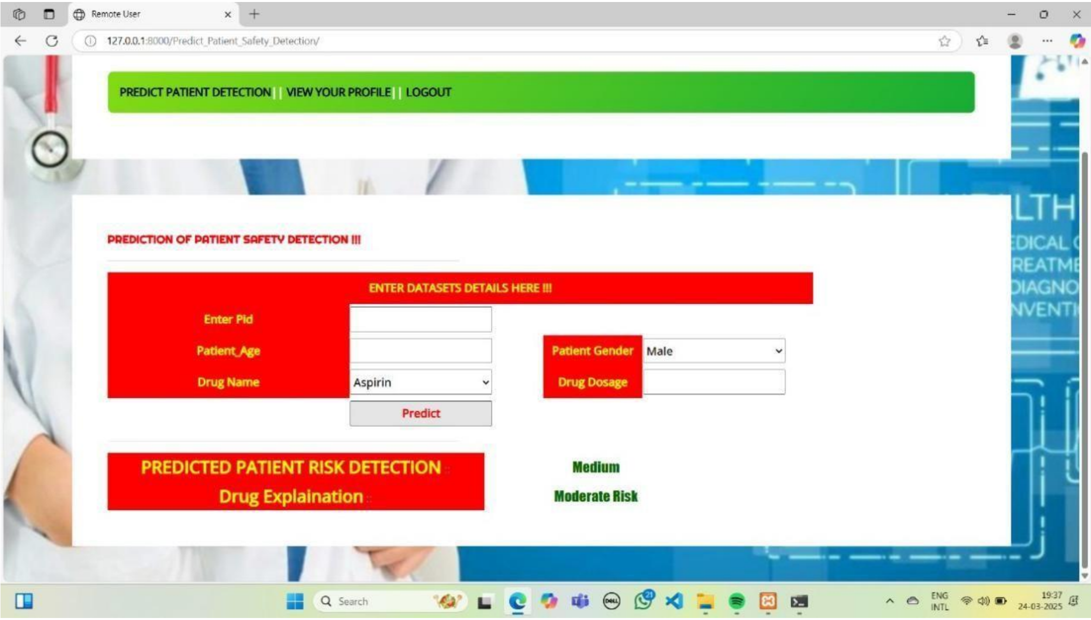

Remote User
127.0.0.1:8000/Predict_Patient_Safety_Detection/
PREDICT PATIENT DETECTION || VIEW YOUR PROFILE || LOGOUT
PREDICTION OF PATIENT SAFETY DETECTION !!!
ENTER DATASETS DETAILS HERE !!!
Enter Pid
Patient_Age
Drug Name
Aspirin
Patient Gender
Male
Drug Dosage
Predict
PREDICTED PATIENT RISK DETECTION
Drug Explaination
Medium
Moderate Risk

FIG 6.4:

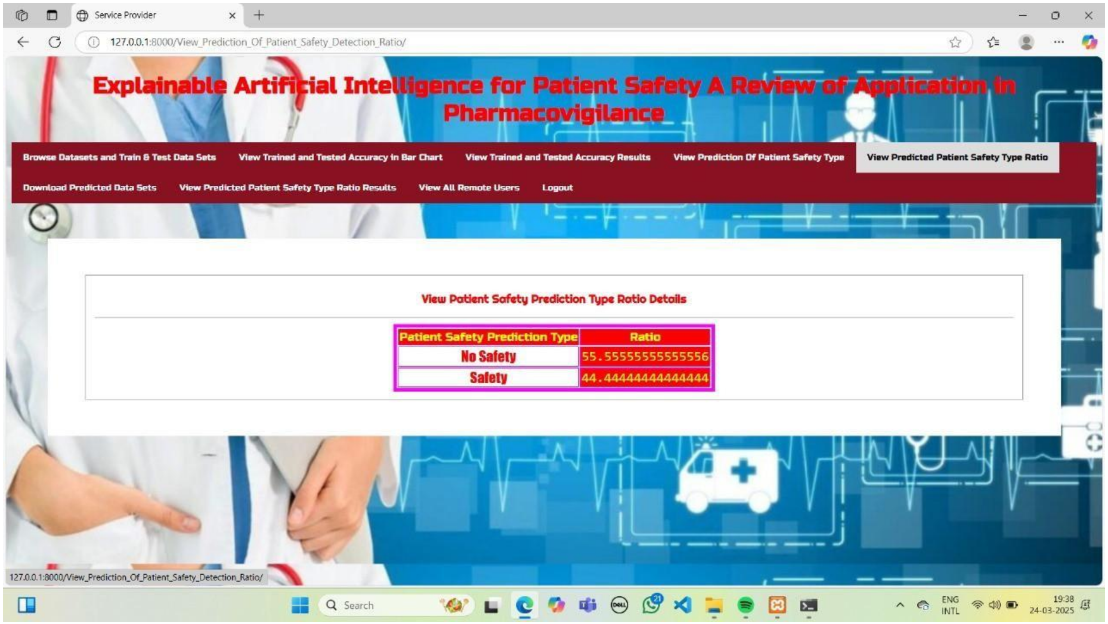

Service Provider
127.0.0.1:8000/View_Prediction_Of_Patient_Safety_Detection_Ratio/
Explainable Artificial Intelligence for Patient Safety A Review of Application in Pharmacovigilance
Browse Datasets and Train & Test Data Sets
View Trained and Tested Accuracy in Bar Chart
View Trained and Tested Accuracy Results
View Prediction Of Patient Safety Type
View Predicted Patient Safety Type Ratio
Download Predicted Data Sets
View Predicted Patient Safety Type Ratio Results
View All Remote Users
Logout
View Patient Safety Prediction Type Ratio Details
Patient Safety Prediction Type
Ratio
No Safety
55.5555555555556
Safety
44.4444444444444

FIG 6.6:

CHAPTER-7

CONCLUSION AND FUTURE SCOPE

7.1 CONCLUSION

In this study, we reviewed PV XAI papers and discussed recent research trends and the need for XAI research. Unlike other areas where XAI and AI are developing together, PV XAI research is still in its infancy. There are not many papers on PV XAI and the methodology is limited to a few models. However, studies are slowly beginning to show the potential of XAI research for medication monitoring and patient safety, collecting ADR and ADE information, extracting drug-drug interactions, and predicting drug treatment effects. As in other areas, as awareness of XAI methods grows, we expect to see AI used in pharmacyovigilance and patient safety in many more ways in the coming years than those identified in this review, and the positive potential of XAI for drug therapy, ADRs and interactions is very promising. However, it is clear that the growth of this field may be limited by the lack of validated and established uses of XAI in real-world healthcare settings, and this is an area that requires further investigation. Therefore, the challenges and future prospects of XAIs in pharmacovigilance should be discussed with continued interest

7.2 FUTURE ENHANCEMENT

In future works, we will expand the diversity of experiments in terms of devices, subjects, and environment conditions to further improve our patient safety identificatio

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