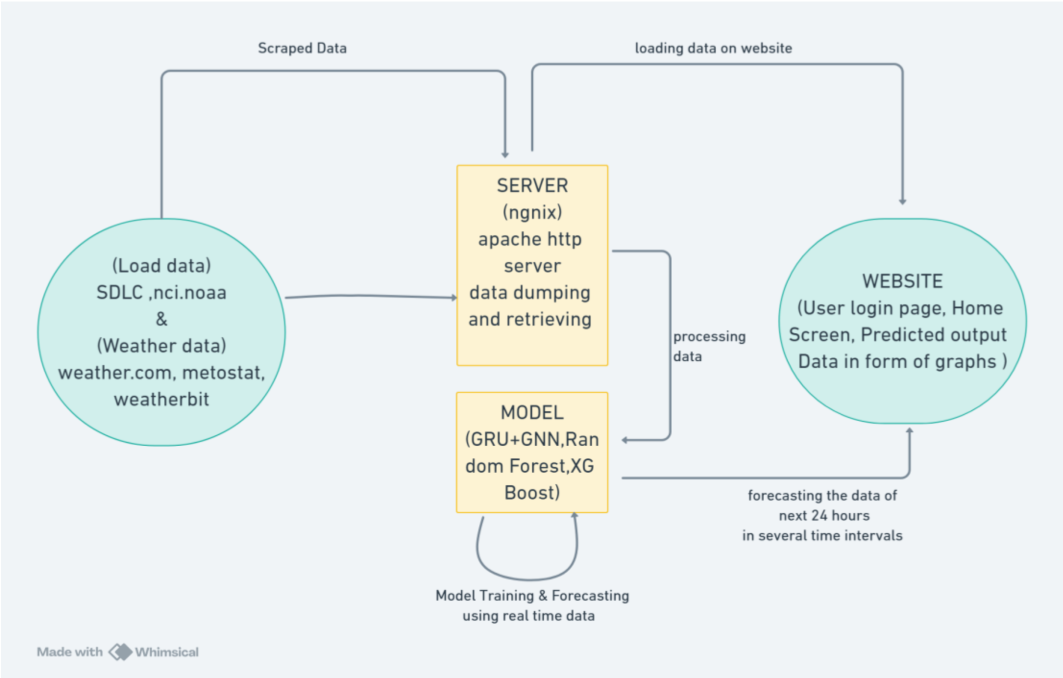
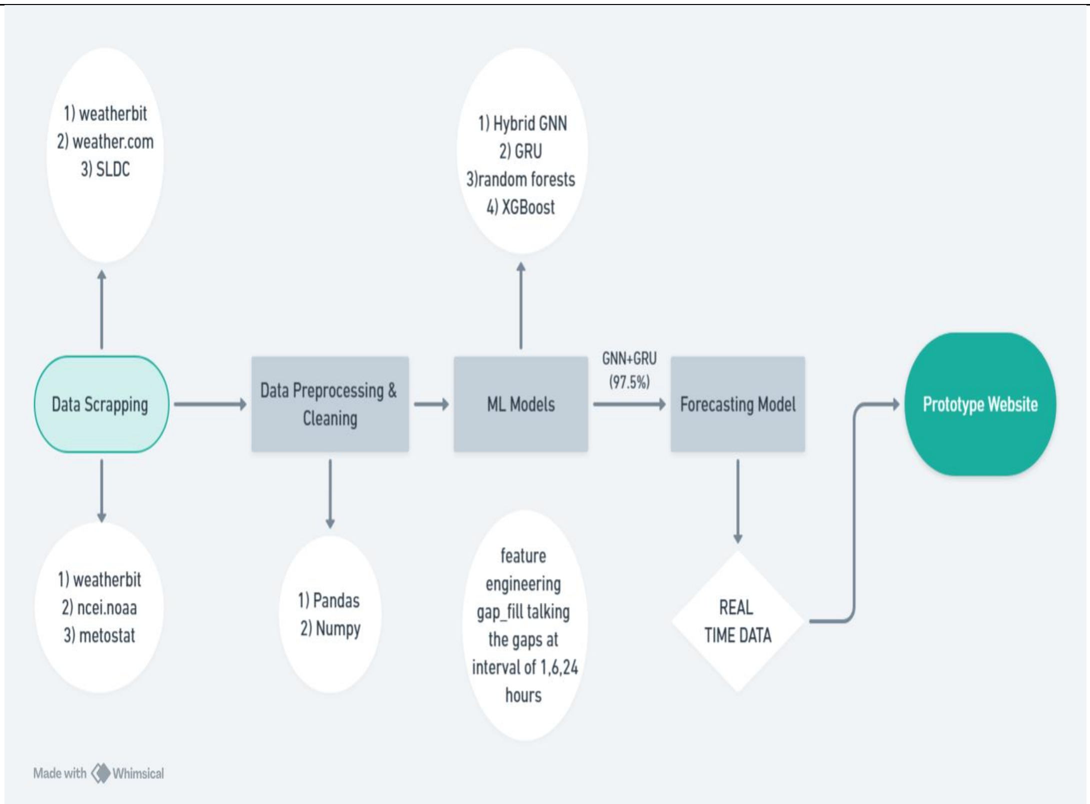
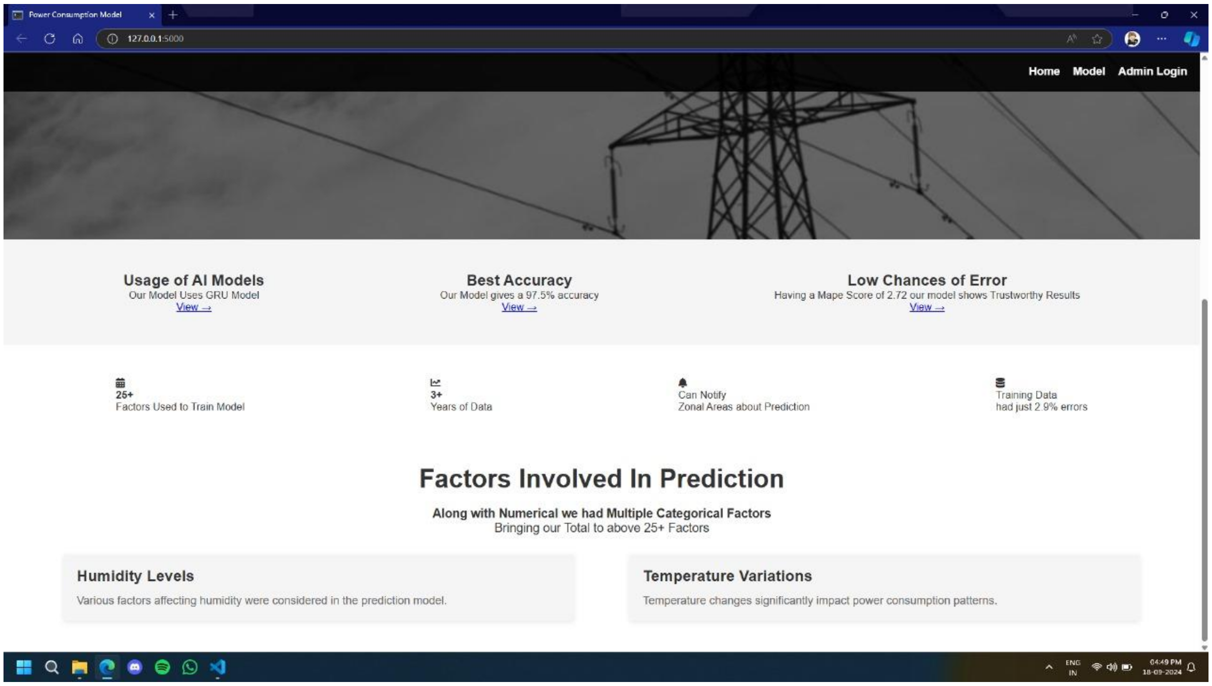
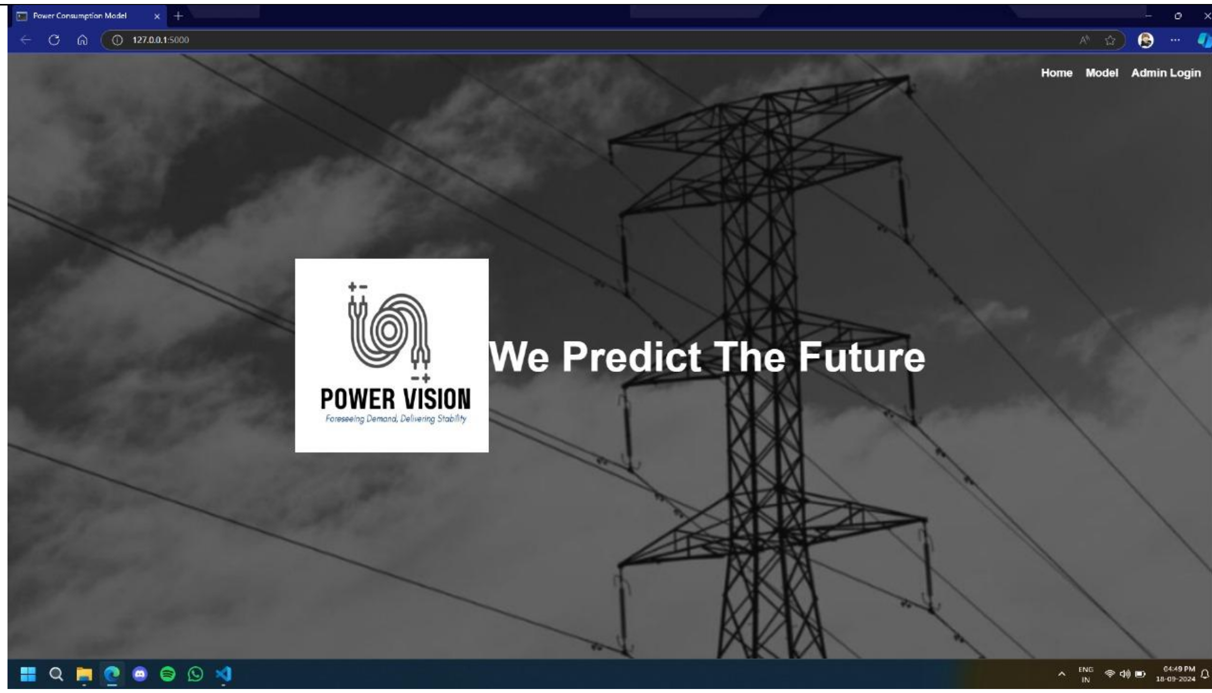
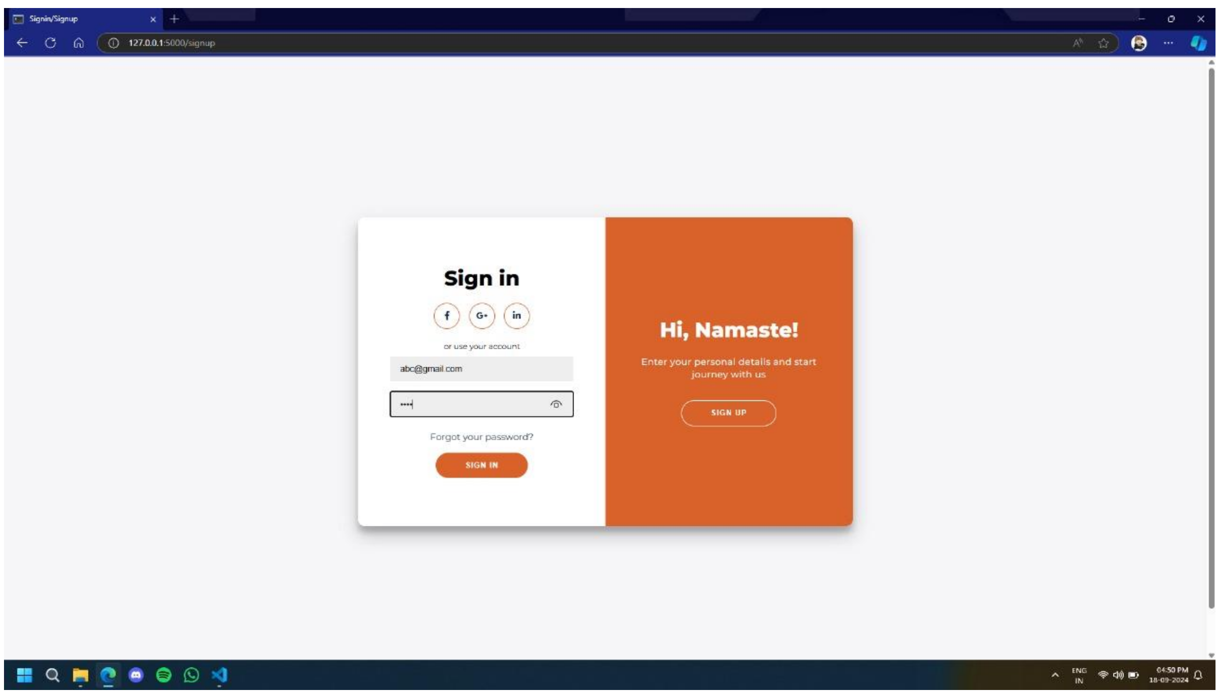
PSID: 1624	Project Summary Report	Team ID: SIH125

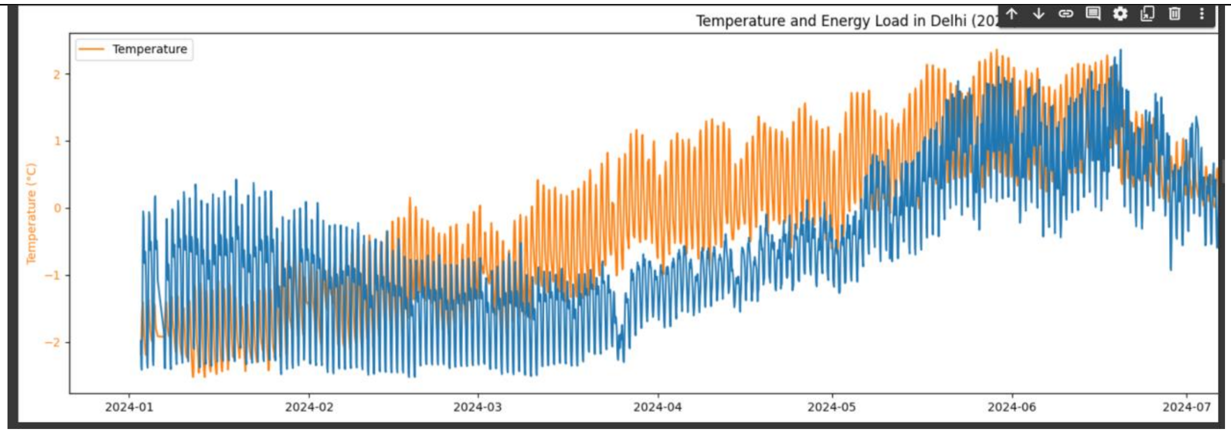
Title	To develop an Artificial Intelligence (AI) based model for electricity demand projection including peak demand projection for Delhi Power system.	**Theme** **Software**
Objective	Enhance power acquisition planning by better aligning real demand with electricity procurement to reduce supply and demand imbalances. This will result in lower operating expenses, improved grid reliability, and better energy control. The main objective of the model is to ensure Delhi possesses a reliable and secure electrical system electrical system capable of managing its unique load profile and unpredictable demand patterns.	
Synopsis (Background & Purpose)	The synopsis of the AI-based forecasting model is as follows: The project aims to develop an AI-powered model that accurately predicts the power demand for Delhi by analysing its unique load profile and various influencing factors such as temperature, public holidays, humidity, . By enhancing power purchase planning, the model will minimize supply-demand imbalances, improve grid stability, and optimize energy management. This will lead to better alignment between power procurement and actual needs, resulting in cost savings and more reliable electricity distribution. The model will play a critical role in supporting a stable and efficient electricity system for Delhi.	
Methodology (Flow Chart, Process Chart, etc.) Along with Real Time Product Picture		

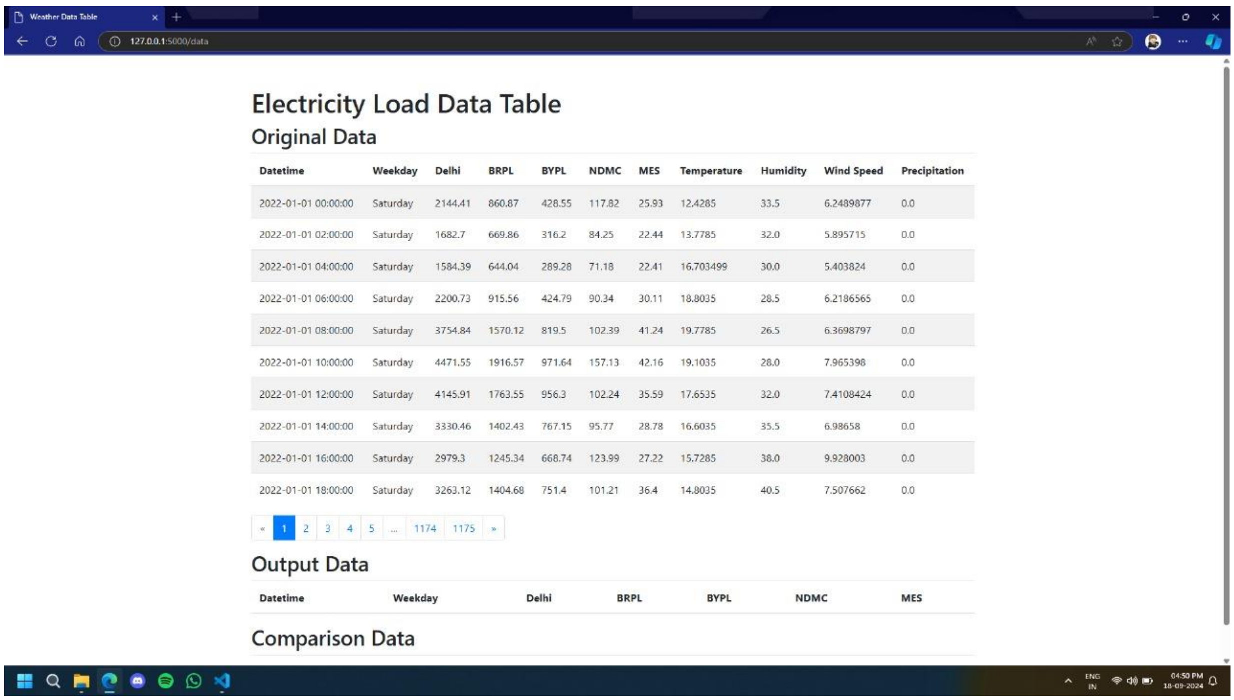

1) weatherbit
2) weather.com
3) SLDC
1) Hybrid GNN
2) GRU
3)random forests
4) XGBoost
Data Scrapping
Data Preprocessing & Cleaning
ML Models
GNN+GRU (97.5%)
Forecasting Model
Prototype Website
1) weatherbit
2) ncei.noaa
3) metostat
1) Pandas
2) Numpy
feature engineering gap_fill talking the gaps at interval of 1,6,24 hours
REAL TIME DATA
Made with Whimsical


Power Consumption Model
127.0.0.1:5000
Home
Model
Admin Login
Usage of AI Models
Our Model Uses GRU Model
View →
Best Accuracy
Our Model gives a 97.5% accuracy
View →
Low Chances of Error
Having a Mape Score of 2.72 our model shows Trustworthy Results
View →
25+
Factors Used to Train Model
3+
Years of Data
Can Notify
Zonal Areas about Prediction
Training Data
had just 2.9% errors
Factors Involved In Prediction
Along with Numerical we had Multiple Categorical Factors
Bringing our Total to above 25+ Factors
Humidity Levels
Various factors affecting humidity were considered in the prediction model.
Temperature Variations
Temperature changes significantly impact power consumption patterns.


Power Consumption Model
127.0.0.1:5000
Home
Model
Admin Login
POWER VISION
Foreseeing Demand, Delivering Stability
We Predict The Future


Signin/Signup
127.0.0.1:5000/signup
Sign in
or use your account
abc@gmail.com
Forgot your password?
SIGN IN
Hi, Namaste!
Enter your personal details and start journey with us
SIGN UP





Electricity Load Data Table

Original Data

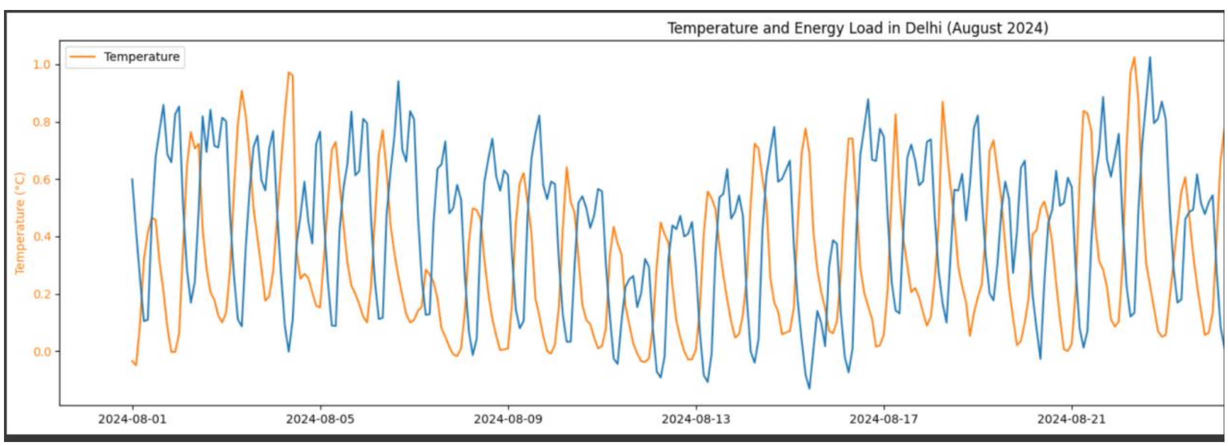
Datetime	Weekday	Delhi	BRPL	BYPL	NDMC	MES	Temperature	Humidity	Wind Speed	Precipitation
2022-01-01 00:00:00	Saturday	2144.41	860.87	428.55	117.82	25.93	12.4285	33.5	6.2489877	0.0
2022-01-01 02:00:00	Saturday	1682.7	669.86	316.2	84.25	22.44	13.7785	32.0	5.895715	0.0
2022-01-01 04:00:00	Saturday	1584.39	644.04	289.28	71.18	22.41	16.703499	30.0	5.403824	0.0
2022-01-01 06:00:00	Saturday	2200.73	915.56	424.79	90.34	30.11	18.8035	28.5	6.2186565	0.0
2022-01-01 08:00:00	Saturday	3754.84	1570.12	819.5	102.39	41.24	19.7785	26.5	6.3698797	0.0
2022-01-01 10:00:00	Saturday	4471.55	1916.57	971.64	157.13	42.16	19.1035	28.0	7.965398	0.0
2022-01-01 12:00:00	Saturday	4145.91	1763.55	956.3	102.24	35.59	17.6535	32.0	7.4108424	0.0
2022-01-01 14:00:00	Saturday	3330.46	1402.43	767.15	95.77	28.78	16.6035	35.5	6.98658	0.0
2022-01-01 16:00:00	Saturday	2979.3	1245.34	668.74	123.99	27.22	15.7285	38.0	9.928003	0.0
2022-01-01 18:00:00	Saturday	3263.12	1404.68	751.4	101.21	36.4	14.8035	40.5	7.507662	0.0

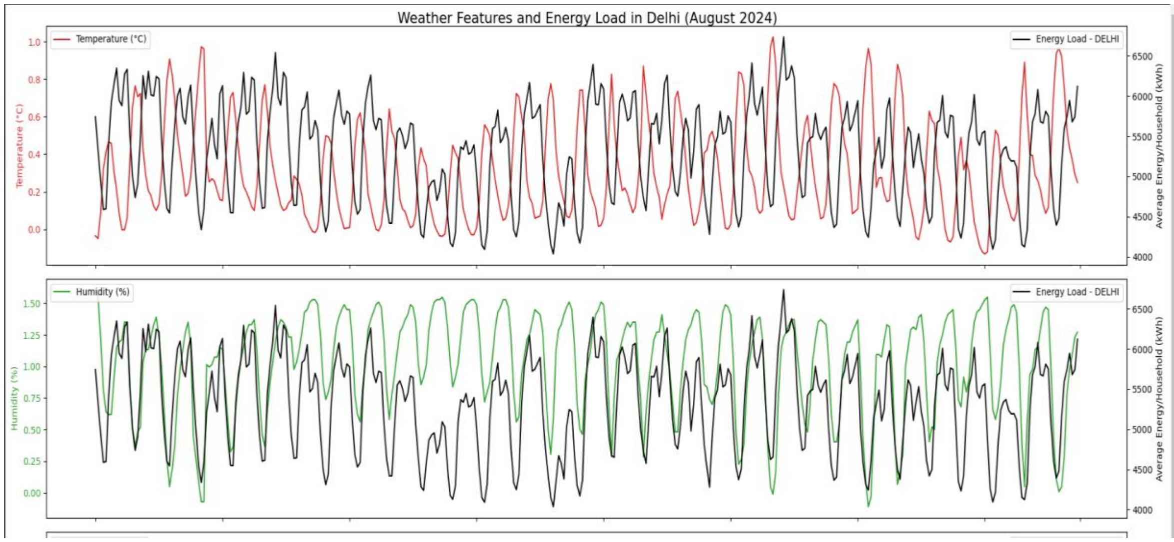
« 1 2 3 4 5 ... 1174 1175 »

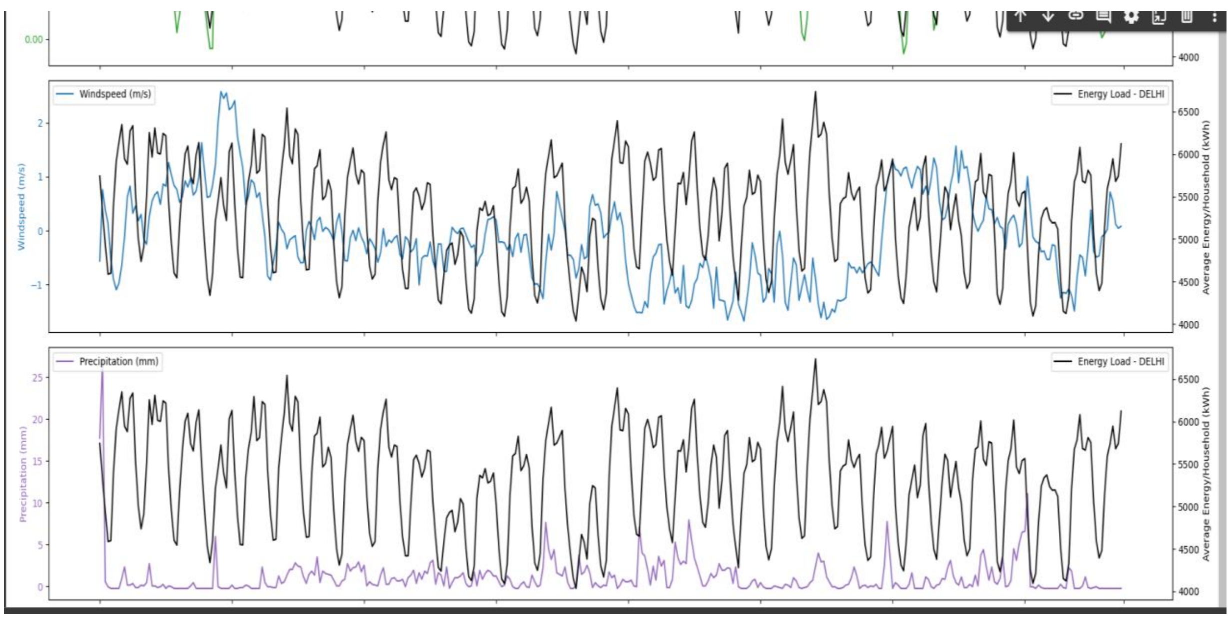
Output Data

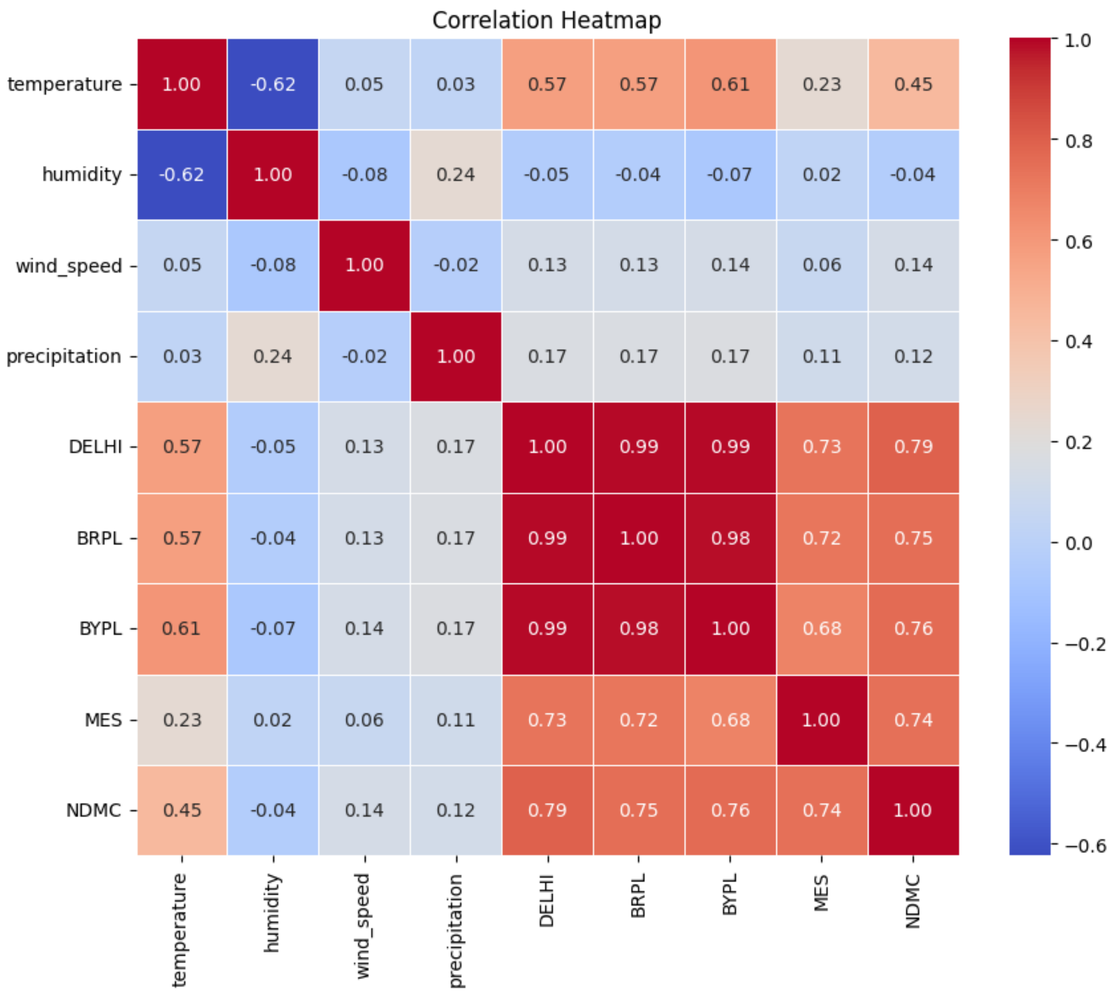
Datetime	Weekday	Delhi	BRPL	BYPL	NDMC	MES

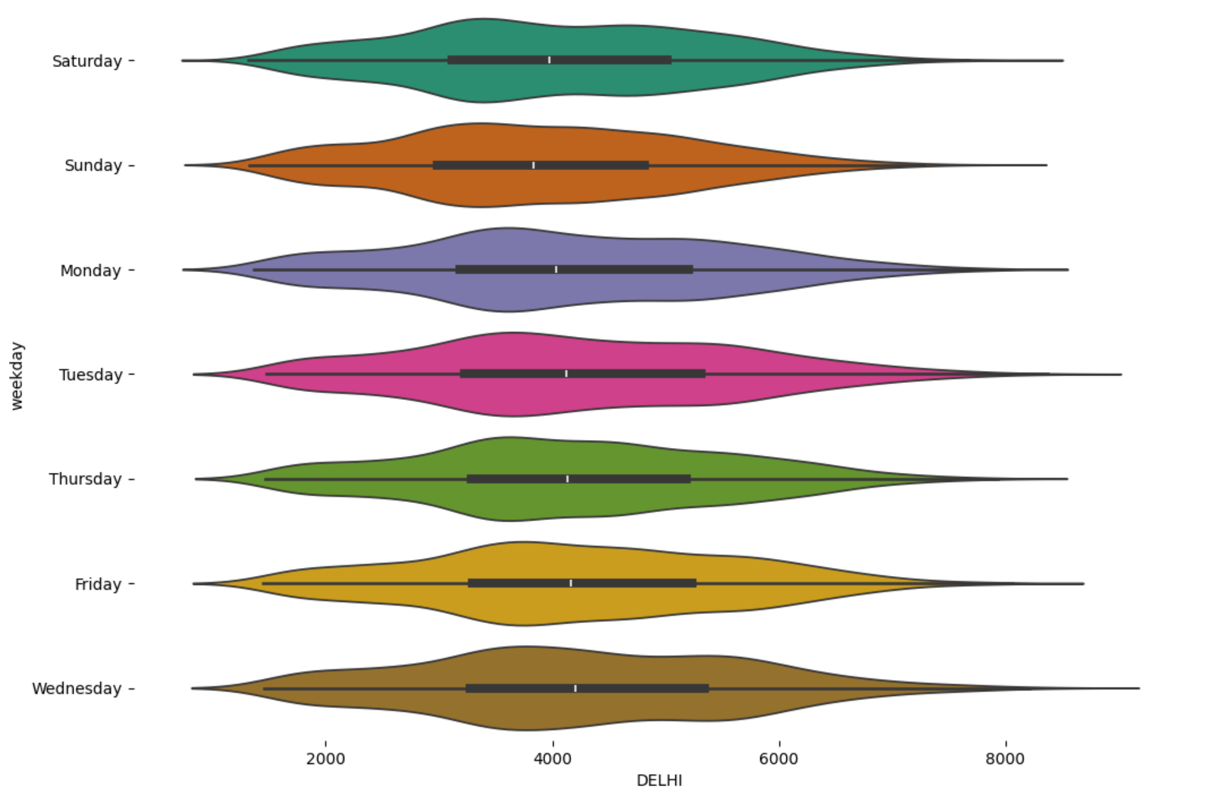
Comparison Data

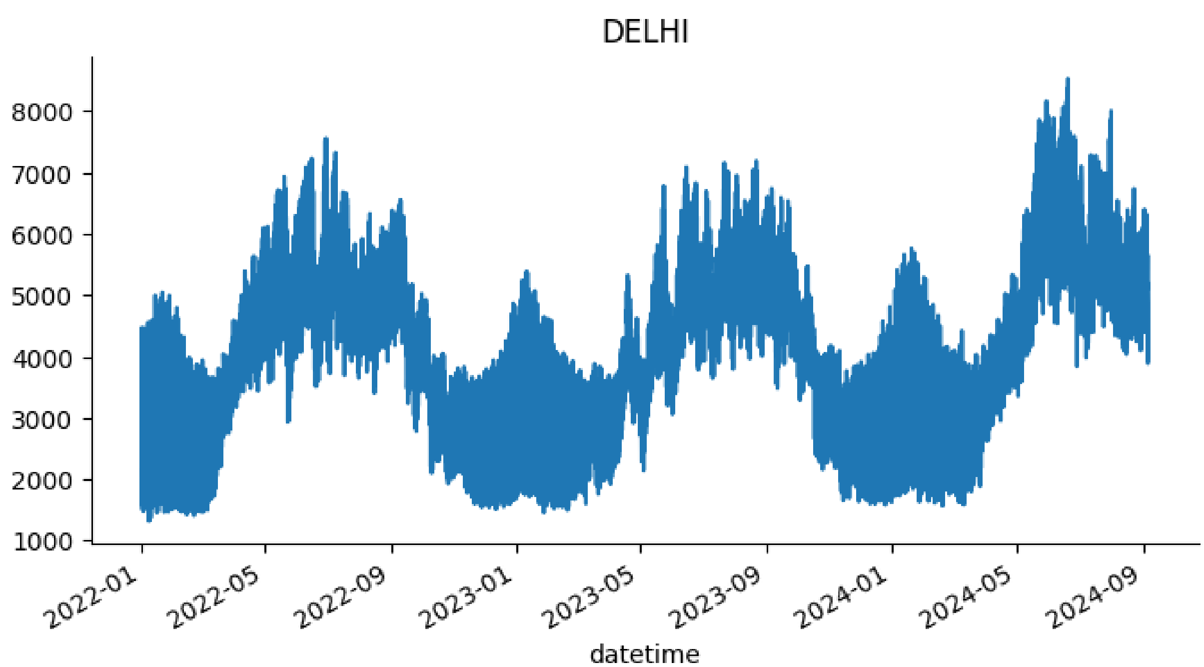


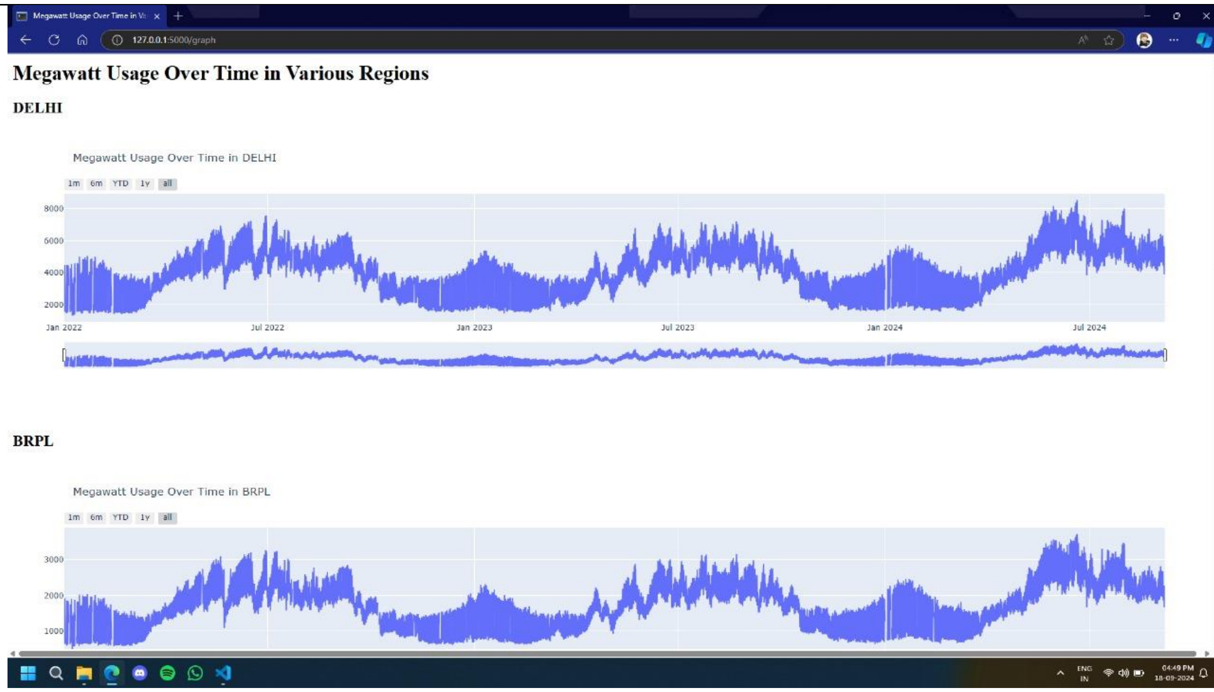

Weather Features and Energy Load in Delhi (August 2024)
Temperature (°C)
Energy Load - DELHI
Average Energy/Household (kWh)
Humidity (%)
Energy Load - DELHI
Average Energy/Household (kWh)

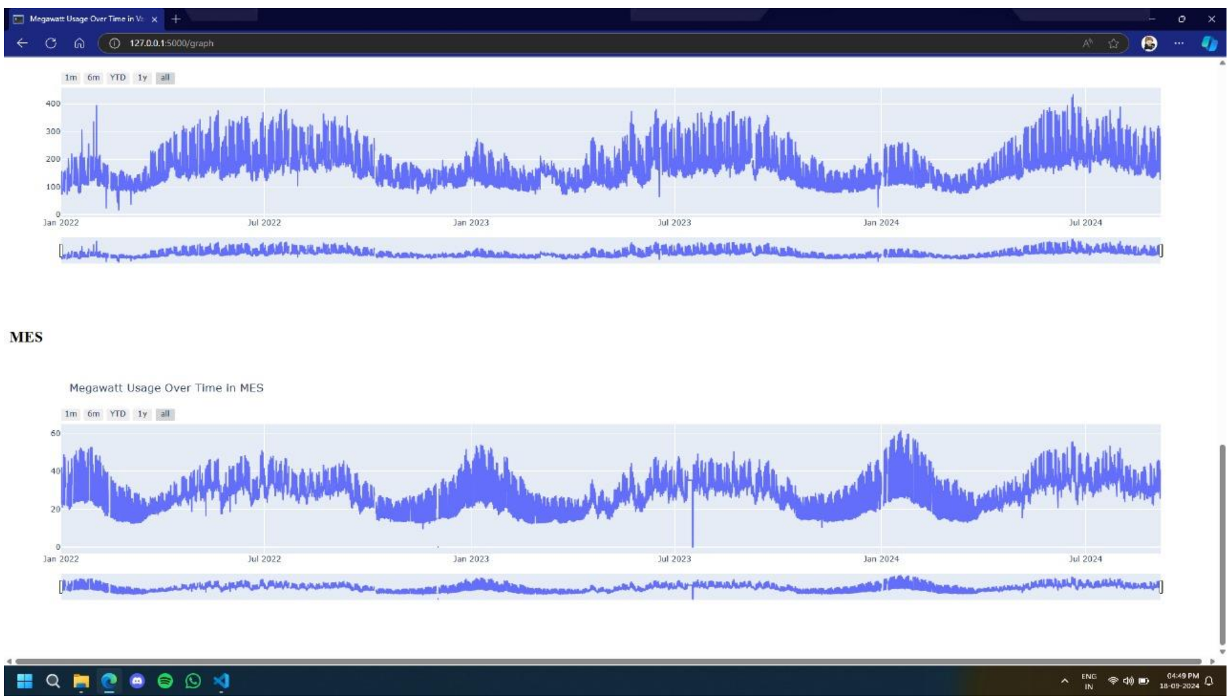

Windspeed (m/s)
Energy Load - DELHI
Average Energy/Household (kWh)
Precipitation (mm)
Energy Load - DELHI
Average Energy/Household (kWh)


Correlation Heatmap
temperature
humidity
wind_speed
precipitation
DELHI
BRPL
BYPL
MES
NDMC
1.00 -0.62 0.05 0.03 0.57 0.57 0.61 0.23 0.45
-0.62 1.00 -0.08 0.24 -0.05 -0.04 -0.07 0.02 -0.04
0.05 -0.08 1.00 -0.02 0.13 0.13 0.14 0.06 0.14
0.03 0.24 -0.02 1.00 0.17 0.17 0.17 0.11 0.12
0.57 -0.05 0.13 0.17 1.00 0.99 0.99 0.73 0.79
0.57 -0.04 0.13 0.17 0.99 1.00 0.98 0.72 0.75
0.61 -0.07 0.14 0.17 0.99 0.98 1.00 0.68 0.76
0.23 0.02 0.06 0.11 0.73 0.72 0.68 1.00 0.74
0.45 -0.04 0.14 0.12 0.79 0.75 0.76 0.74 1.00
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6

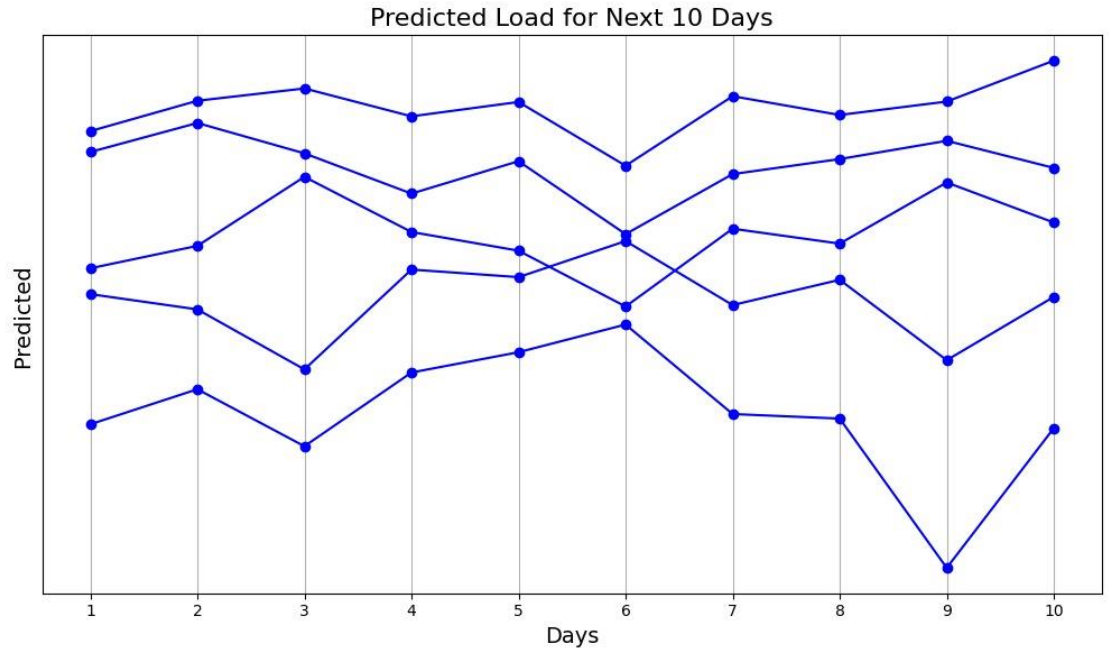

Saturday
Sunday
Monday
Tuesday
Thursday
Friday
Wednesday
weekday
2000
4000
6000
8000
DELHI

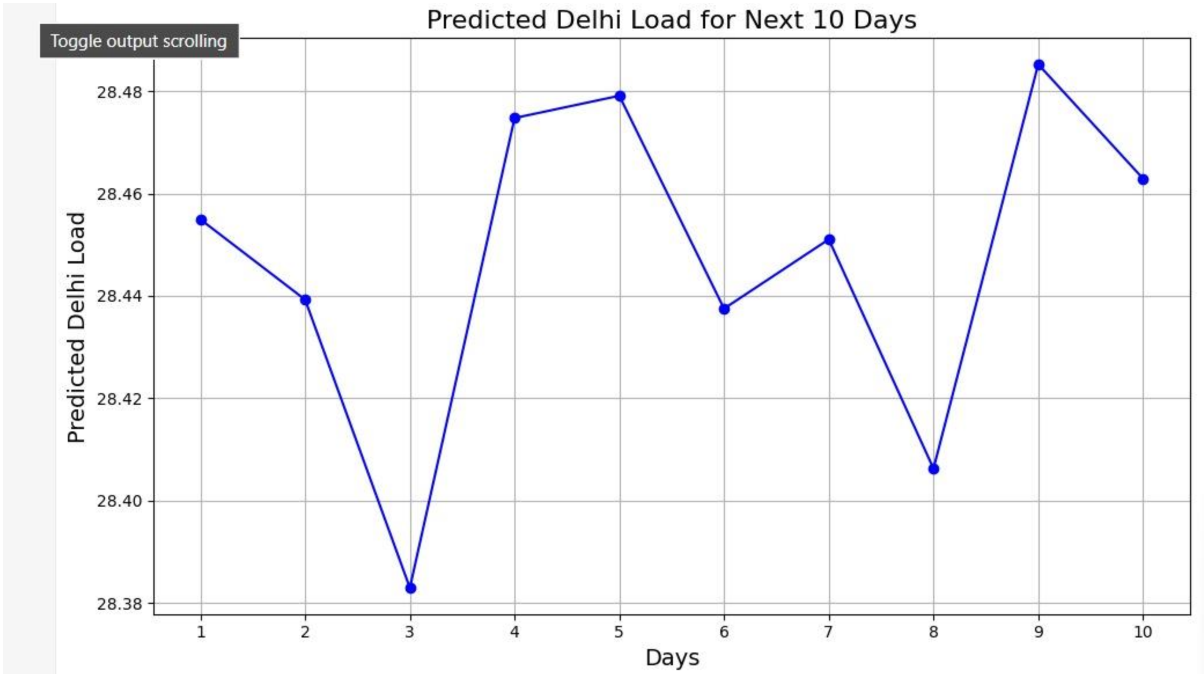

DELHI
8000
7000
6000
5000
4000
3000
2000
1000
2022-01
2022-05
2022-09
2023-01
2023-05
2023-09
2024-01
2024-05
2024-09
datetime


Megawatt Usage Over Time in Va
127.0.0.1:5000/graph
Megawatt Usage Over Time in Various Regions
DELHI
Megawatt Usage Over Time in DELHI
1m
6m
YTD
1y
all
8000
6000
4000
2000
Jan 2022
Jul 2022
Jan 2023
Jul 2023
Jan 2024
Jul 2024
BRPL
Megawatt Usage Over Time in BRPL
1m
6m
YTD
1y
all
3000
2000
1000
04:49 PM
18-09-2024


Megawatt Usage Over Time in Va
127.0.0.1:5000/graph
1m
6m
YTD
1y
all
400
300
200
100
0
Jan 2022
Jul 2022
Jan 2023
Jul 2023
Jan 2024
Jul 2024
MES
Megawatt Usage Over Time in MES
1m
6m
YTD
1y
all
60
40
20
0
Jan 2022
Jul 2022
Jan 2023
Jul 2023
Jan 2024
Jul 2024
04:49 PM
18-09-2024

Products (Workshops, materials, skills developed)**& Product** **Availability**	Data Scrapping Websites: SDLC, nci.noaa ,CA(Central Elecctricity Authority), Delhi govt, open data portal (Load) and weather.com, metostat, weatherbit , IMD(india meteorological department),OGD(Open Government Data) (weather data) Libraries used : Pandas, Numpy, Sklearn , Keras , Tenserflow , Seaborn , Matplotlib Models Used: Random Forest, Grid searchcv, XG Boost, LSTM, GRU, GNN, GNN+GRU(Hybrid) Frameworks use: Jupyter Notebook, Google Collab, VS Code, ngnix, apache http server
Outcomes & Future Plan	Graphs and scores using various Models: DELHI: RMSE: 145.35 MAPE: 2.73% R2: 0.99 BRPL: RMSE: 74.48 MAPE: 3.33% R2: 0.98 BYPL: RMSE: 40.22 MAPE: 4.02% R2: 0.98 NDMC: RMSE: 10.05 MAPE: 4.30% R2: 0.98 MES: RMSE: 1.70 MAPE: 3.74% R2: 0.96 Using GRU+GNN(Hybrid):





Scores for Other Algorithms:

RANDOM FORESTS

```
[22] from sklearn.ensemble import RandomForestRegressor
     from sklearn.metrics import mean_absolute_error # Import the mean_absolute_error function

     rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
     rf_model.fit(X_train, y_train)
     rf_predictions = rf_model.predict(X_test)
     rf_mae = mean_absolute_error(y_test, rf_predictions)
     print(f'Random Forest MAE: {rf_mae}')
```

```
Random Forest MAE: 242.0375607189829
```

10.Using Gradient Boost

```
[23] from sklearn.ensemble import GradientBoostingRegressor

     gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
     gb_model.fit(X_train, y_train)
     gb_predictions = gb_model.predict(X_test)
     gb_mae = mean_absolute_error(y_test, gb_predictions)
     print(f'Gradient Boosting MAE: {gb_mae}')
```

```
Gradient Boosting MAE: 345.6451016799796
```

11.Using XgBoost

```
[24] from xgboost import XGBRegressor

     xgb_model = XGBRegressor(n_estimators=100, random_state=42)
     xgb_model.fit(X_train, y_train)
     xgb_predictions = xgb_model.predict(X_test)
     xgb_mae = mean_absolute_error(y_test, xgb_predictions)
     print(f'XGBoost MAE: {xgb_mae}')



     # Define MAPE calculation function
     def calculate_mape(y_true, y_pred):
         return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

     # Calculate MAPE
     xgb_mape = calculate_mape(y_test, xgb_predictions)
     print(f'XGBoost MAPE: {xgb_mape}')
```

```
XGBoost MAE: 225.62625449749632
XGBoost MAPE: 5.618300337389346
```

```
[ ]
import pandas as pd

# Sample dataset assuming it has been loaded into a pandas DataFrame
data = pd.read_csv('preprocessed_data.csv', parse_dates=['datetime'])

# If the load is combined from DELHI, BRPL, BYPL, NDMC columns
data['combined_load'] = data['DELHI'] + data['BRPL'] + data['BYPL'] + data['NDMC']

# Extract year and month for grouping
data['year_month'] = data['datetime'].dt.to_period('M')  # Format 'YYYY-MM' for each row

# Group by year and month
peak_loads_by_month = data.groupby('year_month').apply(
    lambda x: x.loc[x['DELHI'].idxmax()]
    )

    # Select only relevant columns (datetime, combined_load)
peak_loads_by_month = peak_loads_by_month[['datetime', 'DELHI']]

    # Display peak loads and their corresponding datetime for each month
print(peak_loads_by_month)
```

```
                      datetime    DELHI
year_month
2022-01    2022-01-21 10:00:00  5043.67
2022-02    2022-02-04 10:00:00  4796.15
2022-03    2022-03-31 16:00:00  4586.09
2022-04    2022-04-29 16:00:00  6095.75
2022-05    2022-05-20 00:00:00  6936.23
2022-06    2022-06-29 16:00:00  7560.51
2022-07    2022-07-08 16:00:00  7324.27
2022-08    2022-08-11 00:00:00  6329.57
2022-09    2022-09-09 16:00:00  6543.56
2022-10    2022-10-04 16:00:00  4928.83
2022-11    2022-11-10 18:00:00  3835.48
2022-12    2022-12-28 10:00:00  4868.39
2023-01    2023-01-10 10:00:00  5388.76
```

Future Work:

1. We will be adding green energies such as Solar powers consumption zone, The areas of low load predictions can use green energies whereas the areas of high load prediction can get direct supply.
2. We are going to make an more optimised approach of graph representation of various regions so that just by clicking the coordinates we can predict the load supplies of that regions(i.e. Agricultural, Domestic, Industrial and commercial).
3. This model uses Hybrid(GRU&GNN) which is highly scalable with high accuracy of 98% and can be used for various cities across the Globe.