Project Report

Title: Early prediction for chronic kidney disease detection

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EARLY PREDICTION FOR CHRONIC KIDNEY DISEASE DETECTION: A PROGRESSIVE APPROACH TO HEALTH MANAGEMENT

1.INTRODUCTION:

1.1Overview

Welcome to the introduction of our project on early prediction for chronic kidney disease detection! Chronic kidney disease (CKD) is a progressive condition that affects the functionality of the kidneys, leading to a gradual decline in kidney function over time. Detecting CKD in its early stages is crucial for effective management and intervention, as it allows for timely medical interventions to slow down or prevent further damage to the kidneys.

Our project aims to develop a predictive model that utilizes machine learning algorithms to identify individuals at risk of developing CKD in the early stages. By analyzing various factors such as medical history, laboratory test results, and patient demographics, our model will generate accurate predictions to identify individuals who may require further evaluation and intervention.

The primary objective of our project is to improve the early detection of CKD, as early intervention can significantly impact patient outcomes, including better management of symptoms, improved quality of life, and reduced healthcare costs. Our project has the potential to revolutionize the field of CKD detection by providing a reliable and efficient tool for healthcare providers to identify patients at risk of CKD at an early stage, enabling them to take appropriate preventive measures.

Through this project, we aim to contribute to the field of healthcare by leveraging the power of machine learning to improve patient care, facilitate early detection of CKD, and ultimately help save lives. We are excited about the potential impact of our project and look forward to sharing our findings with the medical community and stakeholders involved in CKD management.

1.2. Purpose:

The purpose of our early prediction for chronic kidney disease (CKD) detection project is multifold:

- **Early Intervention:** Early detection of CKD allows for timely medical interventions, such as lifestyle changes, medication management, and close monitoring, to slow down or prevent further damage to the kidneys. By identifying individuals at risk of CKD in the early stages, our project aims to facilitate early intervention and improve patient outcomes.

- **Improved Patient Care:** Early prediction of CKD can help healthcare providers proactively manage patients' health by identifying those who require further evaluation and intervention. This can result in better patient care, including more effective treatment plans, improved symptom management, and enhanced quality of life for individuals with CKD.

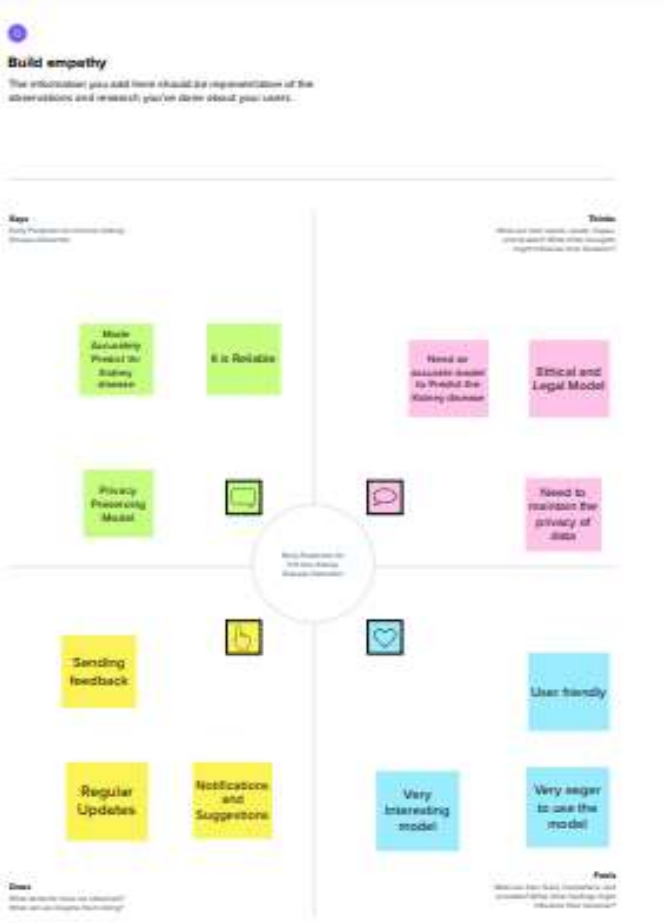
- **Cost-Effective Healthcare:** Early detection of CKD can potentially reduce healthcare costs by preventing or delaying the need for expensive treatments such as dialysis or kidney transplantation. By identifying individuals at risk of CKD early, our project aims to contribute to cost-effective healthcare by enabling preventive measures and reducing the burden of CKD on the healthcare system.

- **Advancement of Healthcare Field**: Our project aims to contribute to the field of healthcare by leveraging the power of machine learning and predictive analytics to improve CKD detection. By developing accurate and efficient predictive models, we seek to advance the field of CKD detection and provide healthcare providers with a reliable tool for early prediction, ultimately improving patient care and outcomes.

Overall, the purpose of our project is to utilize machine learning techniques to develop a predictive model that can aid in early detection of CKD, leading to timely interventions, improved patient care, and potentially cost-effective healthcare.

2.PROBLEM DEFINATION & DESIGN THINKING

2.1.Empathy map:



2.2.Ideation & Brainstorming map

Write down any ideas that come to mind that address your problem statement.

10 minutes

TIP

You can select a sticky note and hit the pencil [switch to sketch] icon to start drawing!

vishnu

- Data collection and mangement
- Data Analysis
- Data Preprocessing
- Model development

nagaraj

- Model Validation
- Model Training
- Model Testing

veeraiah

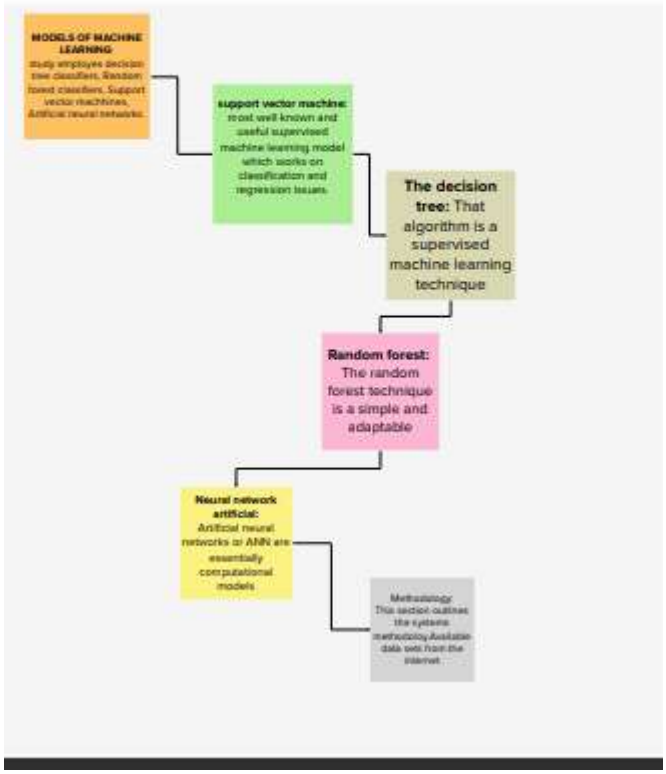
- Integration with Heasystemith care
- Compliance
- Continuous Improvement

ananth

- Learning Algorithm
- ANN Model
- Random Forest
- Decisiomodeln Tree

Group ideas

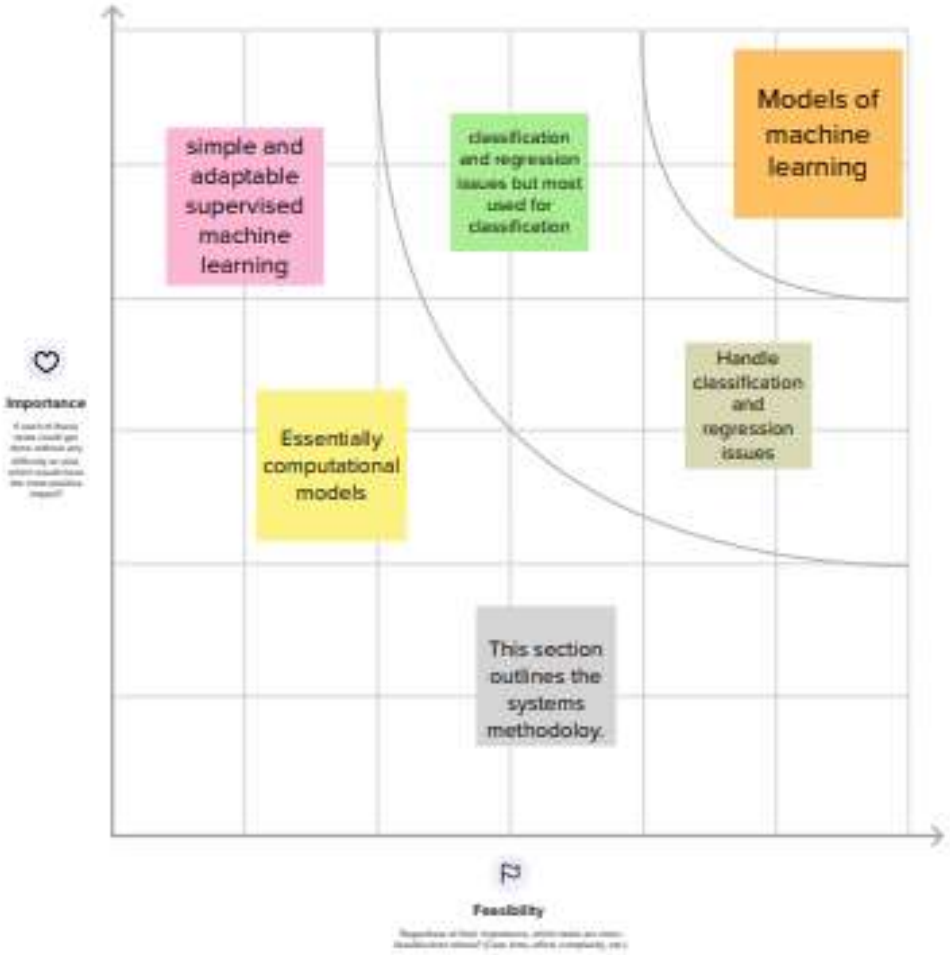
Take turns sharing your ideas while clustering similar or related notes as you go. Once all sticky notes have been grouped, give each cluster a sentence-like label. If a cluster is bigger than six sticky notes, try and see if you and break it up into smaller sub-groups.



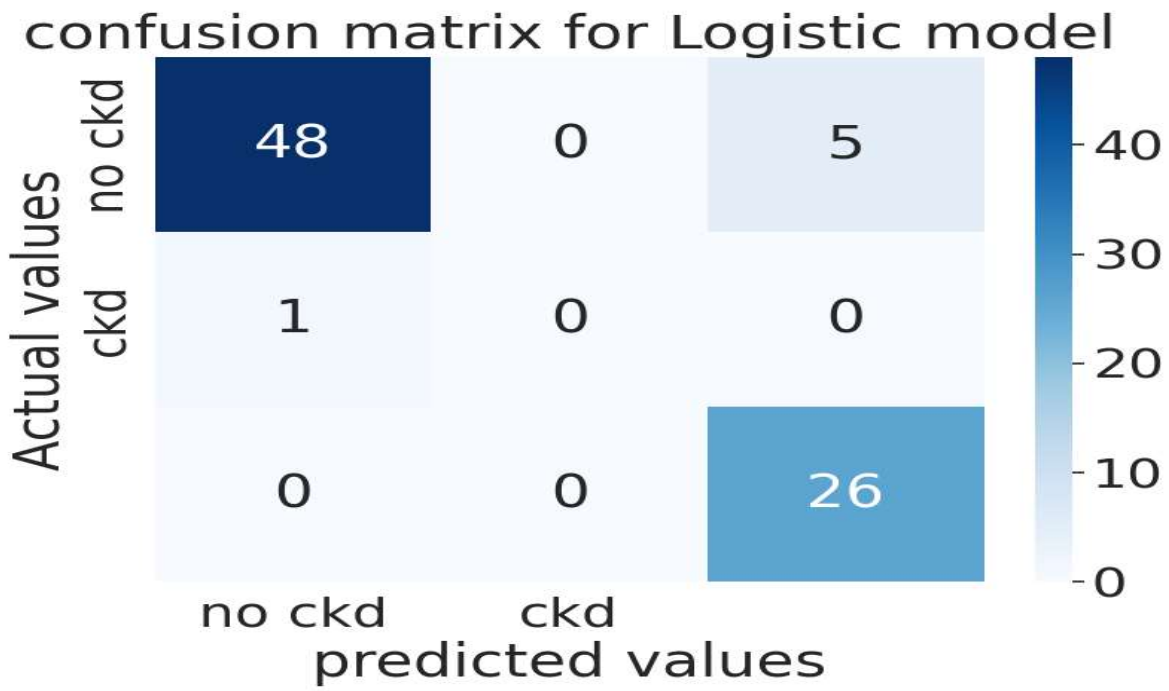
Prioritize

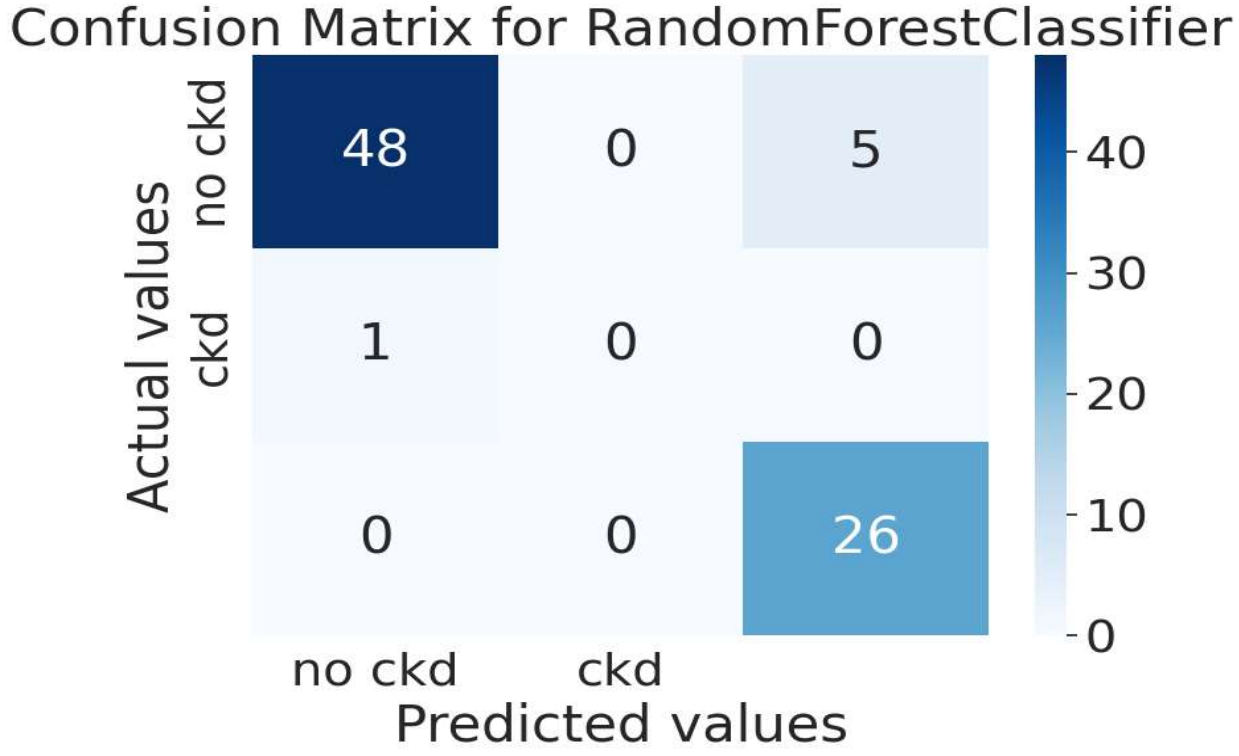
Your team should all be on the same page about what's important moving forward. Place your ideas on this grid to determine which ideas are important and which are feasible

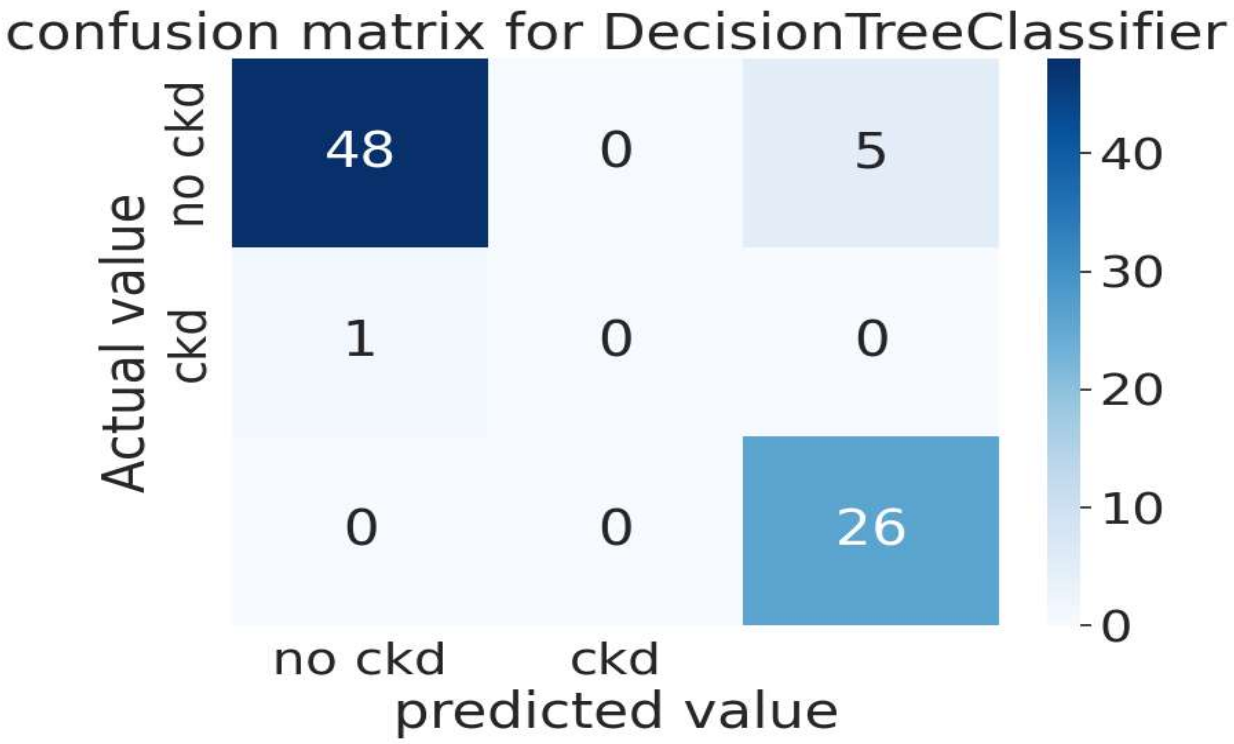
20 minutes

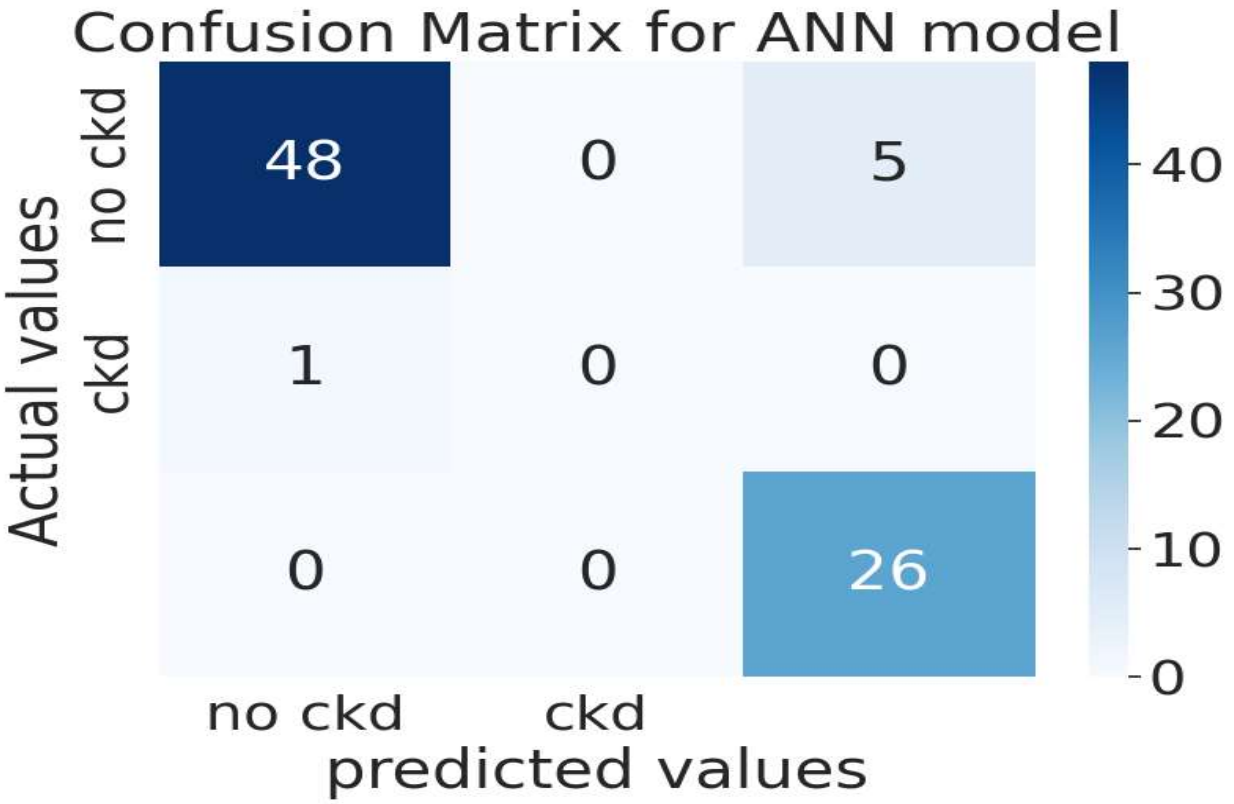


3.RESULT:


confusion matrix for Logistic model
Actual values
no ckd
ckd
48
0
5
1
0
0
0
0
26
40
30
20
10
0
no ckd
ckd
predicted values


Confusion Matrix for RandomForestClassifier
Actual values
no ckd
ckd
48
0
5
1
0
0
0
0
26
40
30
20
10
0
no ckd
ckd
Predicted values


confusion matrix for DecisionTreeClassifier
Actual value
no ckd
ckd
48
0
5
1
0
0
0
0
26
40
30
20
10
0
no ckd
ckd
predicted value


Confusion Matrix for ANN model
Actual values
no ckd
ckd
48
0
5
1
0
0
0
0
26
40
30
20
10
0
no ckd
ckd
predicted values

4.ADAVANTAGES AND DISADAVANTAGES

Advantages of a chronic kidney disease (CKD) detection project:

1.Early Detection: One of the major advantages of a CKD detection project is the ability to identify CKD in its early stages, allowing for timely medical interventions. Early detection enables healthcare providers to implement preventive measures, slow down or prevent further kidney damage, and improve patient outcomes.

2.Improved Patient Outcomes: Early detection of CKD can result in better patient outcomes, including improved symptom management, enhanced quality of life, and reduced risk of complications. Timely interventions based on early detection can help patients better manage their condition and potentially delay the progression of CKD.

3.Cost-effective Healthcare: Early detection of CKD can lead to cost-effective healthcare by preventing or delaying the need for expensive treatments such as dialysis or kidney transplantation. Detecting CKD early can help in implementing preventive measures and managing CKD more effectively, potentially reducing the burden of CKD on the healthcare system.

4.Enhanced Patient Care: A CKD detection project can aid healthcare providers in proactively managing patients' health by identifying individuals at risk of CKD early. This can result in personalized treatment plans, closer monitoring, and more informed decision-making, leading to improved patient care and outcomes.

Disadvantages of a CKD detection project:

1.False Positives/Negatives: Like any predictive model, a CKD detection project may have false positives or false negatives, leading to incorrect predictions. False positives may result in unnecessary interventions, while false negatives may lead to missed opportunities for early detection and intervention.

2.Data Limitations: The accuracy and reliability of a CKD detection project heavily depend on the quality and availability of data used for model training. Limited or biased data may affect the performance and generalizability of the model, leading to potential inaccuracies or biases in predictions.

3.Ethical and Privacy Concerns: A CKD detection project may involve the use of sensitive patient data, which raises ethical and privacy concerns. Ensuring data privacy, informed consent, and compliance with relevant regulations such as HIPAA (Health Insurance Portability and Accountability Act) is critical to safeguard patient confidentiality and privacy.

4.Implementation Challenges: Implementing a CKD detection project in a clinical setting may present challenges such as integration with existing healthcare systems, adoption by healthcare providers, and resource constraints. Overcoming these challenges and effectively integrating the model into clinical workflows may require careful planning, coordination, and resource allocation.

5.Cost and Resource Requirements: Developing and maintaining a CKD detection project may require significant costs and resources, including data acquisition, model development, validation, and deployment. Adequate funding, expertise, and infrastructure may be required to successfully implement and sustain the project.

In conclusion, while a CKD detection project has several advantages, including early detection, improved patient outcomes, and cost-effective healthcare, it may also face challenges related to false positives/negatives, data limitations, ethical and privacy concerns, implementation challenges, and resource requirements. Careful consideration and mitigation of these challenges are essential to ensure the successful development and implementation of a CKD detection project.

5.APPLICATIONS

The application of a chronic kidney disease (CKD) detection project can have several potential applications in various healthcare settings, including:

1.Clinical Decision Support: The CKD detection project can be integrated into electronic health record (EHR) systems to provide healthcare providers with real-time decision support. This can aid clinicians in identifying patients at risk of CKD during routine clinical encounters, guiding them in appropriate screening, monitoring, and management strategies.

2.Population Health Management: The CKD detection project can be used as a population health management tool to identify individuals at risk of CKD within a specific population or community. This can help healthcare organizations target preventive measures, education, and interventions to reduce the overall burden of CKD in the population.

3.Telehealth and Remote Monitoring: The CKD detection project can be incorporated into telehealth and remote monitoring programs to identify individuals at risk of CKD who may be receiving care remotely. This can enable remote monitoring of kidney function, timely interventions, and remote patient education to manage CKD effectively.

4.Health Insurance and Payer Applications: Health insurance providers and payers can utilize the CKD detection project to identify individuals at risk of CKD and implement targeted interventions to manage the condition and reduce healthcare costs. This can include tailored care plans, reimbursement strategies, and disease management programs.

5.Research and Public Health: The CKD detection project can contribute to research and public health efforts by providing insights into the prevalence, risk factors, and outcomes of CKD in specific populations. This can aid in understanding the epidemiology of CKD, identifying high-risk groups, and informing public health policies and interventions.

6.Patient Self-Management: The CKD detection project can empower patients to actively manage their kidney health by providing personalized risk assessments, monitoring tools, and education. This can help patients make informed decisions about their lifestyle, medications, and regular check-ups to prevent or delay the progression of CKD.

Overall, the application of a CKD detection project can have diverse and valuable applications in clinical practice, population health management, telehealth, health insurance, research, public health, and patient self-management, ultimately leading to improved CKD detection, management, and patient outcomes.

6.CONCLUSION

In conclusion, a chronic kidney disease (CKD) detection project holds significant promise in improving early detection and management of CKD, leading to better patient outcomes and cost-effective healthcare. By leveraging predictive modeling and data-driven approaches, a CKD detection project can aid healthcare providers in identifying individuals at risk of CKD, implementing timely interventions, and tailoring care plans to manage CKD effectively. However, it is important to acknowledge potential challenges such as false positives/negatives, data limitations, ethical and privacy concerns, implementation challenges, and resource requirements that may need to be addressed during the development and implementation of a CKD detection project.

Despite these challenges, the potential benefits of a CKD detection project are substantial, including early detection, improved patient outcomes, enhanced population health management, and better utilization of healthcare resources. By integrating the CKD detection project into clinical practice, telehealth, health insurance, research, public health, and patient self-management, it can contribute to a holistic approach to CKD care and support proactive management of CKD in diverse healthcare settings.

Ultimately, a well-designed and carefully implemented CKD detection project can be a valuable tool in the fight against CKD, helping to identify CKD early, optimize management strategies, and improve patient outcomes. Continued research, innovation, and collaboration among stakeholders are essential to further refine and optimize CKD detection projects for wider adoption and maximum impact in clinical practice and population health management.

7.FUTURE SCOPE

The future scope of a chronic kidney disease (CKD) detection project is promising, with potential advancements and opportunities for further development and utilization. Some potential future scopes of a CKD detection project may include:

1.Advancements in Artificial Intelligence and Machine Learning: Rapid advancements in artificial intelligence (AI) and machine learning (ML) technologies may enable more sophisticated and accurate predictive models for CKD detection. These advancements may allow for the integration of more diverse data sources, such as wearable devices, genetic data, and social determinants of health, to improve the accuracy and timeliness of CKD prediction algorithms.

2.Personalized Risk Assessment: The future scope of a CKD detection project may involve personalized risk assessment, taking into consideration an individual's unique risk factors, genetics, lifestyle, and comorbidities. This can help healthcare providers tailor interventions and care plans to an individual's specific needs, resulting in more targeted and effective CKD management strategies.

3.Telehealth and Remote Monitoring: The use of telehealth and remote monitoring in healthcare has seen significant growth, especially in the wake of the COVID-19 pandemic. The future scope of a CKD detection project may involve further integration of telehealth and remote monitoring technologies to enable remote monitoring of kidney function, virtual consultations, and patient education, enhancing CKD management in remote or underserved areas.

4.Integration with Digital Health Solutions: The integration of CKD detection projects with digital health solutions, such as mobile apps, patient portals, and electronic health record systems, can provide patients and healthcare providers with seamless access to CKD risk assessment tools, monitoring dashboards, educational resources, and care coordination tools.

5.Population Health Management: The future scope of a CKD detection project may involve wider adoption in population health management strategies, such as targeted screening programs, community-based interventions, and policy-level interventions to address the burden of CKD at a population level. This can involve collaborations between healthcare organizations, public health agencies, and policymakers to implement evidence-based interventions and policies aimed at CKD prevention and management.

6.Implementation in Low-Resource Settings: CKD is a global health issue, and the future scope of a CKD detection project may involve implementation in low-resource settings, where access to healthcare resources and infrastructure may be limited. Simplified and cost-effective CKD detection tools, such as point-of-care tests or mobile health applications, may be developed to enable early detection and management of CKD in resource-constrained settings.

7.Integration with Precision Medicine Approaches: Precision medicine, which involves tailoring medical interventions based on an individual's unique characteristics, is gaining traction in healthcare. The future scope of a CKD detection project may involve integration with precision medicine approaches, such as genomic data, to identify individuals at higher risk of CKD and provide targeted interventions based on their genetic profile.

In conclusion, the future scope of a CKD detection project holds significant potential for advancements and wider utilization in clinical practice, telehealth, digital health, population health management, low-resource settings, and precision medicine. Continued research, innovation, and collaborations among stakeholders are critical to unlocking the full potential of CKD detection projects and improving CKD outcomes at individual and population levels.

8.APPENDIX

A. Source code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings('ignore')
plt.style.use('fivethirtyeight')
%matplotlib inline
pd.set_option('display.max_columns', 26)

data = pd.read_csv('kidney_disease.csv')
data.head()
data.drop('id', axis = 1, inplace = True)
data.columns = ['age',
                'blood_pressure',
                'specific_gravity',
                'albumin',
                'sugar',
                'red_blood_cells',
                'pus_cell',
                'pus_cell_clumps',
                'bacteria',
                'blood_glucose_random',
                'blood_urea',
                'serum_creatinine',
                'sodium',
                'potassium',
                'haemoglobin',
                'packed_cell_volume',
                'white_blood_cell_count',
                'red_blood_cell_count',
                'hypertension',
                'diabetes_mellitus',
                'coronary_artery_disease',
```

```
                'appetite',
                'peda_edema',
                'aanemia',
                'class'
               ]
data.head()
data.describe()
data.info()
data.isnull().any()
data['packed_cell_volume']     = pd.to_numeric(data['packed_cell
_volume']    , errors='coerce')
data['white_blood_cell_count'] = pd.to_numeric(data['white_blood
_cell_count'], errors='coerce')
data['red_blood_cell_count']   = pd.to_numeric(data['red_blood_c
ell_count']  , errors='coerce')

data.info()
data.isnull().any()

data['blood_glucose_random'].fillna(data['blood_glucose_random']
.mean(),inplace=True)
data['blood_pressure'].fillna(data['blood_pressure'].mean(),inpl
ace=True)
data['blood_urea'].fillna(data['blood_urea'].mean(),inplace=True
)
data['haemoglobin'].fillna(data['haemoglobin'].mean(),inplace=Tr
ue)
data['packed_cell_volume'].fillna(data['packed_cell_volume'].mod
e()[0],inplace=True)
data['potassium'].fillna(data['potassium'].mean(),inplace=True)
data['red_blood_cell_count'].fillna(data['red_blood_cell_count']
.mode()[0],inplace=True)
data['serum_creatinine'].fillna(data['serum_creatinine'].mean(),
inplace=True)
data['sodium'].fillna(data['sodium'].mean(),inplace=True)
data['white_blood_cell_count'].fillna(data.median())

data['age'].fillna(data['age'].mode()[0],inplace=True)
```

```
data['hypertension'].fillna(data['hypertension'].mode()[0],inpla
ce=True)
data['pus_cell_clumps'].fillna(data['pus_cell_clumps'].mode()[0]
,inplace=True)
data['appetite'].fillna(data['appetite'].mode()[0],inplace=True)
data['albumin'].fillna(data['albumin'].mode()[0], inplace=True)
data['pus_cell'].fillna(data['pus_cell'].mode()[0],inplace=True)
data['red_blood_cells'].fillna(data['red_blood_cells'].mode()[0]
,inplace=True)
data['coronary_artery_disease'].fillna(data['coronary_artery_dis
ease'].mode()[0],inplace=True)
data['bacteria'].fillna(data["bacteria"].mode()[0],inplace=True)
data['aanemia'].fillna(data['aanemia'].mode()[0],inplace=True)
data['sugar'].fillna(data['sugar'].mode()[0],inplace=True)
data['diabetes_mellitus'].fillna(data['diabetes_mellitus'].mode(
)[0],inplace=True)
data['peda_edema'].fillna(data['peda_edema'].mode()[0],inplace=T
rue)
data[ 'specific_gravity'].fillna(data[ 'specific_gravity'].mode(
)[0],inplace=True)

catcols=set(data.dtypes[data.dtypes=='O'].index.values)

for i in catcols:

catcols.remove('red_blood_cell_count')
catcols.remove('packed_cell_volume')
#catcols.remove('white_blood_cell_count')
print(catcols)

catcols=['aanemia','peda_edema','appetite','bacteria','class','c
oronary_artery_disease','diabetes_mellitus','hypertension','pus_
cell','pus_cell_clumps','red_blood_cells']

from sklearn.preprocessing import LabelEncoder
for i in catcols:
  print("LABEL ENCODING OF:",i)
  LEi=LabelEncoder()
  c=data[i]
```

```
  print(c)
  data[i]=LEi.fit_transform(data[i])
  c=data[i]
  print(c)
  print("*"*100)
contcols=set(data.dtypes[data.dtypes!='0'].index.values)
print(contcols)
for i in contcols:
  print("Continous Columns :",i)
  c=data[i]
contcols.remove('specific_gravity')
contcols.remove('albumin')
contcols.remove('sugar')
print(contcols)

contcols.add('red_blood_cell_count')
contcols.add('packed_cell_volume')
contcols.add('white_blood_cell_count')
print(catcols)

catcols.add('specific_gravity')
catcols.add('albumin')
catcols.add('sugar')
print(catcols)

data['coronary_artery_disease']=data.coronary_artery_disease.rep
lace('\tno','no')
c(data['coronary_artery_disease'])

data['diabetesmellitus']=data.diabetesmellitus.replace(to_replac
e={'\tno':'\tyes':'yes','yes':})
c(data['diabetesmellitus'])

data.describe()
sns.distplot(data.age)
import matplotlib.pyplot as plt
fig=plt.figure(figsize=(5,5))
plt.xlabel('age')
plt.ylabel('blood pressure')
```

```
plt.title("age vs blood scatter plot")

plt.figure(figsize=(20,15),facecolor='white')
plotnumber=1
for column in contcols:
  if plotnumber<=11:
    ax=plt.subplot(3,4,plotnumber)
    plt.scatter(data['age'],data[column])
    plt.xlabel(column,fontsize=20)
    plotnumber+=1
    plt.show()
f,ax=plt.subplots(figsize=(18,10))
sns.heatmap(data.corr(),annot=True,fmt=".2f",ax=ax,linewidths=0.
5,linecolor='orange')
plt.xticks(rotation=45)
plt.yticks(rotation=45)
plt.show

sns.countplot(data['class'])
setcols=['red_blood_cells','pus_cell','blood_glucose_random','bl
ood_urea','peda_edema','aanemia','diabetes_mellitus','coronary_a
rtery_disease']
x=pd.DataFrame(data,columns=setcols)
y=pd.DataFrame(data,columns=['class'])
print(x.shape)
print(y.shape)

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2
,random_state=2)

# Creating ANN skleton view
classification = Sequential()
classification.add(Dense (30, activation='relu'))
classification.add (Dense (128, activation='relu'))
classification.add(Dense (64, activation='relu'))
classification.add(Dense (32, activation='relu'))
classification.add(Dense(1, activation='sigmoid'))
```

```
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=10,criterion='entr

from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier(n_estimators=10,criterion='entr
y_predict_train = rfc.predict(x_train)
     y_predict=dtc.predict(x_test)

y_predict

from sklearn.metrics import accuracy_score,classification_report
y_predict=lgr.predict(x_test)
#logistic Regression
y_pred=lgr.predict([[1,1,121.000000,36.0,0,0,1,0]])
print(y_pred)
(y_pred)
DecisionTree classifier
y_pred=dtc.predict([[1,1,121.000000,36.0,0,0,1,0]])
print(y_pred)
(y_pred)
#Random Forest Classifier
y_pred=rfc.predict([[1,1,121.000000,36.0,0,0,1,0]])
print(y_pred)
(y_pred)
classification.save("ckd.h5")
def predict_exit(sample_value):
  #convert list to numpy array
  sample_value=np.array(sample_value)
  #Reshape because sample_value contains only 1 record
  sample_value=sample_value.reshape(1,-1)
  #Feature scaling
  sample_value=sc.transform(sample_value)
  return classifier.predict(sample_value)

test=classification.predict([[1,1,121.000000,36.0,0,0,1,0]])
if test==1:
    print('prediction:High chance of CKD!')
else:
    print('prediction:Low chance of CKD.')
```

```
dfs = []
models = [
          ('LogReg', LogisticRegression()),
          ('RF', RandomForestClassifier()),
          ('DecisionTree', DecisionTreeClassifier()),
         ]
results=[]
    names = []
    scoring=['accuracy', 'precision_weighted', 'recall_weighted'
, 'f1_weighted', 'roc_auc']
    target_names=['NO CKD', 'CKD']
    for name, model in models:
        kfold = model_selection.KFold(n_splits=5, shuffle=True,
random_state=90210)
        cv_results = model_selection.cross_validate(model, x_tra
in, y_train, cv=kfold,scoring=scoring)
        clf = model.fit(x_train, y_train)
        y_pred = clf.predict(x_test)
        print(name)
        print(classification_report(y_test,y_pred,target_names=t
arget_names))
        results.append(cv_results)
        names.append(name)
        this_df = pd.DataFrame(cv_results)
        this_df['model']=name
        dfs.append(this_df)
final = pd.concat(dfs, ignore_index-True)
return final
#plotting confusion matrix
plt.figure(figsize=(8,6))
sns.heatmap(cm, cmap='Blues',annot=True, xticklabels=['no ckd','
ckd'], yticklabels=['no ckd','ckd'])
plt.xlabel('predicted values')
plt.ylabel('Actual values')
plt.title('confusion matrix for Logistic model')
plt.show()
#plotting confusion matrix
plt.figure(figsize=(8,6))
```

```
sns.heatmap(cm, cmap='Blues',annot=True,xticklabels=['no ckd','c
kd'],yticklabels=['no ckd','ckd'])
plt.xlabel('Predicted values')
plt.ylabel('Actual values')
plt.title('Confusion Matrix for RandomForestClassifier')
plt.show()

bootstraps = []
for model in list(set(final.model.values)):
    model_df=final.loc[final.model==model]
    bootstrap=model_df.sample(n=30,replace=True)
    bootstraps.append(bootstrap)

bootstrap_df=pd.concat(bootstraps,ignore_index=True)
result_long=pd.melt(bootstraps_df,id_vars=['model'],var_name='me
trics',value_name='value')
time_matrics=['fit_time','score_time']#fit time matrics
## PERFORMANCE METRICS
result_long_nofit=result_long.loc[result_long['metrics'].isin(ti
me_matrics)]# get df without fit data
result_long_nofit=result_long_nofit.sort_values(by='values')
## TIME METRICS
result_long_fit=result_long.loc[result_long['mrteics'].isin(time
_metrics)]# df with fit data
result_long_fit=result_long_fit.sort_values(by='values')

bootstraps = []
for model in list(set(final.model.values)):
    model_df=final.loc[final.model==model]
    bootstrap=model_df.sample(n=30,replace=True)
    bootstraps.append(bootstrap)

bootstrap_df=pd.concat(bootstraps,ignore_index=True)
result_long=pd.melt(bootstraps_df,id_vars=['model'],var_name='me
trics',value_name='value')
time_matrics=['fit_time','score_time']#fit time matrics
## PERFORMANCE METRICS
result_long_nofit=result_long.loc[result_long['metrics'].isin(ti
me_matrics)]# get df without fit data
```

```
result_long_nofit=result_long_nofit.sort_values(by='values')
## TIME METRICS
result_long_fit=result_long.loc[result_long['mrteics'].isin(time
_metrics)]# df with fit data
result_long_fit=result_long_fit.sort_values(by='values')
```