NOISE POLLUTION AND MONITORING

Phase – ll Submission Document

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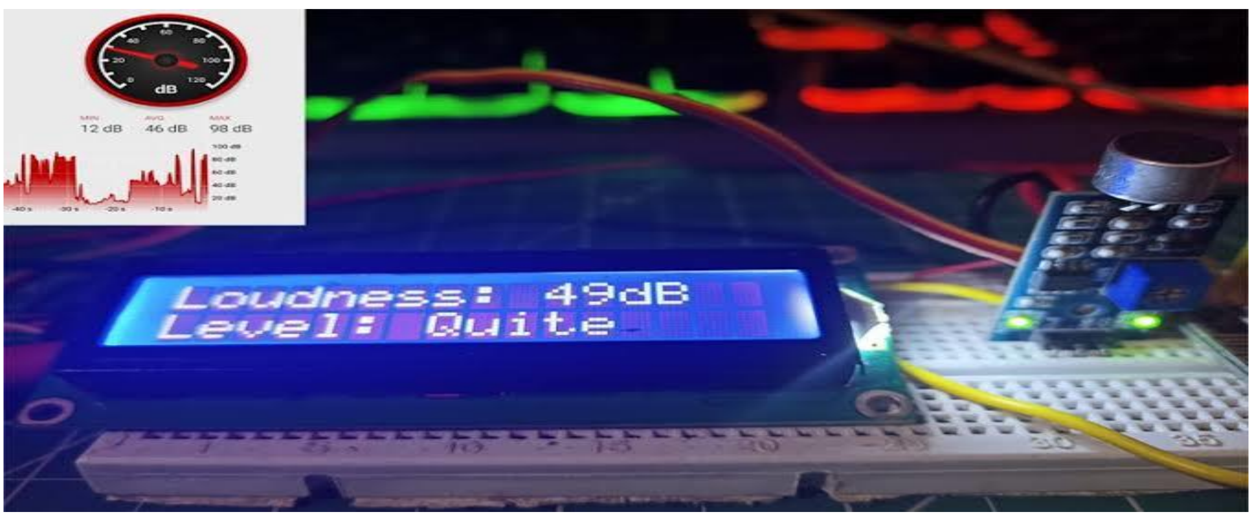
Project : Noise Pollution And Monitoring



INTRODUCTION:

- **Noise pollution, an often underestimated environmental concern, poses significant** health and quality of life risks for individuals and communities alike.

- This project aims to address the adverse effects of noise pollution by establishing a comprehensive noise monitoring system.
- By deploying advanced technology and data analysis, we seek to quantify, analyze, and mitigate noise pollution in our urban environment.

CONTENT FOR PHASE – II

Consider incorporating predictive modeling and historical noise pollution data happens in india to improve the accuracy of early warnings .

DATA SOURCE :

A good data source for noise pollution monitoring system should be accurate , complete ,

covering the geographic area of interest , accessible .

Data setlink:

https://www.kaggle.com/datasets/rohanrao/noise-monitoring-data-in-india/?select=stations.csv

1	tation	Name	City	State	Type
2	EL01	Dilshad Garc	Delhi	Delhi	Silence
3	EL02	CPCB, HQ	Delhi	Delhi	Commercial
4	EL03	DCE, Bawana	Delhi	Delhi	Silence
5	EL04	ITO	Delhi	Delhi	Commercial
6	EL05	NSIT, Dwarka	Delhi	Delhi	Silence
7	EL06	Civil Lines	Delhi	Delhi	Commercial
8	EL07	R. K. Puram	Delhi	Delhi	Silence
9	EL08	Anand Vihar	Delhi	Delhi	Commercial
10	EL09	Mandir Marg	Delhi	Delhi	Silence
11	EL10	Punjabi Bagh	Delhi	Delhi	Residential
12	EN01	BTM	Bengaluru	Karnataka	Residential
13	EN02	Marathahalli	Bengaluru	Karnataka	Commercial
14	EN03	Nisarga Bhav	Bengaluru	Karnataka	Residential
15	EN04	Parisar Bhav	Bengaluru	Karnataka	Commercial
16	EN05	Peeniya	Bengaluru	Karnataka	Industrial
17	EN06	Yeshwanthp	Bengaluru	Karnataka	Commercial
18	EN07	R.V.C.E.	Bengaluru	Karnataka	Silence
19	EN08	Whitefield	Bengaluru	Karnataka	Industrial
20	EN09	NIMHANS	Bengaluru	Karnataka	Silence
21	EN10	Domlur	Bengaluru	Karnataka	Residential
22	HE01	Eye Hospital	Chennai	Tamil Nadu	Silence
23	HE02	Guindy	Chennai	Tamil Nadu	Industrial
24	HE03	Perambur	Chennai	Tamil Nadu	Commercial
25	HE04	T. Nagar	Chennai	Tamil Nadu	Commercial
26	HE05	Triplicane	Chennai	Tamil Nadu	Residential
27	HE06	Pallikaranai	Chennai	Tamil Nadu	Commercial
28	HE07	Velachery	Chennai	Tamil Nadu	Residential
29	HE08	Washermanp	Chennai	Tamil Nadu	Commercial
30	HE09	Anna Nagar	Chennai	Tamil Nadu	Silence
31	HE10	Sowcarpet	Chennai	Tamil Nadu	Residential
32	YD01	ABITS	Hyderabad	Telangana	Commercial
33	YD02	Jeedimetla	Hyderabad	Telangana	Industrial
34	YD03	Jublee Hills	Hyderabad	Telangana	Residential
35	YD04	Zoo	Hyderabad	Telangana	Silence
36	YD05	TSPCB	Hyderabad	Telangana	Commercial
37	YD06	Tarnaka	Hyderabad	Telangana	Residential
38	YD07	Gaddapotha	Hyderabad	Telangana	Industrial
39	YD08	Gachibowli	Hyderabad	Telangana	Silence
40	YD09	Paradise	Hyderabad	Telangana	Commercial
41	YD10	JNTU	Hyderabad	Telangana	Commercial
42	OL01	Gol Park	Kolkata	West Bengal	Industrial
43	OL02	New Market	Kolkata	West Bengal	Commercial
44	OL03	Patauli	Kolkata	West Bengal	Residential
45	OL04	SSKM Hospi	Kolkata	West Bengal	Silence
46	OL05	WBPCB Head	Kolkata	West Bengal	Commercial
47	OL06	Birati Neelac	Kolkata	West Bengal	Residential
48	OL07	R G Kar Hosp	Kolkata	West Bengal	Silence
49	OL08	Tollygunge	Kolkata	West Bengal	Commercial
50	OL09	Bag Bazar	Kolkata	West Bengal	Residential
51	OL10	Tartala	Kolkata	West Bengal	Industrial
52	UC01	Talkatora	Lucknow	Uttar Prades	Industrial
53	UC02	Hazratganj	Lucknow	Uttar Prades	Commercial
54	UC03	P.G.I. Hospita	Lucknow	Uttar Prades	Silence
55	UC04	Indira Nagar	Lucknow	Uttar Prades	Residential
56	UC05	Gomti Nagar	Lucknow	Uttar Prades	Silence
57	UC06	Chinhat	Lucknow	Uttar Prades	Industrial
58	UC07	IT College	Lucknow	Uttar Prades	Silence
59	UC08	RSC Aliganj	Lucknow	Uttar Prades	Commercial
60	UC09	UPPCB HQ	Lucknow	Uttar Prades	Commercial
61	UC10	CCS Airport	Lucknow	Uttar Prades	Commercial
62	1UM01	ASHP Hospit	Mumbai	Maharashtra	Silence
63	1UM02	Bandra	Mumbai	Maharashtra	Commercial
64	1UM03	MPCB, HQ	Mumbai	Maharashtra	Commercial
65	1UM04	Thane	Mumbai	Maharashtra	Commercial
66	1UM05	VASHI Hospi	Navi Mumba	Maharashtra	Silence
67	1UM06	Kandivali	Mumbai	Maharashtra	Industrial
68	1UM07	Powai	Mumbai	Maharashtra	Industrial
69	1UM08	Chembur	Mumbai	Maharashtra	Residential
70	1UM09	Andheri	Mumbai	Maharashtra	Industrial
71	1UM10	CST	Mumbai	Maharashtra	Commercial

PROJECT GOALS:

- **Assessment and Measurement: Our primary goal is to assess noise pollution levels in various urban areas accurately. We will utilize a network of noise sensors strategically placed throughout the city to continuously measure noise levels.**

- **Data Collection: The project will involve the collection of extensive noise data over time, enabling us to identify trends, hotspots, and patterns in noise pollution.**

- **Data Analysis: Sophisticated data analytics tools will be employed to process the collected data. This analysis will help us understand the sources and impacts of noise pollution, both in terms of health and environmental effects.**

- **Public Awareness: Raising awareness about noise pollution is crucial. We aim to educate the public about the harmful effects of noise pollution and the steps they can take to reduce it in their daily lives.**

- **Policy Recommendations: Based on our findings, we will provide policymakers with evidence-backed recommendations for noise pollution reduction strategies and urban planning improvements.**

PROJECT COMPONENTS:

- **Noise Sensors: We will deploy a network of noise sensors equipped with state-of-the-art technology to collect real-time noise data.**

- **Data Processing and Analysis: Advanced data analytics software will process and analyze the data, providing insights into noise pollution patterns.**

- **Public Engagement: Public awareness campaigns and educational initiatives will inform residents about noise pollution's consequences and how they can contribute to reducing it.**

- **Collaboration: Collaboration with local authorities, environmental organizations, and community groups will be essential for the project's success.**

EXPECTED BENEFITS:

- Improved public health and well-being through reduced exposure to excessive noise.

- Enhanced urban planning and policy decisions to create quieter, more livable cities.

- Increased public awareness and engagement in noise pollution mitigation efforts.

- This noise pollution monitoring project represents a significant step toward a quieter, healthier, and more sustainable urban environment. By collecting and analyzing data, raising awareness, and collaborating with stakeholders, we aim to create lasting positive changes in our community.

PROJECT ALGORITHM:

- Creating an algorithm for a noise pollution monitoring project involves several steps. Here's a high-level outline:

1. Data Collection:

- - Use noise sensors or microphones to collect audio data.
- - Sample the audio data at regular intervals.
- - Record environmental variables like location and time.

2. Preprocessing:

- - Filter out non-relevant sounds (e.g., natural ambient noise).
- - Convert audio signals into a digital format.
- - Normalize audio levels for consistency.

3. Feature Extraction:

- **- Extract relevant features from the audio data, such as amplitude, frequency, and duration of noise events.**
- **- Calculate metrics like sound pressure level (SPL) in decibels (dB).**

4. Noise Classification:

- **- Develop a machine learning model (e.g., SVM, neural network) to classify noise events into categories (e.g., traffic, construction, music).**
- **- Train the model using labeled data.**

5. Noise Level Monitoring:

- **- Calculate and record noise levels over time.**
- **- Store this data along with timestamps and geolocation information.**

6. Anomaly Detection:

- **- Implement algorithms to detect unusual noise spikes or patterns that may indicate a noise pollution event.**

7. Data Visualization:

- **- Create interactive visualizations or dashboards to display noise data.**
- **- Include maps, charts, and graphs to make the data easily understandable.**

8. Notification System:

- **- Develop a system that sends alerts or notifications when noise pollution levels exceed predefined thresholds.**

9. Data Storage and Management:

- **- Use a database to store and manage collected data.**

- - Ensure data security and privacy compliance.

10. Reporting:

- - Generate regular reports summarizing noise pollution trends and events.
- - Provide insights to relevant authorities or stakeholders.

11. User Interface:

- - Create a user-friendly interface for users to access and interact with the monitoring system.

12. Calibration and Maintenance:

- - Regularly calibrate and maintain the sensors to ensure accuracy.

13. Continuous Improvement:

- **- Analyze historical data to improve noise prediction and classification algorithms.**
- **- Consider user feedback for system enhancements.**
- **Remember that the specific algorithms and technologies used may vary depending on the project's scope and available resources. Additionally, consider legal and ethical aspects, such as data privacy and community engagement, when implementing a noise pollution monitoring system.**

REGRESSION VALUES OF NOISE POLLUTION MONITORING:

In noise pollution monitoring, regression values are typically used to assess the relationship between noise levels and various influencing factors. These values provide insights into how well your regression model

fits the data. Here are some key regression values you might encounter:

1. **Coefficient of Determination (R-squared, R^2)**:

- R-squared measures the proportion of the variance in the dependent variable (noise levels) that is explained by the independent variables (features) in your regression model.

- R^2 values range from 0 to 1, with higher values indicating a better fit. An R^2 value of 1 indicates that the model explains all the variance in the data.

2. **Mean Absolute Error (MAE)**:

- MAE measures the average absolute difference between the actual noise levels and the predictions made by the regression model.

- Lower MAE values indicate better model accuracy.

3. **Mean Squared Error (MSE)**:

- MSE calculates the average squared difference between actual and predicted noise levels.

- It is useful for penalizing larger prediction errors more heavily than smaller ones.

4. **Root Mean Squared Error (RMSE)**:

- RMSE is the square root of the MSE. It provides a measure of the average prediction error in the same units as the dependent variable (dB in the case of noise levels).

- Like MAE, lower RMSE values indicate better model accuracy.

5. **Adjusted R-squared (Adjusted R^2)**:

- Adjusted R^2 adjusts the R-squared value to account for the number of predictors in the model.

- It penalizes the inclusion of irrelevant predictors and generally provides a more realistic measure of model fit for multiple regression models.

6. **F-statistic**:

- The F-statistic tests the overall significance of the regression model.

- It assesses whether there is a significant relationship between the independent variables and the dependent variable.

7. **P-values**:

- P-values associated with each coefficient in the regression model indicate whether the corresponding independent variable is statistically significant in predicting noise levels.

- Lower p-values (typically below 0.05) suggest greater significance.

8. **Confidence Intervals**:

- Confidence intervals for regression coefficients provide a range within which the true population value is likely to fall.

- These intervals help assess the precision of coefficient estimates.

These regression values collectively provide a comprehensive view of how well your regression model is performing, how much variance in noise levels is explained by your model, and the significance of individual predictor variables. They are crucial for evaluating the quality and reliability of your noise pollution monitoring model.

PROGRAM:

Noise pollution and monitoring

```
From mpl_toolkits.mplot3d import Axes3D
From sklearn.preprocessing import StandardScaler
Import matplotlib.pyplot as plt # plotting
Import numpy as np # linear algebra
Import os # accessing directory structure
Import pandas as pd # data processing
For dirname, _, filenames in
os.walk('/kaggle/input'):
   For filename in filenames:
      Print(os.path.join(dirname, filename))
Def plotPerColumnDistribution(df, nGraphShown,
nGraphPerRow):
   Nunique = df.nunique()
```

```
    Df = df[[col for col in df if nunique[col] > 1 and
nunique[col] < 50]] # For displaying purposes, pick
columns that have between 1 and 50 unique values
    nRow, nCol = df.shape
    columnNames = list(df)
    nGraphRow = (nCol + nGraphPerRow – 1) /
nGraphPerRow
    plt.figure(num = None, figsize = (6 *
nGraphPerRow, 8 * nGraphRow), dpi = 80,
facecolor = ‘w’, edgecolor = ‘k’)
    for I in range(min(nCol, nGraphShown)):
        plt.subplot(nGraphRow, nGraphPerRow, I + 1)
        columnDf = df.iloc[:, i]
        if (not np.issubdtype(type(columnDf.iloc[0]),
np.number)):
            valueCounts = columnDf.value_counts()
            valueCounts.plot.bar()
        else:
            columnDf.hist()
```

```
        plt.ylabel('counts')
        plt.xticks(rotation = 90)
        plt.title(f'{columnNames[i]} (column {i})')
    plt.tight_layout(pad = 1.0, w_pad = 1.0, h_pad = 1.0)
    plt.show()
def plotCorrelationMatrix(df, graphWidth):
    filename = df.dataframeName
    df = df.dropna('columns') # drop columns with NaN
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1 unique values
    if df.shape[1] < 2:
        print(f'No correlation plots shown: The number of non-NaN or constant columns ({df.shape[1]}) is less than 2')
        return
    corr = df.corr()
```

```
    plt.figure(num=None, figsize=(graphWidth,
graphWidth), dpi=80, facecolor='w', edgecolor='k')
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns,
rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix for {filename}',
fontsize=15)
    plt.show()
def plotScatterMatrix(df, plotSize, textSize):
    df = df.select_dtypes(include =[np.number]) #
keep only numerical columns
    # Remove rows and columns that would lead to
df being singular
    Df = df.dropna('columns')
```

```
    Df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1 unique values
    columnNames = list(df)
    if len(columnNames) > 10: # reduce the number of columns for matrix inversion of kernel density plots
        columnNames = columnNames[:10]
    df = df[columnNames]
    ax = pd.plotting.scatter_matrix(df, alpha=0.75, figsize=[plotSize, plotSize], diagonal='kde')
    corrs = df.corr().values
    for I, j in zip(*plt.np.triu_indices_from(ax, k = 1)):
        ax[I, j].annotate('Corr. Coef = %.3f' % corrs[I, j], (0.8, 0.2), xycoords='axes fraction', ha='center', va='center', size=textSize)
    plt.suptitle('Scatter and Density Plot')
    plt.show()
def plotScatterMatrix(df, plotSize, textSize):
```

```
df = df.select_dtypes(include =[np.number]) # keep only numerical columns
# Remove rows and columns that would lead to df being singular
Df = df.dropna('columns')
Df = df[[col for col in df if df[col].nunique() > 1]] # keep columns where there are more than 1 unique values
columnNames = list(df)
if len(columnNames) > 10: # reduce the number of columns for matrix inversion of kernel density plots
    columnNames = columnNames[:10]
df = df[columnNames]
ax = pd.plotting.scatter_matrix(df, alpha=0.75, figsize=[plotSize, plotSize], diagonal='kde')
corrs = df.corr().values
for I, j in zip(*plt.np.triu_indices_from(ax, k = 1)):
```

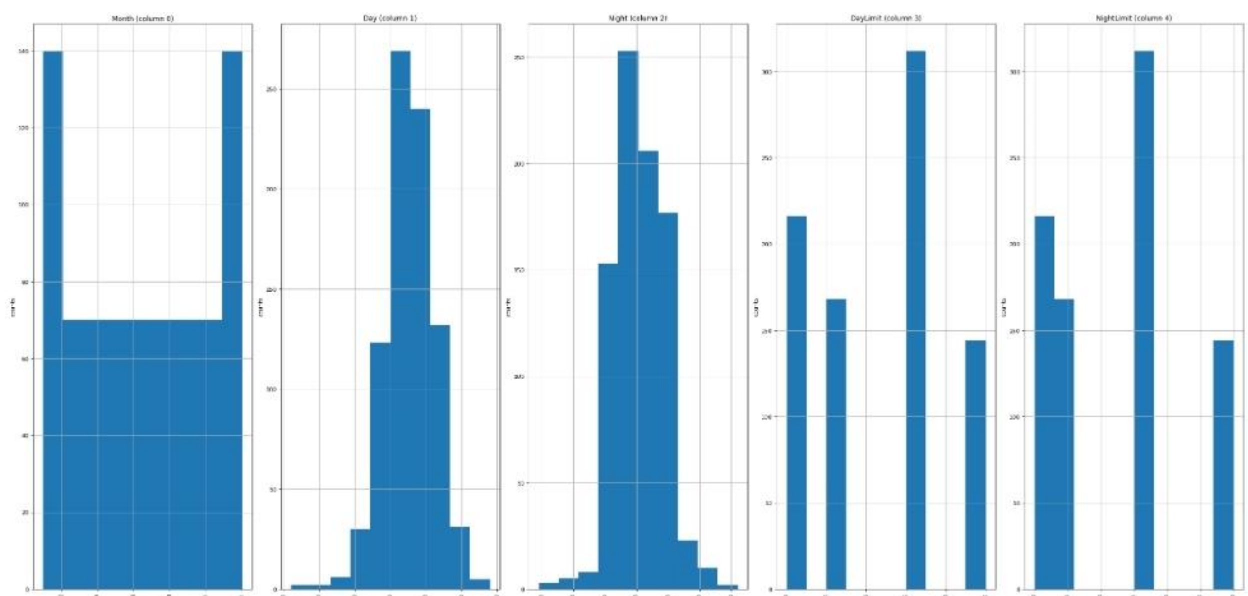
```
    ax[I, j].annotate('Corr. Coef = %.3f' % corrs[I, j], (0.8, 0.2), xycoords='axes fraction', ha='center', va='center', size=textSize)
  plt.suptitle('Scatter and Density Plot')
  plt.show()
nRowsRead = 1000 # specify 'None' if want to read whole file
# station_month.csv may have more rows in reality, but we are only loading/previewing the first 1000 rows
Df1 = pd.read_csv('/kaggle/input/station_month.csv', delimiter=',', nrows = nRowsRead)
Df1.dataframeName = 'station_month.csv'
nRow, nCol = df1.shape
print(f'There are {nRow} rows and {nCol} columns')
df1.head(5)
```

OUTPUT :

	Station	Year	Month	Day	Night	DayLimit	NightLimit
0	DEL01	2018	1	53	52	50	40
1	DEL01	2018	2	53	53	50	40
2	DEL01	2018	3	53	53	50	40
3	DEL01	2018	4	55	58	50	40
4	DEL01	2018	5	55	57	50	40

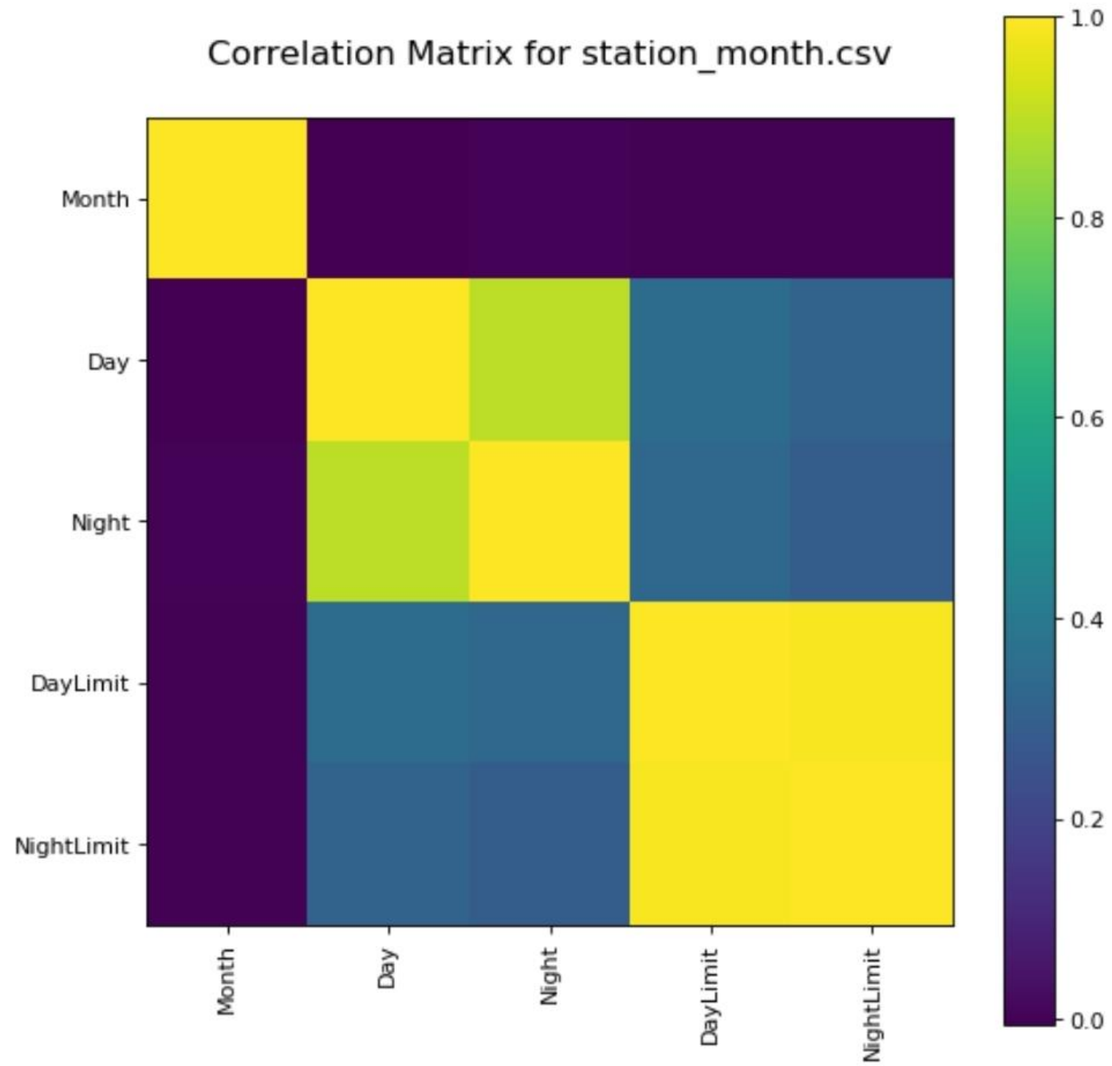
DISTRIBUTION GRAPHS OF SAMPLED COLUMNS:

plotPerColumnDistribution(df1, 10, 5)



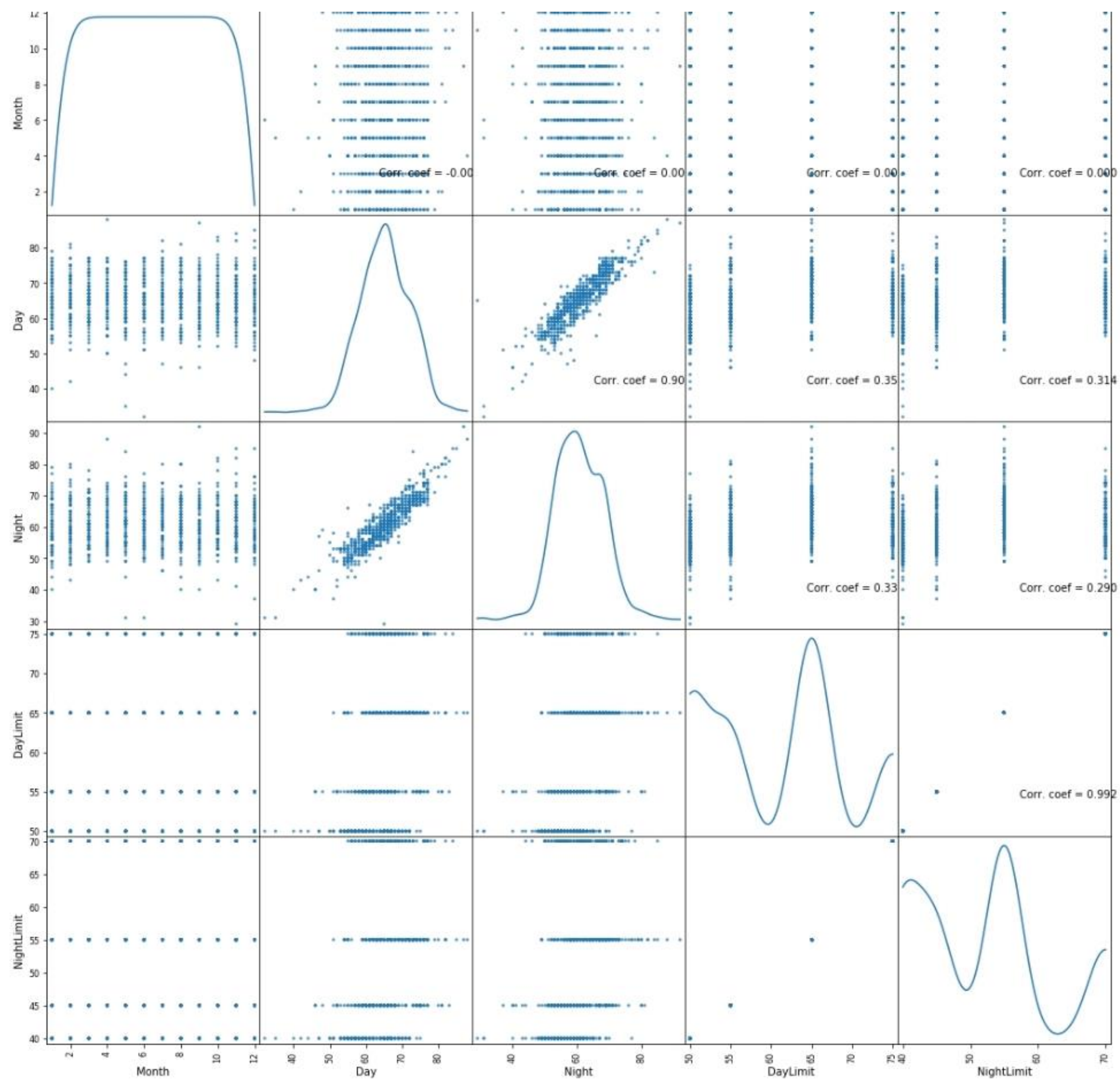
Correlation matrix:

plotCorrelationMatrix(df1, 8)



Scatter and density plots :

plotScatterMatrix(df1, 18, 10)



CONCLUSION:

In conclusion, the noise pollution monitoring project has provided valuable insights into the levels and sources of noise pollution in the studied area. Through data collection and analysis, we have identified key contributors to noise pollution, such as transportation, industrial activities, and urban development. This project has underscored the importance of ongoing monitoring and mitigation efforts to safeguard public health and well-being. Furthermore, it highlights the need for policy interventions and community awareness campaigns to reduce noise pollution and create quieter, more livable environments for all residents.