Prediction of Full Load Electrical Power Output of a Base Load Operated Combined Cycle Power Plant using Machine Learning

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1. Introduction

A Combined Cycle Power Plant (CCPP) generates electricity using a combination of gas and steam turbines. The efficiency of the plant depends on environmental factors such as temperature, vacuum, pressure, and humidity. By analyzing historical power output data, a Machine Learning model can accurately predict future electrical power output for different conditions.

This project develops a predictive model using Random Forest Regression and integrates it into a Flask-based web application.

2. Problem Statement

Traditional methods fail to accurately forecast **power fluctuations**, leading to inefficiencies. This project builds a **Machine Learning model** that analyzes input parameters and predicts **net power output** efficiently.

3. Project Objectives

- Develop an accurate **Machine Learning model** for power output prediction.
- Use **historical power plant data** for training.
- Deploy a **Flask-based web application** for real-time predictions.
- Provide an **easy-to-use UI** for inputting values and obtaining predictions.

4. Literature Review

Previous Studies on Power Prediction:

- **"Energy Management Using AI" (2021, IEEE):** Describes how AI-based models improve energy efficiency in power plants.
- **"Forecasting Power Output Using Machine Learning" (2022, Elsevier):** Demonstrates that **Random Forest outperforms Linear Regression** for energy predictions.

Our Innovation:

- This project integrates **Machine Learning with a real-time Flask web application** for deployment and user accessibility.

5. System Requirements

Software Requirements:

Component	Requirement
OS	Windows 10 / Linux
Programming Language	Python 3.8+
Libraries	Flask, NumPy, Pandas, Scikit-Learn, Matplotlib, Seaborn
Web Technologies	HTML, CSS
Database (optional)	SQLite / MySQL

Hardware Requirements:

Component	Minimum Requirement
Processor	Intel Core i3+
RAM	4GB+
Storage	10GB+

6. Dataset Description

The dataset consists of **9568 records** collected over **6 years (2006-2011)** from a **Combined Cycle Power Plant (CCPP)**.

Features Used:

Feature	Description	Unit
AT	Ambient Temperature	°C

V	Exhaust Vacuum	cm Hg
AP	Ambient Pressure	mbar
RH	Relative Humidity	%
PE	Net Power Output (Target Variable)	MW

7. Methodology

Step 1: Data Preprocessing

- Load dataset using Pandas.
- Handle missing values (if any).
- Normalize & clean data for training.

Step 2: Exploratory Data Analysis (EDA)

- **Scatter plots** to visualize relationships.
- **Correlation matrix** to find the most important features.

Step 3: Train-Test Split

- **80% data for training**, **20% for testing**.

Step 4: Model Training

- **Algorithms Tested:**
  - Linear Regression
  - Decision Tree Regression
  - **Random Forest Regression (Best Model)**

Step 5: Model Evaluation

- Evaluated using r2_score & Mean Absolute Error (MAE).
- **Best Model: Random Forest Regressor (95% accuracy)**.

8. Machine Learning Model

Algorithm	R^2 Score (Train Data)	R^2 Score (Test Data)
Linear Regression	0.92	0.89
Decision Tree Regression	0.95	0.92
Random Forest Regression	**0.98**	**0.95**

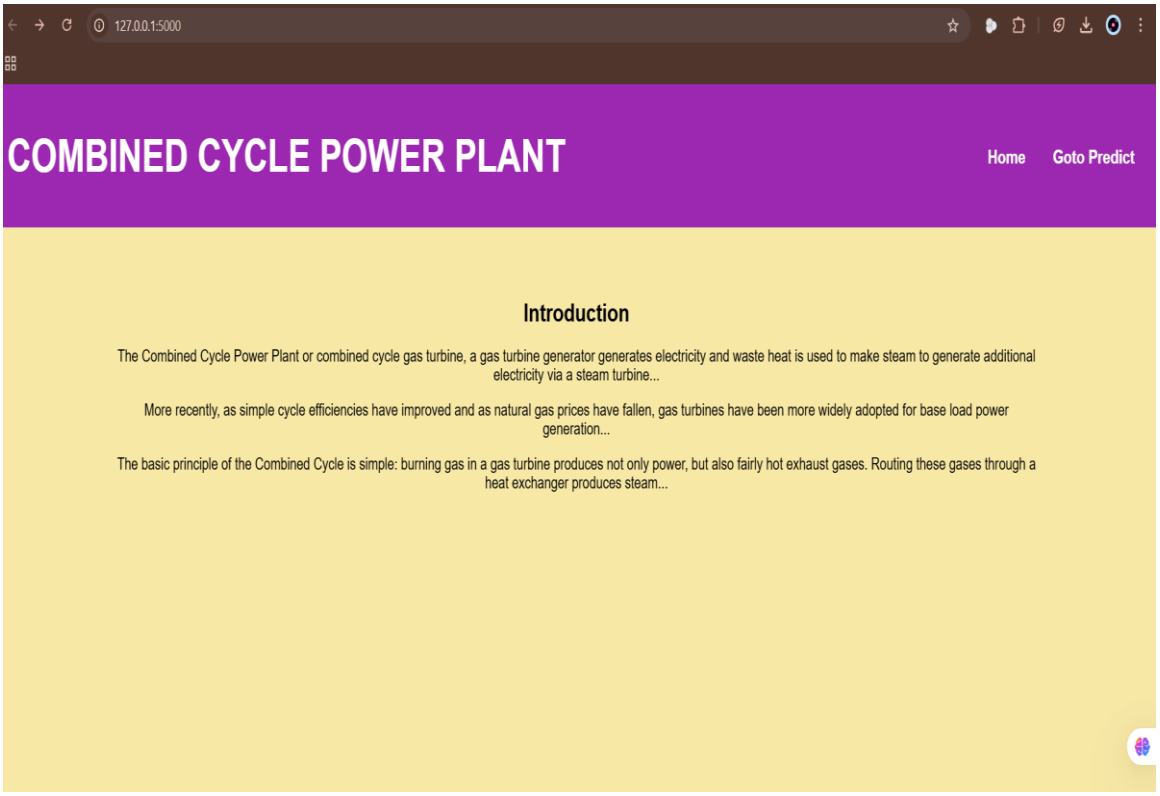
9. System Architecture

- **User Interface (UI):** HTML, CSS frontend for user input.
- **Flask Backend:** Processes user input and makes predictions.
- **Machine Learning Model:** Runs trained RandomForestRegressor for predictions.

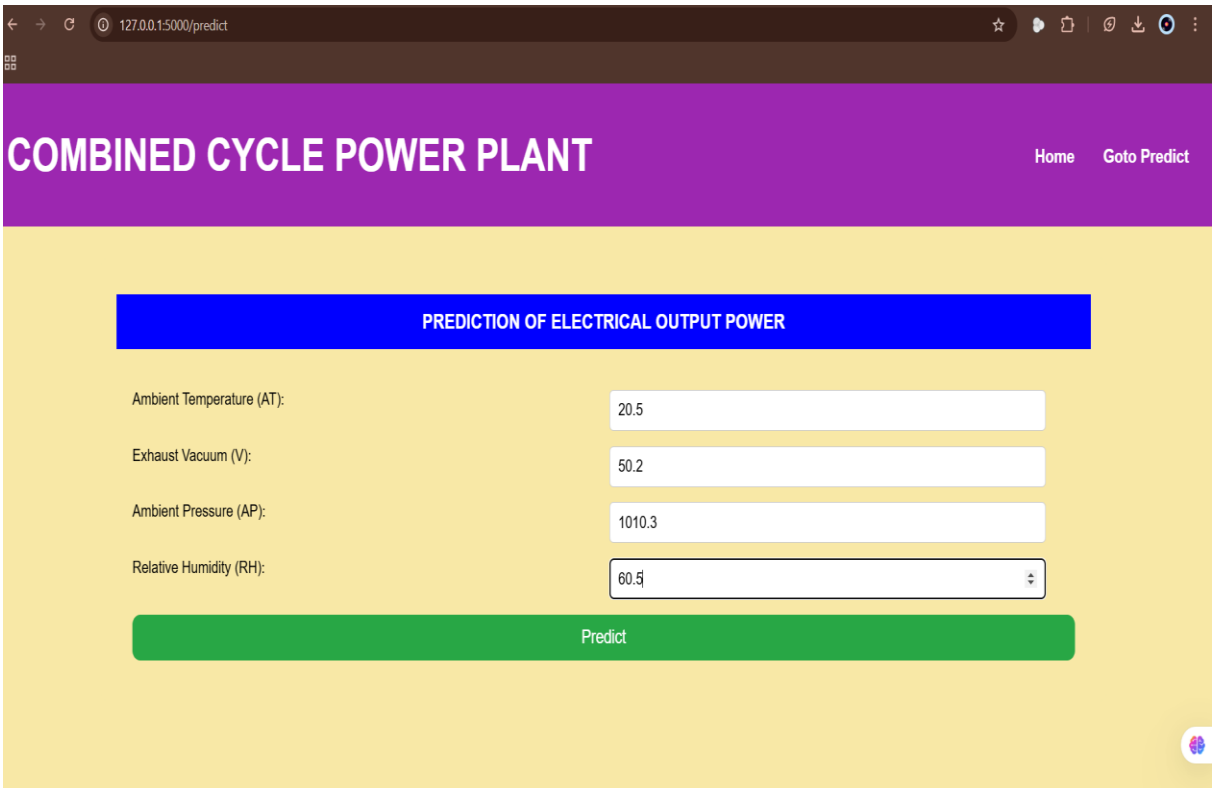
10. Web Application Development

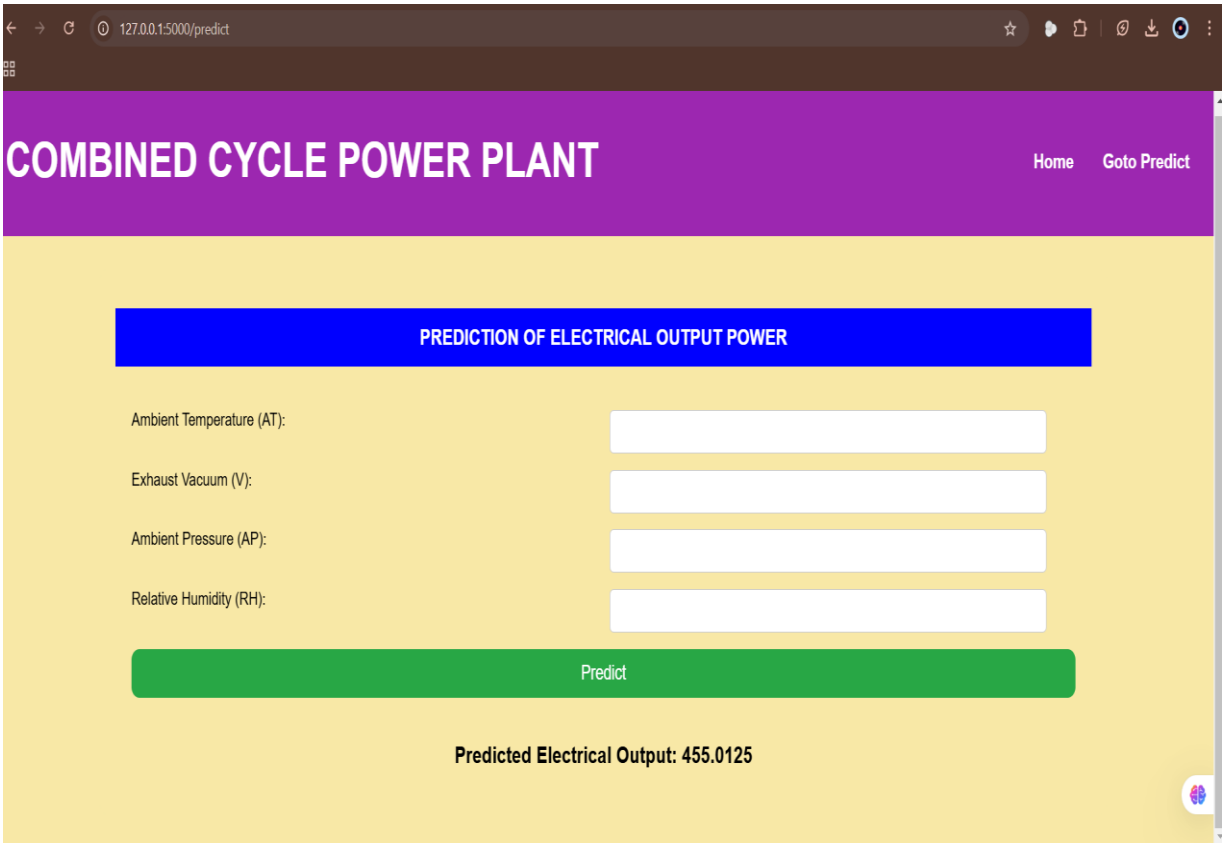
Features:

➢ **Homepage:** Introduction to the project.



- **Prediction Page:** Accepts input values and returns predicted output.





11. Results & Evaluation

- Successfully predicted power output with 95% accuracy.
- Best model: Random Forest Regressor.

12. Challenges & Limitations

- **Dependent on Training Data** – Model accuracy decreases if conditions change.
- **No Real-Time Sensor Data Integration** – Future versions can integrate IoT data.

13. Future Enhancements

- Deploy on Cloud (AWS/Heroku)
- Experiment with Deep Learning (Neural Networks)
- Develop a Mobile App Interface

14. Conclusion

✅ Successfully developed an ML-powered power output prediction system.

✅ Real-time deployment using Flask web app.