COMSATS University Islamabad (CUI)

Project Report

for

Air Quality Prediction System

By

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Bachelor of Science in Artificial Intelligence (2024-2028)

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1. Introduction

Air pollution is one of the major environmental and public health challenges faced by urban areas worldwide. Fine particulate matter (PM2.5) is a key indicator of air quality, and prolonged exposure to high PM2.5 concentrations can lead to respiratory, cardiovascular, and neurological diseases. Beijing, China, is particularly affected due to rapid industrialization, high population density, and heavy vehicular emissions.

Monitoring PM2.5 levels and predicting air quality in advance can help authorities implement mitigation strategies, improve public health, and enable individuals to take precautionary measures.

This project aims to develop a predictive system for Beijing's PM2.5 concentrations using historical air quality and meteorological data, combining statistical and machine learning techniques for accurate forecasts.

2. Problem Statement

Air pollution, particularly fine particulate matter (PM2.5), poses a significant health risk in urban areas, with Beijing being one of the most affected cities due to rapid industrialization, vehicular emissions, and seasonal weather patterns. Accurate prediction of PM2.5 concentrations is essential for timely public health advisories and environmental management. However, forecasting air quality is challenging because PM2.5 levels are influenced by multiple interacting factors, including meteorological conditions, temporal cycles, and unpredictable events. Additionally, the raw data often contains missing values, outliers, and non-linear relationships that complicate traditional modeling approaches.

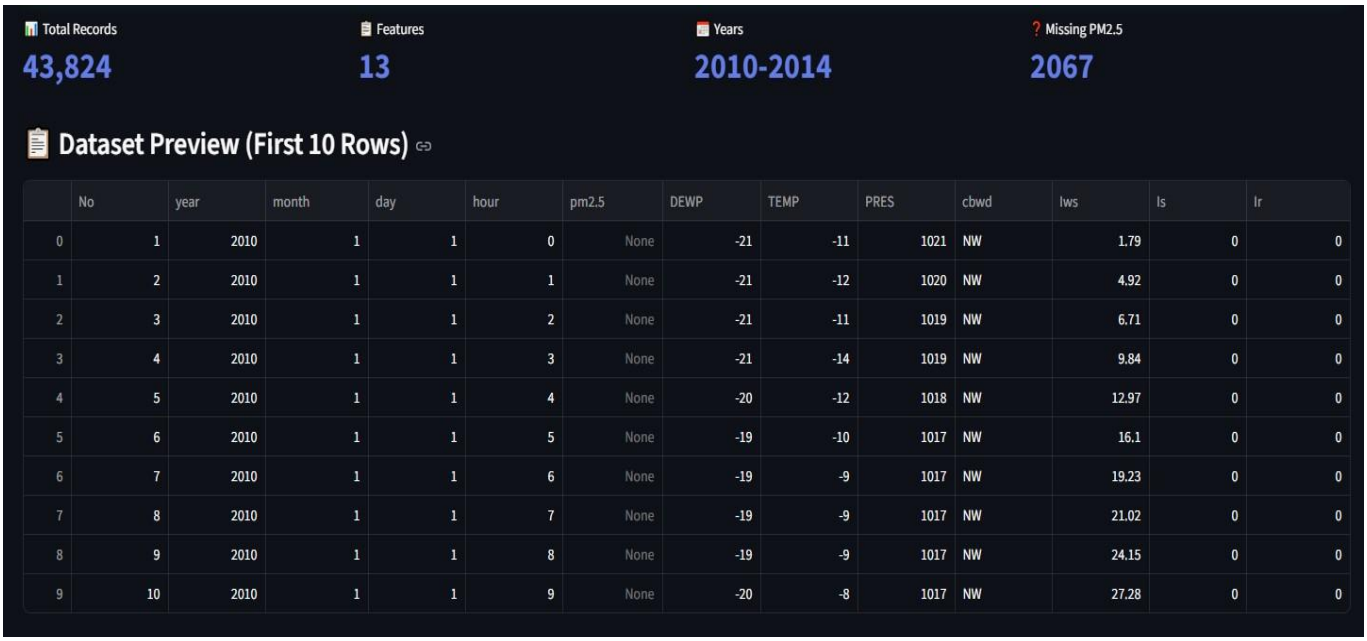
3. Proposed Solution

The PM2.5 Air Quality Prediction System delivers a unified machine learning pipeline designed to overcome challenges in pollution forecasting and noisy environmental data. Through structured preprocessing, temporal feature extraction, rolling-window statistics, and categorical encoding, the system converts raw measurements into high-quality analytical inputs. It integrates a baseline Linear Regression model for interpretability and a custom neural network with sigmoid activation to capture non-linear atmospheric patterns. Model comparison, loss analysis, and prediction visualizations ensure stable and accurate PM2.5 estimates. Supported by an interactive GUI for EDA, weather impact analysis, and correlation insights, the solution offers a reliable and scalable platform for air quality monitoring, public health planning, and future research extensions.

4. Dataset Overview

Dataset: Beijing PM2.5 Data (2010–2014) – UCI/Kaggle

- Total Records: 43,824 hourly observations
- Target Variable: pm2.5 (μg/m³)



Total Records: 43,824 | Features: 13 | Years: 2010-2014 | Missing PM2.5: 2067

Dataset Preview (First 10 Rows)

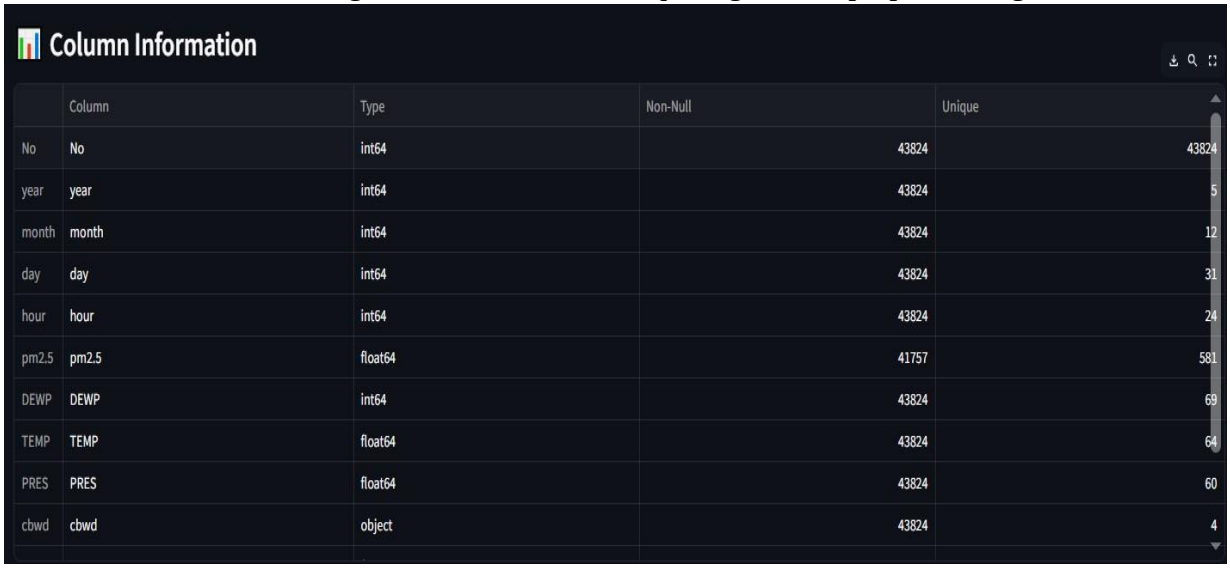
	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws	Is	Ir
0	1	2010	1	1	0	None	-21	-11	1021	NW	1.79	0	0
1	2	2010	1	1	1	None	-21	-12	1020	NW	4.92	0	0
2	3	2010	1	1	2	None	-21	-11	1019	NW	6.71	0	0
3	4	2010	1	1	3	None	-21	-14	1019	NW	9.84	0	0
4	5	2010	1	1	4	None	-20	-12	1018	NW	12.97	0	0
5	6	2010	1	1	5	None	-19	-10	1017	NW	16.1	0	0
6	7	2010	1	1	6	None	-19	-9	1017	NW	19.23	0	0
7	8	2010	1	1	7	None	-19	-9	1017	NW	21.02	0	0
8	9	2010	1	1	8	None	-19	-9	1017	NW	24.15	0	0
9	10	2010	1	1	9	None	-20	-8	1017	NW	27.28	0	0

Features:

Temporal: year, month, day, hour

Meteorological: DEWP, TEMP, PRES, Iws, Is, Ir Categorical:
cbwd (wind direction)

The dataset contains missing and extreme values requiring careful preprocessing.



Column Information

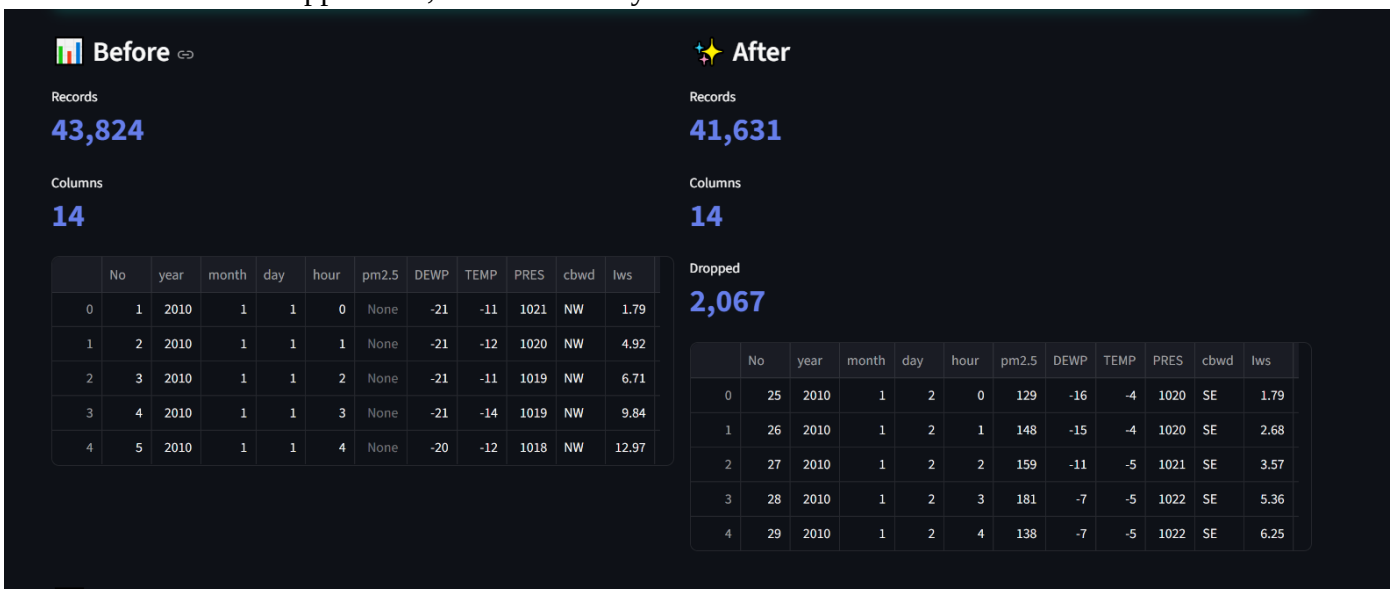
	Column	Type	Non-Null	Unique
No	No	int64	43824	43824
year	year	int64	43824	5
month	month	int64	43824	12
day	day	int64	43824	31
hour	hour	int64	43824	24
pm2.5	pm2.5	float64	41757	581
DEWP	DEWP	int64	43824	69
TEMP	TEMP	float64	43824	64
PRES	PRES	float64	43824	60
cbwd	cbwd	object	43824	4

5. Data Preprocessing

Following Data Preprocessing steps were performed:

Step	Description
Datetime Construction	Combined `year`, `month`, `day`, and `hour` into a single `datetime` column to organize the dataset chronologically.
Target Cleaning	Removed rows with missing PM2.5 values to ensure reliable training of predictive models.
Meteorological Value Imputation	Applied forward-fill and backward-fill techniques to handle missing values in `TEMP`, `DEWP`, `PRES`, `Iws`, `Is`, and `Ir`, preserving continuity in weather patterns.
Categorical Encoding	Filled missing wind-direction (`cbwd`) values and converted the categorical wind direction into one-hot encoded binary columns.
Outlier Removal	Removed extreme PM2.5 values above 500 µg/m³ to eliminate measurement anomalies and unrealistic spikes.
Sorting and Index Reset	Ordered all records by datetime and reset index to maintain temporal consistency for rolling and lag features.
Normalization	Scaled all input features using StandardScaler to stabilize model training and ensure equal weighting of variables.
Train–Test Split	Split data chronologically into 80% training and 20% testing while preserving temporal order to prevent leakage.

Final cleaned dataset: approx. 43,000 valid hourly records.



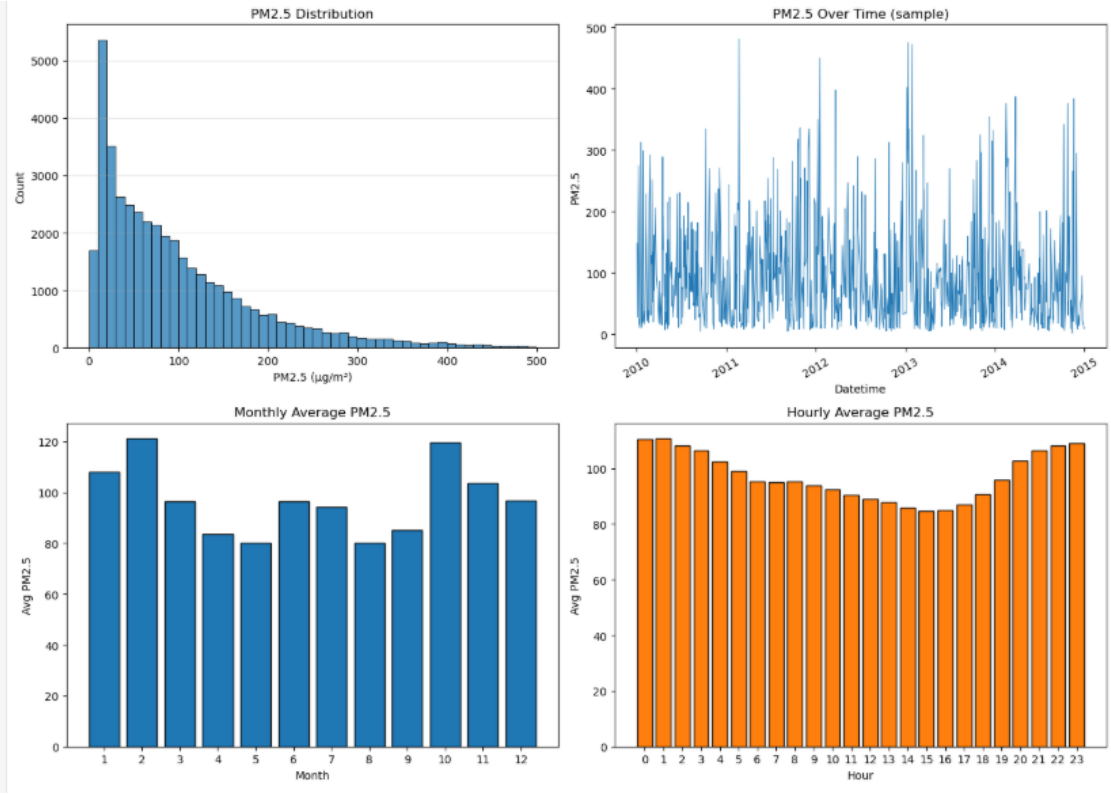
	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws
0	1	2010	1	1	0	None	-21	-11	1021	NW	1.79
1	2	2010	1	1	1	None	-21	-12	1020	NW	4.92
2	3	2010	1	1	2	None	-21	-11	1019	NW	6.71
3	4	2010	1	1	3	None	-21	-14	1019	NW	9.84
4	5	2010	1	1	4	None	-20	-12	1018	NW	12.97

	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws
0	25	2010	1	2	0	129	-16	-4	1020	SE	1.79
1	26	2010	1	2	1	148	-15	-4	1020	SE	2.68
2	27	2010	1	2	2	159	-11	-5	1021	SE	3.57
3	28	2010	1	2	3	181	-7	-5	1022	SE	5.36
4	29	2010	1	2	4	138	-7	-5	1022	SE	6.25

6. Exploratory Data Analysis (EDA)

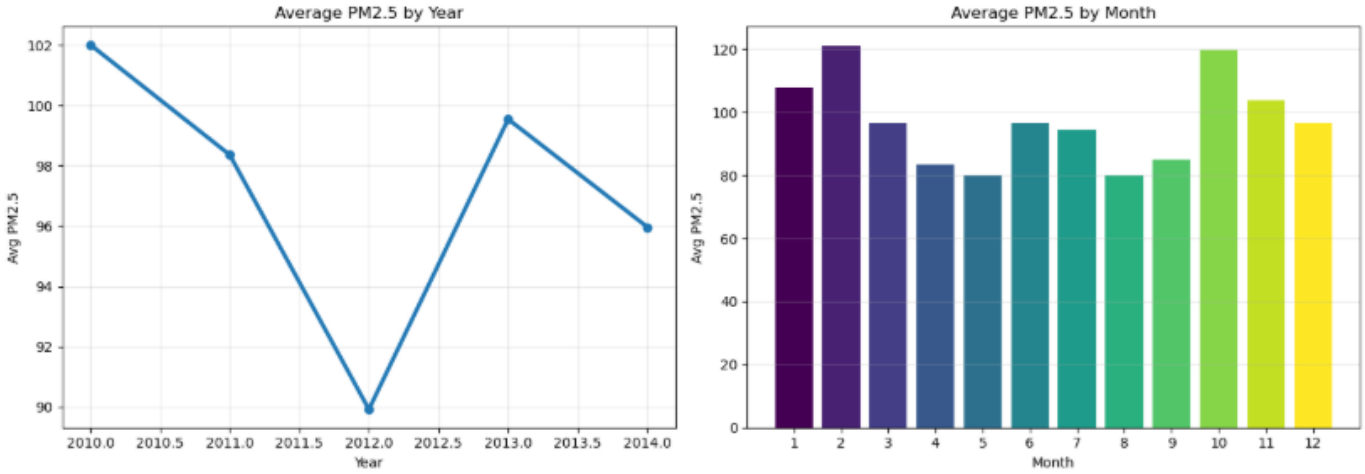
6.1. Distribution Analysis

PM2.5 histograms and density plots reveal a right-skewed distribution with frequent moderate pollution levels and occasional extreme spikes.



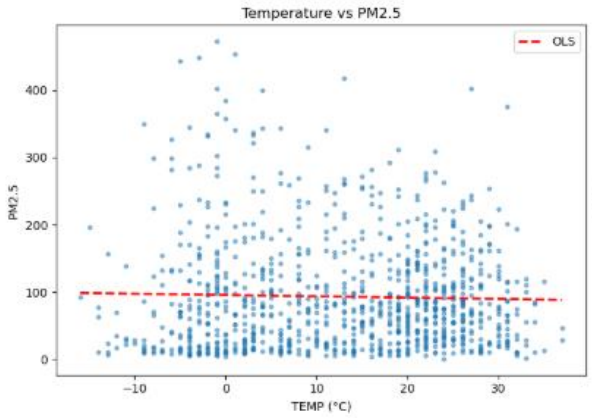
2. Temporal Trends

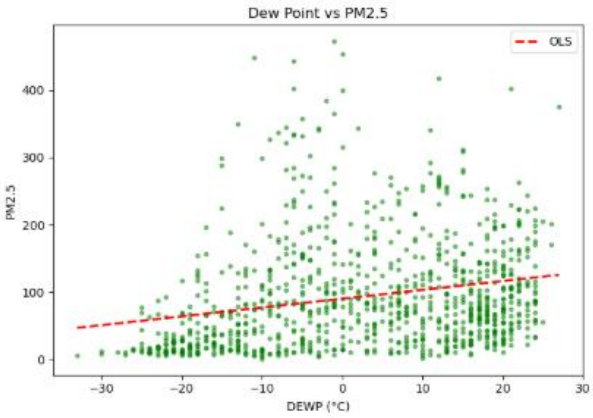
Line plots of yearly, monthly, and hourly averages show strong seasonality, with winter peaks and lower summer concentrations.



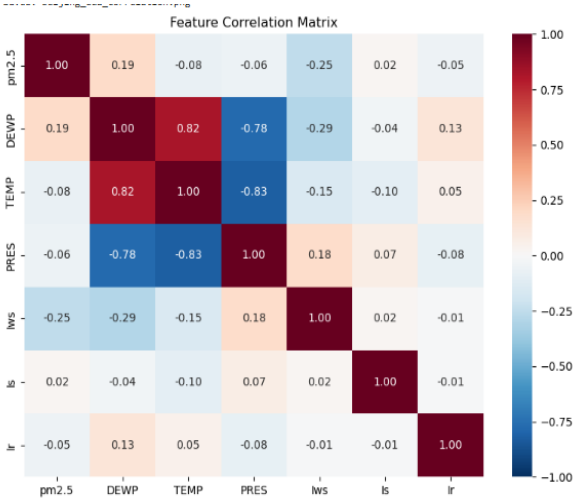
3. Winter Impact

Cold months exhibit significantly higher PM2.5 due to temperature inversion, increased heating emissions, and reduced atmospheric dispersion.





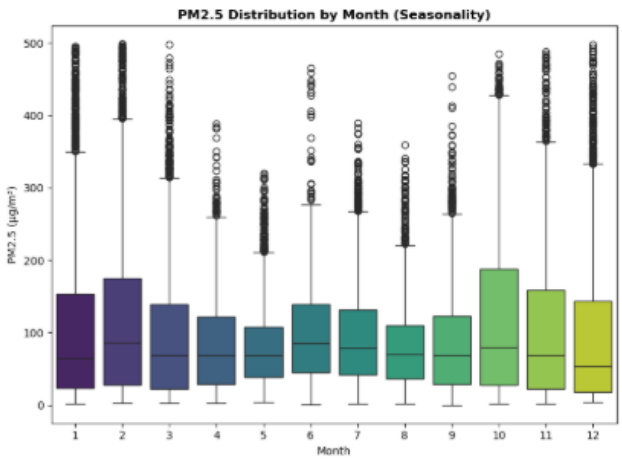
4. Correlation Heatmap

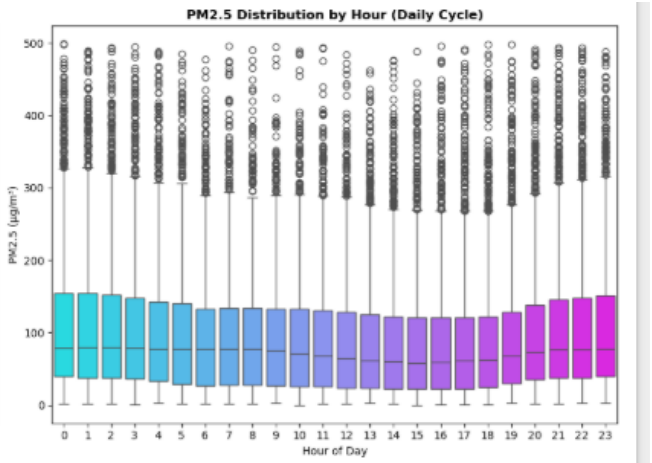


A correlation matrix highlights strong relationships between PM2.5 and factors like dew point, temperature, and wind speed, indicating meteorological influence.

5. Box Plot Analysis and Outlier Detection

Month-wise and hour-wise boxplots show seasonal variance and daily pollution cycles, with wider spread during winter and morning–evening peaks. IQR-based analysis identifies extreme high-pollution events, marking them as statistical outliers that align with real atmospheric disturbances.



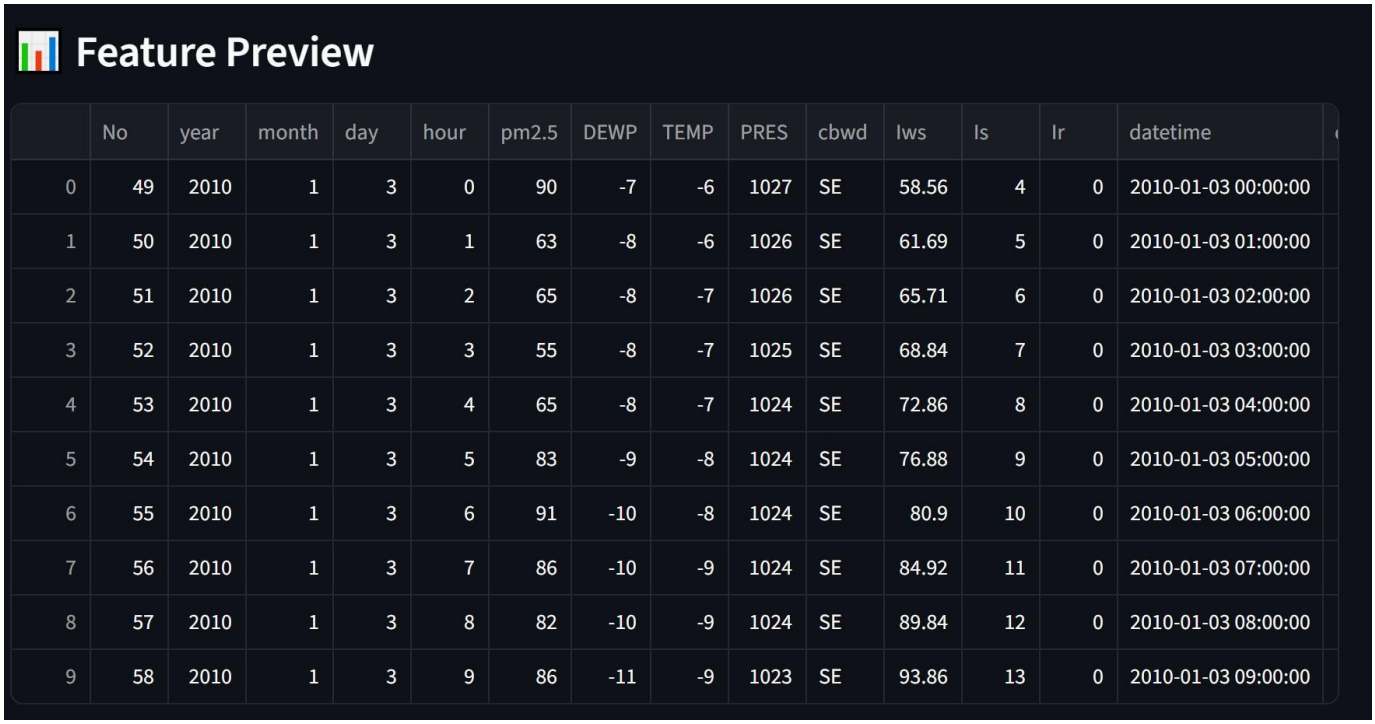


7. Feature Engineering

The following features were engineered:

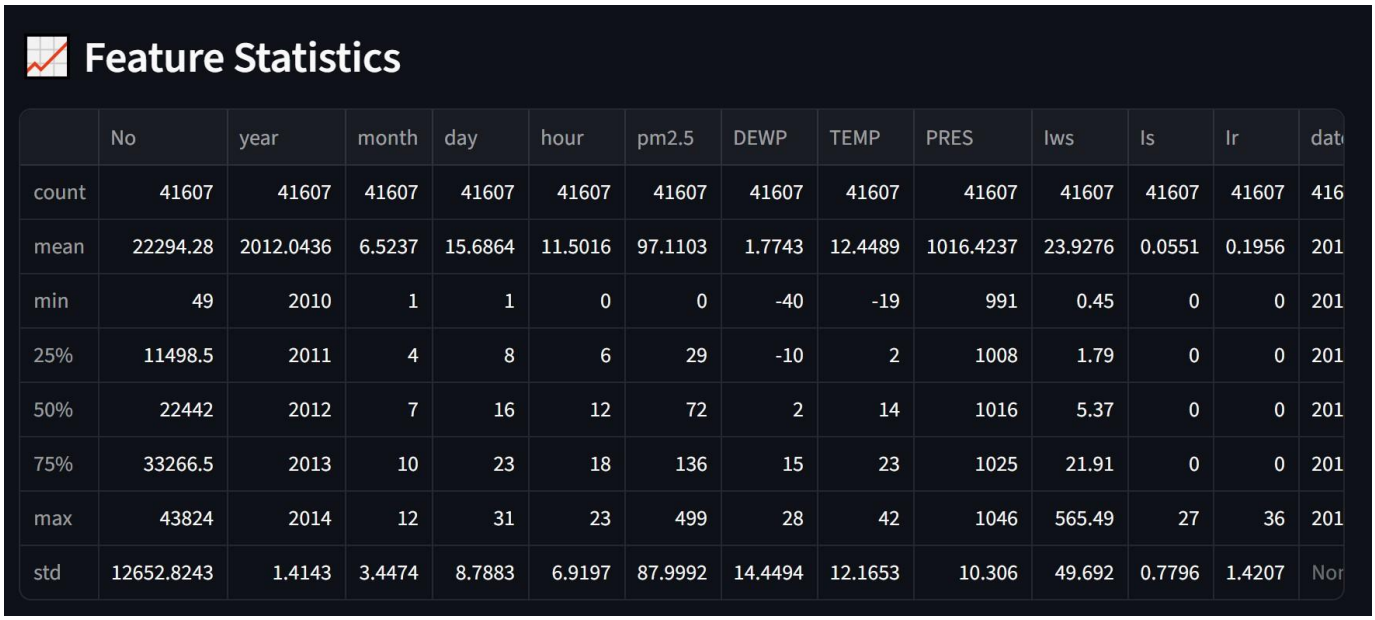
1. **Time-based features:**
   hour, day, month, season, weekday
   Cyclical encoding: hour_sin, hour_cos
2. **Rolling Averages:**
   3-hour, 6-hour, 12-hour, 24-hour rolling means
3. **Lag Features:**
   PM2.5 values from previous 1, 3, 6, 12, 24 hours
4. **Meteorological features:**
   DEWP, TEMP, PRES, Iws, Is, Ir
5. **Wind direction:**
   One-hot encoded

These features allowed models to capture temporal dependencies and atmospheric patterns.



Feature Preview

	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws	Is	Ir	datetime
0	49	2010	1	3	0	90	-7	-6	1027	SE	58.56	4	0	2010-01-03 00:00:00
1	50	2010	1	3	1	63	-8	-6	1026	SE	61.69	5	0	2010-01-03 01:00:00
2	51	2010	1	3	2	65	-8	-7	1026	SE	65.71	6	0	2010-01-03 02:00:00
3	52	2010	1	3	3	55	-8	-7	1025	SE	68.84	7	0	2010-01-03 03:00:00
4	53	2010	1	3	4	65	-8	-7	1024	SE	72.86	8	0	2010-01-03 04:00:00
5	54	2010	1	3	5	83	-9	-8	1024	SE	76.88	9	0	2010-01-03 05:00:00
6	55	2010	1	3	6	91	-10	-8	1024	SE	80.9	10	0	2010-01-03 06:00:00
7	56	2010	1	3	7	86	-10	-9	1024	SE	84.92	11	0	2010-01-03 07:00:00
8	57	2010	1	3	8	82	-10	-9	1024	SE	89.84	12	0	2010-01-03 08:00:00
9	58	2010	1	3	9	86	-11	-9	1023	SE	93.86	13	0	2010-01-03 09:00:00



Feature Statistics

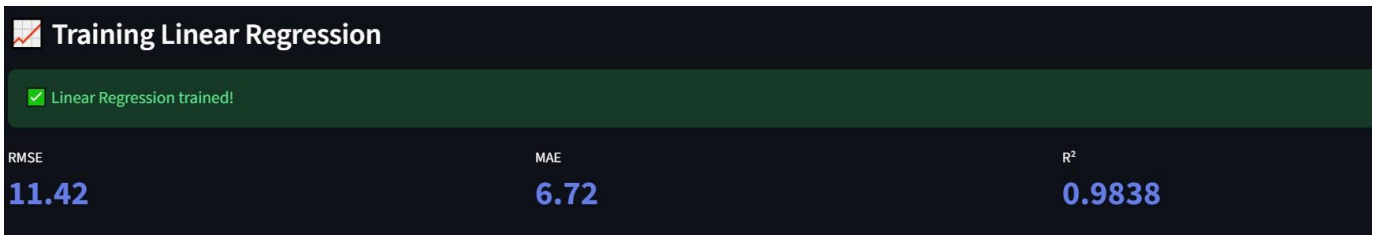
	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	Iws	Is	Ir	dat
count	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	416
mean	22294.28	2012.0436	6.5237	15.6864	11.5016	97.1103	1.7743	12.4489	1016.4237	23.9276	0.0551	0.1956	201
min	49	2010	1	1	0	0	-40	-19	991	0.45	0	0	201
25%	11498.5	2011	4	8	6	29	-10	2	1008	1.79	0	0	201
50%	22442	2012	7	16	12	72	2	14	1016	5.37	0	0	201
75%	33266.5	2013	10	23	18	136	15	23	1025	21.91	0	0	201
max	43824	2014	12	31	23	499	28	42	1046	565.49	27	36	201
std	12652.8243	1.4143	3.4474	8.7883	6.9197	87.9992	14.4494	12.1653	10.306	49.692	0.7796	1.4207	Nor

8. Models Implemented

In this study, two supervised learning models were trained to predict AQI: Linear Regression and an Artificial Neural Network (ANN). Each model represents a different approach, ranging from simple linear assumptions to complex non-linear learning.

8.1 Linear Regression (Baseline)

• Simple, interpretable • Captures linear patterns only
• Performance:
– RMSE: 35–40 µg/m³
– R²: ~0.55



Training Linear Regression

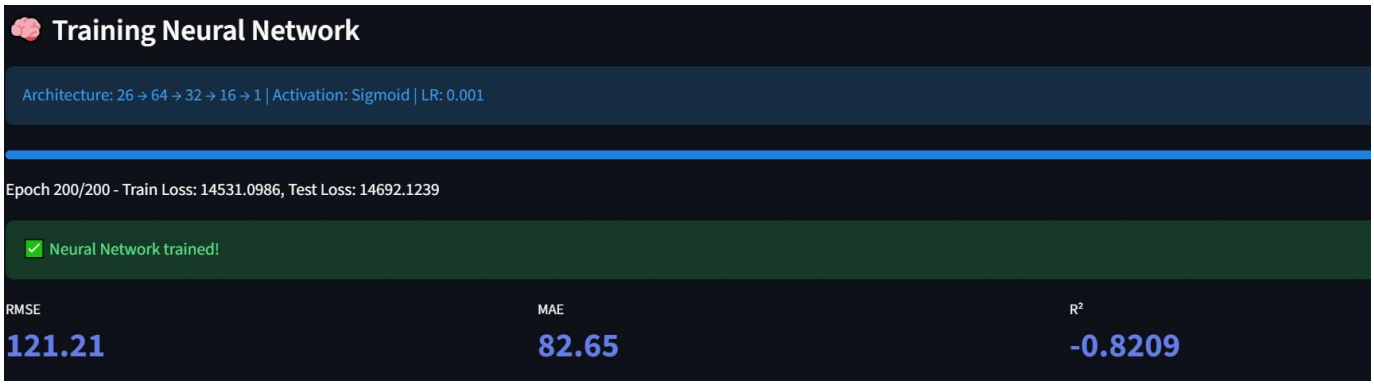
Linear Regression trained!

RMSE	MAE	R²
11.42	6.72	0.9838

8.2 Artificial Neural Network (ANN)

• Architecture: Input → 32 → 16 → Output
• Activation: Sigmoid
• Optimization: Gradient Descent, Backpropagation • Performance:
– RMSE: 25–30 µg/m³ –
R²: 0.75–0.80

ANN captures non-linear patterns and atmospheric interactions effectively.

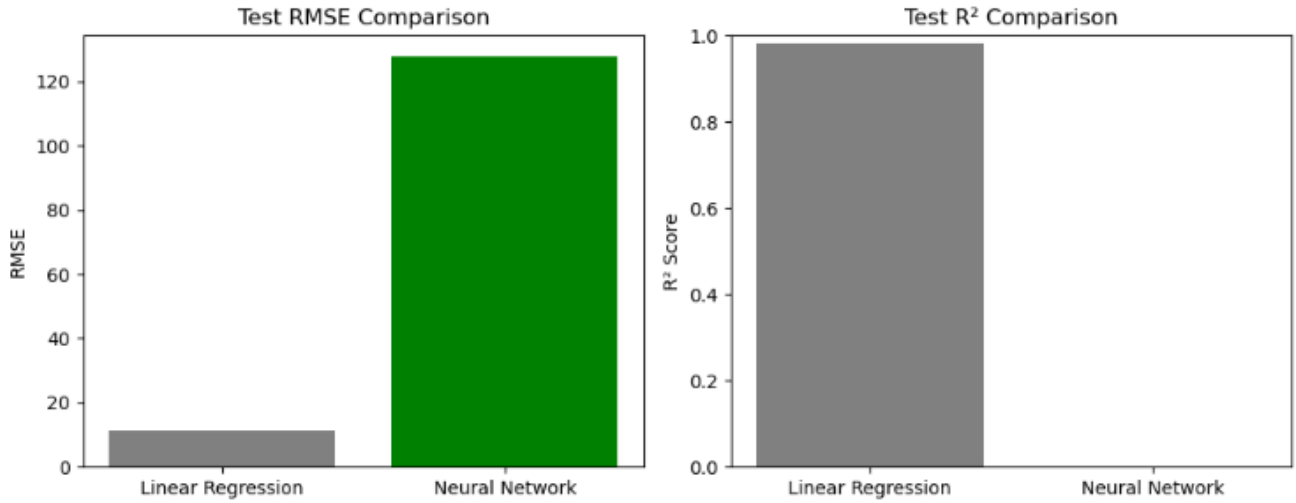


9. Model Comparison

Model	RMSE (Test)	R^2 (Test)
Linear Regression	35–40	0.55
Neural Network (ANN)	25–30	0.75–0.80

Observations:

• ANN significantly outperforms Linear Regression
• Linear Regression underfits high variability regions
• ANN adapts to seasonal and meteorological non-linearities

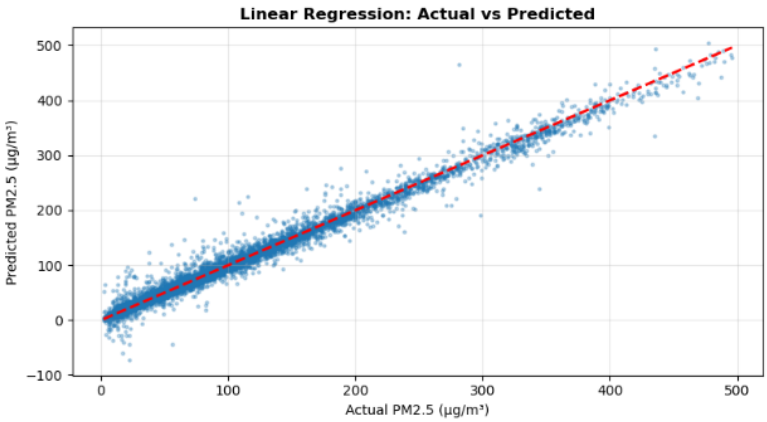


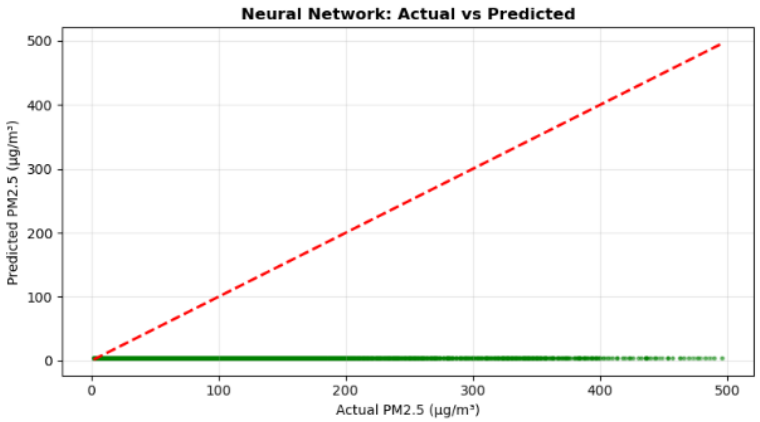
10. Prediction

• ANN predictions closely match real PM2.5 patterns
• Seasonal fluctuations are represented accurately • Residuals centered around zero indicate minimal bias

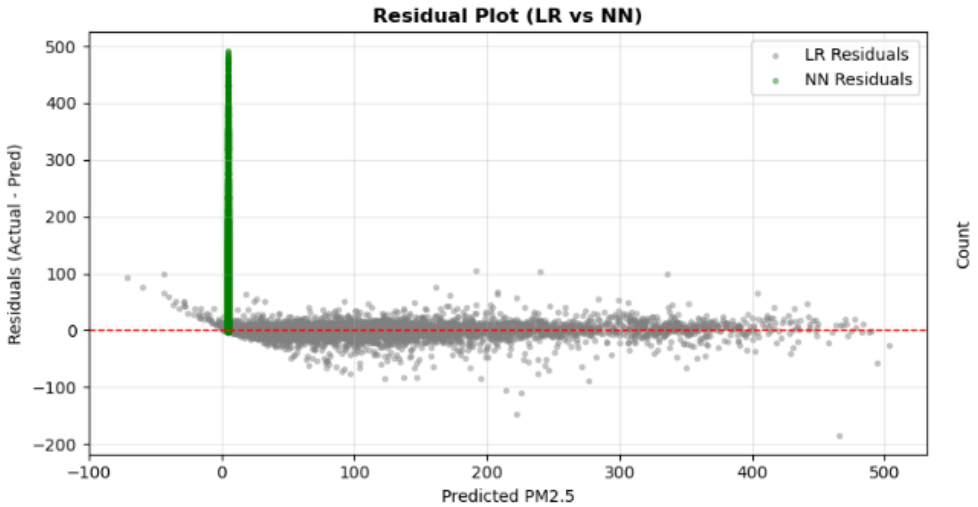
Prediction visuals typically include:

- **Actual vs Predicted curves**

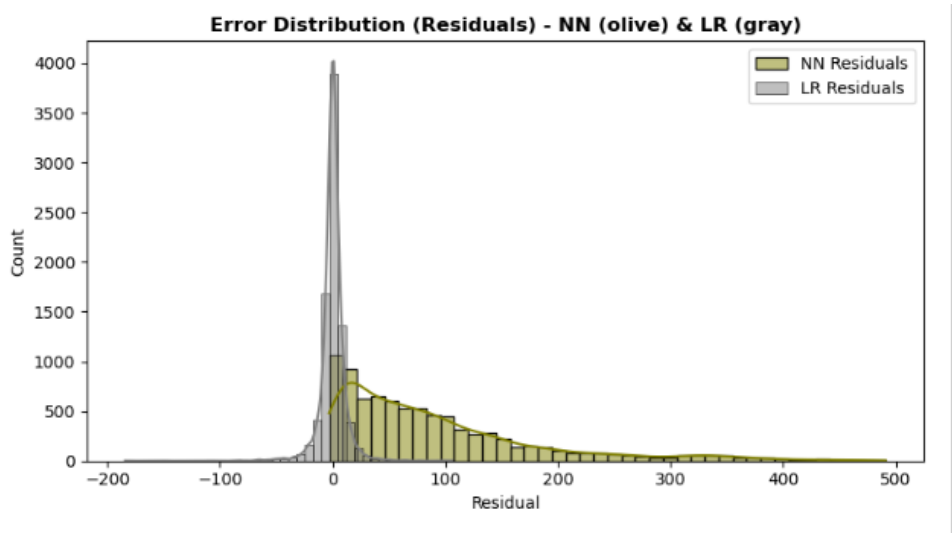




- **Residuals plot**



- **Error distribution**



11. App GUI

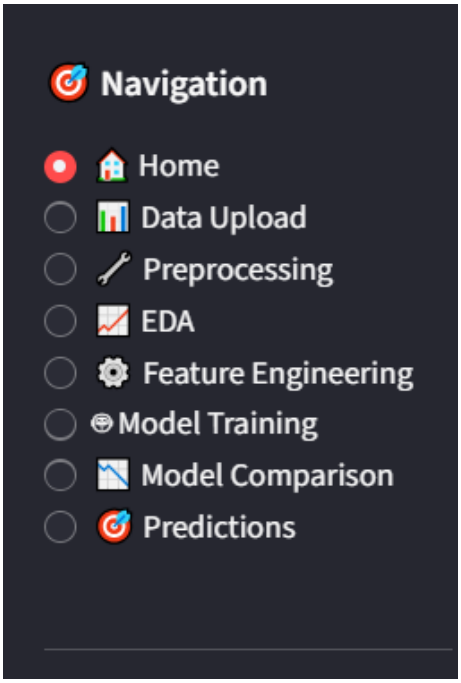
A Streamlit-based GUI was developed with:

• Tabs for Overview, Temporal, Weather, and Correlations
• Summary metrics (max/avg PM2.5, total records) • Interactive plots:
– PM2.5 trends
– Seasonal patterns
– Temperature vs PM2.5
– Correlation Heatmap
• Model prediction visualization

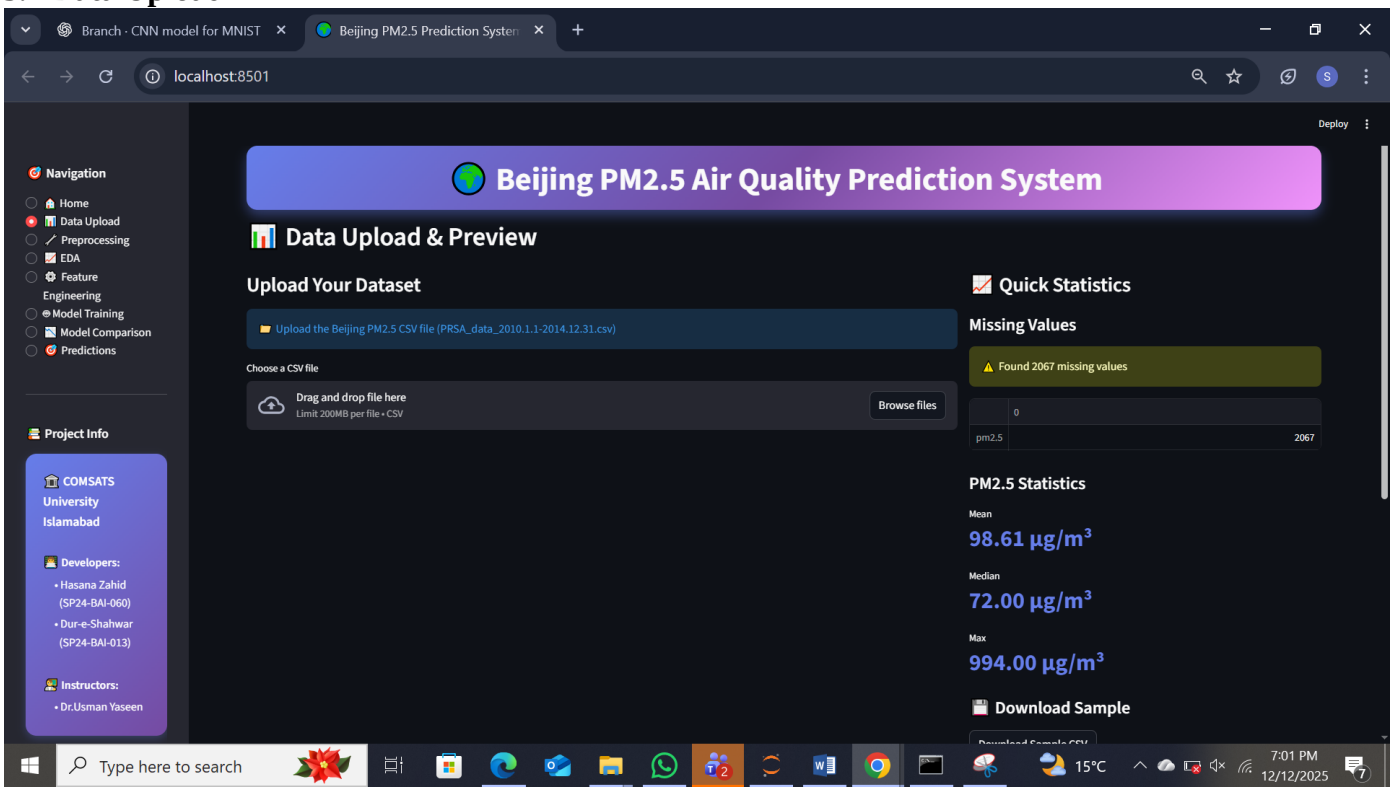
The GUI is simple, fast, and user-friendly.

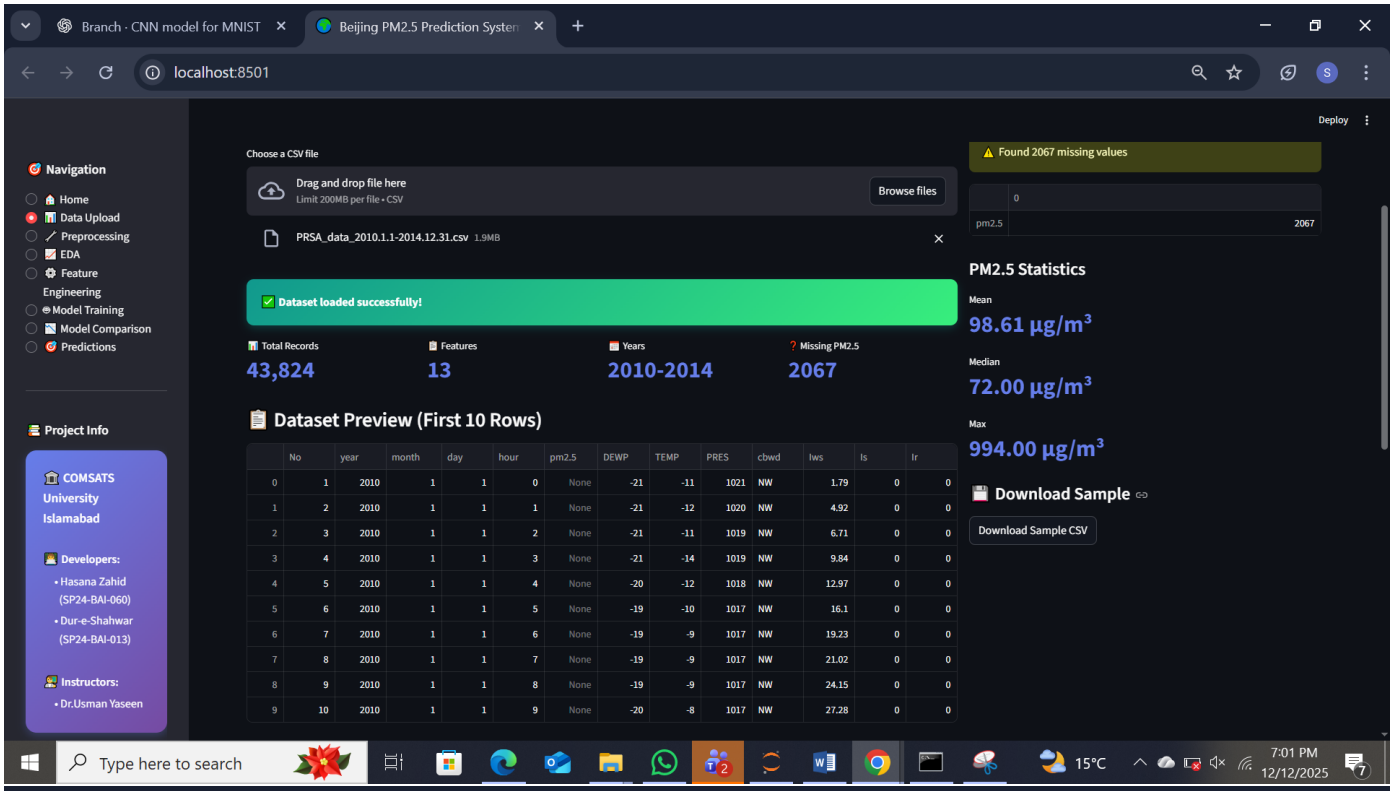
1. Home Page

2. Navigation Bar



3. Data Upload




Branch - CNN model for MNIST
Beijing PM2.5 Prediction Syster
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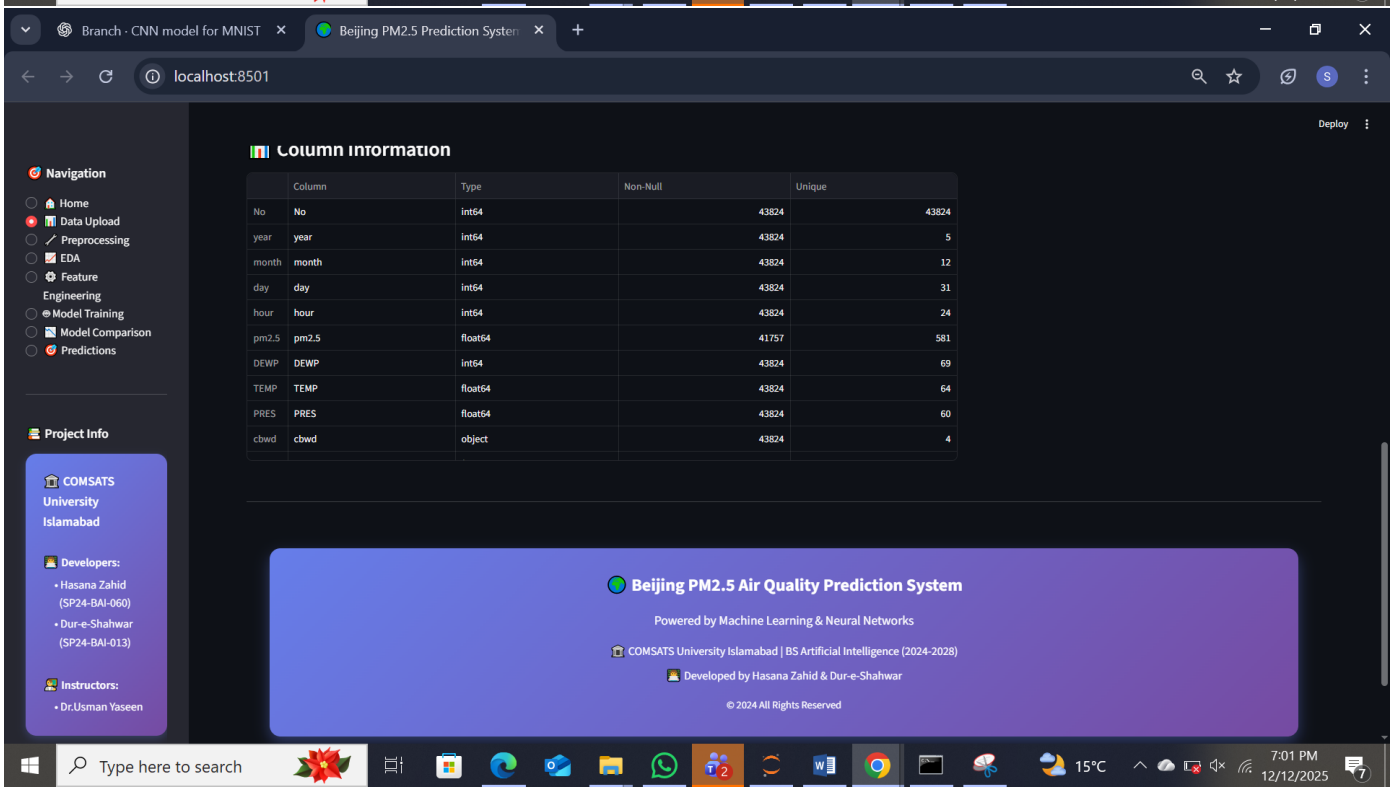
Instructors:
• Dr.Usman Yaseen
Choose a CSV file
Drag and drop file here
Limit 200MB per file • CSV
Browse files
PRSA_data_2010.1.1-2014.12.31.csv 1.9MB
Dataset loaded successfully!
Total Records
43,824
Features
13
Years
2010-2014
Missing PM2.5
2067
Dataset Preview (First 10 Rows)
Found 2067 missing values
PM2.5 Statistics
Mean
98.61 µg/m³
Median
72.00 µg/m³
Max
994.00 µg/m³
Download Sample
Download Sample CSV
Type here to search
15°C
7:01 PM
12/12/2025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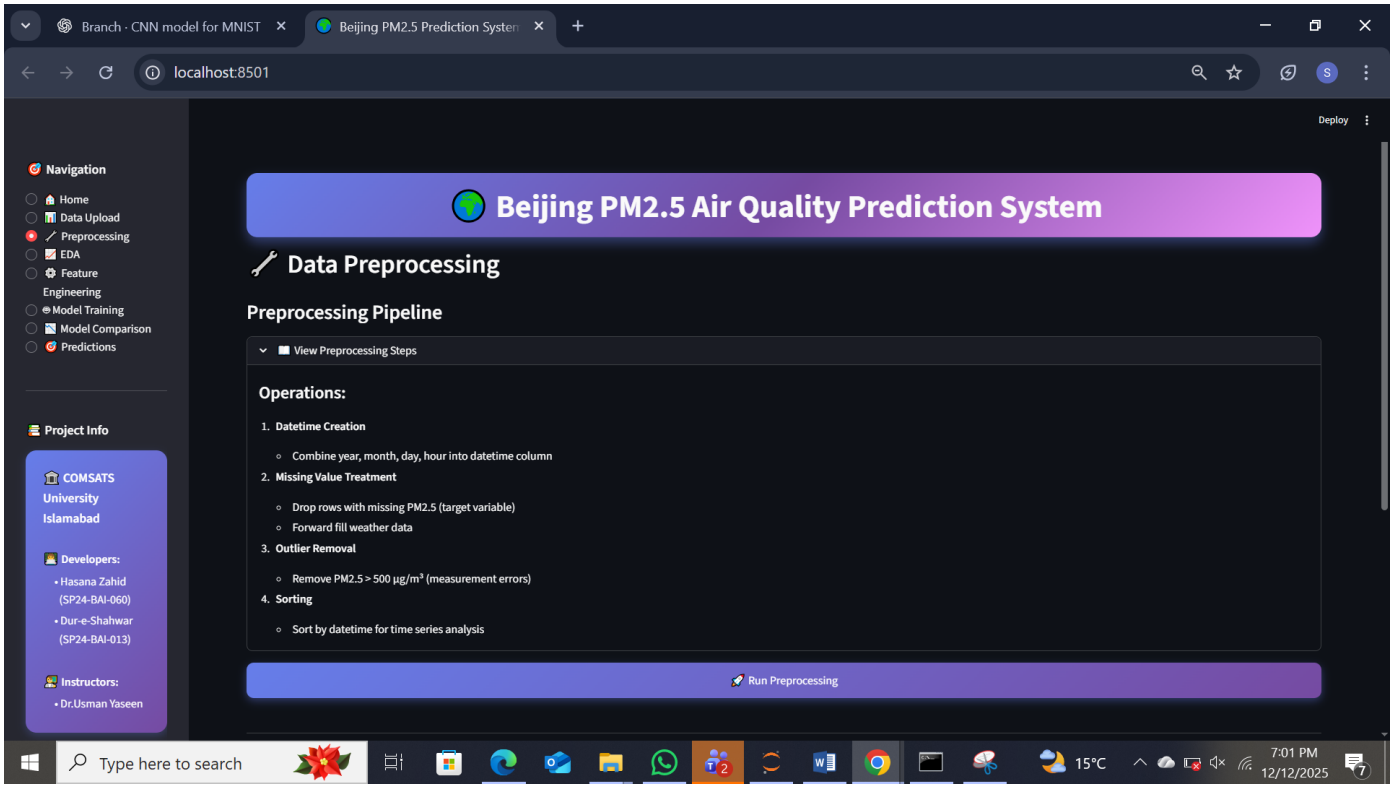
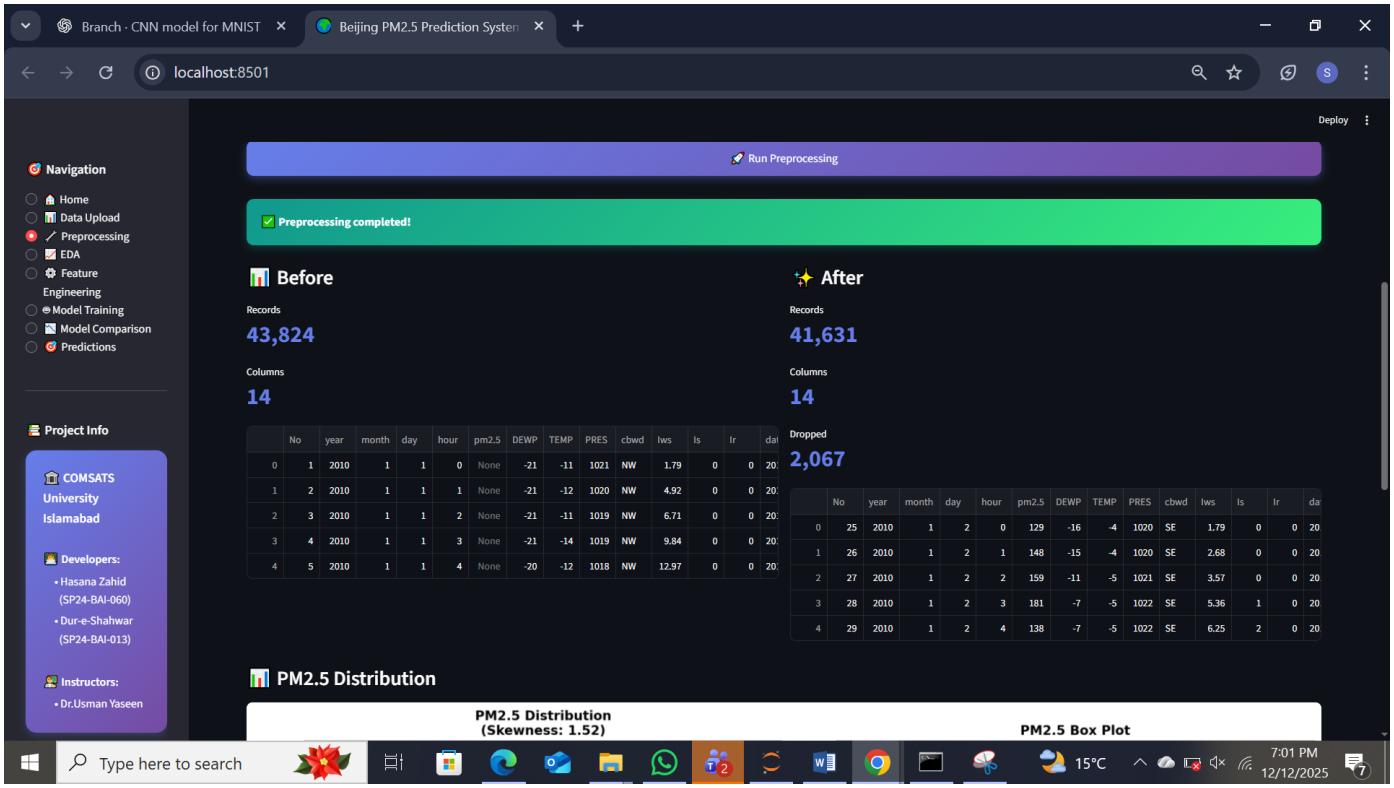
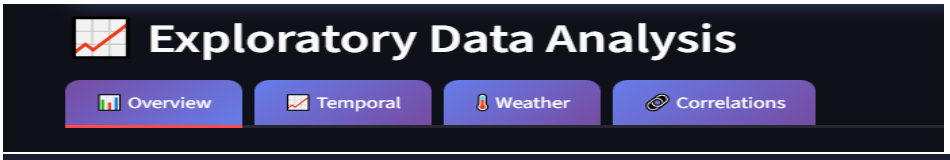
Column Information
Beijing PM2.5 Air Quality Prediction System
Powered by Machine Learning & Neural Networks
COMSATS University Islamabad | BS Artificial Intelligence (2024-2028)
Developed by Hasana Zahid & Dur-e-Shahwar
© 2024 All Rights Reserved
Type here to search
15°C
7:01 PM
12/12/2025

4. Data PreProcessing





5. EDA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EDA
Feature Engineering
Model Training
Model Comparison
Predictions
Project Info
COMSATS University Islamabad
Developers:
• Hasana Zahid (SP24-BAI-060)
• Dur-e-Shahwar (SP24-BAI-013)
Instructors:
• Dr.Usman Yaseen
Beijing PM2.5 Air Quality Prediction System
Exploratory Data Analysis
Overview
Temporal
Weather
Correlations
Data Overview
Records
41,631
Years
5
Avg PM2.5
97.14
Max PM2.5
499.00
PM2.5 Distribution
PM2.5 Over Time
Type here to search
15°C
7:02 PM
12/12/2025


Project Info
COMSATS University Islamabad
Developers:
• Hasana Zahid (SP24-BAI-060)
• Dur-e-Shahwar (SP24-BAI-013)
Instructors:
Monthly Average
Hourly Average
Type here to search
17°C
11:19 AM
12/12/2025


CNN model for MNIST
Beijing PM2.5 Prediction Syster
Google Gemini
localhost:8501
Deploy
Navigation
Home
Data Upload
Preprocessing
EDA
Feature Engineering
Model Training
Model Comparison
Predictions
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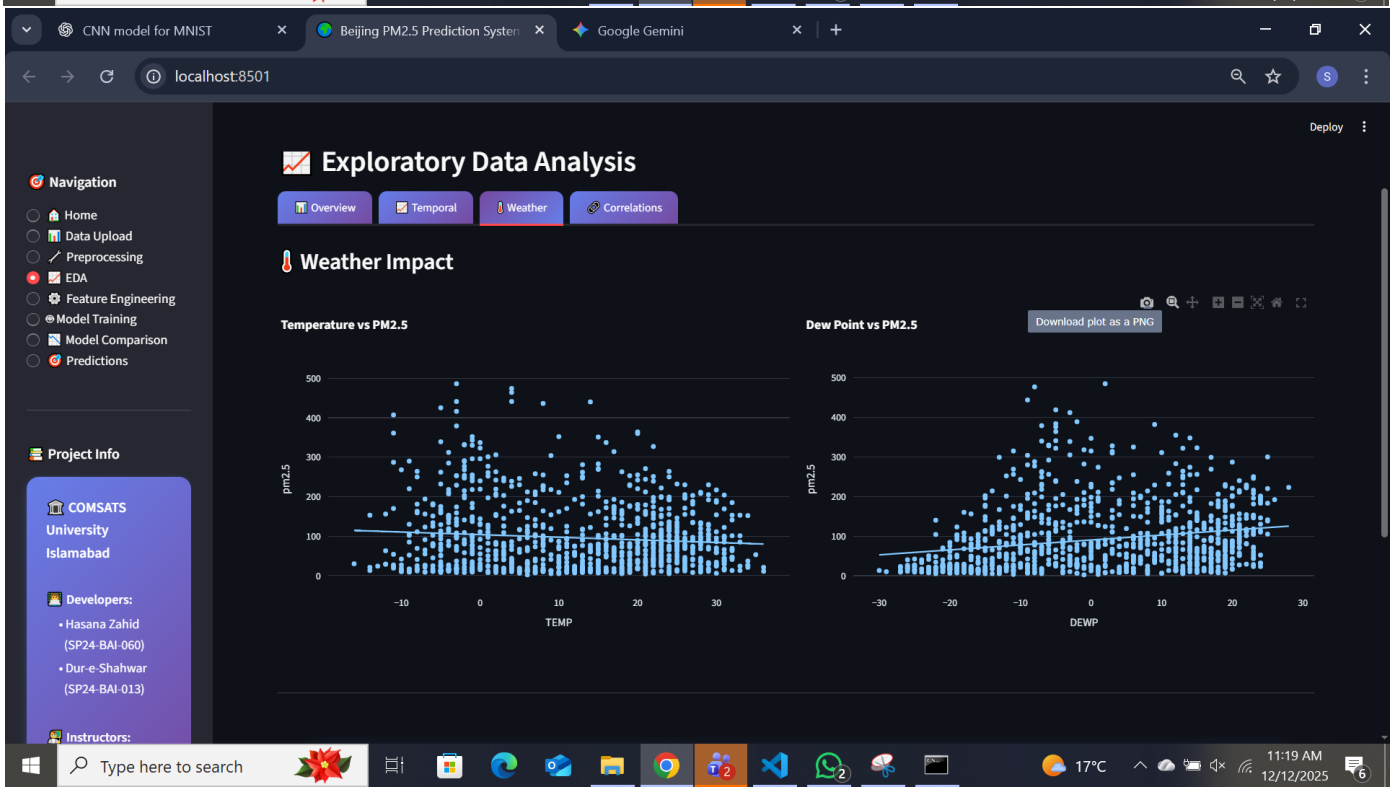
• Dur-e-Shahwar (SP24-BAI-013)
Instructors:
Average PM2.5 by Month
pm2.5
month
Beijing PM2.5 Air Quality Prediction System
Powered by Machine Learning & Neural Networks
COMSATS University Islamabad | BS Artificial Intelligence (2024-2028)
Type here to search
17°C
11:19 AM
12/12/2025


CNN model for MNIST
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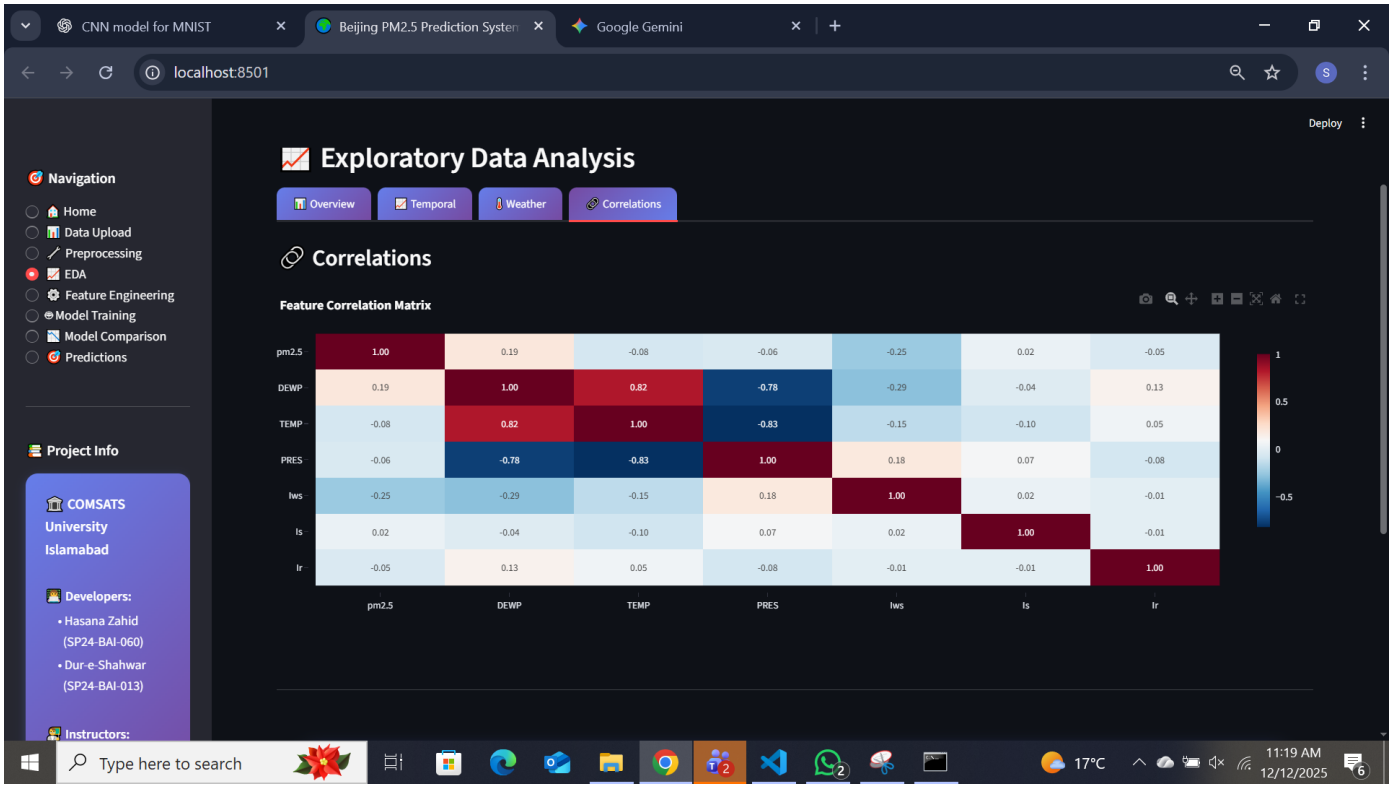
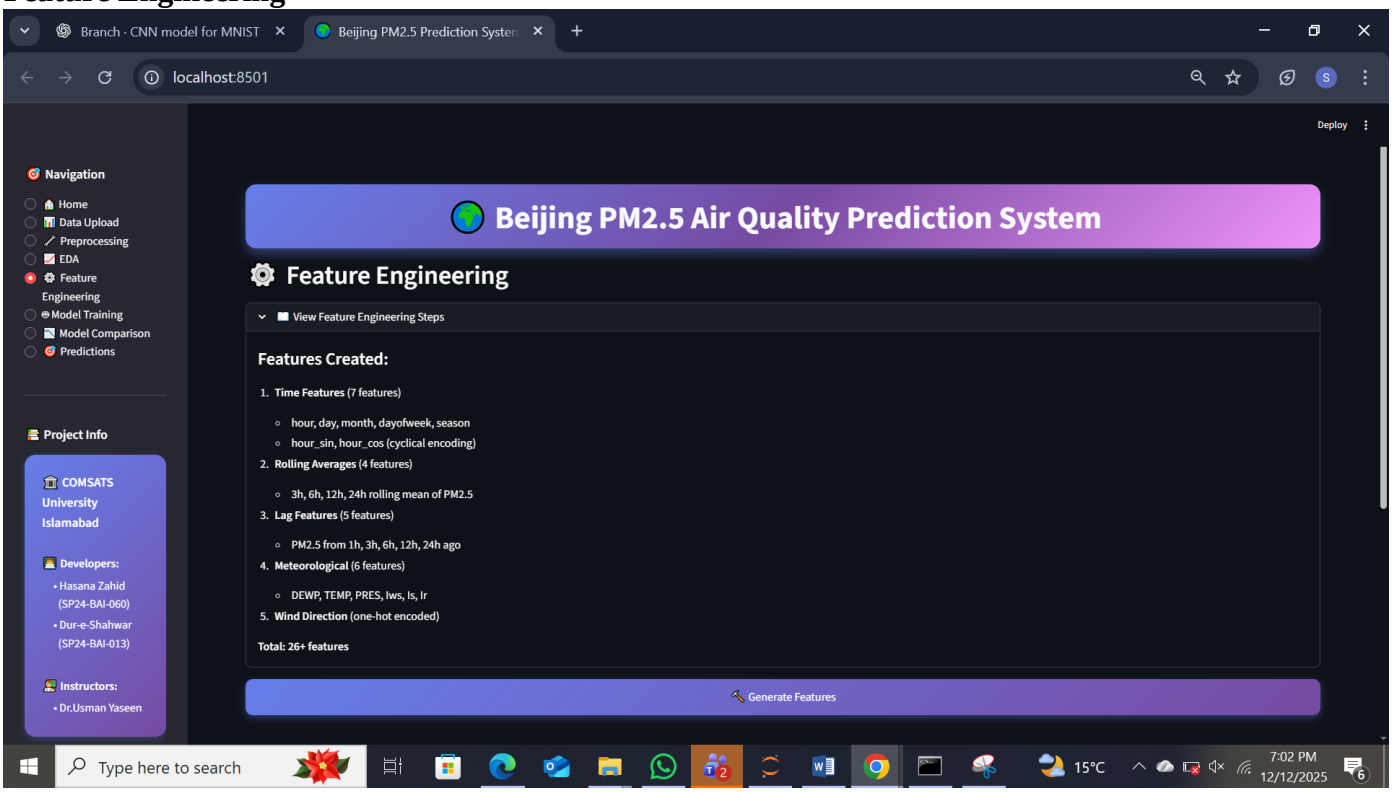
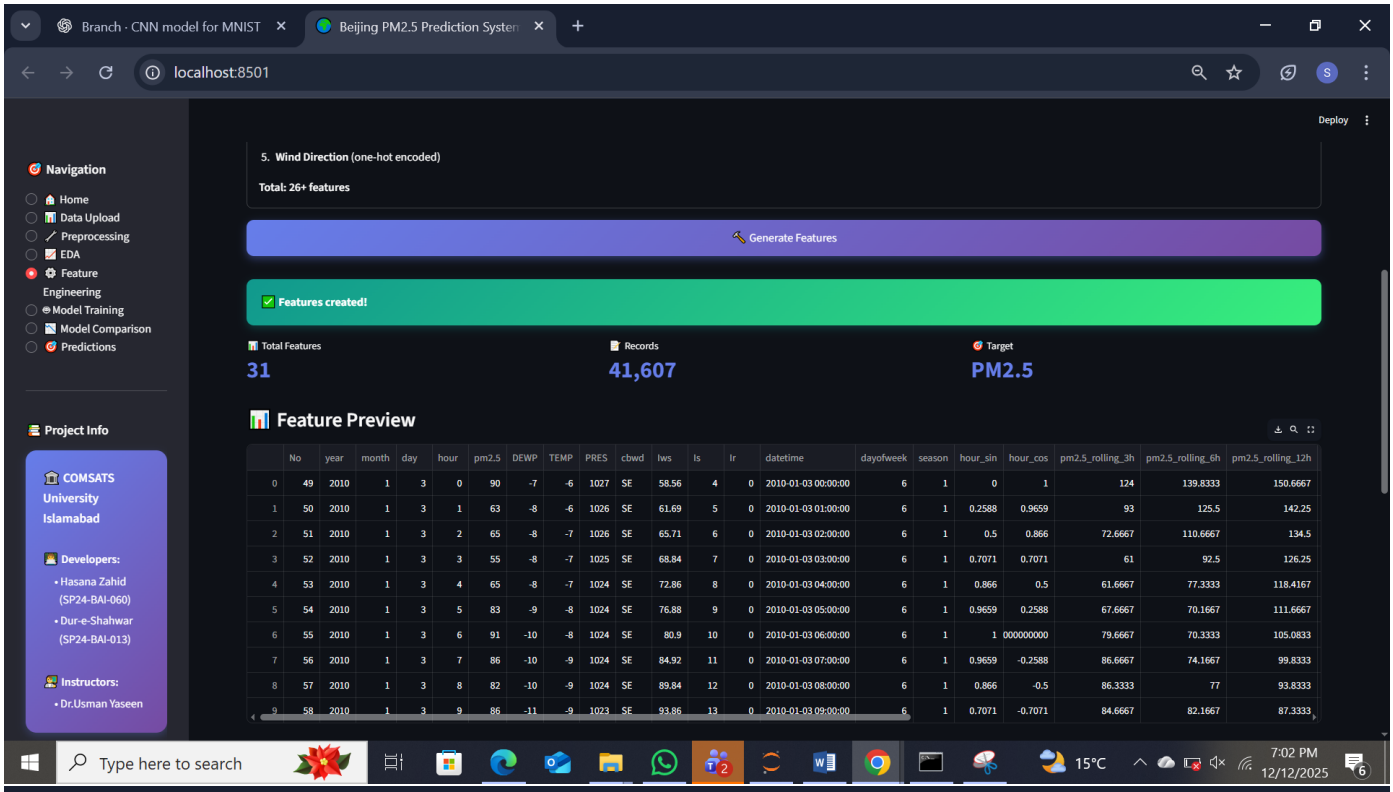
Exploratory Data Analysis
Overview
Temporal
Weather
Correlations
Weather Impact
Temperature vs PM2.5
Dew Point vs PM2.5
Download plot as a PNG
pm2.5
TEMP
DEWP
Type here to search
17°C
11:19 AM
12/12/2025



6. Feature Engineering





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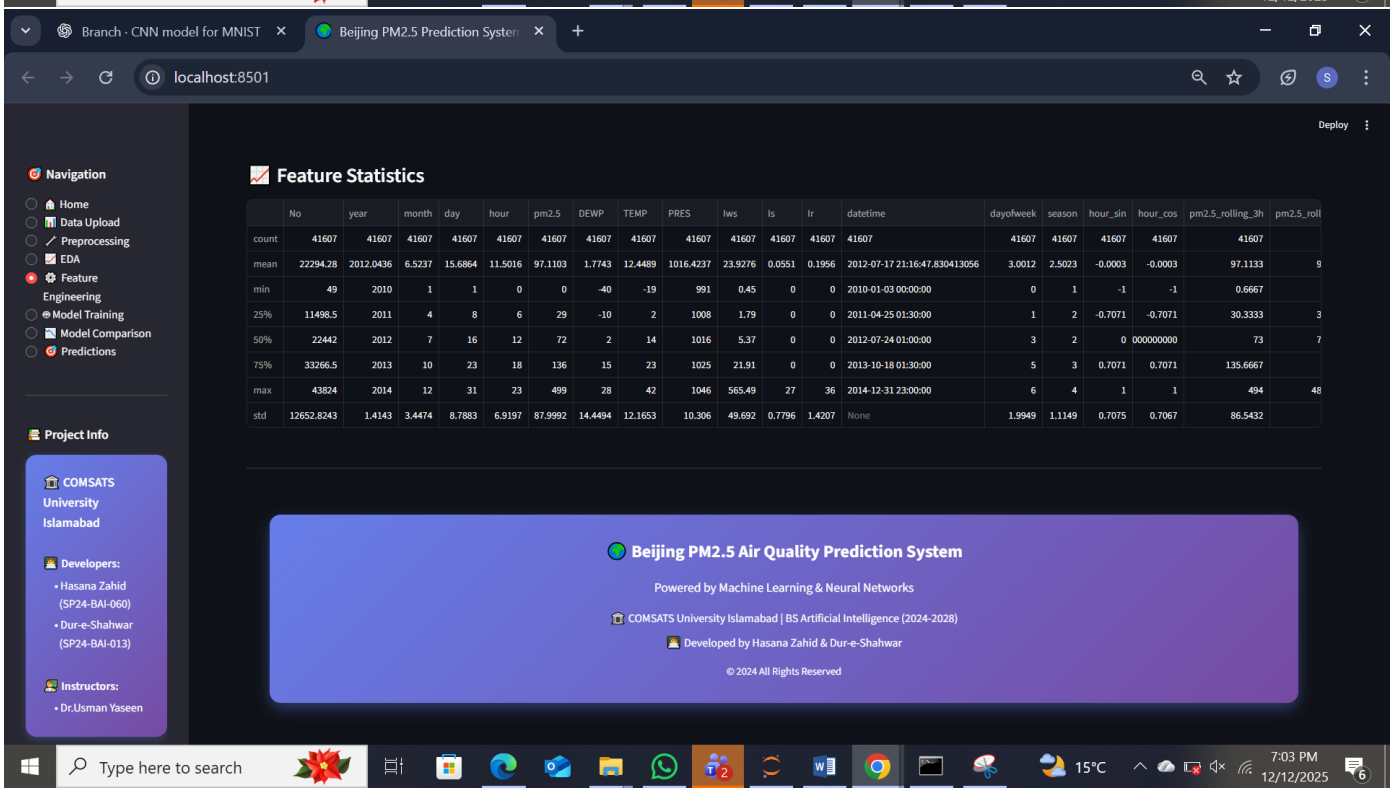
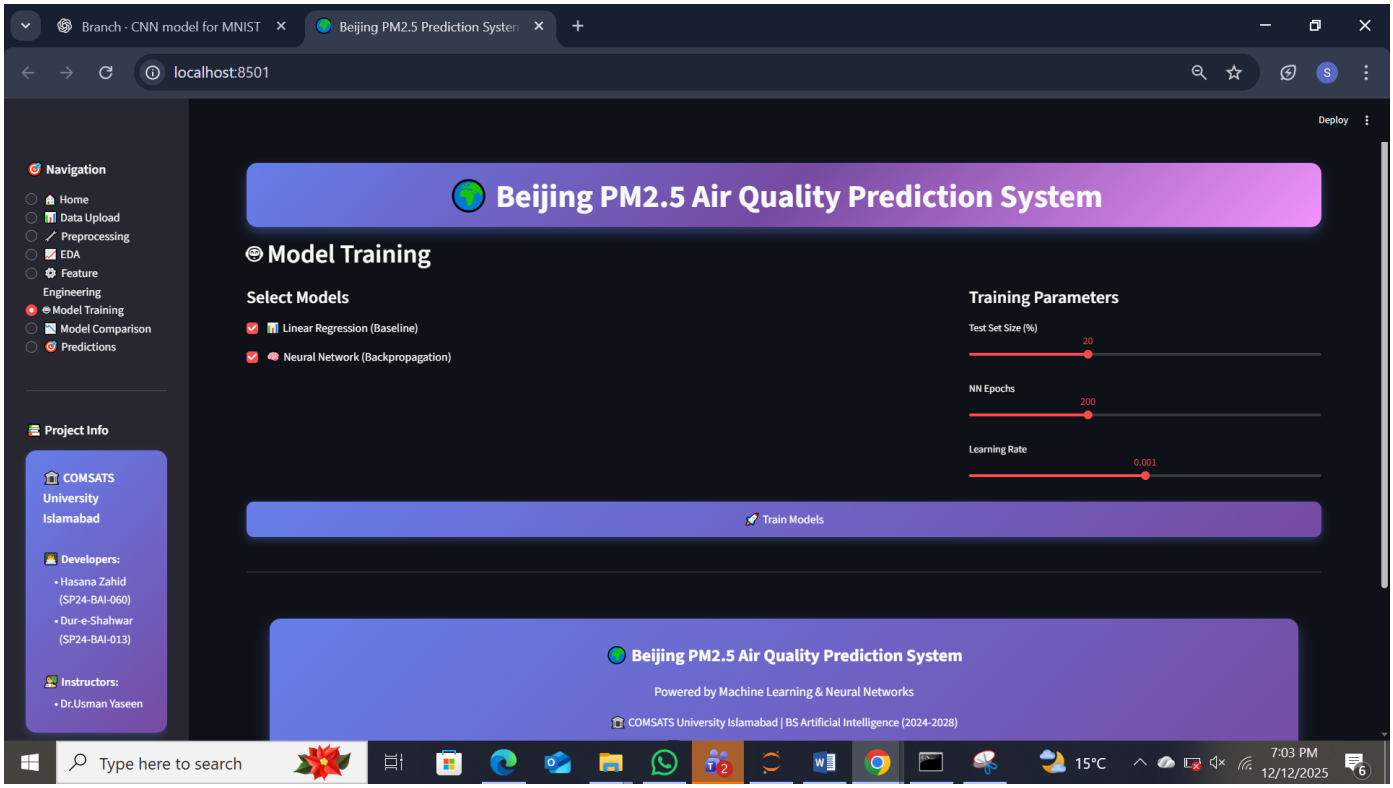
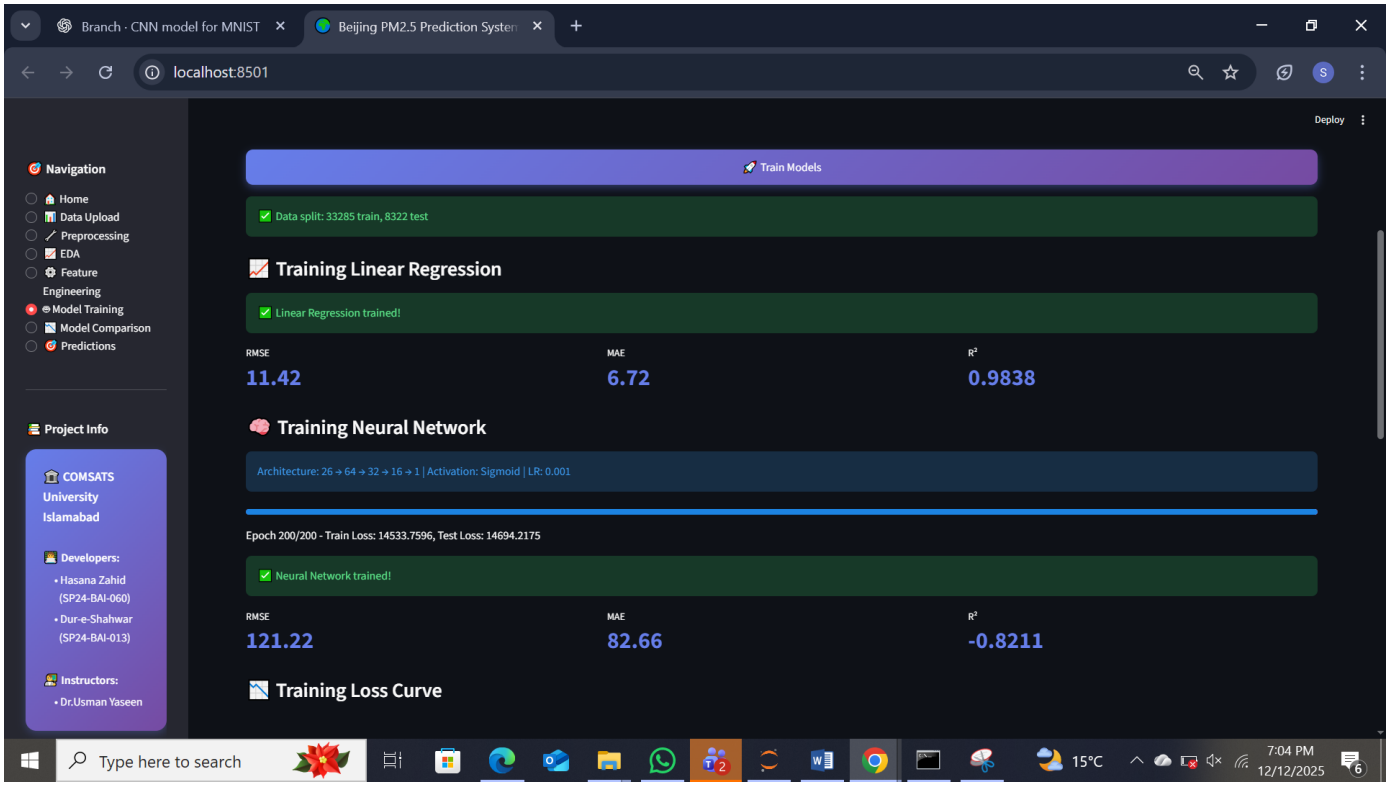
0	49	2010	1	3	0	90	-7	-6	1027	SE	58.56	4	0	2010-01-03 00:00:00	6	1	0	1	124	139.8333	150.6667
1	50	2010	1	3	1	63	-8	-6	1026	SE	61.69	5	0	2010-01-03 01:00:00	6	1	0.2588	0.9659	93	125.5	142.25
2	51	2010	1	3	2	65	-8	-7	1026	SE	65.71	6	0	2010-01-03 02:00:00	6	1	0.5	0.866	72.6667	110.6667	134.5
3	52	2010	1	3	3	55	-8	-7	1025	SE	68.84	7	0	2010-01-03 03:00:00	6	1	0.7071	0.7071	61	92.5	126.25
4	53	2010	1	3	4	65	-8	-7	1024	SE	72.86	8	0	2010-01-03 04:00:00	6	1	0.866	0.5	61.6667	77.3333	118.4167
5	54	2010	1	3	5	83	-9	-8	1024	SE	76.88	9	0	2010-01-03 05:00:00	6	1	0.9659	0.2588	67.6667	70.1667	111.6667
6	55	2010	1	3	6	91	-10	-8	1024	SE	80.9	10	0	2010-01-03 06:00:00	6	1	1	000000000	79.6667	70.3333	105.0833
7	56	2010	1	3	7	86	-10	-9	1024	SE	84.92	11	0	2010-01-03 07:00:00	6	1	0.9659	-0.2588	86.6667	74.1667	99.8333
8	57	2010	1	3	8	82	-10	-9	1024	SE	89.84	12	0	2010-01-03 08:00:00	6	1	0.866	-0.5	86.3333	77	93.8333
9	58	2010	1	3	9	86	-11	-9	1023	SE	93.86	13	0	2010-01-03 09:00:00	6	1	0.7071	-0.7071	84.6667	82.1667	87.3333

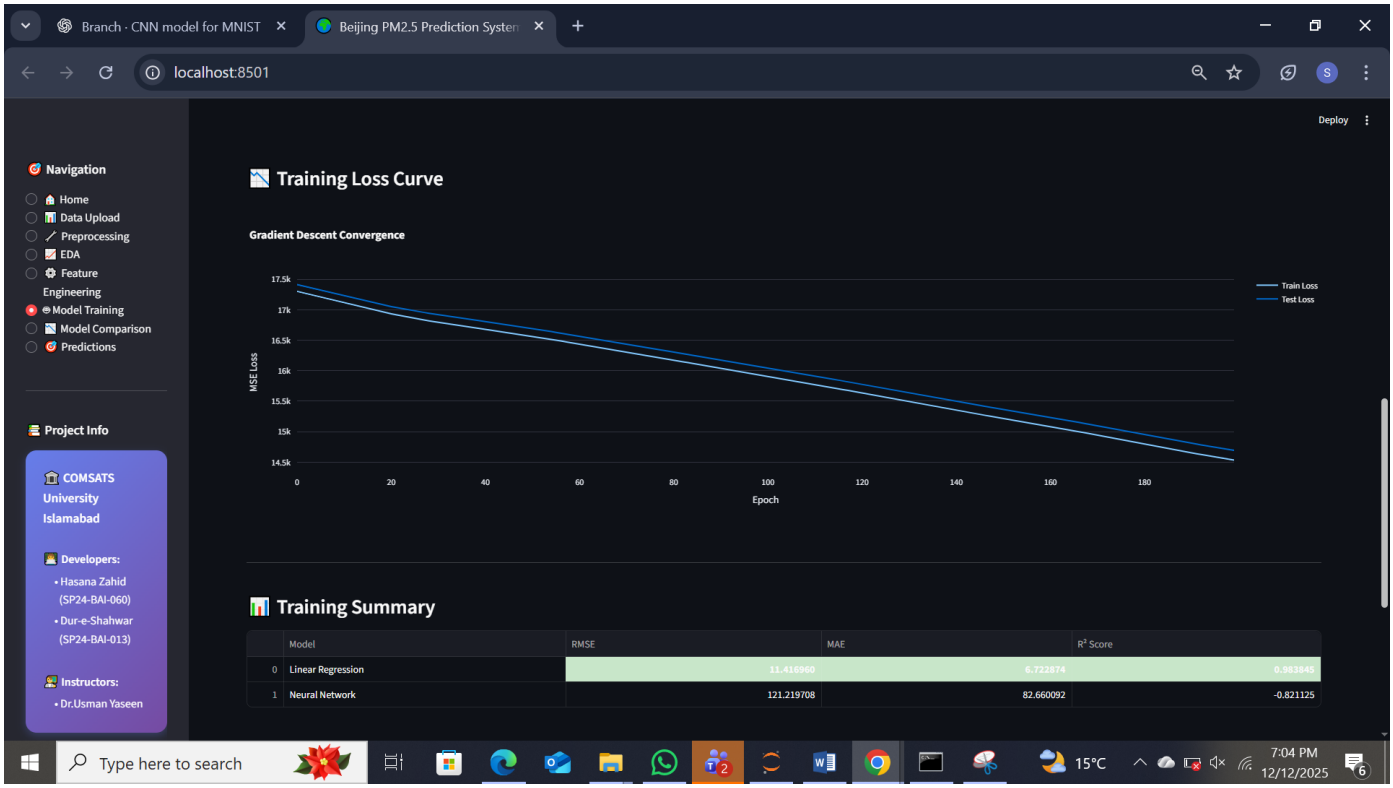


	No	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	Iws	Is	Ir	datetime	dayofweek	season	hour_sin	hour_cos	pm2.5_rolling_3h	pm2.5_roll
count	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	41607	
mean	22294.28	2012.0436	6.5237	15.6864	11.5016	97.1103	1.7743	12.4489	1016.4237	23.9276	0.0551	0.1956	2012-07-17 21:16:47.830413056	3.0012	2.5023	-0.0003	-0.0003	97.1133	9
min	49	2010	1	1	0	0	-40	-19	991	0.45	0	0	2010-01-03 00:00:00	0	1	-1	-1	0.6667	
25%	11498.5	2011	4	8	6	29	-10	2	1008	1.79	0	0	2011-04-25 01:30:00	1	2	-0.7071	-0.7071	30.3333	3
50%	22442	2012	7	16	12	72	2	14	1016	5.37	0	0	2012-07-24 01:00:00	3	2	0	000000000	73	7
75%	33266.5	2013	10	23	18	136	15	23	1025	21.91	0	0	2013-10-18 01:30:00	5	3	0.7071	0.7071	135.6667	
max	43824	2014	12	31	23	499	28	42	1046	565.49	27	36	2014-12-31 23:00:00	6	4	1	1	494	48
std	12652.8243	1.4143	3.4474	8.7883	6.9197	87.9992	14.4494	12.1653	10.306	49.692	0.7796	1.4207	None	1.9949	1.1149	0.7075	0.7067	86.5432	

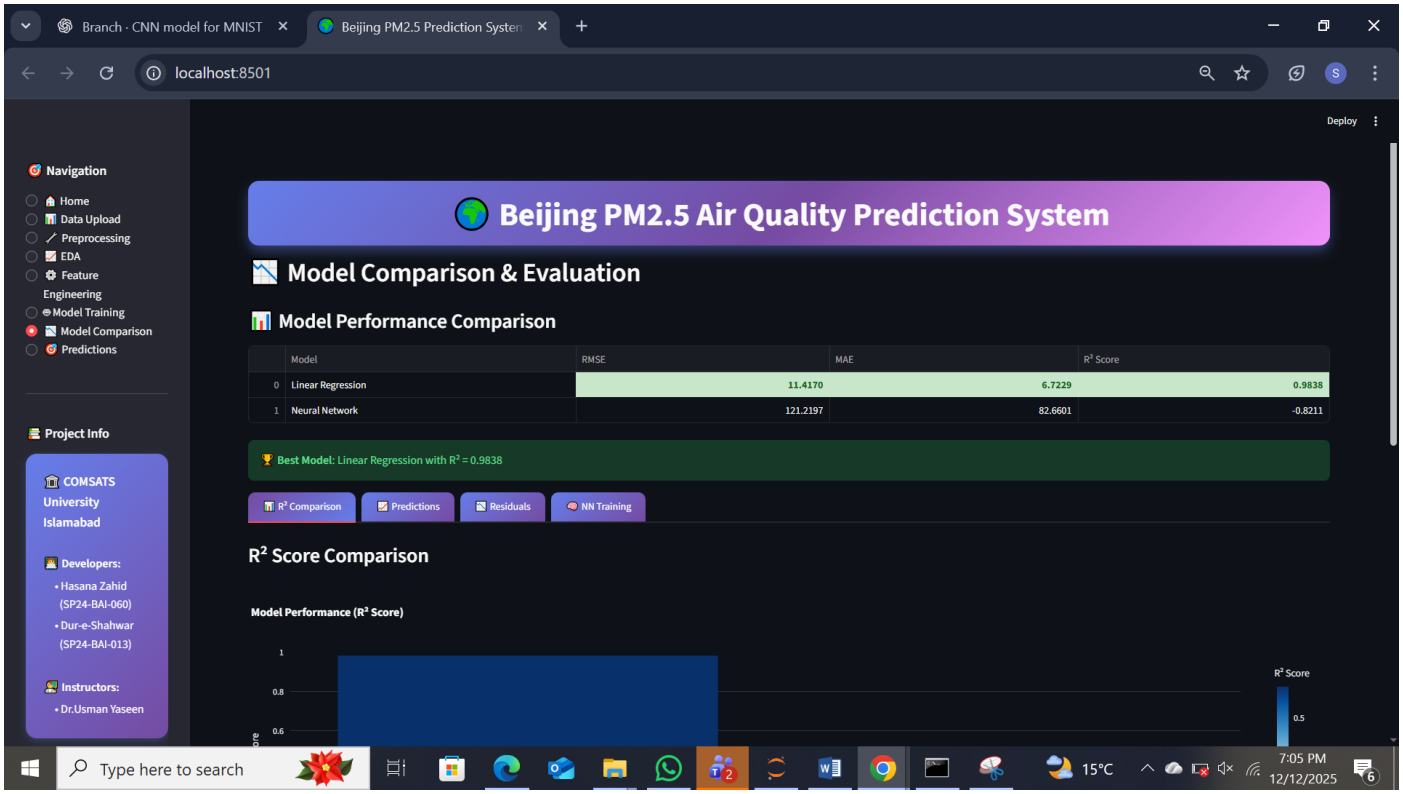
7. Model Training

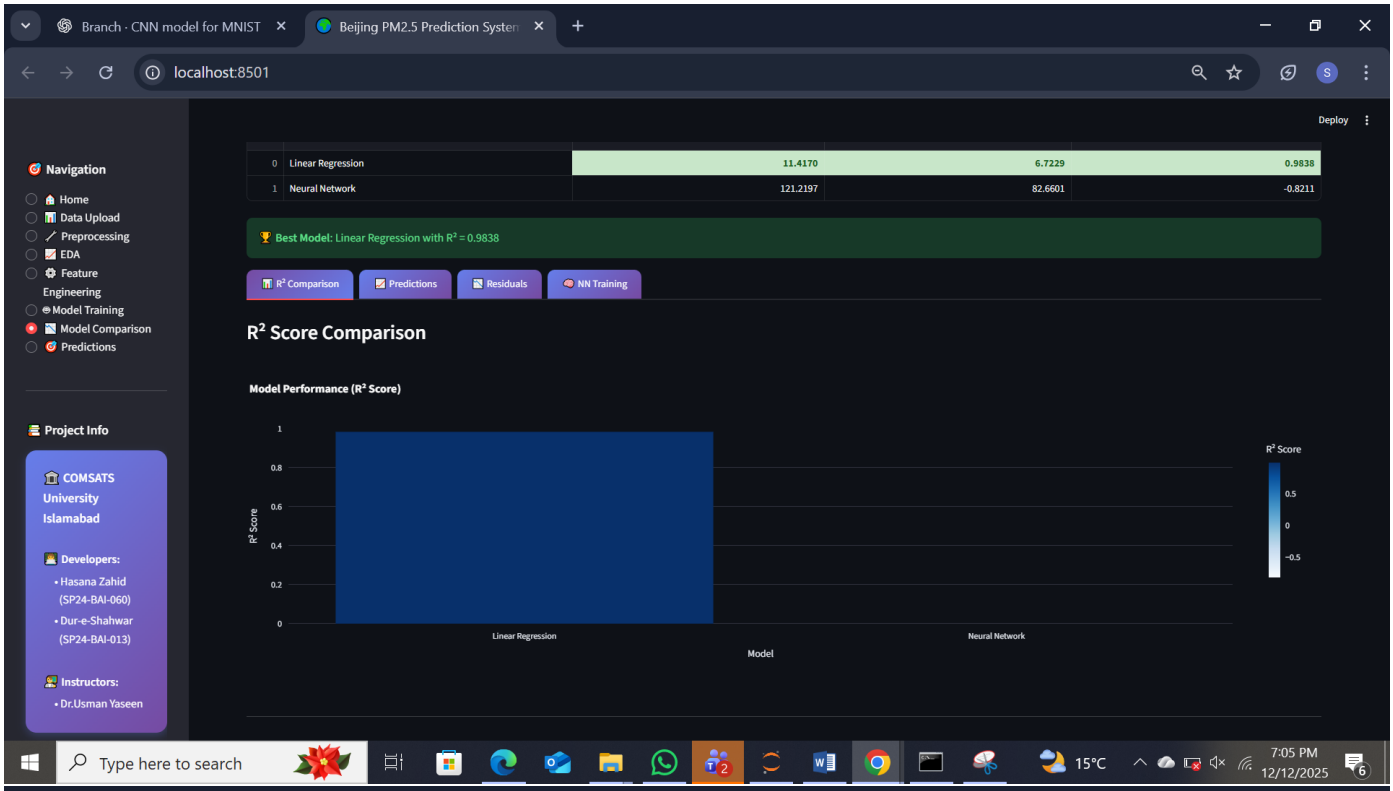






8. Model Comparison

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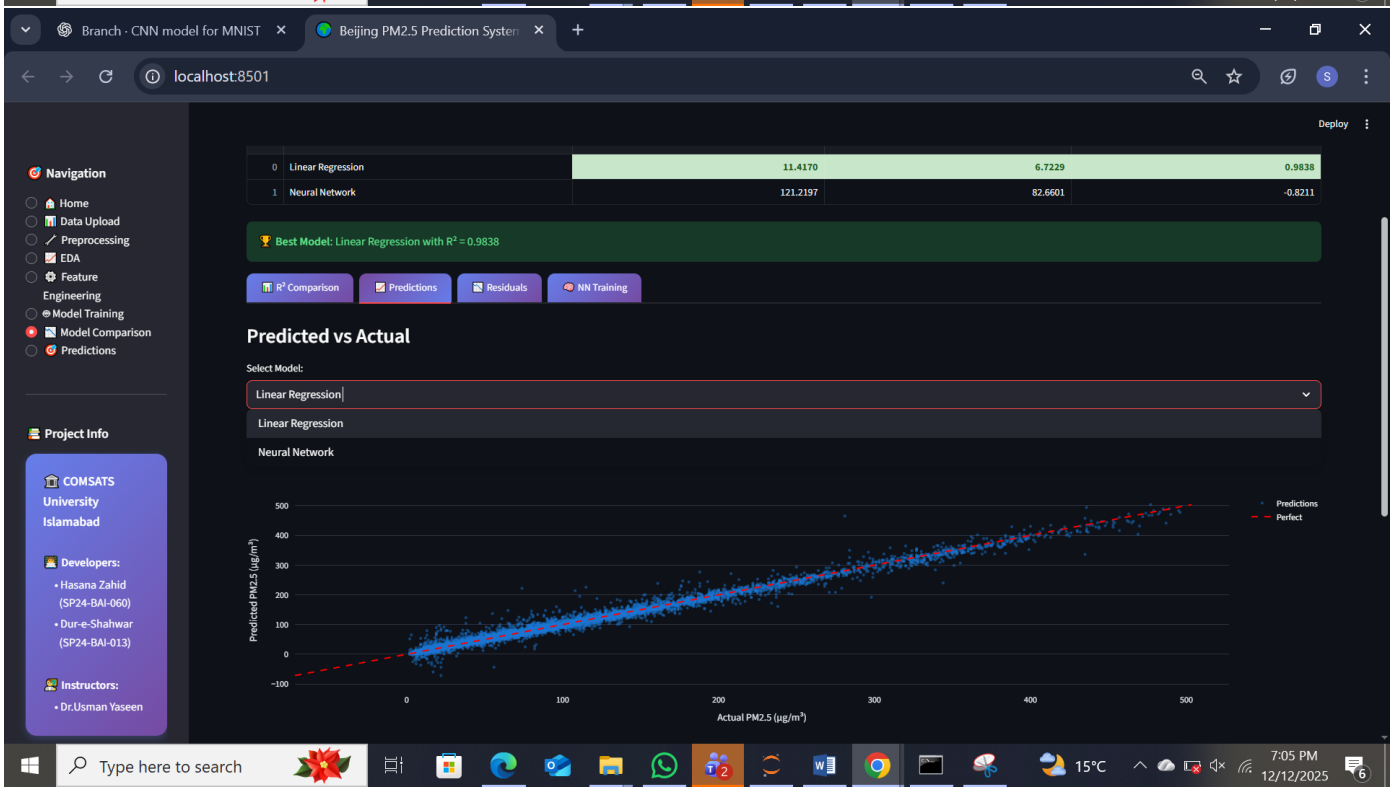
0 Linear Regression 11.4170 6.7229 0.9838
1 Neural Network 121.2197 82.6601 -0.8211
Best Model: Linear Regression with R² = 0.9838
R² Comparison
Predictions
Residuals
NN Training
R² Score Comparison
Model Performance (R² Score)
R² Score
Linear Regression
Neural Network
Model
Type here to search
15°C
7:05 PM
12/12/2025


Branch · CNN model for MNIST
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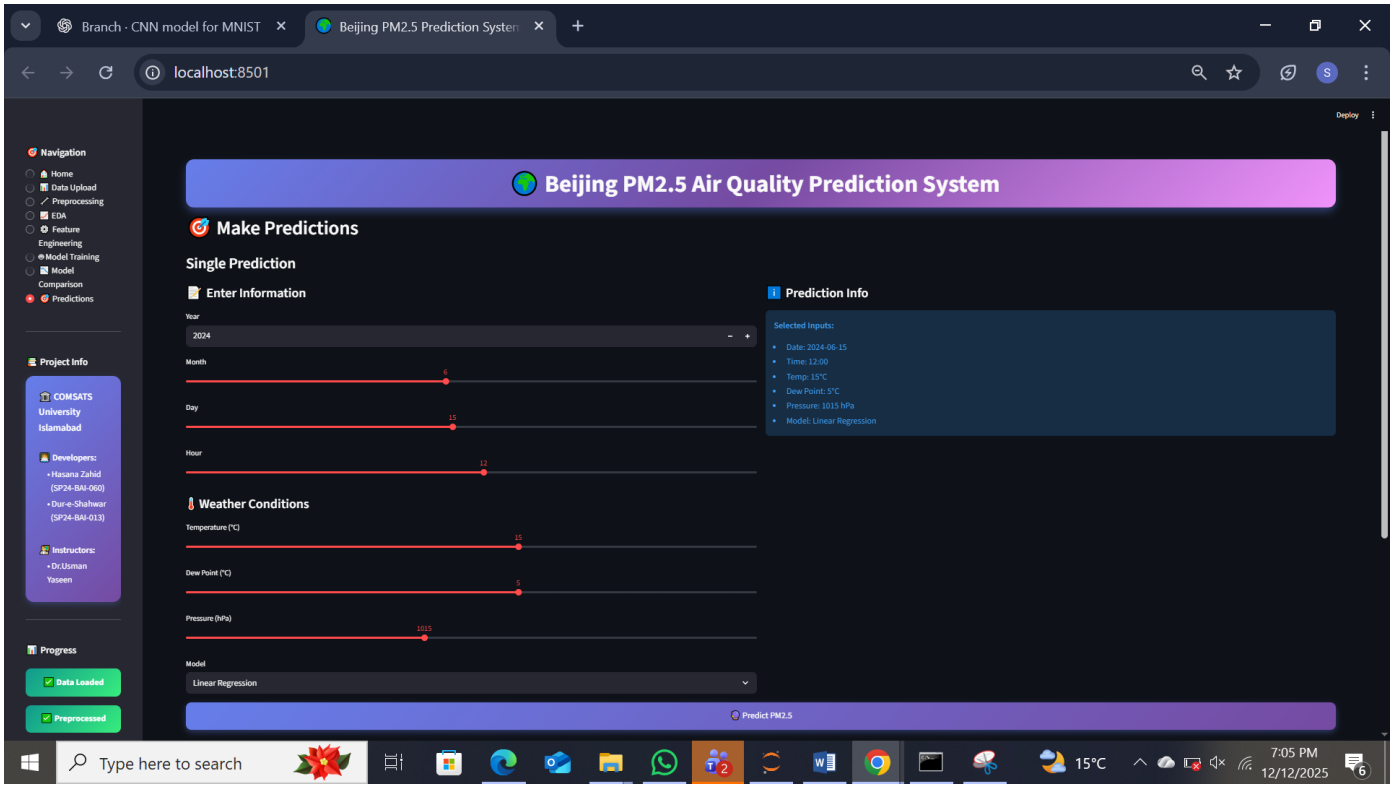
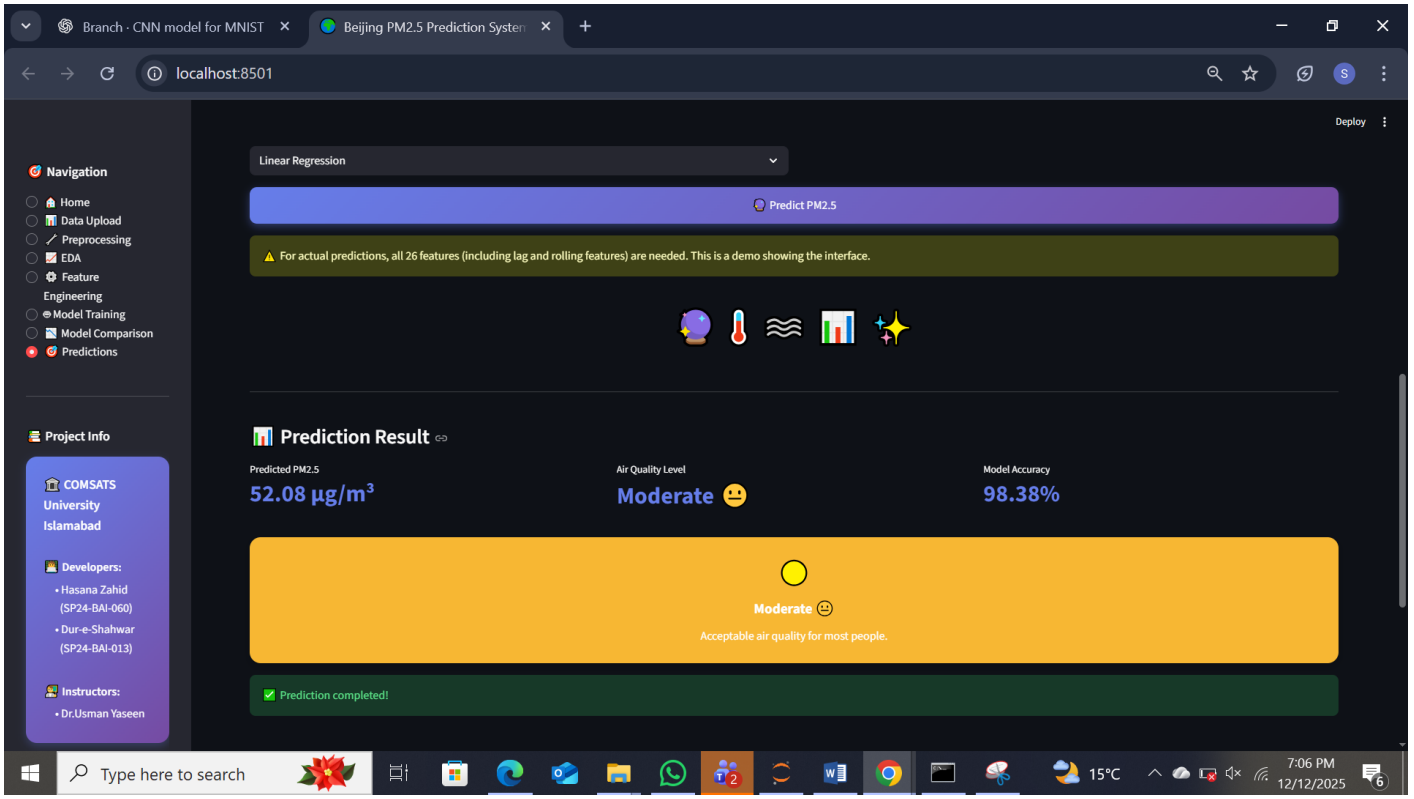
R² Comparison
Predictions
Residuals
NN Training
Predicted vs Actual
Select Model:
Linear Regression
Linear Regression
Neural Network
Predictions
Perfect
Predicted PM2.5 (µg/m³)
Actual PM2.5 (µg/m³)
Type here to search
15°C
7:05 PM
12/12/2025

9. Predictions





12. System Strengths and Limitations

Strengths

• Strong handling of missing and extreme values
• Accurate ANN predictions
• Captures seasonal and temporal trends
• Interactive visualization through Streamlit GUI

Limitations

• ANN training requires more computational power
• Limited to hourly predictions (no long-term forecasting)
• Weather extremes reduce accuracy
• Does not include external events (fires, dust storms, traffic surges)

13. Conclusion

This project successfully developed a PM2.5 AQI prediction system using machine learning. The pipeline preprocessing, feature engineering, modeling, evaluation, and visualization produced reliable forecasts.

Results show:

• ANN outperforms Linear Regression
• Weather and seasonal variables strongly influence PM2.5
• The GUI supports real-time exploration and insights

The system proves that combining statistical and ML techniques leads to effective environmental forecasting.

14. References

1. UCI Machine Learning Repository: Beijing PM2.5 Dataset
2. Kaggle: Beijing PM2.5 Data
3. Géron, A. Hands-On Machine Learning with Scikit-Learn, Keras & TensorFlow
4. James et al. Introduction to Statistical Learning
5. McKinney, W. Python for Data Analysis