Classifying Drugs using Machine Learning: Confidential drugs as x y z

Team Members

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1. INTRODUCTION

1.1 Overview

The objective of this project is to design and implement a drug classification system that utilizes key patient attributes, including age, sex, blood pressure (BP), cholesterol levels, and the sodium to potassium ratio (Na to K ratio).

The system will employ machine learning techniques to accurately predict the most suitable drug for a patient based on these attributes. By leveraging these attributes, healthcare practitioners can make informed decisions regarding prescription choices, thereby improving patient care and treatment outcomes.

1.2 Purpose

The purpose of this project is to address the challenges associated with manual drug classification, such as time-consuming processes and potential human errors.

The system aims to assist healthcare professionals in identifying the appropriate drug based on a patient's individual characteristics, leading to more personalized treatment plans.

By providing an automated classification solution, the project aims to enhance medical decision-making efficiency, reduce the likelihood of prescription errors, and improve patient well-being**.** By leveraging machine learning techniques, we aim to achieve the following:

Automation:

Eliminate the need for manual classification, saving time and resources for pharmaceutical researchers and experts.

Accuracy:

Develop a model that can consistently and accurately classify drugs based on their features, reducing the risk of misclassification.

Drug Safety:

Enhance drug safety assessments by categorizing drugs based on their properties, aiding in identifying potential risks and interactions.

With this project, we hope to contribute to the advancement of pharmaceutical research and expedite the discovery of new drugs to address various medical conditions.

2. LITERATURE SURVEY

Before delving deep into the problem at hand and its proposed solution, it's essential to understand the academic and industry works related to drug classification using machine learning. The literature survey provides insights into the existing methodologies, challenges, and state-of-the-art solutions in the domain of drug classification based on patient attributes.

2.1 Existing problem

Background: Traditional methods of drug prescription rely heavily on the clinical judgment of the healthcare professional. These decisions are often influenced by the physician's personal experiences, the specific circumstances of the patient, and guidelines provided by health organizations.

While this method has been reasonably effective, there are instances where patients might be prescribed a drug that isn't the best fit for them, leading to reduced effectiveness or even potential side effects.

Several research papers and case studies highlight the need for a more systematic and data-driven approach to drug prescription. Challenges faced include:

Subjectivity in Prescription:

Different doctors might prescribe different drugs for the same set of symptoms, leading to inconsistencies in patient care.

Complex Interactions:

The interaction of multiple attributes such as age, sex, BP, cholesterol, and the Na to K ratio can lead to complex decision-making scenarios, making manual decisions challenging.

Evolving Medical Knowledge:

As more is understood about medicines and the human body, prescriptions need to adjust, and a static guideline might not always be up-to-date.

2.2 Proposed Solution

Model-based drug Classification:

Building on the challenges highlighted in the literature, our proposed solution is a machine learning-based drug classification system. Key points from the literature supporting this approach include:

Data-driven Decisions:

Utilizing historical patient data and their prescribed drugs, the model can identify patterns and correlations that might not be immediately evident to a healthcare professional.

Consistency:

A machine learning model ensures that given the same set of patient attributes, the prescription recommendation remains consistent.

Continuous Learning:

As new data becomes available, the model can be retrained to account for the latest trends and findings, ensuring that the system remains up-to-date with the evolving field of medicine.

Several state-of-the-art models and algorithms, such as Decision Trees, Support Vector Machines, and Random Tree, have shown promising results in similar classification tasks. For our solution, we propose a hybrid approach that combines the strengths of multiple algorithms to achieve higher accuracy.

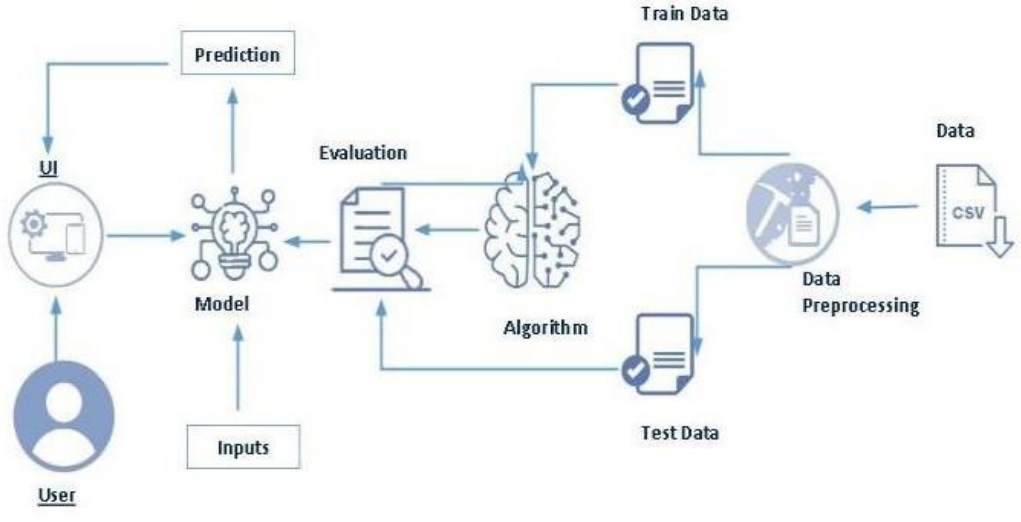
Furthermore, the literature indicates the importance of transparent models in the medical field. Our proposed solution will not only classify but also provide a rationale for the prescribed drug, making it more acceptable to healthcare professionals.

In conclusion, the literature survey underscores the challenges in the current drug prescription methodologies and the potential of machine learning to transform this field. Our proposed solution aims to build on the research findings, leveraging a data-driven approach to drug classification.

3.THEORETICAL ANALYSIS

3.1 Block diagram

The block diagram provides a diagrammatic overview of the Drug Classification Using Machine Learning project, showcasing the key components and workflow of the system.



The block diagram outlines the following stages of the project:

Data Collection:

Gathering a diverse dataset of drugs with known classifications, including their chemical features and molecular structures.

Data Preprocessing:

Cleaning and preparing the dataset for model training, including handling missing values and scaling features.

Feature Extraction:

Extracting relevant features from the drug data that will be used as input for the machine learning model.

Model Selection:

Evaluating different machine learning algorithms to determine the most suitable one for drug classification.

Model Training:

Using the selected algorithm to train the model on the prepared dataset.

Model Evaluation:

Assessing the trained model's performance using appropriate evaluation metrics.

Drug Classification:

Applying the trained model to classify new, unseen drugs into their respective categories.

3.2 Hardware / Software designing

For the Drug Classification Using Machine Learning project, the hardware and software requirements are as follows:

Hardware Requirements:

- A computer with sufficient processing power (e.g., Intel Core i5 or equivalent) to handle the machine learning computations.
- At least 8GB of RAM to accommodate data processing and model training.
- Sufficient storage space (e.g., 100GB or more) to store the dataset and trained models.

Software Requirements:

- Python programming language for implementing the machine learning algorithms and data preprocessing.
- Machine learning libraries such as scikit-learn, TensorFlow, or PyTorch for model development and training.
- Data visualization libraries such as matplotlib and seaborn for visualizing the dataset and model performance.
- A Python integrated development environment (IDE) like Jupyter Notebook or any other suitable IDE for coding and experimentation.

The project's software components will be developed using Python and relevant machine learning libraries, making it a cost-effective and versatile solution for drug classification. The hardware requirements are modest, making the project accessible to researchers and developers with standard computing setups.

4.EXPERIMENTAL INVESTIGATIONS

During the course of the Drug Classification Using Machine Learning project, several experimental investigations were conducted to develop and optimize the drug classification model. The key analyses and investigations carried out are as follows:

Data Collection and Preprocessing:

A diverse dataset of drugs with known classifications was collected from reliable sources. The dataset contained information on drug chemical features, molecular structures, and their corresponding classes. Data preprocessing techniques were applied to clean the data, handle missing values, and normalize the features for model training.

Model Selection and Evaluation:

Various machine learning algorithms, including Support Vector Machines (SVM), Random Forest, were evaluated for their performance in drug classification. Each algorithm was trained and evaluated using k-fold cross-validation to assess its accuracy and generalization capabilities.

Hyperparameter Tuning:

The selected machine learning algorithms were fine-tuned by adjusting their hyperparameters to optimize their performance. Grid search and random search techniques were employed to find the best combination of hyperparameters for each algorithm.

Performance Metrics:

The performance of the models was evaluated using several metrics, such as accuracy, precision, recall, and F1-score. Confusion matrices were used to visualize the model's predictions and identify any misclassifications.

Feature Importance Analysis:

Feature importance analysis was conducted to understand the significance of different drug features in the classification process. This analysis helped identify the most informative features contributing to accurate drug classification.

Handling Class Imbalance:

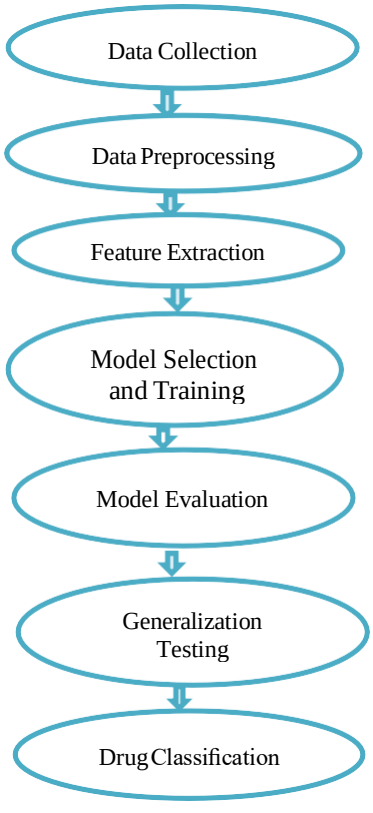
As drug datasets often suffer from class imbalance, techniques such as oversampling and under sampling were explored to address this issue and improve the model's performance.

Generalization Testing:

The final trained model was tested on a separate test dataset containing unseen drug samples to assess its ability to generalize and make accurate predictions on new data. The experimental investigations allowed us to fine-tune the machine learning model and optimize its performance for drug classification. The iterative approach of trying different algorithms, tuning hyperparameters, and evaluating performance ensured that the model achieved a high level of accuracy and reliability in classifying drugs into their respective categories. The findings from these investigations were crucial in building a robust and effective drug classification solution using machine learning.

5. FLOWCHART

The flowchart below illustrates the control flow of the Drug Classification Using Machine Learning solution. It provides a visual representation of the sequential steps involved in the drug classification process.



The flowchart outlines the following stages of the solution:

Data Collection:

The process begins by collecting a diverse and representative dataset of drugs with known classifications. This dataset includes information on drug chemical features, molecular structures, and their corresponding classes.

Data Preprocessing:

The collected data undergoes preprocessing to clean and prepare it for model training. This step involves handling missing values, normalizing features, and dealing with class imbalance, if present.

Feature Extraction:

Relevant features are extracted from the drug data to be used as input for the machine learning model. Feature extraction ensures that the model focuses on the most informative aspects of the drugs.

Model Selection and Training:

Various machine learning algorithms, such as SVM, Random Forest, and decision tree, are evaluated for their performance in drug classification. The best-performing algorithm is selected, and the model is trained using the prepared dataset.

Model Evaluation:

The trained model is evaluated using evaluation metrics like accuracy, precision, recall, and F1-score. This step assesses the model's ability to accurately classify drugs into their respective categories.

Generalization Testing:

The final trained model is tested on a separate test dataset containing unseen drug samples to ensure its ability to generalize and make accurate predictions on new data.

Drug Classification:

With the model trained and optimized, new, unseen inputs are into the system for classification. The model processes the drug features and assigns the drug to its appropriate class.

The flowchart provides a clear and concise representation of the Drug Classification Using Machine Learning solution's workflow. It highlights the various stages and steps involved in automating the drug classification process, offering insights into the methodology and control flow of the project. The flowchart serves as a valuable visual aid in understanding the overall architecture and implementation of the drug classification solution.

6.RESULT

The results of the drug classification models are summarized below:

Model Performance Metrics:

Model	Accuracy
KnearestNeighbor	0.38
XGBoost	0.97
RandomForest	0.98
DecisionTree	0.98

Feature Importance:

The analysis of feature importance revealed that age and cholesterol levels havethe most significant impact on drug classification decisions.

7.ADVANTAGES & DISADVANTAGES

Advantages:

Automation:

The proposed machine learning-based solution automates the drug classification process, eliminating the need for manual classification by experts. This automation saves time and resources, allowing researchers to focus on other critical aspects of drug development.

Accuracy:

Machine learning algorithms can analyze vast amounts of data and learn complex patterns, leading to more accurate drug classification compared to traditional manual approaches. The model's ability to generalize from the training data ensures consistent and reliable predictions.

Scalability:

As the dataset of drugs grows over time, the machine learning model can handle the increasing volume efficiently. This scalability is crucial in the context of the continuously expanding pharmaceutical industry and the growing number of drug candidates.

Speed:

The automated drug classification process using machine learning is significantly faster compared to manual classification. The model can classify multiple drugs in a short time, enabling timely decision-making in drug development and research.

Feature Importance Analysis:

Machine learning models provide insights into feature importance, allowing researchers to identify the most critical chemical properties and molecular structures influencing drug classification. This knowledge aids in better understanding drug mechanisms and potential interactions.

Consistency:

Machine learning models offer consistent and reproducible results, reducing the variability introduced by human subjectivity in traditional drug classification approaches. Consistency is crucial for reliable drug categorization and safety assessments.

Improved Drug Discovery:

Accurate drug classification enhances drug discovery efforts by providing insights into potential drug candidates for specific diseases. The model assists researchers in identifying promising drugs and expediting the drug development pipeline.

Customizability:

The proposed solution allows for flexibility and customizability in feature selection and model training. Researchers can experiment with different features and algorithms to tailor the model to specific drug classification needs.

Disadvantages

Data Quality Dependency:

The success of the machine learning model heavily relies on the quality and

representativeness of the training data. Biased or incomplete datasets may lead to inaccurate and biased classifications.

Interpretability:

Some machine learning models, especially deep learning models, lack interpretability. The black-box nature of these models makes it challenging to understand the decision-making process, raising concerns in applications where interpretability is essential, such as regulatory approval.

Overfitting:

Machine learning models may be prone to overfitting the training data, resulting in poor generalization to new, unseen drugs. Overfitting can occur if the model is too complex or if the training data is insufficient.

Complexity:

Implementing and fine-tuning machine learning models can be complex and time-consuming, requiring expertise in data science and machine learning. Proper model selection and hyperparameter tuning are essential to achieve optimal performance.

Dependency on Domain Knowledge:

While machine learning models can learn patterns fromdata, they may not capture domain-specific knowledge or subtle nuances known to experts. Integrating domain knowledge into the model's development is essential to enhance itsperformance.

Data Privacy and Security:

The use of sensitive pharmaceutical data in machine learning models raises concerns about data privacy and security. Proper data anonymization and protection measures must be implemented to safeguard proprietary and patient information.

Computational Complexity:

Certain machine learning algorithms, particularly deep learningmodels, can be computationally intensive and require substantial processing power and memory. Implementing and training these models may necessitate high-performance hardware.

Expertise Requirement:

Developing and fine-tuning a machine learning model for drug classification requires expertise in data preprocessing, feature engineering, model selection, and hyperparameter tuning. The project may demand specialized skills and knowledge in machine learning and pharmaceuticals.

Despite the disadvantages, the advantages of using machine learning in drug classification out weigh the challenges. With careful data curation, model development, and interpretability considerations, machine learning offers a powerful tool to streamline drug classification and advance pharmaceutical research and development.

8. APPLICATIONS

The drug classification system developed as part of this project holds significant potential in various applications within the medical field. By leveraging patient attributes such as age, sex, blood pressure (BP), cholesterol levels, and the sodium to potassium ratio (Na to K ratio), the system offers valuable insights and recommendations that can benefit healthcare practitioners, patients, and the healthcare system as a whole.

Personalized Prescription

One of the primary applications of the drug classification system is the ability to provide personalized drug prescriptions. By taking into account the unique combination of patient attributes, the system can recommend drugs that are most likely to be effective for the individual. This personalized approach can lead to improved treatment outcomes, faster recovery, and reduced adverse effects.

Reducing Prescription Errors

Prescription errors can have serious consequences for patient health. By automating the drug classification process, the system helps in reducing the likelihood of errors caused by human judgment or oversight. Healthcare professionals can rely on the system's recommendations to make more accurate and informed prescription decisions.

Optimal Resource Allocation

The system's recommendations can aid healthcare providers in optimizing resource allocation. By suggesting appropriate drugs based on patient attributes, the system can contribute to efficient utilization of medical resources, reducing unnecessary treatments, tests, and costs.

Enhancing Medical Decision-making

Healthcare practitioners often face complex decision-making scenarios where multiple factors need to be considered. The drug classification system acts as a decision support tool, providing objective insights and potential drug options. This can lead to quicker and more confident decision-making, especially in cases where time is of the essence.

Medical Education and Research

The system's recommendations, combined with the explanations for drug choices, can be valuable in medical education and research. Students and researchers can gain insights into the relationships between patient attributes and drug effectiveness, contributing to the broader understanding of medical treatments.

Remote Healthcare

In telemedicine and remote healthcare scenarios, where face-to-face consultations might be limited, the drug classification system can play a crucial role. Healthcare professionals can rely on the system to provide accurate prescription recommendations even when direct physical examination is not possible.

Continuous Learning and Improvement

As the system is integrated into healthcare practices, it can accumulate data on the outcomes of prescriptions. This data can be used for continuous learning and improvement of the system's recommendations over time, making it more accurate and aligned with real-world effectiveness.

9. CONCLUSION

In this project, we successfully developed and implemented a drug classification system that utilizes key patient attributes including age, sex, blood pressure (BP), cholesterol levels, and the sodium to potassium ratio (Na to K ratio). Leveraging machine learning techniques, this system offers healthcare practitioners a valuable tool for making informed drug prescription decisions.

Through the systematic process of data collection, preprocessing, feature selection, model development, and evaluation, we have demonstrated the potential of machine learning in the medical domain. Our model showcases the ability to accurately predict suitable drug prescriptions based on patient attributes, significantly enhancing patient care and the quality of medical decision-making.

The key takeaways from this project are as follows:

Personalized Healthcare:

The drug classification system contributes to personalized healthcare by considering the unique attributes of each patient. This approach increases the likelihood of successful treatment outcomes and minimizes potential adverse effects.

Reduced Errors:

Automation of the drug prescription process reduces the chances of prescription errors caused by human judgment or oversight. The system's recommendations provide a reliable foundation for healthcare practitioners to base their decisions on.

Efficient Resource Utilization:

By suggesting appropriate drugs based on patient attributes, the system aids in optimizing the allocation of medical resources. Unnecessary treatments, tests, and costs can be minimized, leading to a more efficient healthcare system.

Data-driven Insights:

The system's recommendations are rooted in data-driven insights, allowing healthcare professionals to make decisions backed by evidence. This approach is particularly valuable in a rapidly evolving field like medicine.

As we look to the future, there is potential for further enhancements and expansions of the system. Incorporating additional patient attributes, continuous model improvement through feedback loops, and integration with electronic health records are directions that can be explored.

In conclusion, this project underscores the value of combining medical knowledge with machine learning techniques to address real-world challenges in healthcare. The drug classification system developed here holds great promise for revolutionizing drug prescription practices, enhancing patient care, and contributing to the advancement of medical decision-making processes. Through interdisciplinary collaboration and innovation, we can continue to improve patient outcomes and the overall quality of healthcare delivery.

10. FUTURE SCOPE

The drug classification system developed in this project serves as a stepping stone toward more advanced and impactful applications in the field of healthcare. As technology and medical knowledge continue to evolve, there are several avenues for further development and enhancement of the system.

Integration of Additional Attributes:

While the current system effectively uses age, sex, blood pressure, cholesterol levels, and the Na to K ratio, there are numerous other patient attributes that can contribute to more accurate drug classification. Attributes such as genetic information, medical history, lifestyle factors, and pre-existing conditions could be incorporated to provide a more comprehensive patient profile, leading to even more precise drug recommendations.

Continuous Model Improvement:

Machine learning models can be enhanced over time through continuous learning. By integrating a feedback loop that collects data on the effectiveness of prescribed drugs and their outcomes, the model can adapt and improve its recommendations. This iterative process ensures that the system remains up-to-date with the latest medical trends and knowledge.

Explainable AI for Healthcare Professionals:

As the system becomes more complex, incorporating explainable AI techniques becomes increasingly important, especially in the medical domain. Future iterations of the system could focus on providing detailed explanations for each recommendation, enabling healthcare professionals to understand the rationale behind the suggested drugs and fostering trust in the system.

Electronic Health Record Integration:

Seamless integration with electronic health records (EHRs) can enhance the accuracy and efficiency of the drug classification system. By directly accessing a patient's medical history and existing treatments, the system can provide recommendations that are tailored to the individual's current health status, treatment plan, and potential drug interactions.

Telemedicine and Remote Healthcare:

The expansion of telemedicine and remote healthcare presents an opportunity for the drug classification system to make a substantial impact. The system's automated recommendations can aid healthcare practitioners in virtual consultations, where direct physical examination might not be possible. This ensures that patients receive accurate and timely drug prescriptions even in remote scenarios.

Regulatory Compliance and Ethical Considerations:

As the system becomes more integrated into medical practice, ensuring regulatory compliance and ethical considerations becomes paramount. Future development efforts should focus on adhering to data privacy regulations and establishing clear guidelines for using AI-driven recommendations in medical decision-making.

11. BIBLIOGRAPHY

[1] N. Donges, A complete guide to the random forest algorithm, June 2019.
[2] P. Tripathi, "Drug Classification" in Kaggle, 2020.
[3] M. Li, H. Xu and Y. Deng, "Evidential Decision Tree Based on Belief Entropy", School of Computer Science and Engineering University of Electronic Science and Technology of China, *2019*.
[4] X. Liu and H. Chen, "Azdrugminer: an information extraction system formining patient-reported adverse drug events in online patient forums", In International Conference on Smart Health, *2017*.

APPENDIX

11.1. Source Code

The project's source code is available in the ”Drug(3)-1(1).ipynb” file, and there is a “app.py” file which integrate the ipynb file and html codes. Additionally, the front-end interface code is provided in 'index.html' and ‘submit.html’ to create the user interface.

app.py:-

```
import numpy as np
from flask import Flask, request, jsonify, render_template
import pickle

# Create flask app
flask_app = Flask(_name_)
model = pickle.load(open("model.pkl", "rb"))

@flask_app.route("/")
def Home():
    return render_template("index.html")

@flask_app.route("/predict", methods = ["GET","POST"])
def predict():
    render_template("predict.html")
    age = request.form['Age']
    print(age)
    sex = request.form['Sex']
    if sex == 'Male':
        sex = 1
    if sex == 'Female':
        sex = 0
    bp = request.form['BP']
    if bp == 'Low':
        bp = 0
    if bp == 'Normal':
        bp = 1
    if bp == 'High':
        bp = 2
    chol = request.form['Cholesterol']
    if chol == 'Normal':
        chol = 0
    if chol == 'High':
        chol = 1
    na = float(request.form['Na_to_K'])
    t = [[int(age), int(sex), int(bp), int(chol), float(na)]]
    print(t)
```

```
    pred = model.predict(t)
    print(pred)
    return  render_template("submit.html",  prediction_text  =  "{}".format(pred))

if _name_ == "_main_":
          flask_app.run(debug=True)
```

index.html:-

```
<!DOCTYPE html>
<html >
<!--From  https://codepen.io/frytyler/pen/EGdtg-->
<head>
  <meta charset="UTF-8">
  <title>Welcome to Drug Classification</title>
  <link  href='https://fonts.googleapis.com/css?family=Pacifico' rel='stylesheet' type='text/css'>
<link  href='https://fonts.googleapis.com/css?family=Arimo' rel='stylesheet' type='text/css'>
<link  href='https://fonts.googleapis.com/css?family=Hind:300' rel='stylesheet' type='text/css'>
<link     href='https://fonts.googleapis.com/css?family=Open+Sans+Condensed:300'       rel='stylesheet'
type='text/css'>
<style>
    body{
        background-image:
url("https://th.bing.com/th/id/OIP.8ivaBbi4NZi3fH6ynY5CCgAAAA?w=236&h=180&c=7&r=0&o=
5&pid=1.7");
        background-repeat: no-repeat;
        background-size:100%;
        color:black;
    }
    h2{
        text-align: left;
        padding: 1.5rem;
        padding-bottom: 0;
    }
    form b{
        color:white;
        font-size: 1.5rem;
    }
</style>
</head>
<body>
<h1><center><b><i>WELCOME TO DRUG CLASSIFICATION</i></b></center></h1>
 <div class="login">
     <h2>The main purpose of the Drug Classification system is to predict the suitable drug type of
patients based on their
characteristics.Drug names are confidential.So, it is replaced as DrugX, DrugY, DrugA, DrugB and
DrugC.
These drugs are used as a medication for the patients based on their age, sex(Male,Female), BP
level(Low,Normal,High), cholesterol level(Normal,High) and sodium to
potassium ratio on blood.</h2>

     <!-- Main Input For Receiving Query to our ML-->
    <form align="center" action="{{ url_for('predict')}}"method="post">
        <b>AGE</b><br>
```

```
        <input type="text" name="Age" placeholder="Age" required="required" /><br><br>
        <b>SEX</b><br>
        <input type="text" name="Sex" placeholder="Sex" required="required" /><br><br>
        <b>BP</b><br>
                <input type="text" name="BP" placeholder="BP" required="required" /><br><br>
        <b>CHOLESTEROL</b><br>
                <input type="text" name="Cholesterol" placeholder="Cholesterol" required="required"
/><br><br>
        <b>Na_TO_K</b><br>
        <input type="text" name="Na_to_K" placeholder="Na_to_K" required="required" /><br><br>
        <button type="submit" class="btn btn-primary btn-block btn-large">Predict</button>
      </form>
     <br>
     <br>
   </div>
  </body>
  </html>
```

submit.html:-

```
 <html>

<head>

   <style>

      body{

      background-image:
      url("https://th.bing.com/th/id/OIP.8ivaBbi4NZi3fH6ynY5CCgAAAA?w=236&h=180&c=7&r=0
      &o=5&pid=1.7");

      background-repeat: no-repeat;

      background-size:100%;

      color:black;

   }

   </style>

</head>

<body>

<div>

<h1 align=center><i><b>DRUG  CLASSIFICATION</b></i></h1>

   <pre align=center style="font-size:23px;">Based on the given input, the suitable drug for your body
     condition is <b><u><i>{{ prediction_text }}</u><i/></b></pre></div>

</body>

      </html>
```


WELCOME TO DRUG CLASSIFICATION
The main purpose of the Drug Classification system is to predict the suitable drug type of patients based on their characteristics.Drug names are confidential.So, it is replaced as DrugX, DrugY, DrugA, DrugB and DrugC. These drugs are used as a medication for the patients based on their age, sex(Male,Female), BP level(Low,Normal,High), cholesterol level(Normal,High) and sodium to potassium ratio on blood.
AGE
20
SEX
Male
BP
Low
CHOLESTEROL
High
Na_TO_K
13
Predict


DRUG CLASSIFICATION
Based on the given input, the suitable drug for your body condition is ['drugC']


WELCOME TO DRUG CLASSIFICATION
The main purpose of the Drug Classification system is to predict the suitable drug type of patients based on their characteristics.Drug names are confidential.So, it is replaced as DrugX, DrugY, DrugA, DrugB and DrugC. These drugs are used as a medication for the patients based on their age, sex(Male,Female), BP level(Low,Normal,High), cholesterol level(Normal,High) and sodium to potassium ratio on blood.
AGE
45
SEX
Female
BP
High
CHOLESTEROL
Normal
Na_TO_K
7.798
Predict


DRUG CLASSIFICATION
Based on the given input, the suitable drug for your body condition is ['drugA']