Project Report

Team ID	PNT2022TMID17716
Project Name	Project - Early chronic Kidney Disease Prediction

1. **INTRODUCTION**

1.1 Project Overview

Chronic kidney disease is detected during the screening of people who are known to be in threat by kidney problems, such as those with high blood pressure or diabetes and those with a blood relative Chronic Kidney Disease(CKD) patients. So the early prediction is necessary in combating the disease and to provide good treatment.

1.2 Purpose

Chronic Kidney Disease (CKD) is considered as an important threat for the society with respect to the health in the present era. This project predicts whether the person is having CKD or not by using minimum number of features.

2. **LITERATURE SURVEY**

2.1 Existing problem

The kidney prediction is a costly and important clinical event with substantial morbidity, it appears less frequently in aging people compared with cardiovascular mortality. The measurement of kidney function and management of kidney disease in older individuals remain challenging now a days. So this project will help the person to predict the disease in online and it can be predicted as early as possible.

2.2 References

1. Prediction of chronic kidney disease using different classification algorithms. Khaled Mohamad Almustafa.
Informatics in Medicine Unlocked 24 (2021) 100631.

In this study, different classifiers were applied for the classification of a CKD dataset. The algorithms were applied using random tree, decision table (DT), K-nearest neighbor (K-NN), J48, stochastic gradient descent (SGD) and Naïve Bayes classifiers, and a prediction model was proposed based on feature selection to efficiently predict CKD cases. Results showed that the J48 and decision table classifiers outperformed the other classifiers with accuracies of 99%, ROCs equal to 0.999 and 0.992, MAEs of 0.0225 and 0.1815, and RMSEs of 0.0807 and 0.2507, respectively. A sensitivity analysis of selected classifiers was implemented to evaluate the performance of these classifiers with changes in their parameters. Additionally, the results showed an enhanced classification performance for K-

NN (K = 1).Naïve Bayes and decision table classification were enhanced to 99.75%, 98.25% and 99.25%, respectively.

2. Analysis of the performance of feature optimization techniques for thediagnosis of machine learning-based chronic kidney disease.
Muhammad Minoar Hossain a, Reshma Ahmed Swarna a, Rafid Mostafiz b, Pabon Shaha a,Lubna Yasmin Pinky a,Mohammad Motiur Rahman a, Wahidur Rahman c, Md. Selim Hossain d,Md. Elias Hossain e, Md. Sadiq Iqbal f.
Machine Learning with Applications 9 (2022) 100330

In this paper,research analysis of several feature optimization approaches along with a max voting ensemble model to establish a highly accurate CKD diagnosis system by using an appropriate feature set. The ensemble model of this research is structured with five existing classifiers.Three types of feature optimization namely feature importance, feature reduction, and feature selection where for each approach two most proficient techniques are analyzed with the mentioned ensemble model. Based on all analysis the research gets a feature optimization technique called Linear discriminant analysis belonging to the feature selection approach provides the most outstanding result of 99.5% accuracy by using 10-fold cross validation.

3. Neural network and support vector machine for the prediction of chronic kidney disease: A comparative study.
Njoud Abdullah Almansour, Hajra Fahim Syed, Nuha Radwan Khayat, Rawan Kanaan Altheeb,Renad Emad Juri, Jamal Alhiyafi, Saleh Alrashed, Sunday O. Olatunji.
Computers in Biology and Medicine 109 (2019) 101–111

In this paper, A dataset of 400 patients and 24 attributes related to diagnosis of chronic kidney disease was used.The classification techniques used in this study include Artificial Neural Network (ANN) and Support Vector Machine (SVM). To perform experiments, all missing values in the dataset were replaced by the mean of the corresponding attributes. Then, the optimized parameters for the Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques were determined by tuning the parameters and performing several experiments. The empirical results from the experiments indicated that ANN performed better than SVM, with accuracies of 99.75% and 97.75%, respectively, indicating that the outcome of this study is very promising.

4. Explainable prediction of chronic renal disease in the colombian population using neural networks and case-based reasoning.
Vásquez-Morales, Gabriel R., et al.
Ieee Access 7 (2019): 152900-152910

In this paper, demographic data of two different populations: people diagnosed with CKD and others without CKD is used. A neural network-based classifier is used to predict whether a person is at a risk of developing CKD. The model achieved an accuracy of 95%. A CaseBased Reasoning(CBR) is used as a twin system for the proposed paradigm for the explanation of CKD predictions. The system was also used to test on population, where 7% of the total population in Colombia were identified as being at risk of developing CKD.

5. Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network.
Fuzhe Ma, Tao Sun , Lingyun Liu , Hongyu Jing.
Future Generation Computer Systems 111 (2020) 17–26

In this paper, Heterogeneous Modified Artifical Neural Network (HMANN) has been proposed for the early detection, segmentation, and diagnosis of chronic renal failure on the Internet of Medical Things (IoMT) platform. Furthermore, the proposed HMANN is classified as a Support Vector Machine and Multilayer Perceptron (MLP) with a Backpropagation (BP) algorithm. The proposed algorithm works based on an ultrasound image which is denoted as a preprocessing step and the region of kidney interest is segmented in the ultrasound image. In kidney segmentation, the proposed HMANN method achieves high accuracy and significantly reducing the time to delineate the contour.

6. A machine learning methodology for diagnosing chronic kidney disease.
Qin, Jiongming, et al.
IEEE Access 8 (2019): 20991-21002.

In this paper, the CKD dataset was from the UCI which has a large number of missing values was used. KNN imputation was used to fill the missing values. Six machine learning algorithms (logistic regression, random forest, support vector machine, k-nearest neighbour, Naive Bayes classifier and feed forward neural network) was developed for the analysis of prediction. The random forest model achieved the best performance with 99.75% accuracy. An integrated model by combining both logistic regression and random forest was also built. This model achieved an accuracy of 99.83% after ten times of simulation.

7. Prediction of chronic kidney disease using machine learning algorithm.
Tekale, Siddheshwar, et al.
International Journal of Advanced Research in Computer and Communication Engineering 7.10 (2018): 92-96.

In this paper, the data of 400 patients with 24 attributes related to CKD was used. Only the 14 optimal attributes for the prediction of CKD were considered. The various machine learning models like Decision Tree, and SVM was built and compared. The SVM achieved an accuracy of 96.75% while the Decision Tree algorithms with 91.75%. SVM performs better than the Decision Tree algorithms but it is time-consuming the Decision Tree algorithms.

8. Generating comparative analysis of early Stage prediction of Chronic Kidney Disease. Rubini, L. Jerlin, and P. Eswaran.
International Journal of Modern Engineering Research (IJMER) 5.7 (2015): 49-55.

In this paper,a a new chronic kidney disease dataset with three classifiers such as radial basis function network, multilayer perceptron, and logistic regression was proposed. Highest accuracy is achieved by MLP(99.75%) RBF Network followed by RBK Network(98.5%) and then Logistic Regression(97.5%).Error rate, sensitivity, specificity, F-score and kappa values are also predicted using these classifiers. Among all these classifiers Multilayer perceptron classifier gave good accuracy.

9. A soft computing approach to kidney diseases evaluation.
Neves, José, et al.
Journal of medical systems 39.10 (2015): 1-9.

In this paper, the dataset consists 24 attributes, forming five main categories. A hybrid decision support system is developed by Neves and his team, allowed to consider incomplete, unknown, and even contradictory information. This is complemented with an approach to computing centered on Artificial Neural Networks, in order to weigh the Degree-of Confidence in terms of reasoning procedures and knowledge representation based on Logic Programming. Their study involved 558 patients with an age average of 51.7 years and the chronic kidney disease was observed in 175 cases.

10. A classification of ckd cases using multivariate kmeans clustering.
Dubey, Abhinandan.
International Journal of Scientific and Research Publications 5.8 (2015): 1-5.

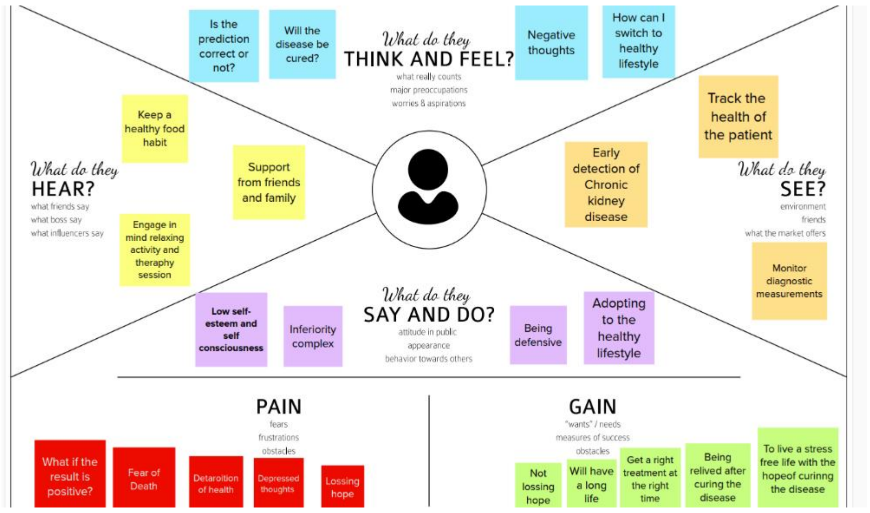
In this paper, an adopted K-means Clustering algorithm with a single mean vector of centroids, to classify and make clusters of varying probability of likeliness of suspect being prone to CKD. They observed and stated that the suspects falling in clusters K1 or K3 are surely suffering from CKD. The probability of a suspect lying in K2 cluster to fall in the class of CKD is 0.50545, which implies that the suspect cannot be classified by their L-factor classifier. However, suspects from clusters K1 & K3 were found to be falling in CKD class with full probability.

2.3 Problem Statement Definition

Kidney diseases affect the normal function of the kidney. Early prediction of kidney disease using classification and regression algorithms are effective that can help the doctors to diagnose the disease within a short duration of time as it is a complex task for the doctors to predict early. The main objective of this project is to analyze the parameters of various classification algorithms and compare their predictive accuracies so asto find out the best classifier for determining the kidney disease. This Project examines data from kidney patients concentrating on relationships kidney enzymes, proteins, age and gender using them to try and predict the likeliness of kidney disease. Here we are building a model by applying various machine learning algorithms find the best accurate model. And integrate to flask-based web application.

3. IDEATION & PROPOSED SOLUTION

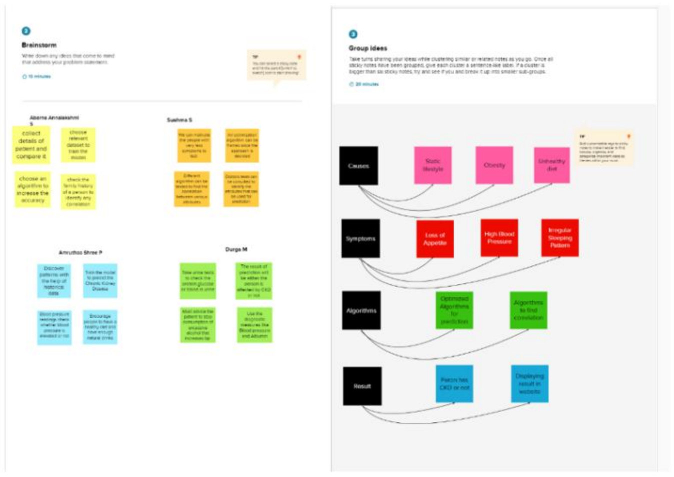
3.1 Empathy Map Canvas



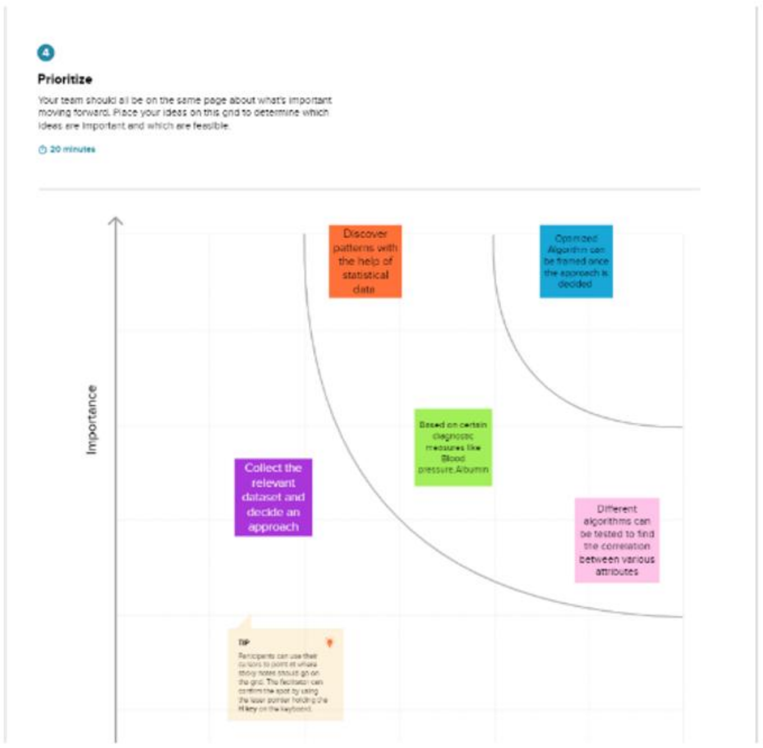
What do they THINK AND FEEL?
what really counts
major preoccupations
worries & aspirations
Is the prediction correct or not?
Will the disease be cured?
Negative thoughts
How can I switch to healthy lifestyle
What do they HEAR?
what friends say
what boss say
what influencers say
Keep a healthy food habit
Support from friends and family
Engage in mind relaxing activity and theraphy session
What do they SEE?
environment
friends
what the market offers
Track the health of the patient
Early detection of Chronic kidney disease
Monitor diagnostic measurements
What do they SAY AND DO?
attitude in public
appearance
behavior towards others
Low self-esteem and self consciousness
Inferiority complex
Being defensive
Adopting to the healthy lifestyle
PAIN
fears
frustrations
obstacles
What if the result is positive?
Fear of Death
Detaroition of health
Depressed thoughts
Lossing hope
GAIN
"wants" / needs
measures of success
obstacles
Not lossing hope
Will have a long life
Get a right treatment at the right time
Being relived after curing the disease
To live a stress free life with the hopeof curinng the disease

3.2 Ideation & Brainstorming

Brainstorm, Idea Listing and Grouping


Brainstorm
Write down any ideas that come to mind that address your problem statement.
10 minutes
Aberna Annalakshmi S
collect details of patient and compare it
choose relevent dataset to train the model
choose an algorithm to increase the accuracy
check the family history of a person to identify any correlation
Sushma S
Amruthaa Shree P
Discover patterns with the help of historical data
Train the model to predict the Chronic Kidney Disease
Encourage people to have a healthy diet and have enough natural drinks
Durga M
Use the diagnostic measures like Blood pressure and Albumin
Group ideas
Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.
20 minutes
Causes
Static lifestyle
Obesity
Unhealthy diet
Symptoms
Loss of Appetite
High Blood Pressure
Irregular Sleeping Pattern
Algorithms
Optimized Algorithms for prediction
Algorithms to find correlation
Result
Patient has CKD or not
Displaying result in website

Idea Prioritization


4
Prioritize
Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible.
20 minutes
Importance
Discover patterns with the help of statistical data
Optimized Algorithm can be framed once the approach is decided
Based on certain diagnostic measures like Blood pressure,Albumin
Collect the relevant dataset and decide an approach
Different algorithms can be tested to find the correlation between various attributes
TIP
Participants can use their cursors to point at where sticky notes should go on the grid. The facilitator can confirm the spot by using the laser pointer holding the H key on the keyboard.

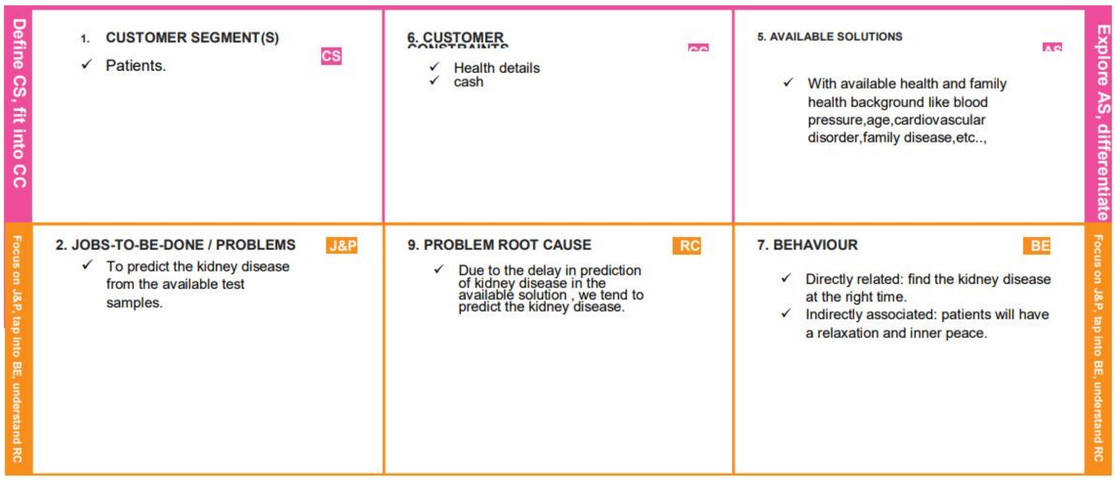
3.3 Proposed Solution

Proposed Solution Template:

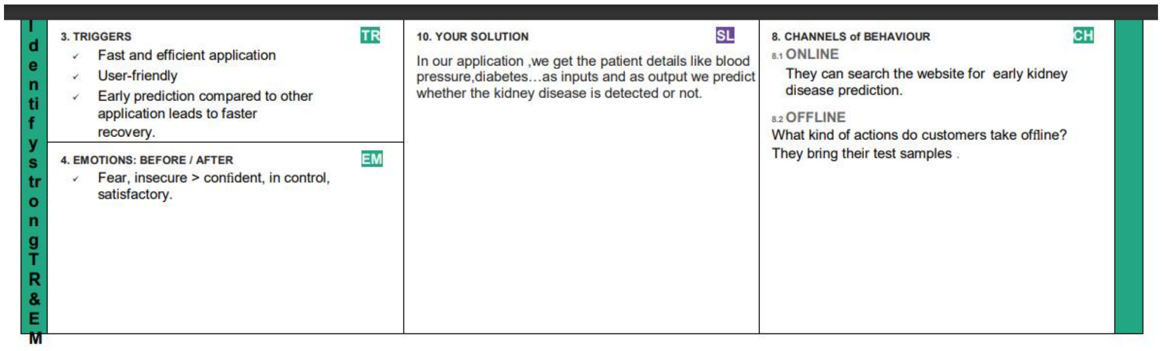
Project team shall fill the following information in proposed solution template.

S.No.	Parameter	Description
1.	Problem Statement (Problem to be solved)	Predicting whether the person is affected by early chronic kidney disease due to issues like high blood pressure, diabetes, high sugar level etc. This may even lead to the death of person if it's found in later stage. So there is need to predict in advance.
2.	Idea / Solution description	The parameters that are collected from the user can be analysed with the trained models to predict the chronic kidney disease in advance. To solve this problem, models are developed using machine learning algorithms to make prediction with higher accuracy.
3.	Novelty / Uniqueness	The model is focused on various parameters which helps to predict the person is affected or not to ensure the high accuracy.
4.	Social Impact / Customer Satisfaction	The main goal to help the person to know whether they are affected by chronic kidney disease or not. Thus, it is necessary to provide higher accuracy results.
5.	Business Model (Revenue Model)	The customers get attracted to the application as they can know their condition from their place instead of travel over a distance to get the results. As all the parameters are analysed, they provide accurate results.
6.	Scalability of the Solution	Through the analysis of all the data and solutions, our solution is scalable. We could optimize it by changing the parameters to predict the disease.

3.4 Problem Solution fit


Define CS, fit into CC
Explore AS, differentiate
Focus on J&P, tap into BE, understand RC
Focus on J&P, tap into BE, understand RC

1. CUSTOMER SEGMENT(S) CS ✓ Patients.	**6. CUSTOMER** ✓ Health details ✓ cash	**5. AVAILABLE SOLUTIONS** ✓ With available health and family health background like blood pressure,age,cardiovascular disorder,family disease,etc..,
2. JOBS-TO-BE-DONE / PROBLEMS J&P ✓ To predict the kidney disease from the available test samples.	**9. PROBLEM ROOT CAUSE** RC ✓ Due to the delay in prediction of kidney disease in the available solution , we tend to predict the kidney disease.	**7. BEHAVIOUR** BE ✓ Directly related: find the kidney disease at the right time. ✓ Indirectly associated: patients will have a relaxation and inner peace.



Identify strong TR & EM

3. TRIGGERS TR
- ✓ Fast and efficient application
- ✓ User-friendly
- ✓ Early prediction compared to other application leads to faster recovery.

4. EMOTIONS: BEFORE / AFTER EM
- ✓ Fear, insecure > confident, in control, satisfactory.

10. YOUR SOLUTION SL

In our application ,we get the patient details like blood pressure,diabetes…as inputs and as output we predict whether the kidney disease is detected or not.

8. CHANNELS of BEHAVIOUR CH

8.1 ONLINE

They can search the website for early kidney disease prediction.

8.2 OFFLINE

What kind of actions do customers take offline?
They bring their test samples .

4. REQUIREMENT ANALYSIS

4.1 Functional requirement

Functional Requirements:

Following are the functional requirements of the proposed solution.

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Form.
FR-2	User Confirmation	Confirmation via retyping password.
FR-3	Obtain Information	The system should be able to get the information for predicting the disease from the user.
FR-4	Displaying Result	The system must be able to display whether the user is affected or not.

4.2 Non-Functional requirements

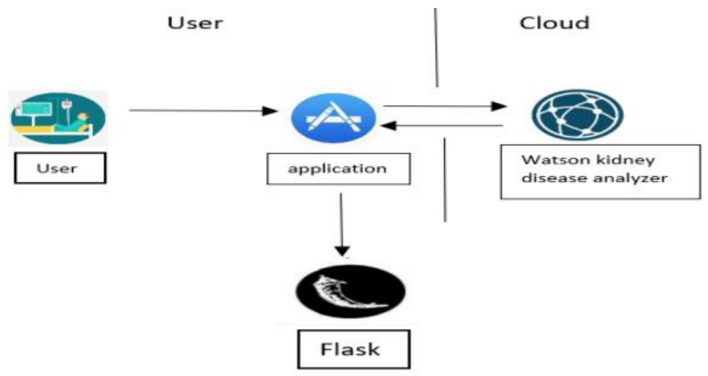
Non-functional Requirements:

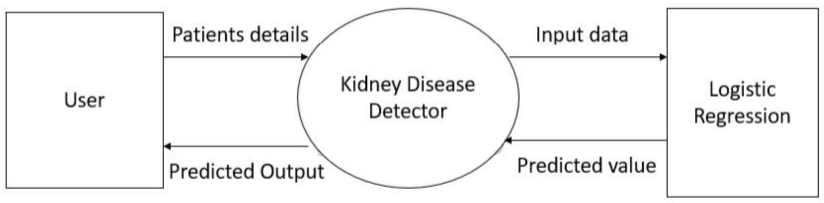
Following are the non-functional requirements of the proposed solution.

FR No.	Non-Functional Requirement	Description
NFR-1	**Usability**	Access to use the application is permitted only to the registered users.
NFR-2	**Security**	Authentication is done for security process.
NFR-3	**Reliability**	The user gets the correct and predicted value and standard results.
NFR-4	**Performance**	The user gets the results faster accessing the application from remote location.
NFR-5	**Availability**	The application is accessible only when the user is online.
NFR-6	**Scalability**	This application can be used anywhere as it is portable(ie.computer,laptop etc).

5. PROJECT DESIGN

5.1 Data Flow Diagrams



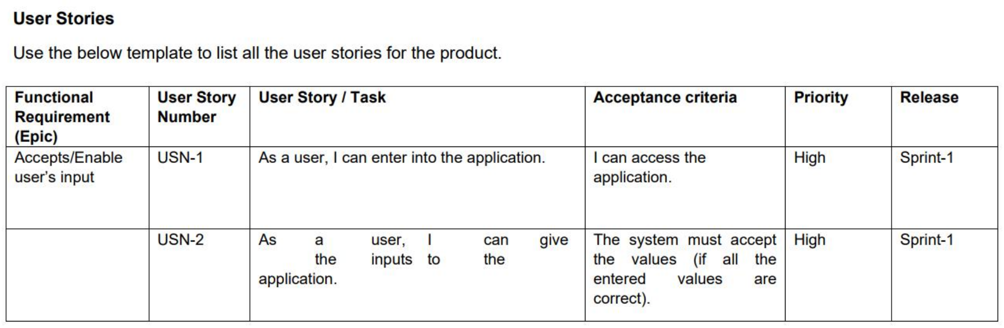


5.2 Solution & Technical Architecture

Table-1 : Components & Technologies:

S.No	Component	Description	Technology
1.	User Interface	An interface for the user to interact with the prediction model	HTML, CSS, JavaScript
2.	User Registration	User can register in the web application	HTML forms
3.	Disease prediction	The user enters the data which is given fed as input to model to predict the disease	Machine Learning with python
4.	Update prediction result	The result of prediction is updated in web UI	Python
5.	Database	Data Type-Numeric	MySQL
6.	Cloud Database	Database Service on Cloud	IBM Cloudant
7.	Machine Learning Model	To predict the early chronic kidney disease using various input parameters	Logistic Regression
8.	Infrastructure (Server / Cloud)	Application Deployment Cloud	IBM Cloud

5.3 User Stories



User Stories

Use the below template to list all the user stories for the product.

Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Accepts/Enable user's input	USN-1	As a user, I can enter into the application.	I can access the application.	High	Sprint-1
	USN-2	As a user, I can give the inputs to the application.	The system must accept the values (if all the entered values are correct).	High	Sprint-1

6. PROJECT PLANNING & SCHEDULING

6.1 Sprint Delivery Schedule

Sprint1	Data collection and preprocessing	30 oct 2022
Sprint2	Data preprocessing and visualization	5 nov 2022
Sprint3	Model Building and dumping pkl file	12 nov 2022
Sprint4	Web page creation using flask and do prediction	19 nov 22

7. CODING & SOLUTIONING (Explain the features added in the project along with code)

Prediction.ipynb

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report,accuracy_score
from sklearn.linear_model import LogisticRegression
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv("C:/Users/Widnows/Desktop/ibm/ibm deployment/chronickidneydisease.csv")
df.head()
df[df.duplicated()]
df.isna().sum()
df2 = df.dropna(axis=0)
df2
df[['htn','dm','cad','pe','ane']] = df[['htn','dm','cad','pe','ane']].replace(to_replace={'yes':1,'no':0})
```

```
df[['rbc','pc']] = df[['rbc','pc']].replace(to_replace={'abnormal':1,'normal':0})
df[['pcc','ba']] = df[['pcc','ba']].replace(to_replace={'present':1,'notpresent':0})
df[['appet']] = df[['appet']].replace(to_replace={'good':1,'poor':0,'no':np.nan})
df['classification'] = df['classification'].replace(to_replace={'ckd':1.0,'ckd\t':1.0,'notckd':0.0,'no':0.0})
df.rename(columns={'classification':'class'},inplace=True)
df['pe'] = df['pe'].replace(to_replace='good',value=0) # Not having pedal edema is good
df['appet'] = df['appet'].replace(to_replace='no',value=0)
df['cad'] = df['cad'].replace(to_replace='\tno',value=0)
df['dm'] = df['dm'].replace(to_replace={'\tno':0,'\tyes':1,' yes':1, '':np.nan})
corr_df = df2.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr_df, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr_df, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.title('Correlations between different predictors')
plt.show()
catcols=set(df2.dtypes[df2.dtypes=='O'].index.values)
Catcols
for i in catcols:
   print("LABEL ENCODING OF:",i)
   LEi=LabelEncoder()
   print(df2[i])
   df2[i]=LEi.fit_transform(df2[i])
   print(df2[i])
   print("*"*100)

X_train, X_test, y_train, y_test = train_test_split(df2.iloc[:,:-1], df2['classification'],test_size = 0.33,
random_state=44,stratify= df2['classification'] )
X_train.head()
X_train.info()
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression()
lgr.fit(X_train,y_train)
y_pred=lgr.predict(X_test)
```

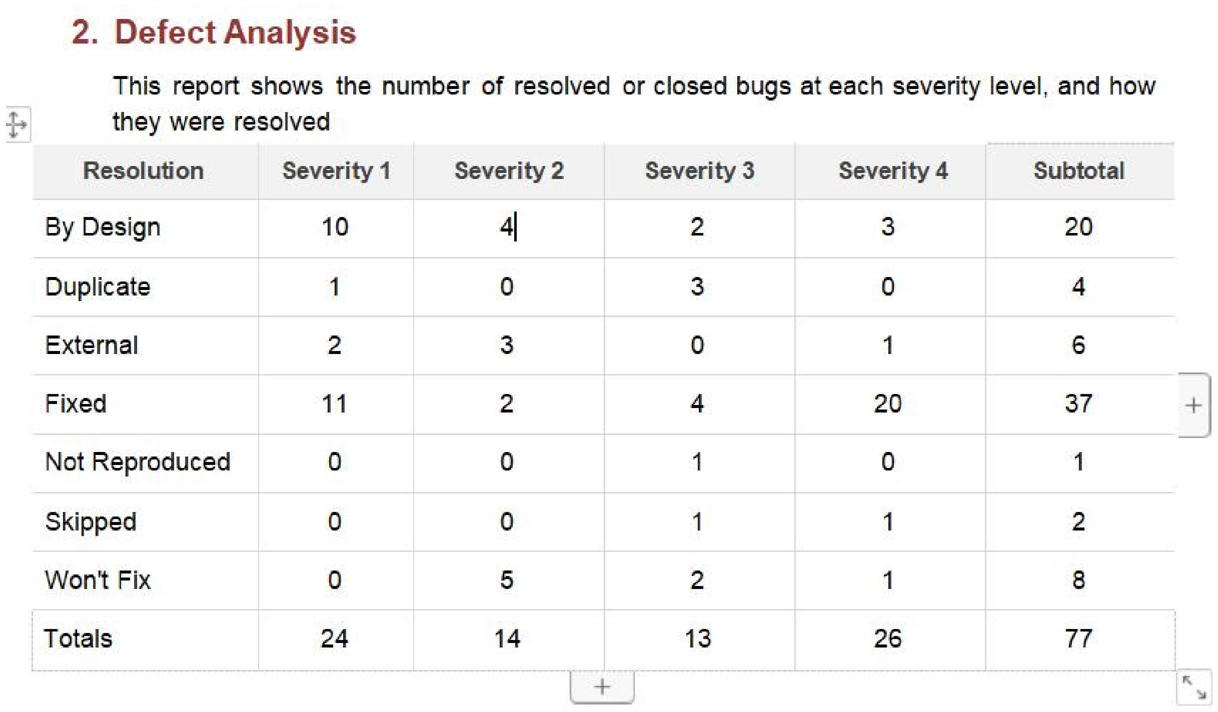
8. TESTING

8.1 Test Cases

Test case id	Feature Type	Component	Test scenario	Steps to execute	Test Data	Expected result
1	Functional	Home Page	Verify user is able to see the home page	1.Enter URL and click go 2.Check whether the home page is visible to user	https://shopenzer.com/	Home page is visible
2	UI	Home Page	Verify all the inputs are provided	1.Enter URL and click go 2.Check whether the home page is visible to user 3.Enter all the datas are provided	https://shopenzer.com/	All the fields are filled with inputs
3	Functional	Home Page	Verify whether the valid inputs are provided	1.Enter URL and click go 2.Check whether the home page is visible to user 3.Enter all the datas are provided 4.Check whether valid inputs are provided	Age:55 bp:122 sugar:134	User should navigate to user account homepage
4	Functional	predict Page	Verify whether the prediction page is navigated	1.Enter all the fields in home page 2.Click Enter to predict	Age:55 bp:122 sugar:134	Navigate and show prediction

			from home page			

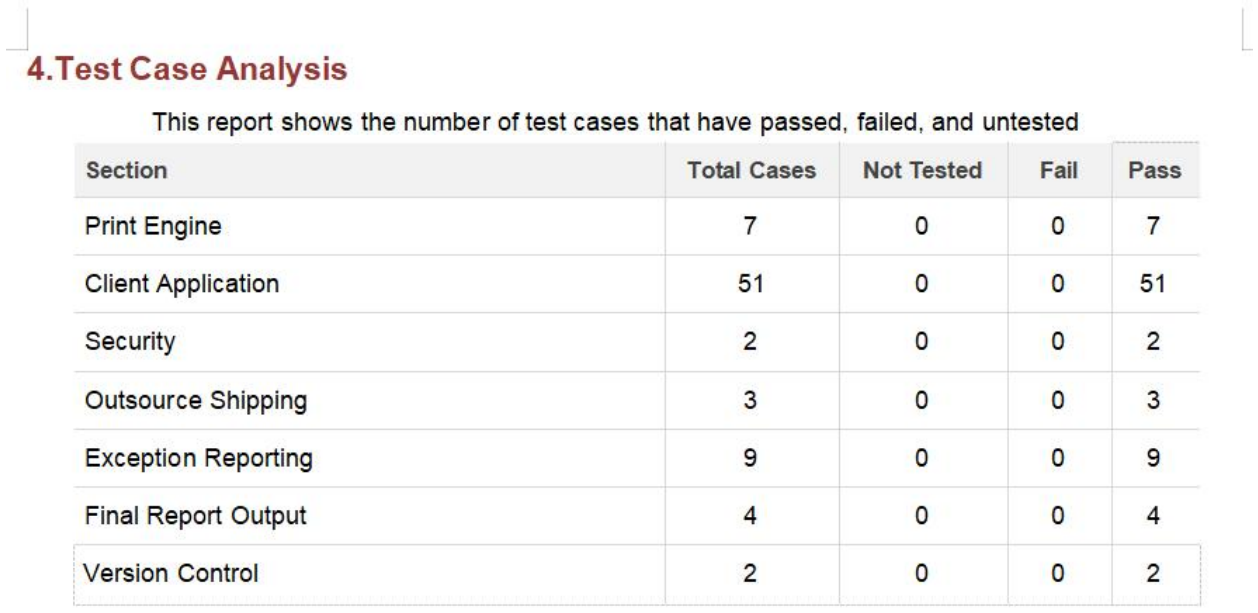
8.2 .User Acceptance Testing



2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77



4.Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

Section	Total Cases	Not Tested	Fail	Pass
Print Engine	7	0	0	7
Client Application	51	0	0	51
Security	2	0	0	2
Outsource Shipping	3	0	0	3
Exception Reporting	9	0	0	9
Final Report Output	4	0	0	4
Version Control	2	0	0	2

9. RESULTS

9.1 Performance Metrics

The Early chronic kidney disease is predicted with good accuracy using the attributes like blood pressure,heomoglobin,artery disease,age,albumin,rbc count,wbc count etc.

10. ADVANTAGES & DISADVANTAGES

The advantage is the early chronic kidney is predicted with few features with good accuracy.

11. CONCLUSION

Thus the website implementation using flask and python was implemented and used for getting the inputs .The prediction of the disease is made successfully.

12. FUTURE SCOPE

The suggestions can be made available.

13. APPENDIX

Source Code

HTML files

Index.html

```
<html>
<head>
<meta http-equiv="Content-Type" content="text/html; charset=UTF-8">
        <title>kidneydisease</title>
<style>
body {
background: linear-gradient(

            rgba(209, 12, 12, 0.75),
            rgba(217, 255, 3, 0.75)),

url( 'https://pharmanewsintel.com/images/site/article_headers/_normal/Chronic_Disease_Manage.png');
            background-repeat: no-repeat;



}.container {
  border: 2px solid #ccc;
  padding: 10px;
  width: 20em;
height:21em;
background-color:white;
}
table.center {
  margin-left: auto;
  margin-right: auto;
}
```

```
.font{
  font-weight: bold;
  font-size: larger;
}


.hello{
opacity: 0.5;
}
</style>
</head>

<body>

<center><p style="font-size:60px;color:aliceblue;">Chronic Disease Prediction</p></center>
<table width="500" height="100" class="center">
<form action="/val" method="post"><center>
<tr class="font">
  <td><label for="age">Age:</label><br></td>
  <td><input type="number" id="age" name="age">
</tr>
<tr class="font">

  <td><label for="bp">Blood Pressure:</label><br>
  <td><input type="number" id="bp" name="bp">
</tr>
<tr class="font">
  <td><label for="sg">Urinary Specific Gravity:</label><br></td>
  <td><input type="number" id="sg" name="sg"></td>
</tr>
  <tr class="font">
  <td><label for="al">albumin:</label><br></td>
  <td><input type="number" id="al" name="al"></td>
</tr>
<tr class="font">
   <td> <label for="su">sugar:</label><br></td>
  <td><input type="number" id="su" name="su"></td>
</tr>
<tr class="font">
<td>
  <label for="rbc">Red Blood Cells:</label><br></td>
<td>  <input type="text" id="rbc" name="rbc"></td>
</tr>
<tr class="font">
```

```
 <td> <label for="pc">Pus cell:</label><br></td>
 <td> <input type="text" id="pc" name="pc"></td>
</tr>
<tr class="font">
  <td><label for="pcc">Pus cell clumps:</label><br></td>
  <td><input type="text" id="pcc" name="pcc"></td>
</tr>
<tr class="font">
  <td><label for="ba">Bacteria:</label><br></td>
 <td> <input type="text" id="ba" name="ba"></td>
</tr>
<tr class="font">
  <td><label for="bgr">Blood Glucose Random:</label><br></td>
  <td><input type="number" id="bgr" name="bgr"></td>
</tr>
<tr class="font">
  <td><label for="bu">Blood urea:</label><br></td>
  <td><input type="number" id="bu" name="bu"></td>
</tr>
<tr class="font">
  <td><label for="sc">Serum creatinine:</label><br></td>
  <td><input type="number" id="sc" name="sc"></td>
</tr>
<tr class="font">
  <td><label for="sod">Sodium:</label><br></td>
  <td><input type="number" id="sod" name="sod"></td>
</tr>
<tr class="font">
  <td> <label for="pot">Potassium:</label><br></td>
  <td><input type="number" id="pot" name="pot"></td>
</tr>
<tr class="font">
  <td><label for="hemo">Hemoglobin:</label><br></td>
  <td><input type="number" id="hemo" name="hemo"></td>
</tr>
<tr class="font">  <td><label for="pcv">PackedCellVolume:</label><br></td>
  <td><input type="text" id="pcv" name="pcv"></td>
</tr>
<tr class="font">
  <td><label for="wc">Whitebloodcellcount:</label><br></td>
  <td><input type="text" id="wc" name="wc"></td>
</tr>
<tr class="font">
  <td><label for="rc">Redbloodcellcount:</label><br></td>
  <td><input type="text" id="rc" name="rc"></td>
</tr>
<tr class="font">  <td><label for="htn">Hypertension:</label><br></td>
  <td><input type="text" id="htn" name="htn"></td>
</tr>
<tr class="font">
  <td><label for="dm">DiabetesMellitus:</label><br></td>
  <td><input type="text" id="dm" name="dm"></td>
</tr>
<tr class="font">
  <td><label for="cad">Coronaryarterydisease:</label><br></td>
  <td><input type="text" id="cad" name="cad"></td>
</tr>
<tr class="font">  <td><label for="appet">Appetite:</label><br></td>
  <td><input type="text" id="appet" name="appet"></td>
</tr>
<tr class="font">  <td><label for="pe">PedalEdema:</label><br></td>
  <td><input type="text" id="pe" name="pe"></td>
</tr>
<tr class="font"> <td> <label for="ane">Aneamia:</label><br></td>
  <td><input type="text" id="ane" name="ane"></td>
</tr></center>
<tr class="font">
  <td><center><button type="submit">Check</button></center></td>
</tr>
</form>
</table>
</body>
</html>
```

Rename.html

```
<html>
<head>
<style>
body {
  background-color: #E6E6FA;
}
</style>
</head>
<body >
<br>
<br>
<br>
```

```
<center><h1>{{answer1}}</h1></center>
<br>


</body>
</html>
```

Rename2.html

```
<html>
<head>
<style>
body {
  background-color: #E6E6FA;
}
</style>
</head>
<body >
<br>
<br>
<br>
<center><h1>{{answer1}}</h1></center>
<br>

</body>
</html>
```

Prediction.ipynb

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report,accuracy_score
from sklearn.linear_model import LogisticRegression
import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv("C:/Users/Widnows/Desktop/ibm/ibm deployment/chronickidneydisease.csv")
df.head()
df[df.duplicated()]
```

```
df.isna().sum()
df2 = df.dropna(axis=0)
df2
df[['htn','dm','cad','pe','ane']] = df[['htn','dm','cad','pe','ane']].replace(to_replace={'yes':1,'no':0})
df[['rbc','pc']] = df[['rbc','pc']].replace(to_replace={'abnormal':1,'normal':0})
df[['pcc','ba']] = df[['pcc','ba']].replace(to_replace={'present':1,'notpresent':0})
df[['appet']] = df[['appet']].replace(to_replace={'good':1,'poor':0,'no':np.nan})
df['classification'] = df['classification'].replace(to_replace={'ckd':1.0,'ckd\t':1.0,'notckd':0.0,'no':0.0})
df.rename(columns={'classification':'class'},inplace=True)
df['pe'] = df['pe'].replace(to_replace='good',value=0) # Not having pedal edema is good
df['appet'] = df['appet'].replace(to_replace='no',value=0)
df['cad'] = df['cad'].replace(to_replace='\tno',value=0)
df['dm'] = df['dm'].replace(to_replace={'\tno':0,'\tyes':1,' yes':1, '':np.nan})
corr_df = df2.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr_df, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr_df, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
plt.title('Correlations between different predictors')
plt.show()
catcols=set(df2.dtypes[df2.dtypes=='O'].index.values)
Catcols
for i in catcols:
    print("LABEL ENCODING OF:",i)
    LEi=LabelEncoder()
    print(df2[i])
    df2[i]=LEi.fit_transform(df2[i])
    print(df2[i])
    print("*"*100)

X_train, X_test, y_train, y_test = train_test_split(df2.iloc[:,:-1], df2['classification'],test_size = 0.33,
random_state=44,stratify= df2['classification'] )
X_train.head()
X_train.info()
```

```
from sklearn.linear_model import LogisticRegression
lgr=LogisticRegression()
lgr.fit(X_train,y_train)
y_pred=lgr.predict(X_test)
```

Flaskfile.ipynb

```
import numpy as np
import pandas as pd
import flask

from flask import Flask, request, redirect, render_template
import pickle

loaded_reg = pickle. load(open('randomreg_chronic.pkl', 'rb'))
app = Flask(__name__,static_url_path="")
@app.route('/',methods=['GET'])
def index():
    return render_template('index.html')
@app.route('/val',methods=['POST'])


def val():
    test=[]
    if request.method == 'POST':
        test.append(float(request.form["age"]))
        test.append(float(request.form["bp"]))
        test.append(float(request.form["sg"]))
        test.append(float(request.form["al"]))
        test.append(float(request.form["su"]))
        rb=request.form["rbc"]
        if rb==0:
            test.append(1)
        else:
            test.append(0)
        pc=request.form["pc"]
        if pc==0:
            test.append(1)
        else:
            test.append(0)
        pcc=request.form["pcc"]
        if pcc==1:
            test.append(1)
        else:
            test.append(0)
```

```
ba=request.form["ba"]
if ba==1:
    test.append(1)
else:
    test.append(0)
test.append(float(request.form["bgr"]))
test.append(float(request.form["bu"]))
test.append(float(request.form["sc"]))
test.append(float(request.form["sod"]))
test.append(float(request.form["pot"]))
test.append(float(request.form["hemo"]))
test.append(float(request.form["pcv"]))
test.append(float(request.form["wc"]))
test.append(float(request.form["rc"]))
ht=request.form["htn"]
if ht==1:
    test.append(1)
else:
    test.append(0)
d=request.form["dm"]
if d==1:
    test.append(1)
else:
    test.append(0)
ca=request.form["cad"]
if ca==1:
    test.append(1)
else:
    test.append(0)
ap=request.form["appet"]
if ap==1:
    test.append(1)
else:
    test.append(0)

p=request.form["pe"]
if p==1:
    test.append(1)
else:
    test.append(0)
an=request.form["ane"]
if an==1:
    test.append(1)
else:
```

```
            test.append(0)
    print(test)
    test_df=pd.DataFrame(test)
    test_df=np.array(test_df).reshape(1, -1)

    ans2=loaded_reg.predict(test_df)
    if int(ans2)==1:
        answer1="You have CHRONIC DISEASE!!!"
        return render_template('rename.html',answer1=answer1)
    else:
        answer1="You don't have CHRONIC DISEASE"

        return render_template('rename2.html',answer1=answer1)

if __name__ == "__main__":
    app.debug=True
    app.run(debug=False)
```

GitHub & Project Demo Link

https://drive.google.com/file/d/1XVWApSJ0ltiLZcf14TYzrN5izIPABNZ2/view?usp=sharing

https://github.com/IBM-EPBL/IBM-Project-2302-1658469423