DRUG RECOMMENDATION SYSTEM BASED ON SENTIMENTAL ANALYSIS OF DRUG REVIEWS

A PROJECT REPORT

Submitted by

TEJASWINI P 211418104290
VIDHYASREE C 211418104308
VILASINI G 211418104310

in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

PANIMALAR ENGINEERING COLLEGE

(An Autonomous Institution, Affiliated to Anna University, Chennai)

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BONAFIDE CERTIFICATE

Certified that this project report **"DRUG RECOMMENDATION SYSTEM BASED ON SENTIMENTAL ANALYSIS OF DRUG REVIEWS"** is the bonafide work of "**TEJASWINI P(211418104290),VIDHYASREE C (211418104308),VILASINI G (211418104310) "** who carried out the project work under my supervision.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

DECLARATION BY THE STUDENT

We Tejaswini P(211418104290), Vidhyasree C(211418104308), Vilasini G(211418104310) hereby declare that this project report titled " Drug Recommendation system based on sentimental analysis of drug reviews" , under the guidance of Dr.K.Valarmathi is the orginial work done by us and we have not plagiarized or submitted to any other degree in any university by us.

ACKNOWLEDGEMENT

We would like to express our deep gratitude to our respected Secretary and Correspondent **Dr.P.CHINNADURAI, M.A., Ph.D.** for his kind words and enthusiastic motivation, which inspired us a lot in completing this project.

We express our sincere thanks to our Directors **Tmt.C.VIJAYARAJESWARI**, **Dr.C.SAKTHI KUMAR,M.E.,Ph.D** and **Dr.SARANYASREE SAKTHI KUMAR B.E.,M.B.A.,Ph.D.,** for providing us with the necessary facilities to undertake this project.

We also express our gratitude to our Principal **Dr.K.Mani, M.E., Ph.D.** who facilitatedus in completing the project.

We thank the Head of the CSE Department, **Dr. S.MURUGAVALLI , M.E.,Ph.D.,** for the support extended throughout the project.

We would like to thank my **Dr.K.Valarmathi** and all the faculty members of the Department of CSE for their advice and encouragement for the successful completion of the project.

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ABSTRACT

Machine learning-based drug recommendation system is based on emotive analysis of drug reviews. During the coronavirus outbreak, legitimate clinical resources were in low supply, such as specialists and healthcare workers, as well as suitable equipment and medicines. Individuals are dying because the entire medical society is under trouble. The number of doctors cannot be increased quickly. As a result, people began taking medications without contacting a doctor. This aggravated the situation. In this tough period, a telemedicine system should be activated as quickly as feasible. Machine Learning has more useful applications and creative work in the automation field. The goal of this project is to create a medicine recommendation system that will lessen the workload of specialists. Medicine recommendation system leverages patient evaluations to predict sentiment using various vectorization methods such as BOW, TF-IDF, and Word2Vec, and then employs multiple algorithms to assist patients in selecting the best drug for a certain ailment. The drug recommender system uses sentiment analysis and feature engineering to prescribe medication based on patient reviews. Sentiment analysis is a set of tactics, methods, and tools for detecting and extracting emotional information from text . Feature engineering is the process of creating extra features from existing ones, with the goal of improving model performance. Precision, recall, f1score, accuracy, and AUC score were used to evaluate the anticipated sentiments. This result is 93% accurate.

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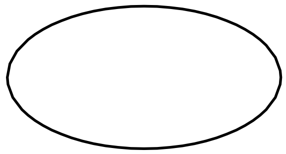
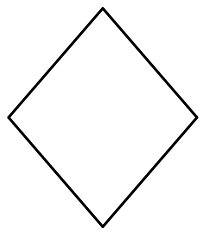
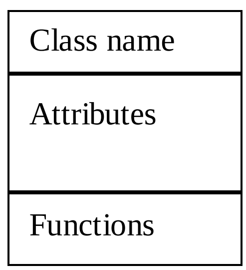
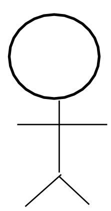
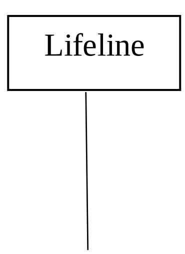
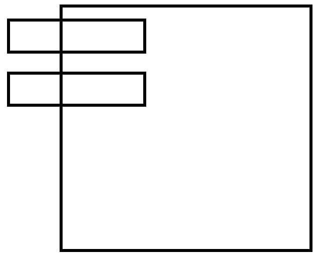
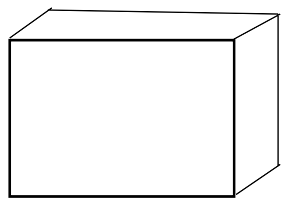
LIST OF SYMBOLS

Symbol Name	Symbol	Description
Entity		An entity is represented by a rectangle which contains the entity's name.
Attribute		In the Chen notation, each attribute is represented by an oval containing attribute's name
Strong Relationship		A relationship where entity is existence-independent of other entities, and PK of Child doesn't contain PK component of Parent Entity.
Class		Represents a collection of similar entities grouped together.
Actor		It aggregates several classes into a single classes.
Lifeline		To visualize the message flow between various components of a system.

State		State of the process.
Component		Represents physical modules which is a collection of components.
Node		Represents physical modules which are a collection of components

LIST OF ABBREVIATIONS

S.NO	ABBREVIATION	EXPANSION
1.	BOW	Bag of words. It is an algorithm used in natural language processing responsible for counting the number of times of all the tokens in review or document.
2.	TF-IDF	Term Frequency-Inverse DocumentFrequency. It assigns a value to a term according to its importance in a document.
3.	Word2Vec	Word to Vector. It is used to produce word embedding.
4.	SVM	It is used for Classification as well as Regression problems.

1. INTRODUCTION

Since the number of coronavirus infections is rapidly increasing, the countries are experiencing a doctor shortage, particularly in rural areas when compared to urban ones. Clinical errors are common these days. Every year, medication errors harm around 200 thousand people in China and 100 thousand in the United States. Over 40% of doctors make mistakes while prescribing because they are guided by their knowledge . Patients who require doctors with broad knowledge of microscopic organisms, antibacterial drugs, and patients require top-level medication . Every day, a new study uncovers new medications and testing. This makes it more difficult for doctors to determine treatment or drugs for a patient based on their symptoms. Item reviews have grown increasingly significant as the internet and web-based technology have evolved.

Individuals have become accustomed to reading reviews and visiting websites before making a purchasing decision. The number of people concerned about their health and looking for answers online. According to a Pew American Research Center survey conducted in 2013, 60 percent of adults searched online for health-related topics, and 35 percent searched for diagnosing health disorders. A medication recommender framework is required in order for specialists or doctors to aid patients in expanding their understanding of medications for certain health concerns.These frameworks use customer surveys to break down their feelings and make recommendations tailored to their specific requirements.

The drug recommender system uses sentiment analysis andfeature engineering to offer drugs based on a specific condition. Sentiment analysis is aset of tactics, methods, and instruments for recognising and extracting emotional information. Five sections of examination work: The introduction section gives a briefoverview of why this research is needed. The related works section provides a succinctoverview of past studies in this field, while the methodology section details the methodsused in this study. The Result section examines model results using multiple metrics, while the discussion part discusses the framework's constraints.

1.1 PROBLEM DEFINITION

The true utility for today's patience is a drug that can entertain them or send them a message in their social lives. Patients just spend money by consuming drugs that are ineffective, and the awards granted to drugs are based on a numerical rating given by consumers. However, a method is required to determine the drug's weight age in terms of direction and production.

2. LITERATURE SURVEY

Intends to provide a medicine recommendation system that will significantly minimise the number of specialists needed. In this study, medicine recommendation system that uses patient reviews to predict sentiment using various vectorization processes such as Bow, TF-IDF, Word2Vec, and Manual Feature Analysis, which can help different classification algorithms recommend the best drug for a given disease. Precision, recall, f1score, accuracy, and AUC score were used to analyse the results, which revealed that the Linear SVC on TF-IDF outperforms all other models by 93 percent.[1]

A health technology assessment is a multidisciplinary strategy to systematically and thoroughly evaluating medical and social issues associated to the usage of a health technology. Surveillance of social media platforms can provide vital information to the clinical community and decision makers on the effectiveness and safety of using health technologies on a patient, which can aid HTA recommendations.[2]

The majority of related feature selection strategies for sentiment classification are unable to overcome issues with evaluating significant features, which lower classification performance. This research provides an improved hybrid feature selection technique based on machine learning approaches to improve sentiment categorization. Finally, the suggested technique's performance is evaluated using the Support Vector Machine (SVM) classifier. The accuracy, precision, recall, and F-measure are used to evaluate the performance.[3]

Sentiment analysis is a research topic that involves categorising these views, opinions, and remarks. Researchers are currently investigating sentiment quantification, which deals with calculating relative frequency of a class of interest under the umbrella of sentiment analysis.[4]

Sentiment Analysis (SA) is concerned with extracting sentiment (identification and classification) from unstructured text data such as product evaluations and microblogs. The use of supervised machine learning (SML), a method that employs datasets with predetermined class labels based on mathematical learning from a training dataset, is one of the most popular approaches for SA. To detect similarities and differences between the train and actual datasets, the Tree Similarity Index (TSI) and Tree Differences Index (TDI), a formula generated from tree structure, have been proposed.[5]

We use supervised machine learning algorithms to develop and compare the performance of five classifiers for categorization issues. The top performing classifier was then used to predict the sentiment polarity of reviews, with an F1-score of 89.42 percent. Then, using a thematic analysis of positive and negative evaluations, we find themes that represent numerous aspects that influence the effectiveness of mental health apps in both positive and negative ways.[6]

The usefulness of various sentiment categorization strategies, ranging from simple rule-based and lexicon-based approaches to more advanced machine learning algorithms, has been detailed in recent studies. Machine learning approaches have fallen short in terms of accuracy, while lexicon-based systems have suffered from a shortage of dictionaries and labelled data. This research presents an integrated framework for improving accuracy and scalability by bridging the gap between lexicon-based and machine learning approaches.[7]

The current research looks at how sentiment analysis can be used in language acquisition. We built RESOLVE, a context-aware emotion synonym suggesting system for educational purposes, to achieve this goal. Importantly, the usage information for each emotion term is provided, including situation descriptions, definitions, and example sentences, in order to aid vocabulary development and word use.[8]

The pharmaceuticals given in appropriate medical items suitable for the patient's current diagnostic are the foundation of effective pharmacotherapy. The fuzzy method to healthcare database analysis is a new tool for generating information that may be used in the ultimate decision-making process of drug selection in medical practise for a defined polymorbid group of patients.[9]

Naive Bayes and Recurrent Neural Networks were used to accomplish multilingual sentiment analysis in this study (RNN). The data show that RNN outperformed Naive Bayes 95.34 percent of the time .[10]

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

Many recommender systems use collaborative filtering (CF) as a successful strategy. The ratings provided to objects by users are the sole source of information for learning to produce recommendations in traditional CF-based techniques. However, in many applications, the ratings are typically relatively sparse, causing CF-based algorithms to severely decrease their recommendation performance. Deep neural networks have seen tremendous success in speech recognition, computer vision, and natural language processing in recent years. The use of deep neural networks in recommender systems, on the other hand, has gotten less attention.

3.2 PROPOSED SYSTEM

We want to create neural network-based solutions to address the key challenge of recommendation via collaborative filtering with implicit feedback in this project. The algorithm will first obtain Drug reviews from the supplied URL, then parse and sanitise the reviews. For each review of the Drug, determine the positive and negative polarity. The Drug is then graded on the various aspects again, and the overall sentiment distribution of the Drug is provided. We create aesthetically beautiful and easy-to-understand graphs that provide summarised feedback using a combination of data aggregation techniques, NLP, linguistic analysis, and popular visualisation approaches. This is accomplished through a thorough sentiment analysis of the data.

3.3 FEASIBILITY STUDY

MARKET FEASIBILITY

Drug recommender system can sustain in a medicine market and it is capable of generating financial surplus for the firm.

SOCIAL FEASIBILITY

Social feasibility can be attained through drug recommender system. The system can help the patients to get the exact review for each drug based on health issues . Thus, it is accepted by all patients and the best product to be launched.

SCHEDULE FEASIBILITY

The proposed system can be completed within two months of time. The system required atleast three reviews for the betterment.

TECHNICAL FEASIBILITY

The hardware requirements for the proposed system are i3 processor with minimum storage capacity of 500GB. The software requirements for the proposed system are Windows 10 operating system and Jupyter Notebook.

3.4 HARDWARE REQUIREMENTS

2GB RAM

Touchpad/Mouse

3GB Disk Space

3.5 SOFTWARE REQUIREMENTS

Debian Linux OS/Windows OS Atom

Coding Language : Python 3.8

Browser

Terminal MySQL

Sqlite Studio Django, HTML, CSS, Bootstrap, Javascript

SYSTEM DESIGN

4.1 ER DIAGRAM

An Entity Relationship (ER) Diagram is a type of flowchart that illustrates how “entities” such as people, objects or concepts relate to each other within a system. ER Diagrams are most often used to design or debug relational databases in the fields of software engineering, business information systems, education and research. Also known as ERDs or ER Models, they use a defined set of symbols such as rectangles, diamonds, ovals and connecting lines to depict the interconnectedness of entities, relationships and their attributes.

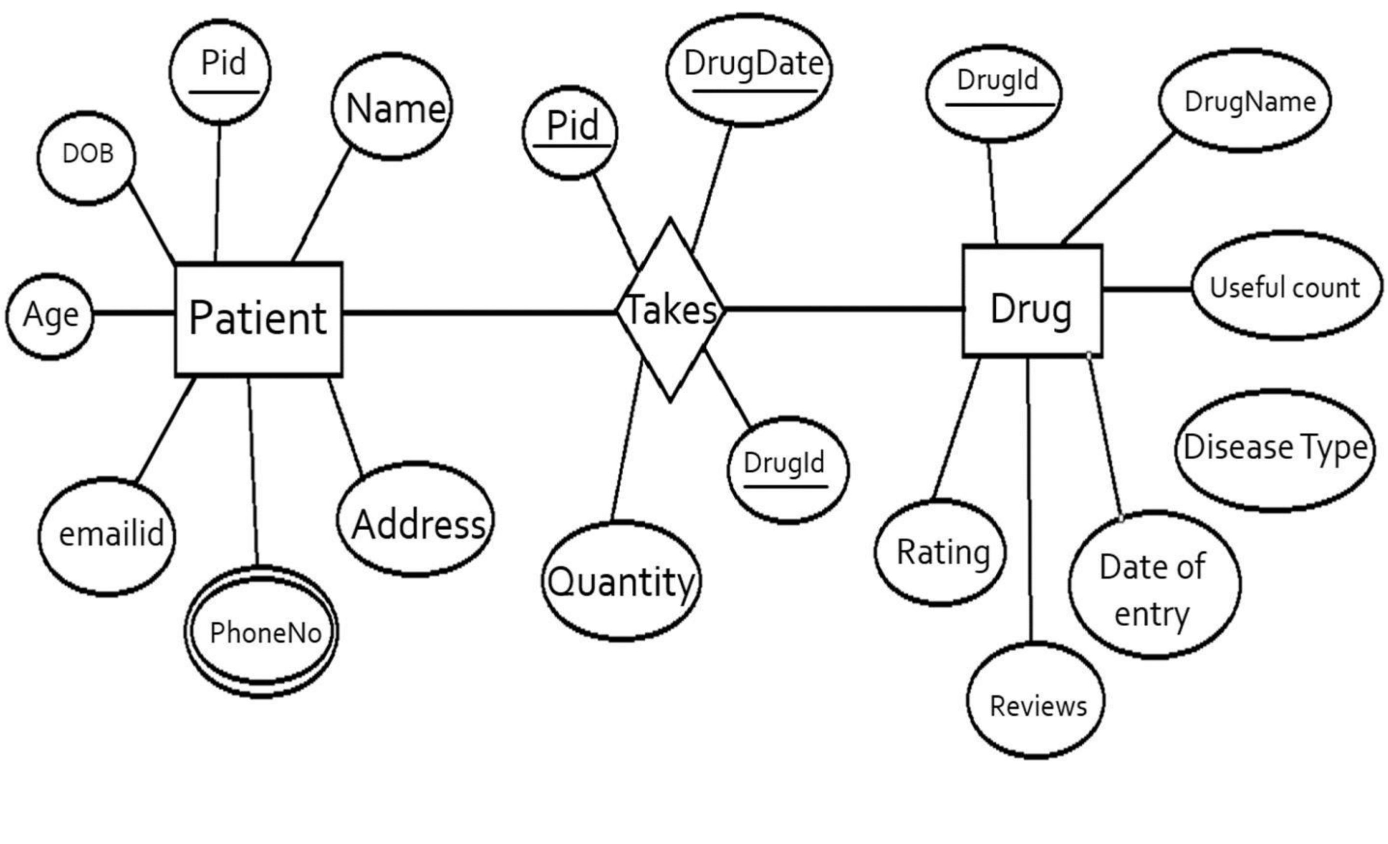


Figure 4.1.1 ER Diagram

4.2 DATA DICTIONARY

4.2.1 PATIENT TABLE

Table Name : Patient

Primary key : PatientId

Description : This table identifies full detail of patient.

TABLE 4.2.1 PATIENT TABLE

Fields	Datatype	Description
PatientId	bigint	AutoNumber
PatientName	varchar	It identifies patient name
Age	int	It identifies patient age
Address	varchar	Address of patient
EmailId	varchar	Mail Id of patient

4.2.2 ADMIN TABLE

Table Name : Admin

Primary key : UserId

Description : This table helps the user to login into the System.

TABLE 4.2.2 ADMIN TABLE

Fields	Datatype	Description
UserId	bigint	AutoNumber
UserName	varchar	It identifies username
Password	varchar	It identifies password
EmailId	varchar	It identifies Email Id

4.2.3 DRUG TABLE

**Table Name : **Drug

**PrimaryId : **DrugId

**Description : **This table identifies the full detail of the drug.

TABLE 4.2.3 DRUG TABLE

Fields	**Datatype**	**Description**
DrugId	bigint	AutoNumber
DrugName	varchar	It identifies drugname
Patient review	varchar	Patient review for particular drugs
Patient condition	varchar	It identifies disease
Count	int	Provides useful count of drug
Date of review	datetime	When the review was entered by patient
Rating	int	10 – star rating

\\

4.2 DATA FLOW DIAGRAM

A data flow diagram (DFD) depicts the "flow" of data through an information system graphically. It varies from a flowchart in that it depicts the data flow rather than the program's control flow. A data flow diagram can be used to visualise data processing as well. The DFD is used to illustrate how a system is broken down into smaller sections and how data flows between them.

LEVEL 0 DFD DIAGRAM

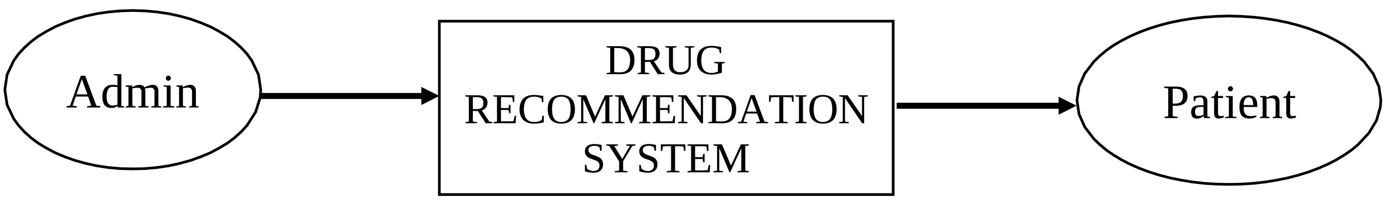


Figure 4.3.1 Zero Level DFD

LEVEL 1 DFD DIAGRAM

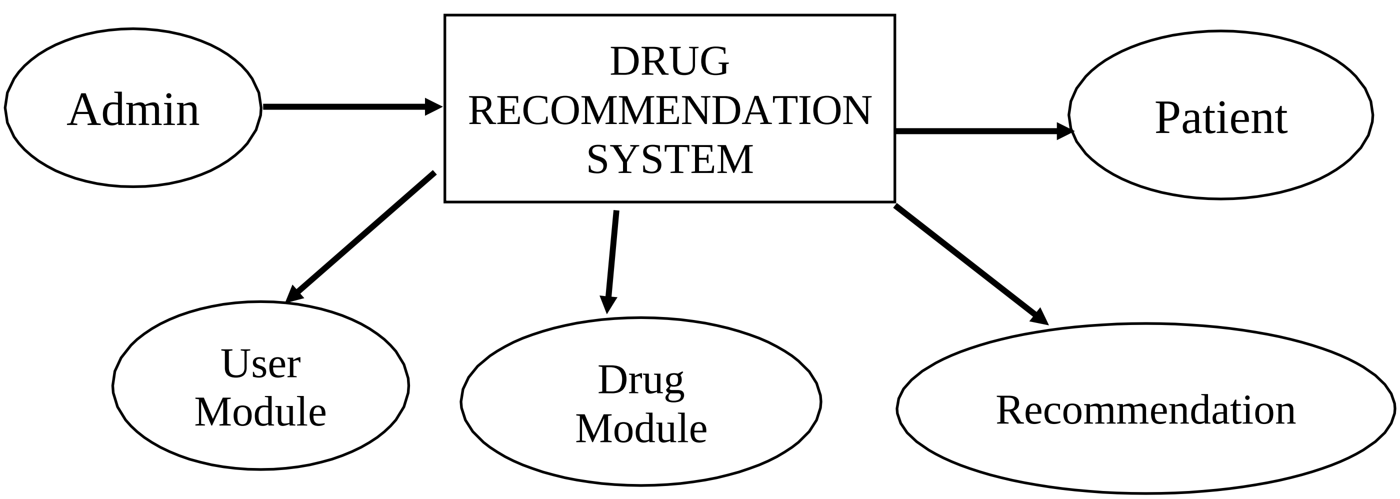


Figure 4.3.2 First Level DFD

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LEVEL 2 DFD DIAGRAM

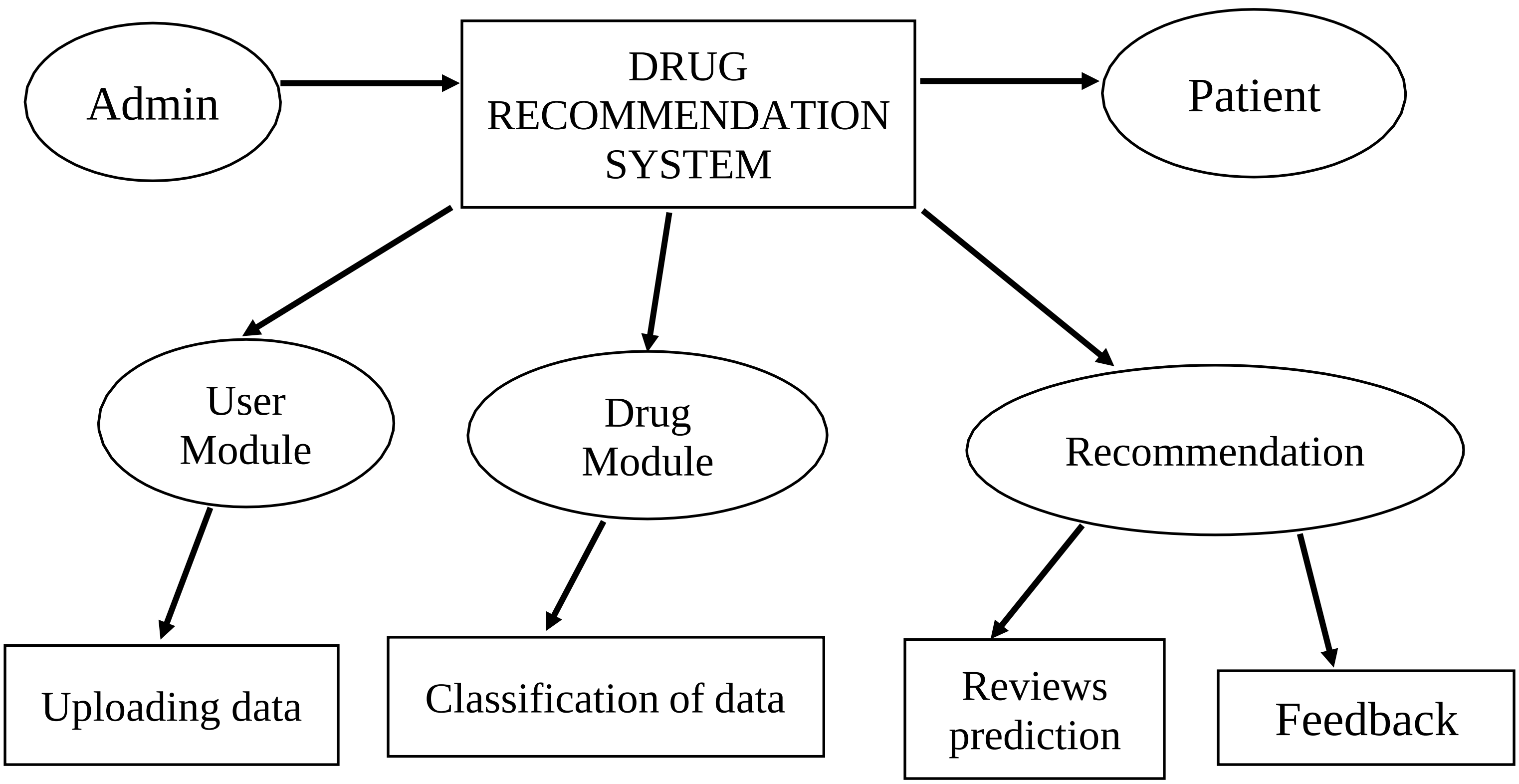

Figure 4.3.3 Second Level DFD

4.3 UML DIAGRAMS

USECASE DIAGRAM

A use case diagram at its simplest is a representation of a user's interaction with the system that shows the relationship between the user and the different use cases in which the user is involved. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well. The use cases are represented by either circles or ellipses.

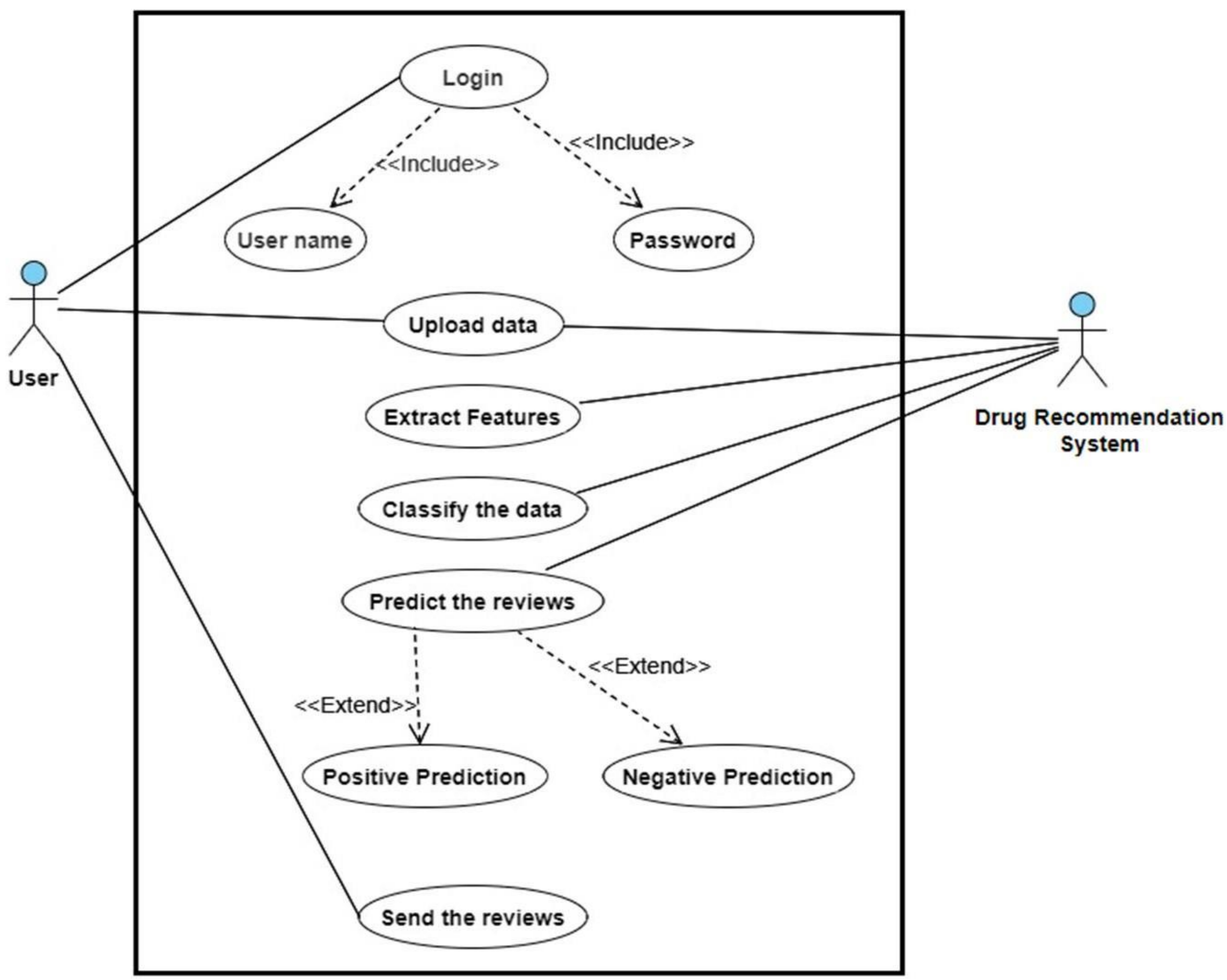

Figure 4.4.1 Usecase Diagram

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CLASS DIAGRAM

A Class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects. The class diagram is the main building block of object-oriented modeling. Class diagrams can also be used for data modeling.

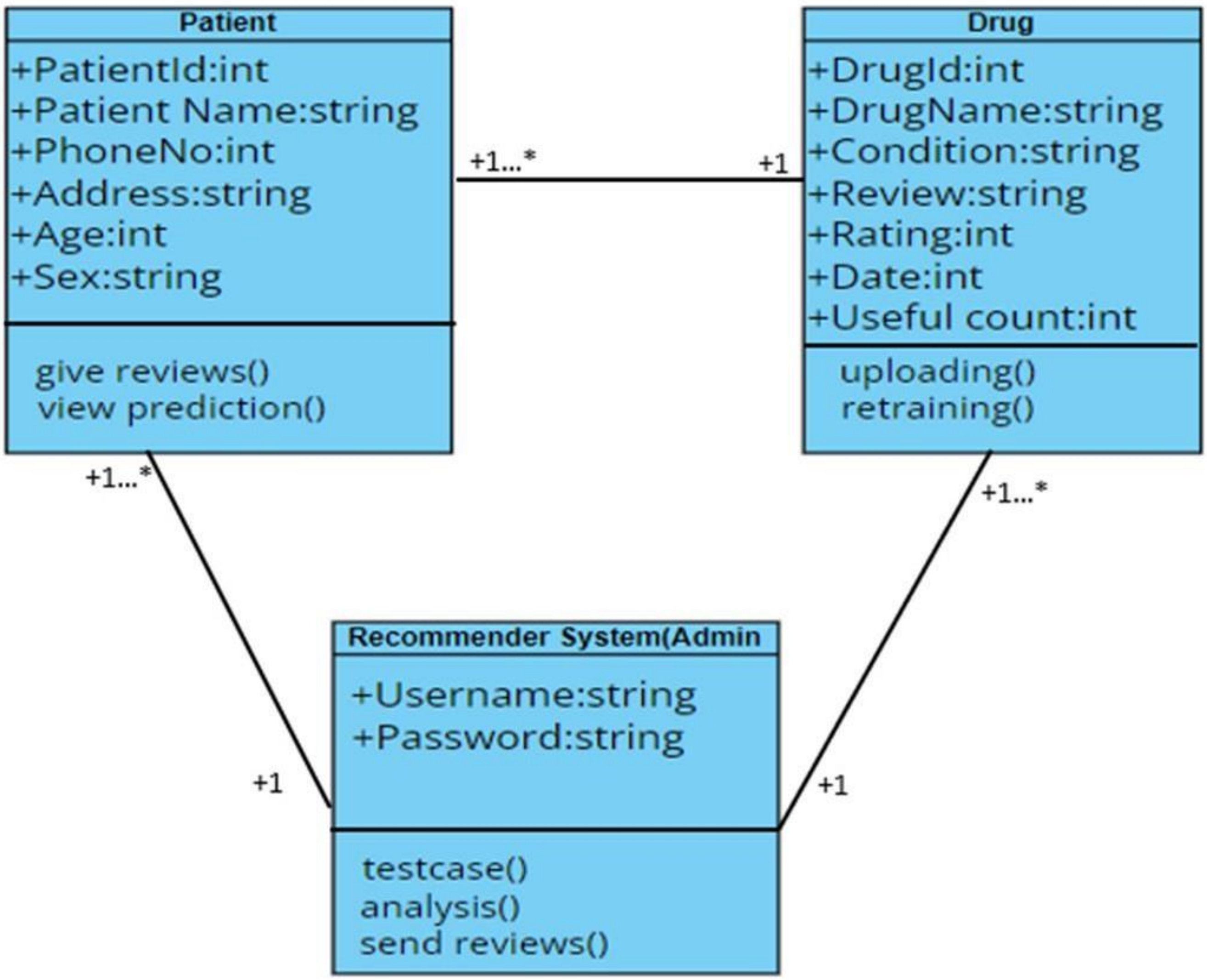

Figure 4.4.2 Class diagram

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SEQUENCE DIAGRAM

A sequence diagram shows object interactions arranged in time sequence. It depicts theobjects involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams or event scenarios.

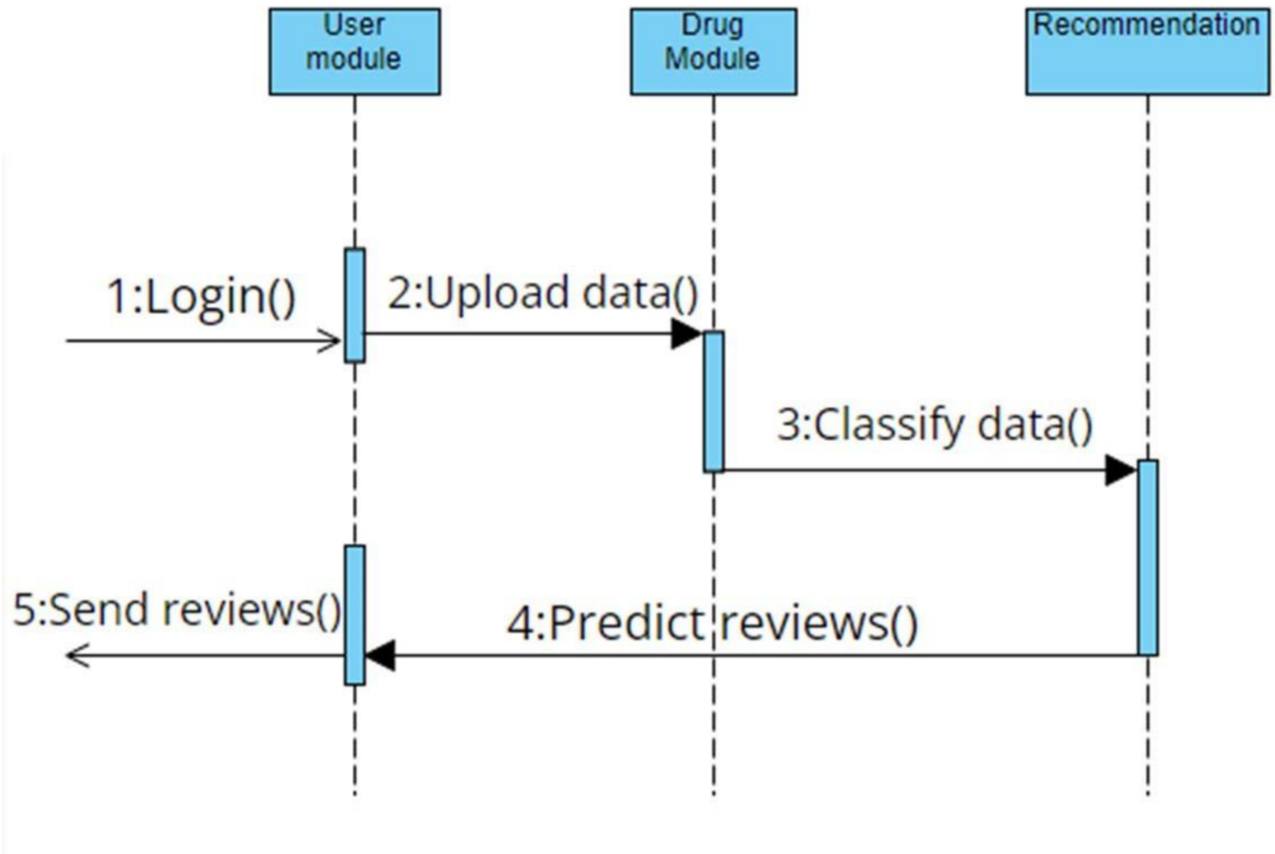

Figure 4.4.3 Sequence Diagram

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COLLABORATION DIAGRAM

The collaboration diagram is used to show the relationship between the objects in a system. Both the sequence and the collaboration diagrams represent the same information but differently. Instead of showing the flow of messages, it depicts the architecture of the object residing in the system as it is based on object-oriented programming. The collaboration diagram, which is also known as a communication diagram, is used to portray the object's architecture in the system.

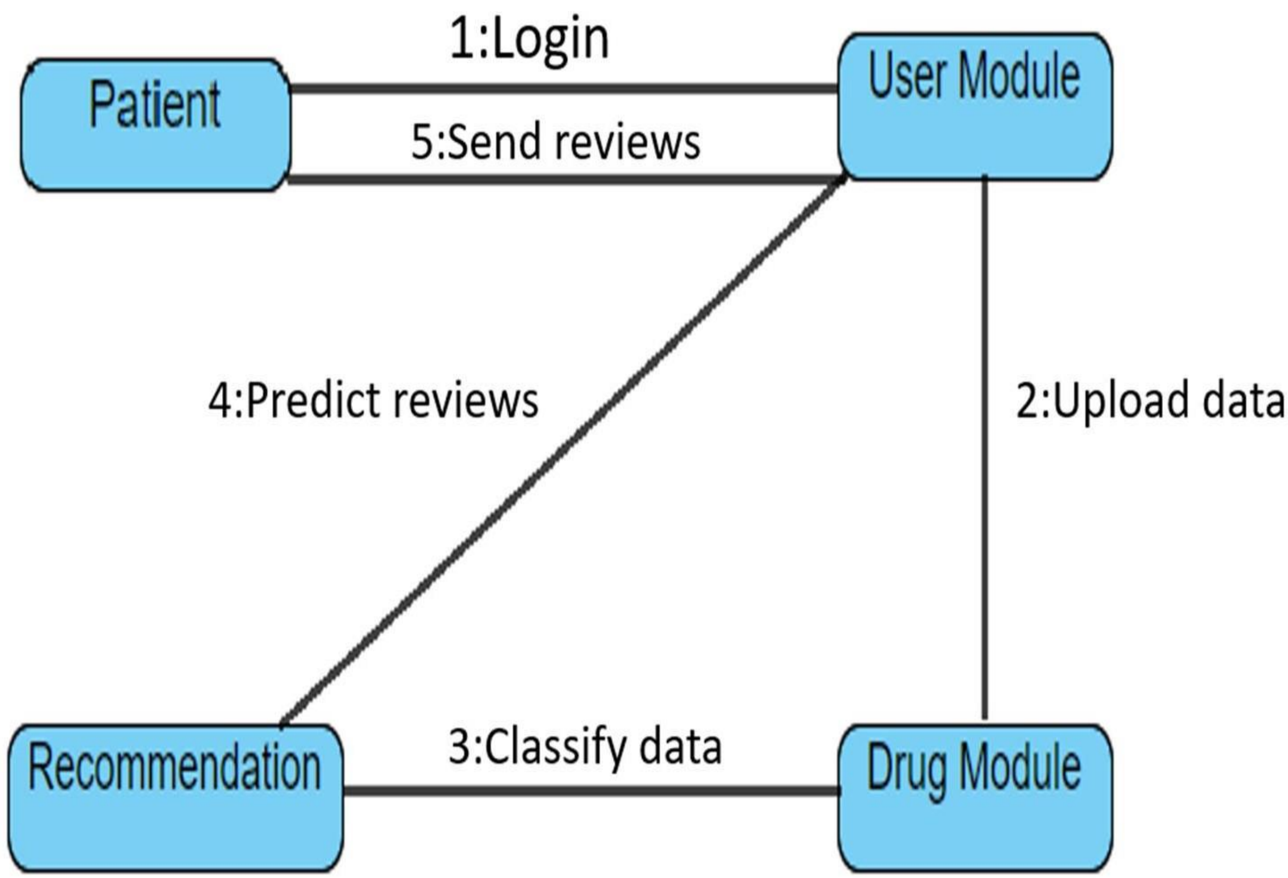


Figure 4.4.4 Collaboration Diagram

COMPONENT DIAGRAM

Component diagram is a special kind of diagram in UML. The purpose is also differentfrom all other diagrams discussed so far. It does not describe the functionality of the system but it describes the components used to make those functionalities. A component diagram depicts how components are wired together to form larger components or software systems. They are used to illustrate the structure of arbitrarily complex systems.

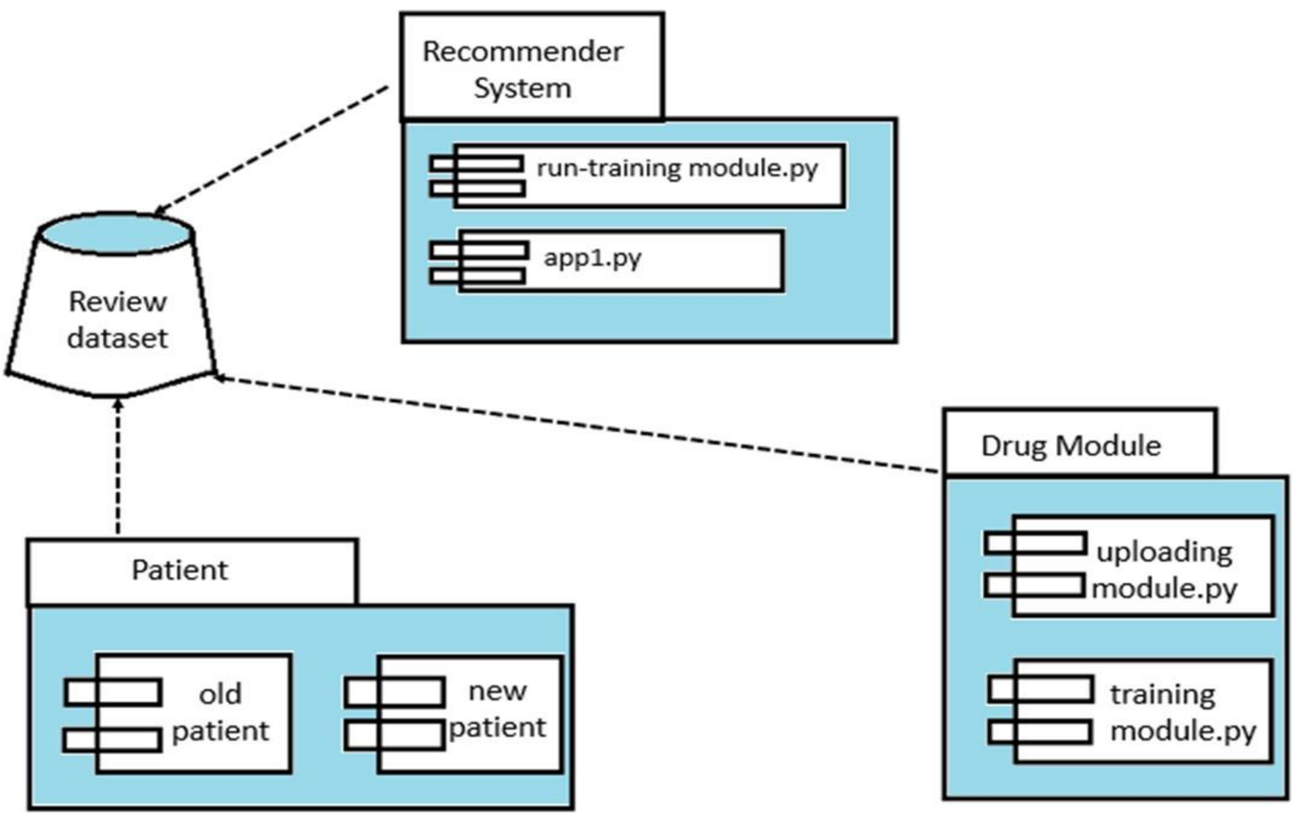


Figure 4.4.5 Component Diagram

DEPLOYMENT DIAGRAM

A deployment diagram is a UML diagram type that shows the execution architecture ofa system, including nodes such as hardware or software execution environments, and the middleware connecting them. Deployment diagrams are typically used to visualize the physical hardware and software of a system. A deployment diagram in the Unified Modeling Language models the physical deployment of artifacts on nodes.

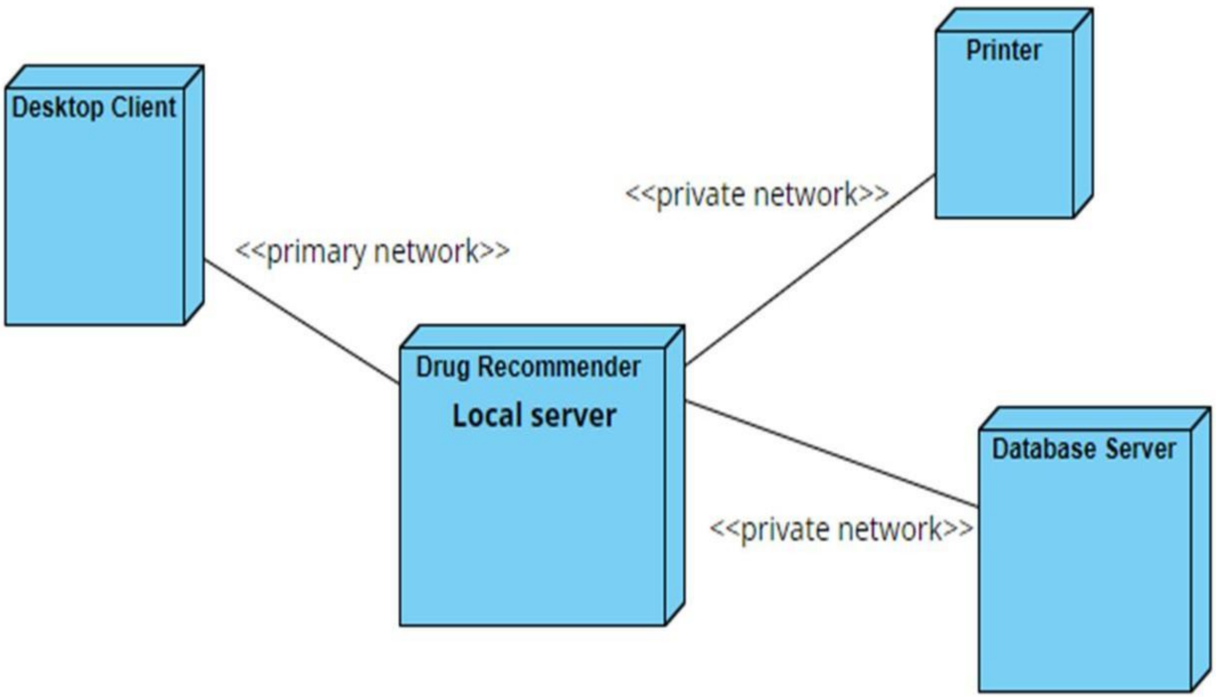


Figure 4.4.6 Deployment Diagram

SYSTEM ARCHITECTURE

5.1 ARCHITECTURE OVERVIEW

The users' requirements document was examined in order to have a better knowledge of the system's requirements. The various approaches to implementing these requirements were examined.The system's physical modules were designed, as well as the operating environment in which they would operate. The algorithm will first obtain Drug reviews from the supplied URL, then parse and clean the reviews. For each review of the Drug, determine the positive and negative polarity. The Drug is then graded on the various aspects again, and the overall sentiment distribution of the Drug is provided. Data is extracted and filtered before being analysed. Subjectivity is checked in every sentence and viewpoint. Indexing (Sentiment Classification) - Each subjective sentence is divided into three categories: positive, negative, and neutral. Delivery (Presentation of Output) - Shows how reviews are received. The Flask API was utilised to construct the ui's back end. A user-friendly application has been created that allows users to enter reviews/comments and receive the sentiment of their comments. Front end development in UI is done with HTML and CSS.

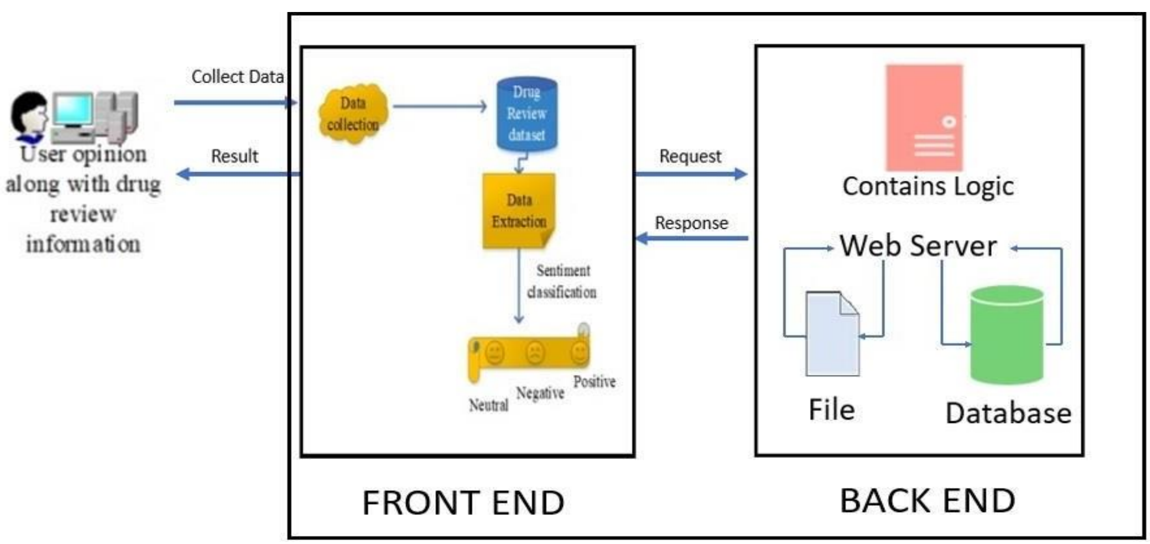


Figure 5.1.1 Architecture Diagram

5.2 MODULE DESIGN SPECIFICATION

Name of the module -1: REGISTRATION

Description

- This module helps the new users to get registered in the drug recommender system.
- The patients can get registered by their username and password.
- A unique ID is generated for each patient by the system after they get registered.

Name of the module -2: PATIENT MODULE

Description

- After registration the patients can login into the system using their unique username and password.
- The patient needs to upload their drugname ,reviews and type of disease for training or testing.

Name of the module -3: DRUG MODULE

Description

The system classifies the data uploaded by patients into six attributes :

- name of drug
- review of patient
- condition of patients
- useful count
- date of review entry
- 10-star patient rating determining overall patient contentment.

Name of the module -4: RECOMMENDATION

Description

- The recommendation module helps in review prediction.
- Based on the sentimental reviews uploaded by the patients, the drug can be predicted as positive or negative.
- The system can provide prediction for multiple patients at the same time.

Name of the module -5: ANALYSIS

Description

- This module provide feedback to the patients.
- Analysis module helps in providing prediction for different drugs and accuracy plot.

5.3 ALGORITHMS

1. LinearSVC

A Linear SVC's goal is to fit data you provide and provide a "best fit" hyperplane that divides or categorises your data. The "predicted" class can then be determined by feeding some features to your classifier.

2. Logistic Regression

This is a supervised machine learning technique for classification issues; it is a predictive analytic algorithm based on the probability notion.

3. Random Forest Classifier

This algorithm is made up of several decision trees. When creating each individual tree,it employs bagging and feature randomization in order to generate an uncorrelated forestof trees whose committee prediction is more accurate than that of any one tree.

4. Multinomial NB Classifier

The multinomial Naive Bayes classifier is good for discrete feature classification. Normally, integer feature counts are required for the multinomial distribution. Fractional counts, such as tf-idf, may also function in practise.

SYSTEM IMPLEMENTATION

6.1 CLIENT SIDE CODING

```
<!DOCTYPE html>
<html>
<head>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1">
<meta http-equiv="X-UA-Compatible" content="IE=edge,chrome=1">
<title>{% block title %}Drugs{% endblock title %}</title>
{% load staticfiles %}

<link rel="stylesheet" type="text/css" href="{% static 'web/css/bootstrap.min.css'%}">
<link  rel='stylesheet'       href='https://maxcdn.bootstrapcdn.com/font-
awesome/4.5.0/css/font- awesome.min.css' >
<link                href='http://fonts.googleapis.com/css?family=Open+Sans:400,300,700'
rel='stylesheet' type='text/css'>
<link rel='stylesheet' href='{% static "web/css/base.css" %}' />

<style type="text/css">
.thumbnail p, .thumbnail h4 { white-space: nowrap;
text-overflow: ellipsis; overflow: hidden;
}
.star-rating {
line-height:32px; font-size:1.25em;
}
.star-rating .fa-star{color: yellow;}
```

```
</style>
</head>
<body style="background-color:black">
<nav class="navbar navbar-inverse">
<div class="container-fluid">

<!-- Header -->
<div class="navbar-header">
<button type="button" class="navbar-toggle" data-toggle="collapse" data-target="#topNavBar">
<span class="icon-bar"></span>
<span class="icon-bar"></span>
<span class="icon-bar"></span>
</button>
<a class="navbar-brand" href="{% url 'index' %}">Drugs</a>
</div>
<!-- Items -->
<div class="collapse navbar-collapse" id="topNavBar">
<ul class="nav navbar-nav ">
<li><a href="{% url 'index' %}">  Home</a></li>

</ul>

<ul class="nav navbar-nav navbar-right">
{% if not request.user.is_authenticated %}
<li>
<a href="{% url 'signup' %}">
<span   aria-hidden="true"></span>  SignUp
```

```
</a>
</li>
<li>
<a href="{% url 'login' %}">
<span aria-hidden="true"></span>  Login
</a>
</li>
{% else %}
<li>
<a href="{% url 'logout' %}">
 Logout
</a>
</li>
{% endif %}
</ul>
</div>
</div>
</nav>
</div>
{% block body %}
{% endblock %}
<nav class="navbar navbar-bottom">
<footer style="background-color:black" class="page-footer font-small">
<hr>
<div class="text-center center-block">
<br />
<a target="_blank" href="https://www.facebook.com/jonesg.heartking.2815"><i id="social-fb" class="fa fa-facebook-square fa-3x social"></i></a>
```

```
<a target="_blank" href="https://www.instagram.com/jonesg_28_heartking/"><i
id="social-tw" class="fa fa-instagram fa-3x social"></i></a>
<a target="_blank" href="mailto:jonesgofficial@gmail.com"><iclass="fa fa-
envelope fa-3x social"></i></a>
<a target="_blank" href="tel:+916364847231"><i id="social-git"class="fa fa-phone
fa-3x"></i></a>
</div>
<hr>
<div class="footer-copyright text-center py-3">© 2019 Copyright:
<a href="#"> Jones G</a>
</div>

</footer>
</nav>
<script type="text/javascript" src="{%static 'web/js/jquery.min.js'%}">
</script>

<script type="text/javascript" src="{%static 'web/js/bootstrap.min.js'%}">
</script>
<script type="text/javascript">
var $star_rating = $('.star-rating .fa');

var SetRatingStar = function() {
return $star_rating.each(function() {
```

```
if (parseInt($star_rating.siblings('input.rating-value').val()) >= parseInt($(this).data('rating'))) { return $(this).removeClass('fa-star-o').addClass('fa-star');
} else {
return $(this).removeClass('fa-star').addClass('fa-star-o');
}
});
};

$star_rating.on('click', function() {
$star_rating.siblings('input.rating-value').val($(this).data('rating')); return SetRatingStar();
});

SetRatingStar();
$(document).ready(function() {

});

</script>
<script type="text/javascript"> function validateForm(){
var x = document.forms["ratingForm"]["rating"].value; if(x=="0"){
alert("Invalid Input"); return false;
}
}
</script>
</body>
</html>
```

6.2 SERVER SIDE CODING

```
from django.urls import path from . import views
urlpatterns = [
path('', views.index, name='index'),

path('<int:Drug_id>/',views.detail                                  ,name='detail'),
path('signup/',views.signUp,name='signup'),    path('home/',views.home,name='home'),
path('error/',views.error,name='error'),              path('login/',views.Login,name='login'),
path('logout/',views.Logout,name='logout'),
path('recommend/',views.recommend,name='recommend')
]

import numpy as np import pandas as pd
from web.models import Myrating import scipy.optimize

def Myrecommend():
def normalizeRatings(myY, myR):
# The mean is only counting Drugs that were rated
Ymean          =          np.sum(myY,axis=1)/np.sum(myR,axis=1)          Ymean          =
Ymean.reshape((Ymean.shape[0],1)) return myY-Ymean, Ymean

def flattenParams(myX, myTheta):
return    np.concatenate((myX.flatten(),myTheta.flatten()))

def reshapeParams(flattened_XandTheta, mynm, mynu, mynf):
assert    flattened_XandTheta.shape[0]    ==    int(mynm*mynf+mynu*mynf)    reX    =
flattened_XandTheta[:int(mynm*mynf)].reshape((mynm,mynf))          reTheta          =
flattened_XandTheta[int(mynm*mynf):].reshape((mynu,mynf)) return reX, reTheta
from flask import Flask, render_template,url_for, request
```

```
from werkzeug.utils import secure_filename
import csv
import pickle
import flask_monitoringdashboard as dashboard
import warnings
import os
from flask_cors import CORS, cross_origin
from applicaton_logging import logger
from trainingModel import trainModel
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC
import pandas
from sklearn import model_selection, preprocessing, naive_bayes
import string
from sklearn.decomposition import LatentDirichletAllocation
from sklearn import svm
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.ensemble import RandomForestClassifier
from flask import Flask,render_template,url_for,request
import pandas as pd

def warns(*args, **kwargs):
    pass
warnings.warn = warns

# load the model from directory
filename = 'pickle_files/drug_LinearSVC.pkl'
model = pickle.load(open(filename, 'rb'))
t = pickle.load(open('pickle_files/d_transform.pkl', 'rb'))

app = Flask(__name__)
# for monitoring
dashboard.bind(app)
# --- Cross Origin Resource Sharing (CORS) ---
CORS(app)

#logging object initialization
logger = logger.App_Logger()
```

```
@app.route('/')
#@cross_origin()
@app.route('/first')
def first():
    return render_template('first.html')
@app.route('/login')
def login():
    return render_template('login.html')


@app.route('/upload')
def upload():
    return render_template('upload.html')
@app.route('/preview',methods=["POST"])
def preview():
    if request.method == 'POST':
        dataset = request.files['datasetfile']
        df = pd.read_csv(dataset,encoding = 'unicode_escape')
        df.set_index('Id', inplace=True)
        return render_template("preview.html",df_view = df)

@app.route('/prediction1')
def home():
    file_object = open("log_file/FlaskApi_log.txt", 'a+')
    logger.log(file_object, '============= Home Page Opened =============')
    file_object.close()
    return render_template('home.html')

@app.route('/bulk_predict',methods=['GET','POST'])
@cross_origin()
def bulk_predict():
    file_object = open("log_file/FlaskApi_log.txt", 'a+')
    logger.log(file_object, '============= Bulk Prediction Started =============')
    if request.method == "POST":
        try:
            f = request.files['csvfile']
            logger.log(file_object, 'File submitted for bulk prediction')
            if f:
                f.save(secure_filename(f.filename))
                logger.log(file_object, 'File saved to directory')
                try:
                    with open(f.filename, encoding='Latin1') as file:
                        csvfile = csv.reader(file)
```

```
                data = []
                review_prediction = []
                for row in csvfile:
                    data.append(row)
            except Exception as e:
                os.remove(f.filename)
                logger.log(file_object,"File uploded is not csv ..")

            for review in data:
                review_prediction.append(model.predict(t.transform(review)))
            logger.log(file_object, 'Data passed to model ')
            length = len(data)
            os.remove(f.filename)
            logger.log(file_object, 'Saved file removed successfully')
            file.close()
            logger.log(file_object, '============= Bulk Prediction Complete
=============')
            file_object.close()
            return render_template("bulk.html", predict_data=review_prediction, data=data,
length=length)
        except Exception as e:
            logger.log(file_object, 'Bulk Upload Failed . ERROR message :  ' + str(e))
            file_object.close()
            return "File uploded should be be csv (.csv extension) "

@app.route('/chart')
def chart():
    return render_template('chart.html')

@app.route('/crime')
def crime():
  return render_template("crime.html")
@app.route('/crimes')
def crimes():
  return render_template("crimes.html")
@app.route('/total')
def total():
  return render_template("total.html")
@app.route('/theft')
def theft():
    return render_template('theft.html')
```

```
@app.route('/predict', methods=['POST'])
@cross_origin()
def predict():
    file_object = open("log_file/FlaskApi_log.txt", 'a+')
    try:
        if request.method == 'POST':
            logger.log(file_object, '============= Single Prediction Started =============')
            message = request.form['message']
            logger.log(file_object, 'Data taken for single prediction')
            data = [message]
            my_prediction = model.predict(t.transform(data))
            logger.log(file_object, 'Data passed to model for prediction ')
            logger.log(file_object, '============= Single Prediction Completed
=============')
            file_object.close()
        return render_template('result.html',prediction=my_prediction)
    except Exception as e:
        logger.log(file_object, 'Single Prediction Failed . ERROR message :  '+str(e))
        file_object.close()
        return 'Something went wrong'

@app.route('/about', methods=['POST'])
@cross_origin()
def about():
    file_object = open("log_file/FlaskApi_log.txt", 'a+')
    logger.log(file_object, '============= About Page Opened =============')
    if request.method == 'POST':
        logger.log(file_object, 'Returning about page')
        file_object.close()
        return render_template('about.html')

@app.route('/retrain',methods=['GET','POST'])
@cross_origin()
def retrain():
    file_object = open("log_file/FlaskApi_log.txt", 'a+')
    try:
        logger.log(file_object, '============= Retraining Model Started =============')
        if request.method == "POST":
            file = request.files['retrain_file']
            if file:
                file.save(secure_filename(file.filename))
                a=trainModel()
                a.trainingModel(file.filename,file_object)
```

```
            logger.log(file_object, '============= Model Retraining Done =============')
            os.remove(file.filename)
            file_object.close()
            return render_template('home.html',text=".... Model Retrained Successfully ....")
    except Exception as e:
        logger.log(file_object, 'Model Retraining Failed . ERROR message :  ' + str(e))
        file_object.close()
        return 'Something went wrong , check your file extension .(should be .csv )'

if __name__ == '__main__':
    # To run on web ..
    #app.run(host='0.0.0.0',port=8080)
    # To run locally ..
    app.run(debug=True)
```

SYSTEM TESTING

7.1 UNIT TESTING

Unit testing entails creating test cases to ensure that the program's internal logic is working properly and that programme inputs result in valid outputs. Validation should be performed on all decision branches and internal code flow. Unit tests are used to test a specific business process, application, and/or system configuration at the component level. Unit tests guarantee that each individual path of a business process follows the published specifications and has clearly defined inputs and outputs. Unit testing is commonly done as part of the software life cycle's combined code and unit test phase, while it's not uncommon for coding and unit testing to be done separately.

7.2 INTEGRATION TESTING

Integration tests are used to see if two or more software components can work togetheras a single application. Testing is mainly concerned with the basic output of screens or fields and is event driven. Integration tests verify that, while individual components were satisfied, the combination of components is right and consistent, as demonstratedby successful unit testing. Intregration testing is designed to reveal the issues that originate from the components. The progressive integration testing of two or more integrated software components on a single platform to induce failures caused by interface faults is known as software integration testing. The integration test's purpose is to ensure that components or software applications work together.

7.3 TEST REPORTS

TABLE 7.3.1 Test Reports Table

S.No	Test Description	Steps	Expected System Response	Status (Pass/Fail)
1	Home Page	Open the drug recommendation website.	The home screen of the system is displayed.	Pass
2	Login Page	Enter the username password.	A message "login success" is displayed.	Pass
3	Upload Page	Upload the drug dataset and click upload button.	A preview of the uploaded dataset is shown.	Pass
4	Testing	Click on test to train the dataset uploaded.	A message "Training successful" is displayed in a dialog box.	Pass
5	Prediction	Enter the patient review on a particular drug.	The system predicts the drug as positive or negative or neutral.	Pass
6	Multiple Prediction	Upload the drug dataset for prediction.	The system predicts the multiple reviews as positive or negative or neutral.	Pass

7	Retraining model	Upload the file that need to be retrained.	A message “Model retrained successfully” is displayed.	Pass
8	Retrained file	Patient can view the retrained dataset.	Retrained data is shown on excel.	Pass
9	Analysis model	Number of different drug with reviews can be viewed.	The system displays a pie chart.	Pass
10	Analysis model	Accuracy plot on training and testing can be viewed.	The system displays a graph.	Pass

CONCLUSION

8.1 RESULTS & DISCUSSION

Depending on the user's star rating, each review was categorised as positive or negative.Positive ratings range from one to five stars, while negative ratings range from one to five stars. All of the algorithms had similar findings, ranging from 89 to 91 percent accuracy. The LGBM model has the best accuracy of 91 percent. After analysing all ofthe models, the combined model predictions of Perceptron (Bow), LinearSVC (TF-IDF), LGBM (Word2Vec), and Random Forest (Manual Features) were incorporated. The major goal is to ensure that each of the four models accurately classifies the recommended top medications.

8.2 CONCLUSION AND FUTURE ENHANCEMENT

CONCLUSION

A novel deep learning-based framework for drug recommender systems has been suggested. The following are the paper's major contributions:

Deep Drug brings together modules for candidate generation, ranking, community detection, matrix factorization, and review mining.

The presented framework is generic, and with a few tweaks, it may be applied to a variety of circumstances besides drug suggestion. It's simple to add a new data source to the framework. For instance, one may sample a set of frames from each Drug, input them to a convolutional neural network, and then add the final feature map to the Drug's representation vector.

FUTURE ENHANCEMENT

In this study, sentiment analysis of drug reviews was used to develop a recommender system employing a variety of machine learning classifiers, including Logistic Regression, Perceptron, Multinomial Naive Bayes, Ridge classifier, Stochastic gradient descent, Linear SVC, and Bow, TF-IDF. Precision, recall, f1score, accuracy, and AUC score were used to evaluate them, and the Linear SVC on TF-IDF outperforms all other models by 93 percent. Future study will include a comparison of other oversampling strategies, as well as algorithm tuning to improve the recommender system's performance.

A.1 SAMPLE SCREENS

A.1.1 HOMEPAGE

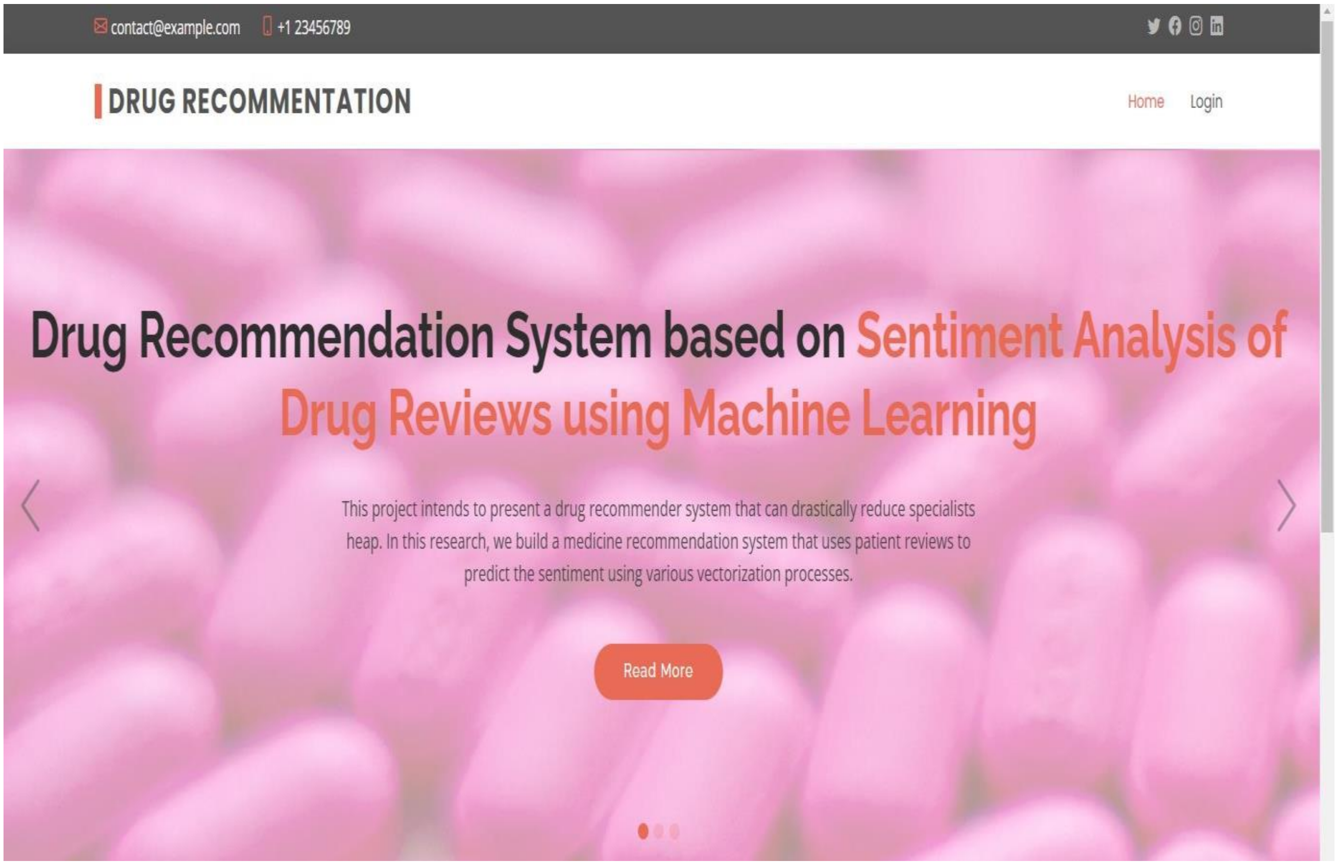


Figure A.1.1 Home Page

A.1.2 LOGIN PAGE

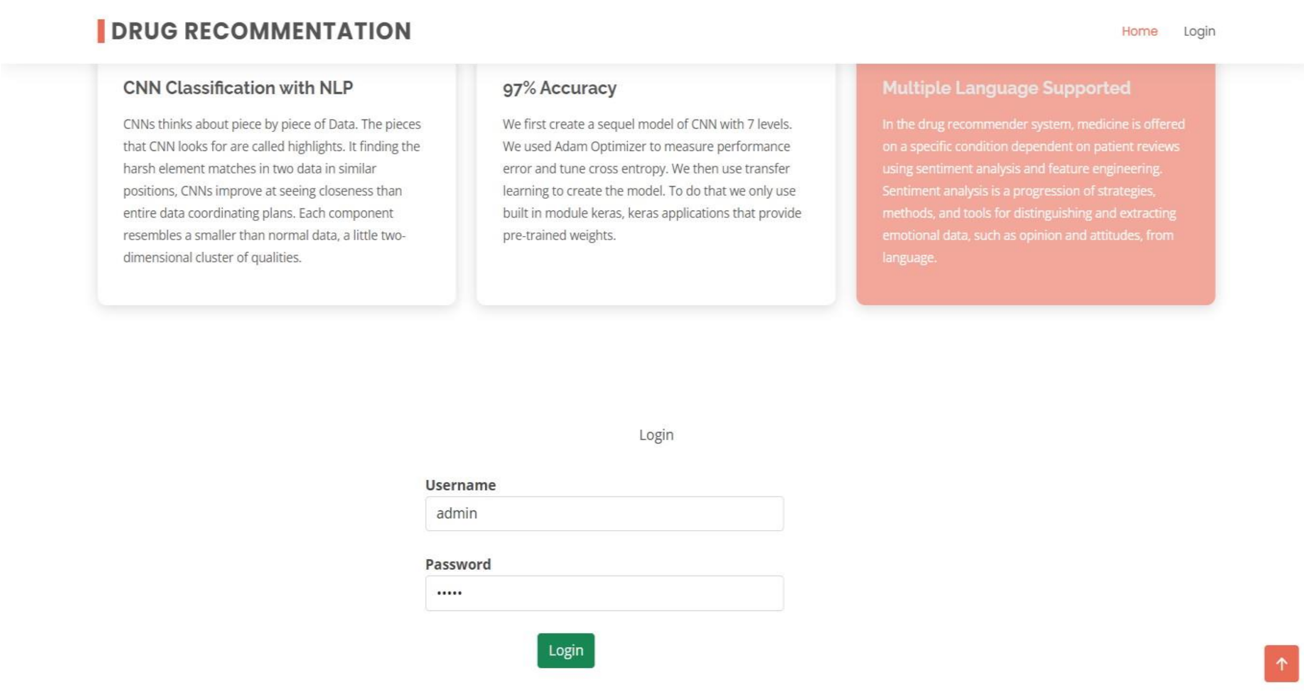


Figure A.1.2 Login Page

A.1.3 UPLOAD PAGE

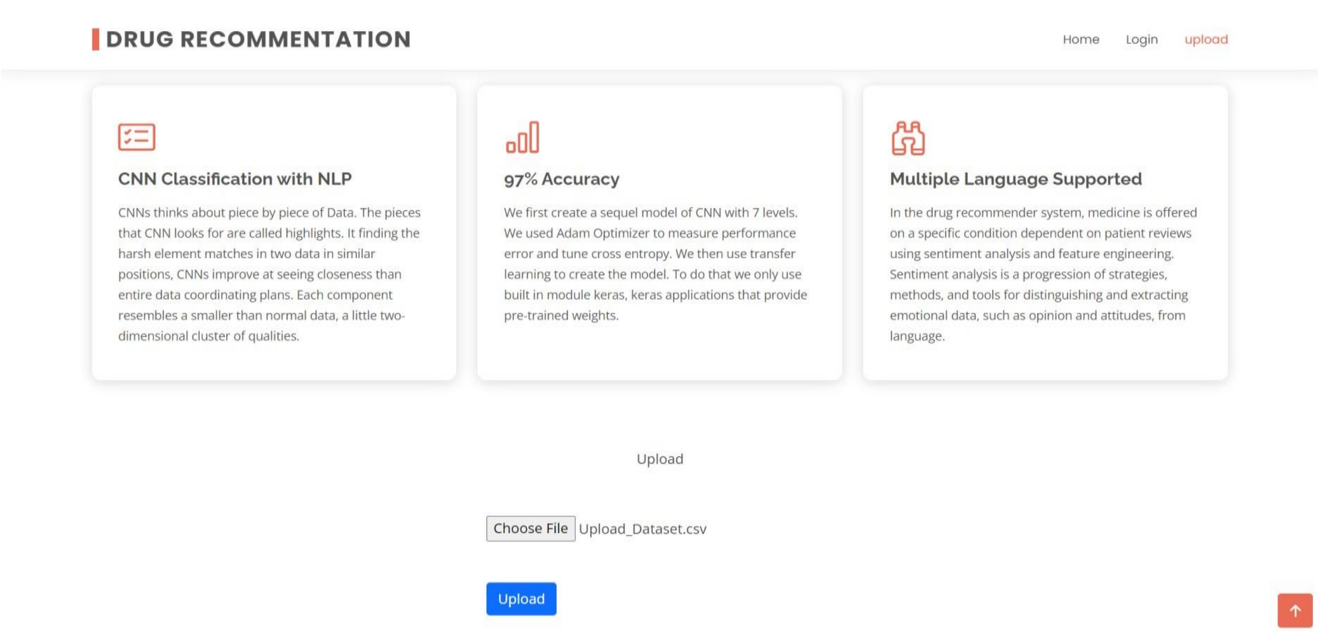


Figure A.1.3 Upload Page

A.1.4 PREVIEW

Figure A.1.4 Preview

A.1.5 TESTING

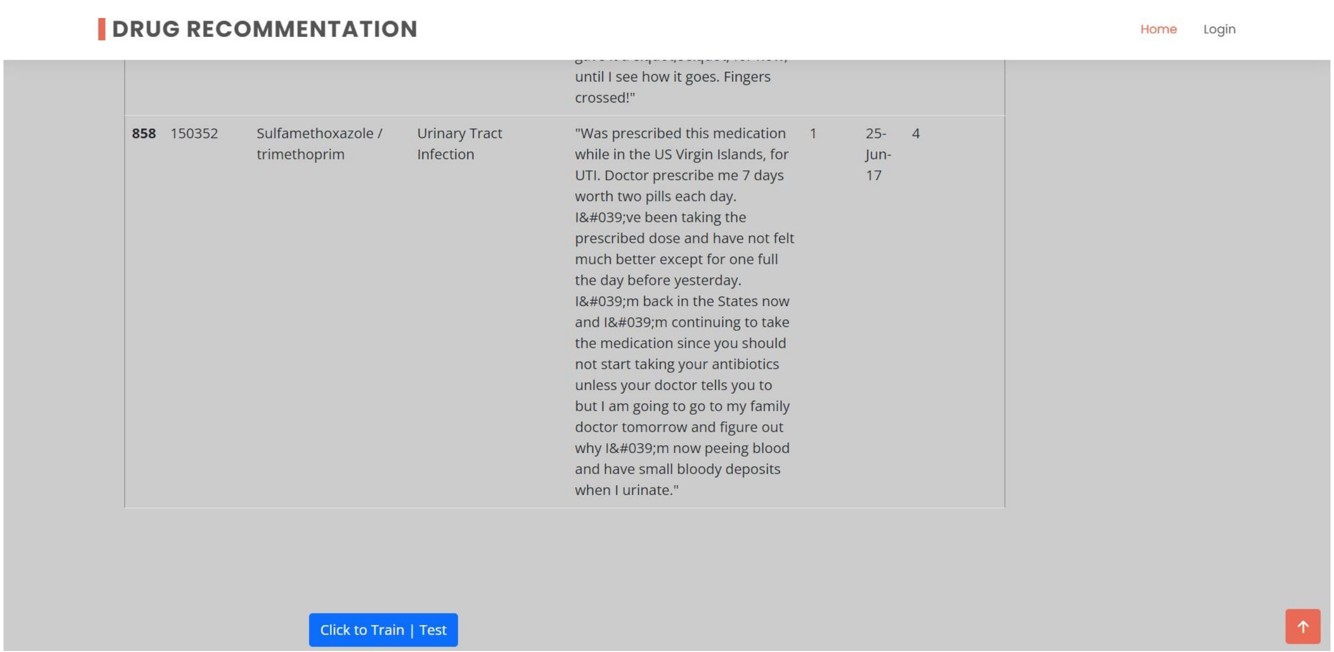


Figure A.1.5 Testing

A.1.6 PREDICTION

Figure A.1.6 Prediction

A.1.7 NEGATIVE REVIEW

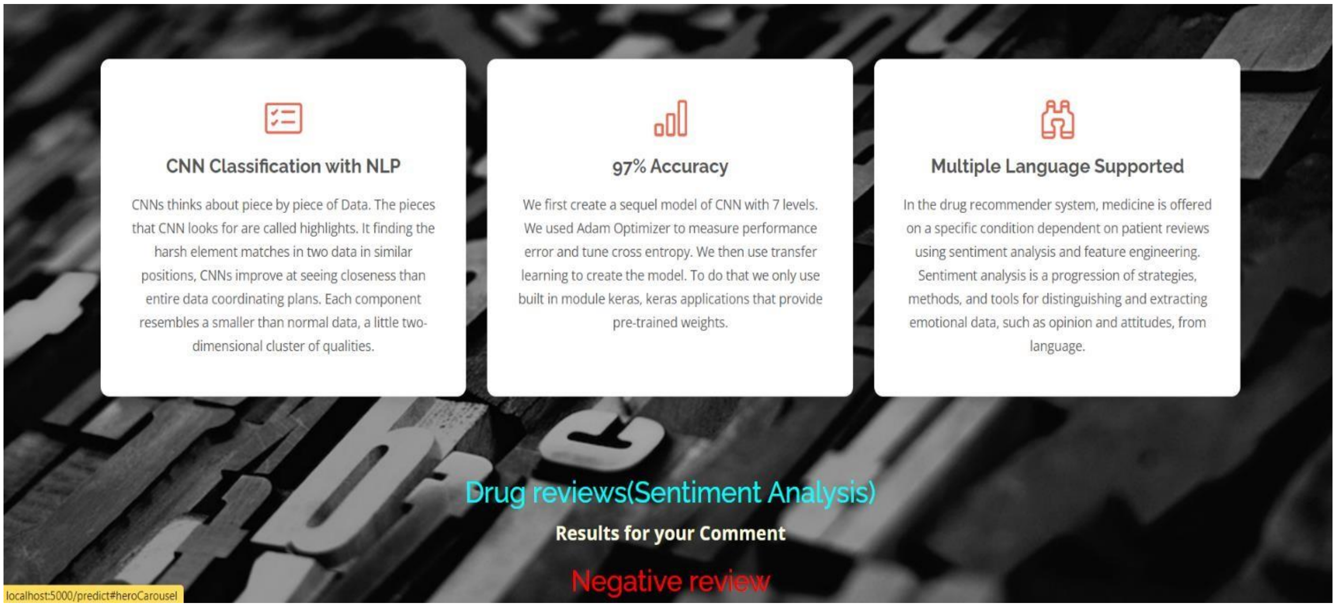


Figure A.1.7 Negative Review

A.1.8 PREDICTION

Figure A.1.8 Prediction

A.1.9 POSITIVE REVIEW

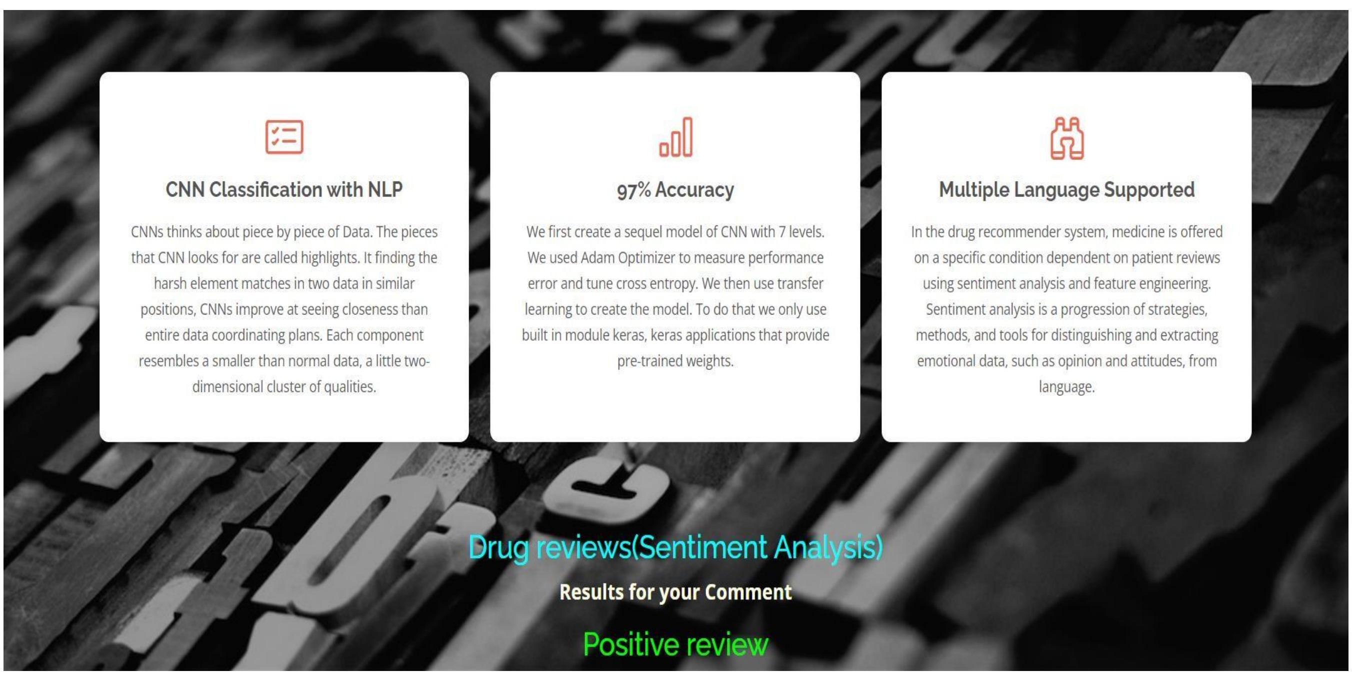
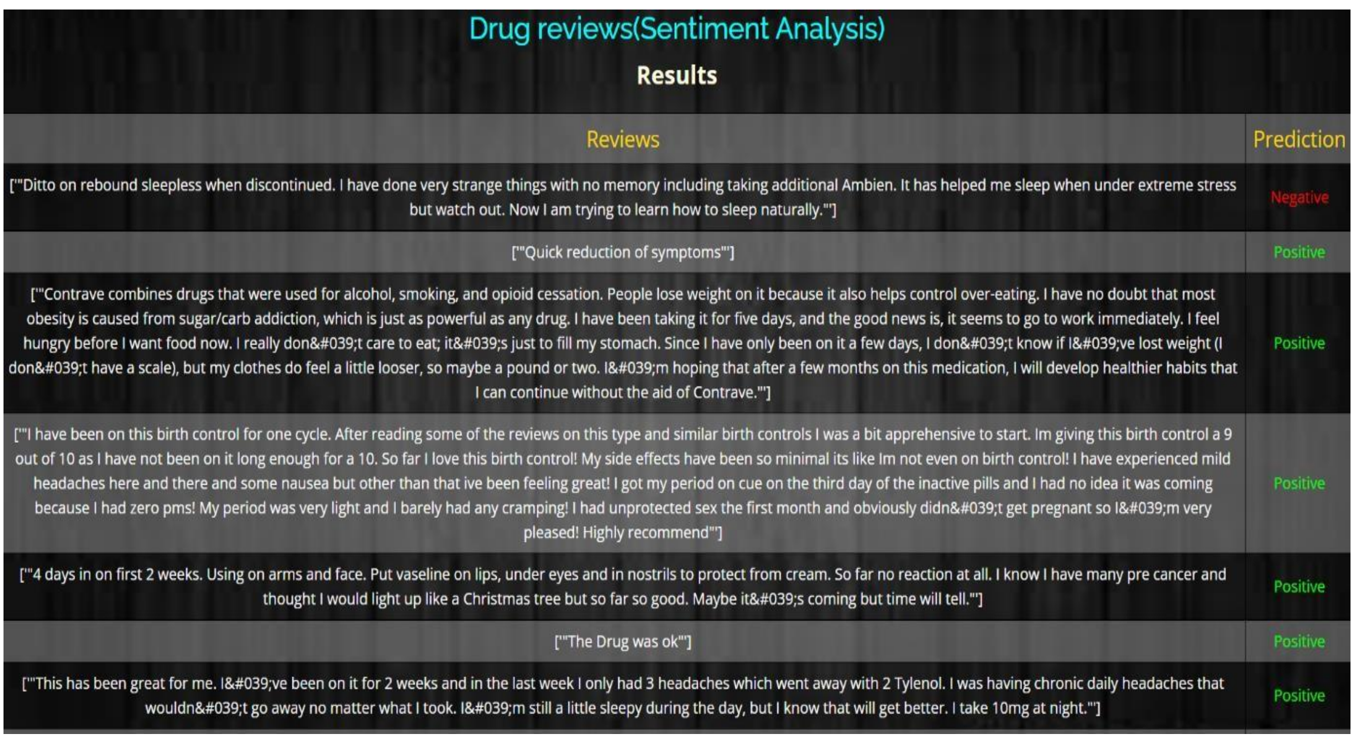


Figure A.1.9 Positive Review

A.1.10 MULTIPLE PREDICTION

Figure A.1.10 Multiple Prediction

A.1.11 PREDICTION RESULTS



Reviews	Prediction
['"Ditto on rebound sleepless when discontinued. I have done very strange things with no memory including taking additional Ambien. It has helped me sleep when under extreme stress but watch out. Now I am trying to learn how to sleep naturally."']	Negative
['"Quick reduction of symptoms"']	Positive
['"Contrave combines drugs that were used for alcohol, smoking, and opioid cessation. People lose weight on it because it also helps control over-eating. I have no doubt that most obesity is caused from sugar/carb addiction, which is just as powerful as any drug. I have been taking it for five days, and the good news is, it seems to go to work immediately. I feel hungry before I want food now. I really don't care to eat; it's just to fill my stomach. Since I have only been on it a few days, I don't know if I've lost weight (I don't have a scale), but my clothes do feel a little looser, so maybe a pound or two. I'm hoping that after a few months on this medication, I will develop healthier habits that I can continue without the aid of Contrave."']	Positive
['"I have been on this birth control for one cycle. After reading some of the reviews on this type and similar birth controls I was a bit apprehensive to start. Im giving this birth control a 9 out of 10 as I have not been on it long enough for a 10. So far I love this birth control! My side effects have been so minimal its like Im not even on birth control! I have experienced mild headaches here and there and some nausea but other than that ive been feeling great! I got my period on cue on the third day of the inactive pills and I had no idea it was coming because I had zero pms! My period was very light and I barely had any cramping! I had unprotected sex the first month and obviously didn't get pregnant so I'm very pleased! Highly recommend"']	Positive
['"4 days in on first 2 weeks. Using on arms and face. Put vaseline on lips, under eyes and in nostrils to protect from cream. So far no reaction at all. I know I have many pre cancer and thought I would light up like a Christmas tree but so far so good. Maybe it's coming but time will tell."']	Positive
['"The Drug was ok"']	Positive
['"This has been great for me. I've been on it for 2 weeks and in the last week I only had 3 headaches which went away with 2 Tylenol. I was having chronic daily headaches that wouldn't go away no matter what I took. I'm still a little sleepy during the day, but I know that will get better. I take 10mg at night."']	Positive

Figure A.1.11 Prediction Results

A.1.12 RETRAINING MODEL

Figure A.1.12 Retraining Model

A.1.13 MODEL RETRAINED

Figure A.1.13 Model Retrained

A.1.14 RETRAINED FILE

1	Unnamed: 0	drugName	condition	review	rating	date	usefulCount
2	206461	Valsartan	Left Ventricular Dysfunction	"It has no side effect, I take it in combination of Bystolic 5 Mg and Fis	9	May 20, 2012	27
3	95260	Guanfacine	ADHD	"My son is halfway through his fourth week of Intuniv. We became	8	April 27, 2010	192
4	92703	Lybrel	Birth Control	"I used to take another oral contraceptive, which had 21 pill cycle,	5	December 14, 2009	17
5	138000	Ortho Evra	Birth Control	"This is my first time using any form of birth control. I'm glad I	8	November 3, 2015	10
6	35696	Buprenorphine / naloxone	Opiate Dependence	"Suboxone has completely turned my life around. I feel healthier, I&	9	November 27, 2016	37
7	155963	Cialis	Benign Prostatic Hyperplasia	"2nd day on 5mg started to work with rock hard erections however e	2	November 28, 2015	43
8	165907	Levonorgestrel	Emergency Contraception	"He pulled out, but he cummed a bit in me. I took the Plan B 26 hours	1	March 7, 2017	5
9	102654	Aripiprazole	Bipolar Disorde	"Abilify changed my life. There is hope. I was on Zoloft and Clonidine	10	March 14, 2015	32
10	74811	Keppra	Epilepsy	" I Ve had nothing but problems with the Keppera : constant shaking	1	August 9, 2016	11
11	48928	Ethinyl estradiol / levonorgestrel	Birth Control	"I had been on the pill for many years. When my doctor changed my	8	December 8, 2016	1
12	29607	Topiramate	Migraine Prevention	"I have been on this medication almost two weeks, started out on 25	9	January 1, 2015	19
13	75612	L-methylfolate	Depression	"I have taken anti-depressants for years, with some improvement	10	March 9, 2017	54
14	191290	Pentasa	Crohn's Disease	"I had Crohn's with a resection 30 years ago and have been mo	4	July 6, 2013	8
15	221320	Dextromethorphan	Cough	"Have a little bit of a lingering cough from a cold. Not giving me much	4	September 7, 2017	1
16	98494	Nexplanon	Birth Control	"Started Nexplanon 2 months ago because I have a minimal amount	3	August 7, 2014	10
17	81890	Liraglutide	Obesity	"I have been taking Saxenda since July 2016. I had severe nausea for	9	January 19, 2017	20
18	48188	Trimethoprim	Urinary Tract Infection	"This drug worked very well for me and cleared up my UTI in a matte	9	September 22, 2017	0
19	219869	Amitriptyline	ibromyalgia	"I've been taking amitriptyline since January 2013 after being c	9	March 15, 2017	39
20	212077	Lamotrigine	Bipolar Disorde	"I've been on every medicine under the sun (it seems) to mana	10	November 9, 2014	18
21	119705	Nilotinib	Chronic Myelogenous Leuke	"I have been on Tasigna for just over 3 years now (300mg x 2 times a	10	September 1, 2015	11
22	12372	Atripla	HIV Infection	"Spring of 2008 I was hospitalized with pnuemonia and diagnosed wit	8	July 9, 2010	11
23	231466	Trazodone	Insomnia	"I have insomnia, it's horrible. My story begins with my PCP pre	10	April 3, 2016	43
24	227020	Etonogestrel	Birth Control	"Nexplanon does its job. I can have worry free sex. The only thing is t	9	August 11, 2014	11
25	41928	Etanercept	Rheumatoid Arthritis	"I live in Western Australia and disturbed by some comments on here	10	September 16, 2017	4
26	213649	Tioconazole	Vaginal Yeast Infection	"Do not use the cream that comes with this. It turned my hoo-ha into	1	April 17, 2017	7
27	51215	Azithromycin	Chlamydia Infection	"Was prescribed one dose over the course of one day, took 4 pills of	7	December 14, 2015	7

Figure A.1.14 Retained File

A.1.15 ANALYSIS MODEL

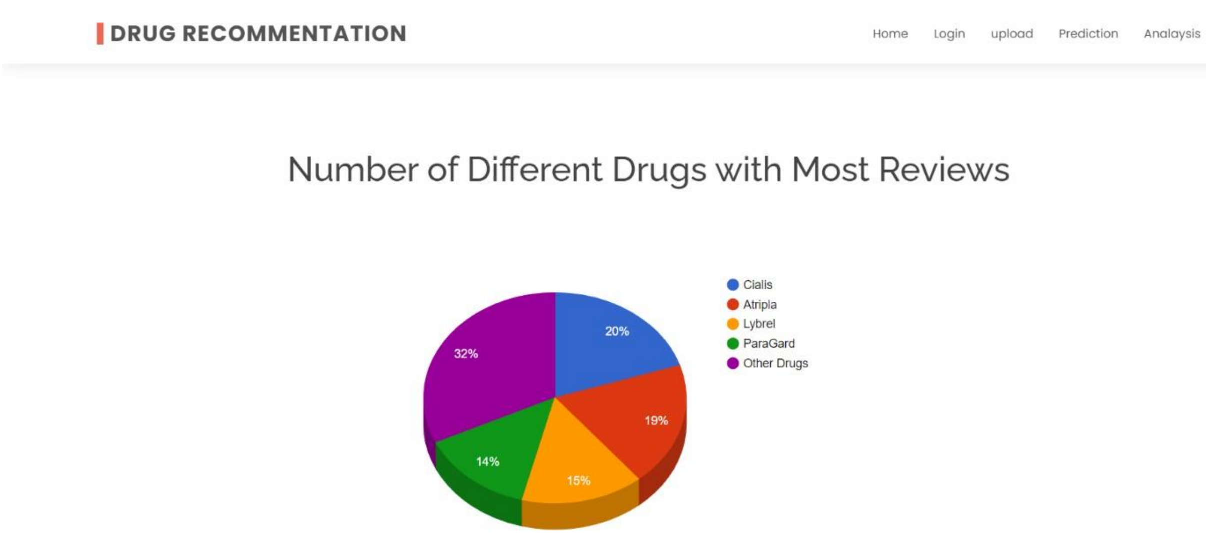


Figure A.1.15 Analysis Model

A.1.16 ACCURACY FILE

Figure A.1.16 Accuracy File

REFERENCES

1. Satvik Garg, (2021), “Drug Recommendation System based on Sentiment Analysis of Drug Reviews using Machine Learning”.

2. Julie Polisena , Martina Andellini, Piergiorgio Salerno , Simone Borsci, Leandro Pecchia , Ernesto Iadanza, (2021), “Case Studies on the Use of Sentiment Analysis to Assess the Effectiveness Safety of Health Technologies: A Scoping Review”.

3. Nur Sysfiqah Mohd Nafis, Suryanti Awang, (2021), “An Enhanced Hybrid Feature Selection Technique Using Term Frequency-Inverse Document Frequency and Support Vector Machine- Recursive Feature Elimination for Sentiment Classification”.

4. Kashif Ayyub, Saqib, Ehsan Ullah Munir, Muhammad Wasif Nisar, Momna Abbasi ,(2020),” Exploring Diverse Features for Sentiment Quantification Using Machine Learning Algorithms”.

5. Azwa Abdul Aziz, Andrew Starkey, (2020) ,” Predicting Supervise Machine Learning Performances for Sentiment analysis Using Contextual-Based Approaches”.

6. Oladapo Oyebode, Felwah Alqahtani, Rita Orji, (2020), “Using Machine Learning and Thematic Analysis Methods to Evaluat Mental Health Apps Based on User Reviews”.

7. Farkhund Iqbal, Jahanzeb Maqbool Hashmi, Benjamin C.M.Fung, Rabia Batool, Asad Masood Khattak, Saiqa, (2019), “A Hybrid Framework for Sentiment Analysis Using Genetic Algorithm Based Feature Reduction”.

8. Mei-Hua Chen, Wei-Fan Chen, Lun-Wei Ku, (2019), “Application of Sentiment Analysis to Language Learning”.

9. Monika Fedorova , Daniela Perdukova , Zdenko Pirnik, Viliam Fedak Ondrej Sukel , Padmanaban Sanjeevikumar, (2019), “Fuzzy system as a promising tool for drugs Selection in medical practise”.

10. V. Goel, A. K. Gupta ,N. Kumar, (2019), “Sentiment Analysis of Multilingual Twitter Data using Natural Language Processing”.

11. Atif &Peng , Dafang & Hassan,Zhang, Limei , Mohammad & Alamri, Yin & Zhang, et al. (2014), “CADRE: Cloud-Assisted Drug Recommendation Service for Online Pharmacies. Mobile Networks and Applications”, pp.348-355.

12. K. W. Bowyer, L. O. Hall, N. V. Chawla and W. P. Kegelmeyer, (2011), “SMOTE: Synthetic Minority Over-sampling Technique”, Journal Of Artificial Intelligence Research, Vol.16, pp. 321-357.

13. Chonghui Guo, Chuanren Liu, Hui Xiong, Leilei Sun and Yanming Xie et al. (2016), “Data-driven Automatic Treatment Regimen Development and Recommendation”, pp.1865–1874.

14. M. Emmanuel and T. N. Tekade, (2016),” Probabilistic aspect mining approach for interpretation and evaluation of drug reviews” , International Conference on Signal Processing, Communication, Power and Embedded System (SCOPES), pp. 1471-1476.

15. X. Jiang and Y. Bao,(2016) , ”An intelligent medicine recommender system framework”, IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), pp. 1383-1388.

16. J. Li, H. Xu, X. He, J. Deng and X. Sun et al. (2016), “Tweet modeling with LSTM recurrent neural networks for hashtag recommendation”, International Joint Conference on Neural Networks (IJCNN),pp.1570-1577.

17. C., Nikolaidis ,Doulaverakis, GalenOWL , G., Kleontas, et al. (2012) , “Ontology-based drug recommendations discovery”.

18. Omer Levy and Yoav Goldberg , (2014),“word2vec Explained: deriving Mikolov et al.’s negative-sampling word-embedding method”.

19. Zhang, Yin & Jin, Rong & Zhou, Zhi-Hua,(2010), “Understanding bag-of-words model: A statistical framework. International Journal of Machine Learning and Cybernetics”.

20. J. Ramos et al., (2003), “Using tf-idf to determine word relevance in document queries”, In Proceedings of the first instructional conference on machinelearning, pp.133–142.

21. Duggan, Fox, Maeve, Susannah, et al.” Health online (2013) Pew Research Internet Project Report.

22. Burkle CM , , Lanier WL ,Wittich CM, et al.(2014)“Medication errors: an overview for clinicians”, Vol. 89, pp.1116-25.

23. CHEN, M. R., WANG, H. F, et al. (2013), “The reason and prevention of hospital medication errors. Practical Journal of Clinical Medicine”, Vol. 4.

24. Bartlett JG, Dowell SF, Fine MJ , Mandell LA, File TM Jr, Musher DM, et al.(2000), "Practice guidelines for the management of community-acquired pneumonia in adults. Infectious Diseases Society of America". Vol.31, pp.347-82.

25. V. Goel, A. K. Gupta ,N. Kumar et al. year 2018,"Sentiment Analysis of Multilingual Twitter Data using Natural Language Processing" ,8th International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India. Page: 208-212..