

# **MLOPS MINI PROJECTREPORT**

## **KIDNEY DISEASE DETECTION USING MULTI-LAYER PERCEPTRON AND STREAMLIT APPLICATION**

### **INTRODUCTION**

Chronic Kidney Disease (CKD) is a major health concern worldwide, often leading to significant morbidity if not diagnosed early. Machine Learning offers powerful tools for early detection by analyzing clinical parameters. In this project, we developed a machine learning model based on a Multi-Layer Perceptron (MLP) classifier to predict the presence of CKD. Furthermore, we built a Streamlit-based web application to allow users to input patient data and receive real-time predictions.

### **MODEL TRAINING AND DEVELOPMENT**

The dataset used for training was provided in CSV format named “new\_model.csv”. It included both numerical and categorical features relevant to kidney health such as Blood Pressure (Bp), Specific Gravity (Sg), Albumin (Al), Sugar (Su), Blood Urea (Bu), and others.

The initial step involved installing necessary libraries like mlflow, numpy, pandas, matplotlib, and scikit-learn. After loading the dataset, a data cleaning process was conducted. The script checked for and reported duplicate entries and missing values, ensuring a clean and reliable dataset. The dataset was then divided into features (X) and labels (y). A 70-30 train-test split was performed, ensuring that the model could be evaluated on unseen data. Standardization was applied to the features using StandardScaler, improving the model’s ability to converge during training. The classification model employed was an MLPClassifier from scikit-learn with the following setup:

- Hidden Layers: One hidden layer with 100 neurons.
- Max Iterations: 1000 for sufficient convergence.
- Random State: 42 for reproducibility.

The model was trained on the scaled training data. After training, predictions were made on the test set and evaluated using Accuracy, Precision, Recall, and F1 Score metrics:

- Accuracy: Approximately 96%,
- Precision: High weighted precision,

- Recall: Excellent sensitivity to CKD instances,
- F1 Score: Balanced measure indicating robust performance.

Additionally, a confusion matrix was plotted for better visualization of true vs. predicted classifications. Finally, the model along with the scaler and label encoders was saved into a single Pickle file (`kidney_disease_model.pkl`) for portability and deployment. The scaler was also saved separately as `scaler.pkl` for modular reuse.











## **APPLICATION DEVELOPMENT AND DEPLOYMENT WITH STREAMLIT CLOUD**

After successfully training and saving the model, we moved toward deploying it for public use by creating an interactive web application using Streamlit. The deployment process was systematic, involving several important steps. The first step was to create a new repository on GitHub. All necessary files, including the trained model (`kidney_disease_model.pkl`), the scaler (`scaler.pkl`), the Streamlit app script (`app.py`), the training script (`Model.py`), the dataset (`new_model.csv`), the `requirements.txt`, and a `.gitignore` file, were committed and pushed to the repository. The repository was organized with clear commit messages to track the development process efficiently. We also included a workflow file inside the `.github/workflows` directory for continuous integration support.

Following the GitHub setup, we implemented Continuous Integration (CI). A GitHub Actions workflow (`main.yml`) was configured to automate the installation of dependencies and verify the code whenever changes were pushed. This ensured that the application remained stable, and any future changes could be smoothly integrated without manual intervention. The CI pipeline automatically set up a Python environment, installed the necessary dependencies from `requirements.txt`, and prepared the Streamlit app for deployment. Once the CI/CD pipeline was successfully tested and validated, we moved to deploy the application using Streamlit Cloud. In Streamlit Cloud:

- We connected our GitHub repository directly to Streamlit Cloud.
- We selected the branch and `app.py` as the main entry point.
- The platform automatically installed the required packages listed in `requirements.txt`.
- After successful deployment, Streamlit Cloud continuously monitored the GitHub repository. Whenever a new commit was pushed, the app was automatically rebuilt and updated.

The deployed Streamlit app offered a simple yet functional user interface. Users could manually input various health parameters related to kidney function such as blood pressure, specific gravity, albumin level, blood urea, and more. The app then processed the inputs using the pre-loaded scaler and model to predict the likelihood of Chronic Kidney Disease. The real-time prediction and instant feedback system made the app highly interactive and easy to use.

 .github/workflows	Update main.yml	5 hours ago
 .gitignore	Create .gitignore	6 hours ago
 Model.py	initial commit	7 hours ago
 README.md	Initial commit	7 hours ago
 app.py	Initial commit: Added Streamlit app and model code	6 hours ago
 kidney disease pediction app	Create kidney disease pediction app	5 hours ago
 kidney_disease_model.pkl	initial commit	7 hours ago
 new_model.csv	initial commit	7 hours ago
 requirements.txt	requirements.txt	6 hours ago
 scaler.pkl	initial commit	7 hours ago

*Figure 1 showing the GitHub repository*

## CI INTEGRATION CODE:

main

+

Q

Go to file

.github/workflows

main.yml

.gitignore

Model.py

README.md

app.py

kidney disease pediction app

kidney\_disease\_model.pkl

new\_model.csv

requirements.txt

scaler.pkl

Code

Blame

39 lines (33 loc) · 1020 Bytes

```

1  name: Streamlit App CI/CD
2
3  on:
4    push:
5      branches: [ main ] # Trigger on pushes to the main branch
6
7  jobs:
8    build:
9      runs-on: ubuntu-latest
10     steps:
11       - name: Checkout code
12         uses: actions/checkout@v4
13
14       - name: Set up Python 3.x
15         uses: actions/setup-python@v5
16         with:
17           python-version: '3.x'
18
19       - name: Install dependencies
20         run: |
21           python -m pip install --upgrade pip
22           pip install -r requirements.txt
23
24       - name: Run basic app check (optional)
25         run: |
26           python app.py --version # Or a simple script to check import errors
27
28     deploy:
29       needs: build
30       runs-on: ubuntu-latest
31       if: github.ref == 'refs/heads/main'
32       steps:
33         - name: Deploy to Streamlit Cloud
34           uses: streamlit/deploy-app@v1.3.0 # Example: Replace with a specific version
35           with:
36             github_token: ${ secrets.GITHUB_TOKEN }
37             app_file: app.py
38             requirements_file: requirements.txt
39             streamlit_version: 'latest'

```

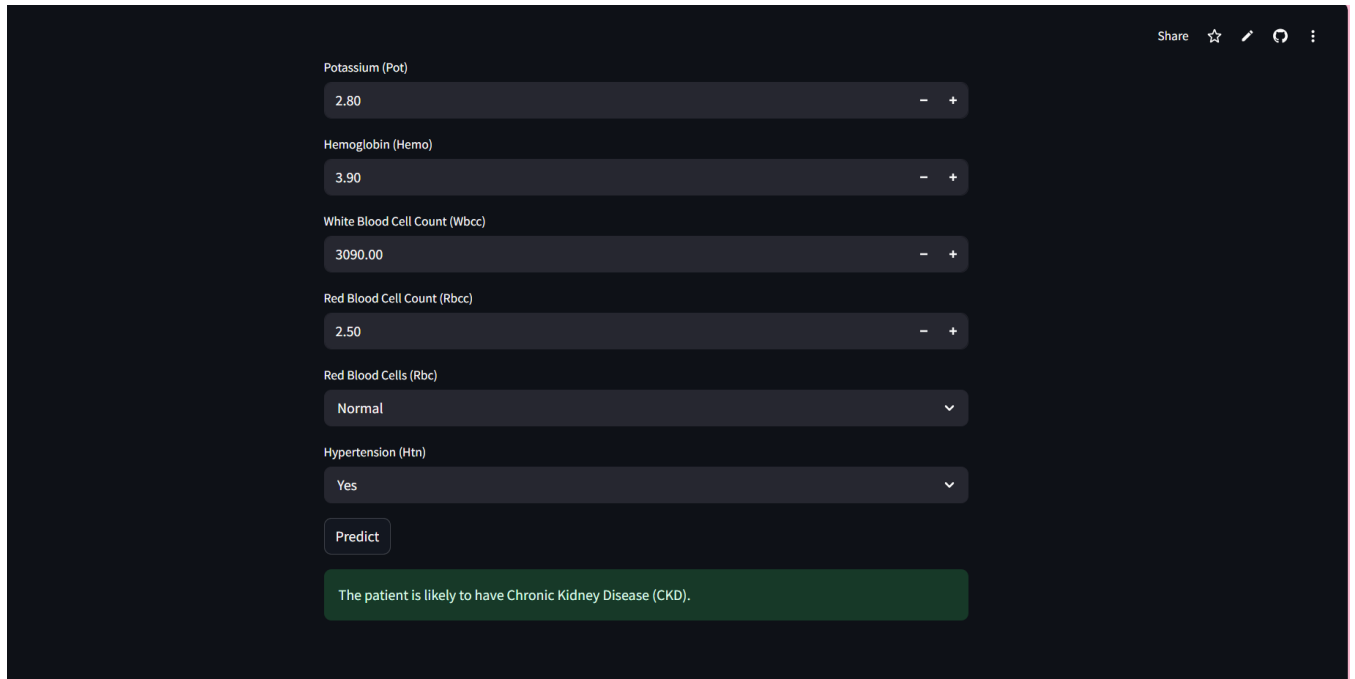
## CONCLUSION

This project successfully demonstrated the development of an end-to-end machine learning system for Chronic Kidney Disease prediction. Starting from thorough data preprocessing and model training using a Multi-Layer Perceptron classifier, we achieved high evaluation metrics, ensuring reliability for real-world use. The deployment pipeline was carefully designed by integrating GitHub version control, setting up continuous integration workflows, and finally hosting the application using Streamlit Cloud. The Streamlit application enables users to easily interact with the predictive model through a user-friendly interface, promoting accessibility beyond traditional clinical settings. The adoption of a CI/CD approach ensures that the system remains scalable, maintainable, and ready for continuous improvement.

The screenshot shows a web browser window with the URL <https://chronic-kidney-disease-prediction-app-hvswxy3vradulzpnouzvn.streamlit.app>. The browser tabs include 'github - Search', 'Abiraame03/Chronic-Kidney-dis...', and 'Streamlit'. The application interface has a dark background and features the title 'Kidney Disease Prediction App' in white. Below the title is the heading 'Enter Patient Details:'. There are seven input fields, each with a label, a value, and minus/plus buttons for adjustment. The inputs are: Blood Pressure (Bp) with value 1.40, Specific Gravity (Sg) with value 1.01, Albumin (Al) with value 1.80, Sugar (Su) with value 1.80, Blood Urea (Bu) with value 11.00, Serum Creatinine (Sc) with value 1.30, and Sodium (Sod) with value 101.10. A 'Manage app' link is visible in the bottom right corner of the app interface. The Windows taskbar at the bottom shows the Start button, a search bar, and several application icons. The system tray on the right indicates the language is 'ENG IN', shows network and volume icons, and displays the time as 5:06 PM on 4/29/2025.

Parameter	Value
Blood Pressure (Bp)	1.40
Specific Gravity (Sg)	1.01
Albumin (Al)	1.80
Sugar (Su)	1.80
Blood Urea (Bu)	11.00
Serum Creatinine (Sc)	1.30
Sodium (Sod)	101.10

By entering the health parameters it has predicted :



Potassium (Pot)

2.80

Hemoglobin (Hemo)

3.90

White Blood Cell Count (Wbcc)

3090.00

Red Blood Cell Count (Rbcc)

2.50

Red Blood Cells (Rbc)

Normal

Hypertension (Htn)

Yes

Predict

The patient is likely to have Chronic Kidney Disease (CKD).

**Github Repository link:** [Abiraame03/Chronic-Kidney-disease-prediction-app: Predicts the kidney disease with the parameters](https://github.com/Abiraame03/Chronic-Kidney-disease-prediction-app)

**Streamlit app link:**

<https://chronic-kidney-disease-prediction-app-hvsxwty3vradulzpnouzvn.streamlit.app/>

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