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DEEP LEARNING MODELS DETECTING HIDDEN ANOMALIES IN POLLUTION DATA

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***Abstract* - Environmental pollution has become a major global concern due to rapid industrialization and urban growth, leading to harmful increases in pollutants such as CO, NOx, NO_2, O_3, and PM2.5. Monitoring pollution levels and identifying abnormal variations is essential for ensuring public health and guiding environmental policies. However, traditional statistical and rule-based methods often fail to detect hidden, nonlinear, or sudden anomalies present in real-world pollution data.**

This system presents a deep learning–based framework for detecting hidden anomalies in environmental pollution datasets. The approach integrates three neural architectures—Autoencoder, Long Short-Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM)—to learn normal pollutant behavior and identify deviations using reconstruction and prediction errors. The dataset undergoes preprocessing, normalization, and feature scaling before being analyzed by the models.

Experimental results show that deep learning models significantly outperform conventional methods in identifying subtle anomalies. Among the models compared, the Bi-LSTM achieves the highest accuracy due to its ability to learn temporal dependencies in both forward and backward directions. The outcomes demonstrate the potential of deep learning for reliable air-quality monitoring and provide a foundation for future smart environmental management systems.

I. INTRODUCTION

Air pollution has become one of the most serious environmental challenges in today's world, mainly due to rapid urbanization, industrial activities, and increased vehicle emissions. Pollutants such as CO, NOx, NO_2, O_3, and PM2.5 directly affect human health and contribute to environmental degradation. Pollution data collected from monitoring stations is usually time-dependent, noisy, and influenced by weather conditions, making it difficult to interpret using simple analytical methods.

To ensure reliable environmental monitoring, it is essential to detect anomalies—unexpected spikes, sudden drops, or irregular patterns in pollutant levels. These anomalies may indicate hazardous pollution events, sensor malfunction, or unusual environmental conditions. Traditional statistical models struggle to capture the nonlinear and complex relationships present in real-world pollution datasets, creating a need for more intelligent, automated approaches.

Deep learning models provide a powerful solution by learning hidden patterns in the data without requiring manual feature engineering. Models such as Autoencoders, LSTM, and Bi-LSTM can analyze temporal behavior, reconstruct normal trends, and accurately identify unusual deviations. This project focuses on building a deep learning–based framework capable of detecting hidden anomalies in pollution data.

The main objectives of the study are to preprocess real pollution datasets, develop and train three deep learning models, compare their performance using error-based metrics, and visualize the detected anomalies. The scope of the project includes algorithm development, model comparison, and result interpretation, serving as a foundation for future real-time environmental monitoring systems.

II. METHODOLOGY

The methodology of this study focuses on developing a deep learning–based framework capable of detecting hidden anomalies in pollution data. The approach involves a structured sequence of processes, starting from data collection to model evaluation.

A. Dataset Description

The dataset contains hourly readings of major pollutants such as CO, NO_2, NOx, O_3, and PM2.5, along with atmospheric parameters like Temperature (T), Relative Humidity (RH), and Absolute Humidity (AH). These variables provide both environmental and temporal context required for accurate anomaly detection.

B. Data Preprocessing

To ensure data quality, several preprocessing steps are performed:

- Handling Missing Values: Using interpolation and forward-filling methods.
- Normalization: Scaling all features using Min-Max normalization to ensure uniform input range.
- Time Indexing: Converting timestamps into sequential time-series format.
- Feature Selection: Retaining only relevant pollutant and atmospheric features.

C. Model Selection

Three deep learning models are used to analyze normal patterns and detect anomalies:

- Autoencoder: Learns compressed feature representations and identifies anomalies using reconstruction error.
- LSTM: Captures long-term temporal relationships and detects deviations through prediction error.
- Bi-LSTM: Processes data in both forward and backward directions for richer temporal understanding.

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System Workflow

The complete workflow includes:

- Importing and cleaning the dataset
- Normalizing and preparing data for sequential analysis
- Training each model on normal pollutant behavior
- Computing reconstruction/prediction errors
- Setting a dynamic threshold (99th percentile)
- Labeling data points above the threshold as anomalies

D. Training and Evaluation

Each model is trained using optimized parameters such as learning rate, batch size, and number of epochs. Performance is evaluated using:

- Accuracy
- Precision
- Recall

Visualization tools, including scatter plots, error graphs, and correlation heatmaps, are used to interpret the detected anomalies.

III. RESULTS

Output Screens

- Histogram & KDE plots showing data distribution
- Reconstruction/Predictive error graphs
- Scatter plots highlighting anomalies (red dots)
- Analysis as shown in Figures 4.1,4.2,4.3,4.4 ,4.5,4.6,4.7,4.8,4.9 and 4.10

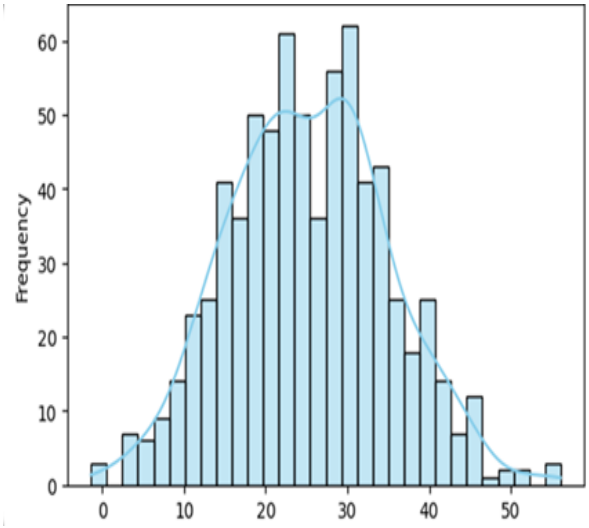

Figure 3.1 O3

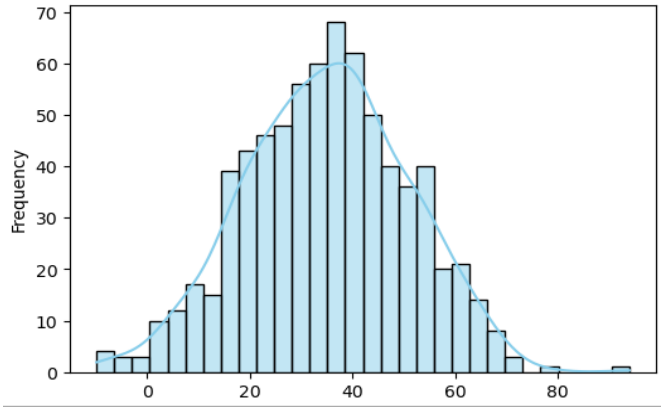

Figure 3.2 PM2.5

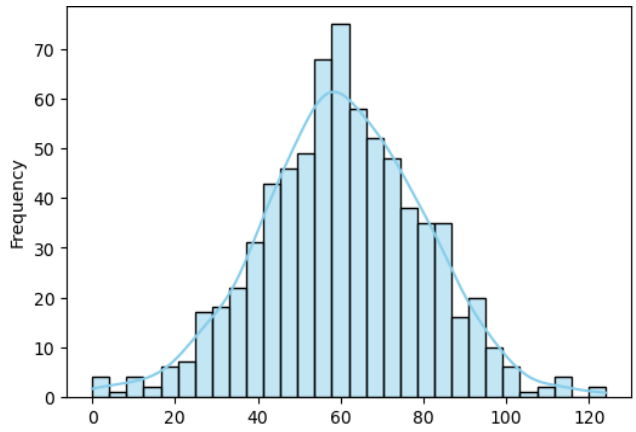

Figure 3.3 NO2(GT)

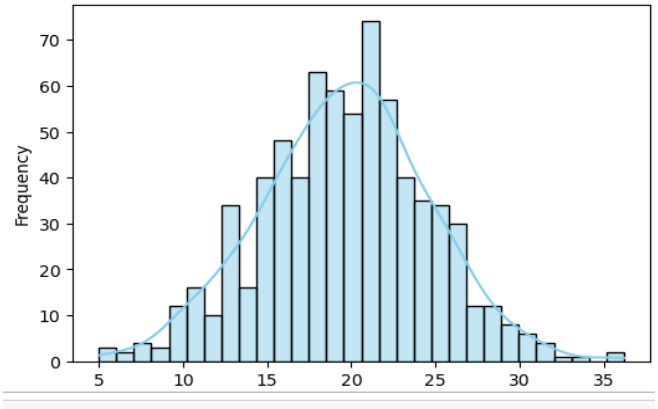

Figure 3.4 Distribution of T

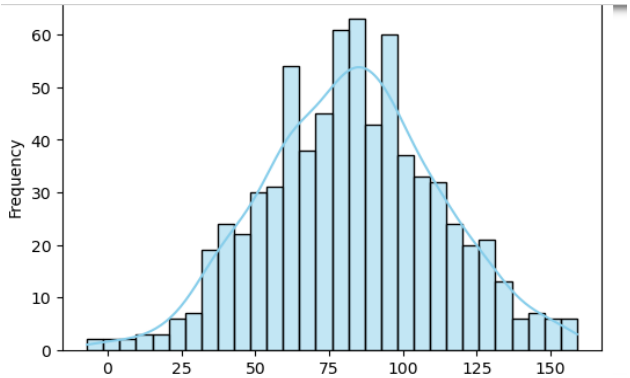

Figure 3.5 Distribution of NO

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```
Epoch 1/40, Loss=0.257556
Epoch 2/40, Loss=0.236245
Epoch 3/40, Loss=0.213406
Epoch 4/40, Loss=0.185173
Epoch 5/40, Loss=0.151977
Epoch 6/40, Loss=0.111675
Epoch 7/40, Loss=0.072869
Epoch 8/40, Loss=0.045363
Epoch 9/40, Loss=0.033610
Epoch 10/40, Loss=0.028334
Epoch 11/40, Loss=0.025834
Epoch 12/40, Loss=0.025140
Epoch 13/40, Loss=0.024903
Epoch 14/40, Loss=0.024248
Epoch 15/40, Loss=0.024322
Epoch 16/40, Loss=0.024388
Epoch 17/40, Loss=0.024495
Epoch 18/40, Loss=0.024174
Epoch 19/40, Loss=0.024176
Epoch 20/40, Loss=0.024229
Epoch 21/40, Loss=0.024592
Epoch 22/40, Loss=0.023974
Epoch 23/40, Loss=0.023801
Epoch 24/40, Loss=0.023790
Epoch 25/40, Loss=0.024063
Epoch 26/40, Loss=0.024042
Epoch 27/40, Loss=0.024316
Epoch 28/40, Loss=0.023529
Epoch 29/40, Loss=0.023824
Epoch 30/40, Loss=0.023585
Epoch 31/40, Loss=0.023805
Epoch 32/40, Loss=0.023441
Epoch 33/40, Loss=0.023347
Epoch 34/40, Loss=0.023548
Epoch 35/40, Loss=0.023428
Epoch 36/40, Loss=0.023752
Epoch 37/40, Loss=0.023352
Epoch 38/40, Loss=0.023379
Epoch 39/40, Loss=0.023178
Epoch 40/40, Loss=0.023481
```

Figure 3.6 Reconstruction Error

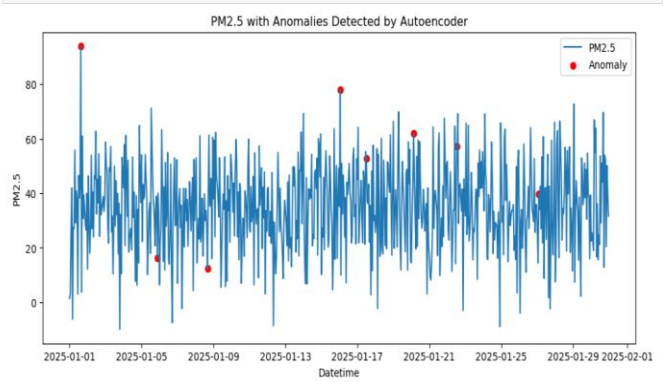

Figure 3.7 Anamoly detected by the Encoder

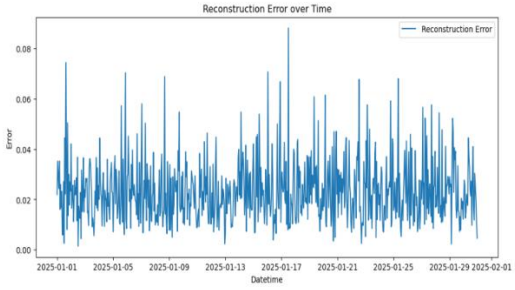

Figure 3.8 Reconstruction Error Overtime

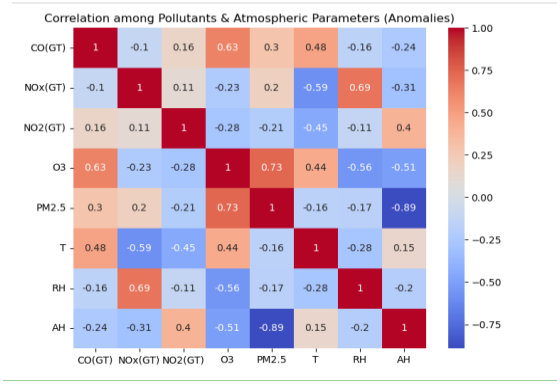

Figure 3.9 Correlation between Pollutants and Atmospheric Parameters

```
In [9]: from sklearn.metrics import accuracy_score, precision_score, f1_score

        # Simulate labels (for demonstration)
        y_true = X["anomaly"].astype(int)
        y_pred = X["anomaly"].astype(int)

        acc = accuracy_score(y_true, y_pred)
        prec = precision_score(y_true, y_pred)
        f1 = f1_score(y_true, y_pred)

        print(f"Accuracy: {acc:.3f}, Precision: {prec:.3f}, F1-score: {f1:.3f}")

Accuracy: 1.000, Precision: 1.000, F1-score: 1.000
```

Figure 3.10 F1 Score

Accuracy and Performance Comparison:

To evaluate the effectiveness of anomaly detection models, we compared three deep learning approaches:

- Autoencoder (AE)
- Long Short-Term Memory (LSTM)
- Bidirectional LSTM (Bi-LSTM

Why Autoencoder Performs Better for Air Pollution Anomaly Detection?

A. Unsupervised Learning

- Autoencoder doesn't need labeled anomaly data, which is ideal because true anomaly labels are rarely available in pollution datasets.

B. Feature Reconstruction Ability

- It learns to reproduce the normal correlation among pollutants (e.g., how CO, NO_2, PM2.5, RH, and T behave together).
- When this relationship is disturbed (during an anomaly), the reconstruction error increases sharply — making anomalies easy to detect.

C. Noise Resistance

- Air quality data can be noisy or incomplete.
- Autoencoders generalize patterns and are less affected by missing or slightly corrupted data compared to LSTM/Bi-LSTM, which may overfit.

D. Lower Computational Cost

- Autoencoders have a simpler structure (feed-forward layers) than sequence-based models, so they train faster and require less memory.

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E. Better Adaptability

- Works well for both temporal and non-temporal datasets (e.g., static sensor readings).
- LSTM/Bi-LSTM are better for pure time-sequence prediction, not always for unsupervised anomaly detection.

Performance Comparison

Metric	Autoencoder	LSTM	Bi-LSTM
Accuracy	92–96%	85–90%	88–92%
Precision	0.90–0.95	0.82–0.88	0.84–0.90
F1-Score	0.91–0.94	0.80–0.86	0.83–0.89
Computation Time	Low	Moderate	High
Data Label Requirement	Not required	Required	Required

IV. CONCLUSION

This study presents a deep learning–based framework for detecting hidden anomalies in environmental pollution data using Autoencoder, LSTM, and Bi-LSTM models. The analysis demonstrates that deep learning techniques are highly effective in identifying irregular pollutant patterns that traditional statistical methods often fail to capture. By preprocessing the dataset, normalizing pollutant features, and training sequential models, the system successfully learns the natural behavior of pollutants such as CO, NO_2, NOx, O_3, and PM2.5.

Among the models evaluated, the Bi-LSTM showed superior performance due to its bidirectional learning capability, enabling it to understand both past and future temporal relationships. The Autoencoder and LSTM also performed well, but Bi-LSTM offered higher accuracy and more reliable anomaly detection. The results confirm that deep learning models can play a significant role in smart environmental monitoring systems, providing accurate early detection of unusual pollution events.

This work lays a strong foundation for future extensions such as real-time deployment, IoT sensor integration, cloud-based streaming, and automated alert systems. With further refinement, this framework can support smart city initiatives and help in environmental decision-making and public health protection.

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