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Time-Series Forecasting of Delhi Air Quality Using Deep Learning

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Content

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Introduction

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Technical Background

- Air Quality Index (AQI) indicates pollution severity and its impact on human health.
- AQI forecasting is a **time-series problem** influenced by past AQI values, weather conditions, and seasonal cycles.
- Delhi's rapid urbanization and industrial activity cause frequent air-quality deterioration, making accurate prediction essential.
- Deep Learning models—especially **RNNs (LSTM, GRU)** and hybrid **CNN+LSTM** architectures—effectively capture:
  - Temporal dependencies
  - Short-term fluctuations
  - Non-linear pollutant–weather relationships

Technical Concepts Used

- **Time Series Forecasting:** Predict future AQI using historical sequences.
- **Feature Engineering:** Lag features (1, 3, 7 days), rolling mean, EWMA, cyclical sin/cos encodings.
- **Deep Learning Models:**
  - LSTM & Stacked LSTM
  - CNN + LSTM hybrid
  - GRU (Gated Recurrent Unit)
- **Normalization:** MinMaxScaler for stable training.
- **Training Techniques:** EarlyStopping, learning rate scheduling, dropout.
- **Evaluation Metrics:** RMSE, R^2 score, residual analysis.

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Motivation

Delhi is among the world's most polluted cities. High AQI leads to:

- Respiratory disease
- Visibility reduction
- School shutdowns
- Mobility restrictions
- Increased hospitalization
  Accurate forecasting helps citizens, health agencies, and government authorities take preventive action.

Problem Statement

Develop a reliable model to **predict next-day AQI** in Delhi using historical pollutant, weather, and engineered features; and identify which deep learning architecture performs best.

Area of Application

- Environmental monitoring
- Smart city planning
- Health & safety advisories
- Real-time pollution dashboards
- Weather & climate analytics
- Government pollution control (CPCB, DPCC)
- AQI mobile applications

Dataset & Input Format

- Delhi AQI Dataset (2017–2025), merged with meteorological data.
- Key inputs: AQI, temperature, humidity, pressure, windspeed, precipitation.
- Engineered features: lag values, rolling mean, EWMA, cyclical encodings, weather one-hot flags.
- **Model Input Format:**
  Each sample = **7-day sliding window** of all engineered features.

Objective

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A. Main Objective

To accurately forecast next-day AQI for Delhi using deep learning sequence models and determine the best-performing architecture.

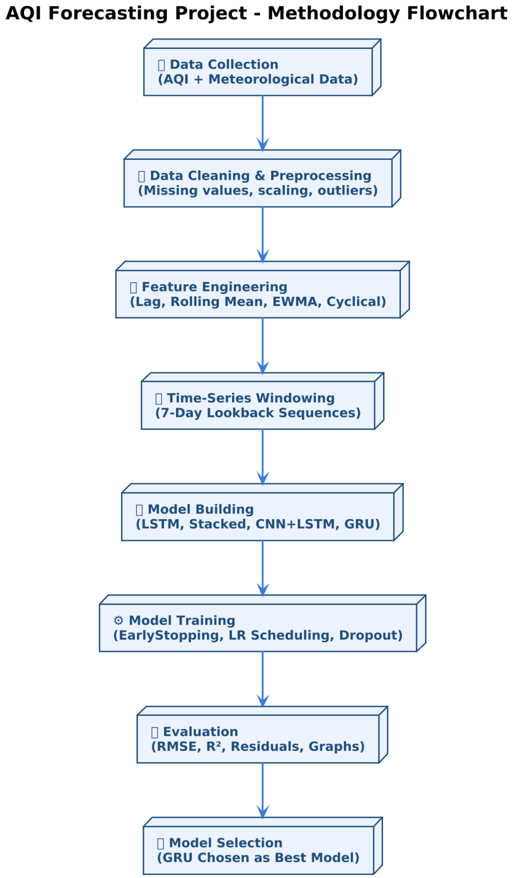
B. Sub Objectives

- Perform feature engineering to enhance forecasting accuracy
- Train and compare LSTM, Stacked LSTM, CNN+LSTM, and GRU models
- Evaluate models using RMSE, R^2, residual plots, and error distribution
- Analyze the impact of temporal features on prediction performance
- Provide a final model recommendation based on evidence

Methodology

A. Steps

A structured approach was followed:



B. Deliverables of Each Step / Phase

Phase	Deliverable
Data Preprocessing	Cleaned dataset, scaled features
Feature Engineering	30+ enhanced features
Modeling	4 deep learning architectures
Training	Trained models with loss curves
Evaluation	RMSE, R^2, prediction graphs
Comparison	Best model selection (GRU)
Final Output	AQI forecast system + report

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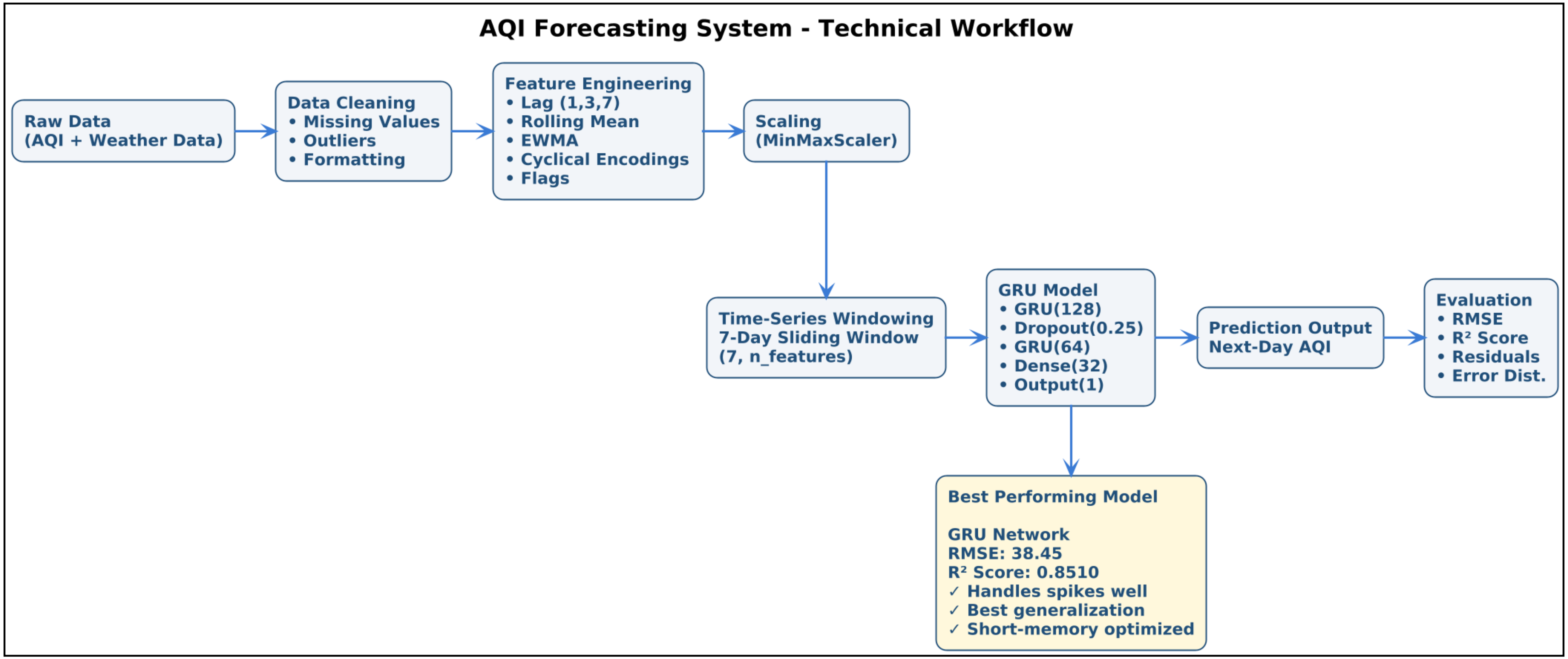
Working Model

A. Technical Diagram



Working Model

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B. Working Module

The system is organized into a series of interconnected modules that together perform end-to-end AQI forecasting:

1. Data Acquisition Module

Collects daily AQI values and meteorological parameters such as temperature, humidity, pressure, windspeed, and weather conditions.

2. Data Preprocessing Module

Handles missing values, removes inconsistencies, formats dates, and prepares the dataset for modeling.

3. Feature Engineering Module

Generates predictive features including lag values, rolling averages, EWMA, cyclical time encodings, and weather flags.

4. Scaling & Windowing Module

Applies MinMax scaling and converts the dataset into 7-day time-series sequences for supervised learning.

5. Model Development Module

Implements and trains multiple deep learning models:
LSTM, Stacked LSTM, CNN+LSTM, and GRU.

6. Evaluation Module

Produces RMSE, R^2 scores, actual vs predicted plots, and residual/error analysis to compare model performance.

7. Model Selection Module

Selects the **GRU model** as the final forecasting architecture based on highest accuracy and stability.

Working Model

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C. Attained Deliverable

The project successfully delivered the following outcomes:

1. Fully Preprocessed & Engineered Dataset

With lag features, rolling statistics, EWMA, cyclical encodings, and weather-based indicators.

2. Multiple Deep Learning Models Developed & Trained

Including LSTM, Stacked LSTM, CNN+LSTM, GRU, and GRU with Huber loss.

3. Final Model Selection

Identification of the **GRU model** as the best performer with:

- **RMSE = 38.45**
- **R^2 = 0.851**

4. Comprehensive Visualizations

Generated training curves, prediction plots, residual charts, and model comparison graphs.

5. End-to-End AQI Forecasting Pipeline

A complete workflow from raw data → preprocessing → modeling → evaluation → prediction.

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A. Test Cases

Test Case	Scenario	Expected Behavior	Model Outcome
Normal AQI Day	Moderate AQI (150–250)	Accurate prediction	GRU predicted within ±40
Seasonal Peak	Winter pollution spikes	Detect rising trend	GRU tracked peaks well
Monsoon Dip	AQI drops to 60–120	Avoid overestimation	GRU stable
Sudden Spike	Outliers (350–500)	Adapt quickly	Best performance
COVID Dip	Unusual low pollution	Adjust predictions	Accurate & stable
Missing Data	Weather gaps	Stay robust	No major deviation

Results

A. Quantitative Performance Metrics

Models Used in This Study

Four deep learning models were implemented and evaluated:

- **Base LSTM** – Single-layer LSTM used as the baseline sequence model.
- **Stacked LSTM** – Deeper LSTM architecture to capture complex temporal patterns.
- **CNN + LSTM** – Convolution layer for feature extraction followed by LSTM for sequence modeling.
- **GRU (Best Model)** – Gated Recurrent Unit offering faster training and strong performance with fewer parameters.

All models were assessed using **RMSE**, **R^2 score**, **Actual vs Predicted plots**, **Residual analysis**, and **Error distributions**.

Model Performance Summary

Model	RMSE ↓	R^2 Score ↑
Base LSTM	45.42	0.7920
Stacked LSTM	45.22	0.7938
CNN + LSTM	54.45	0.7012
GRU (Best Model)	**38.45**	**0.8510**

Interpretation

- **GRU achieved the best results**, with the lowest RMSE and highest R^2 score.
- Base LSTM and Stacked LSTM performed moderately well but frequently underpredicted sharp pollution spikes.
- CNN+LSTM had the weakest performance due to heavy smoothing and inability to capture fast fluctuations in AQI.

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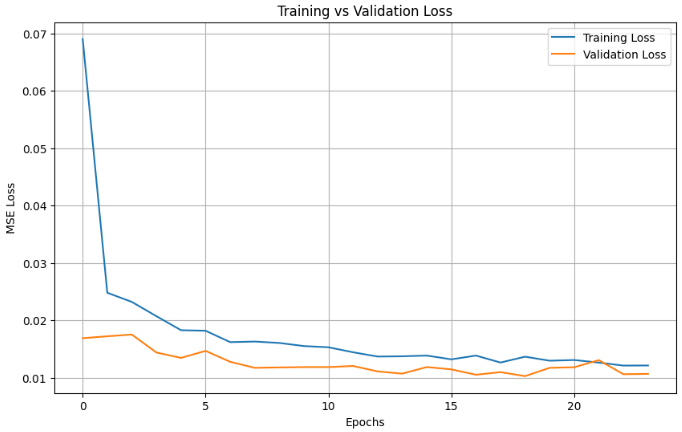
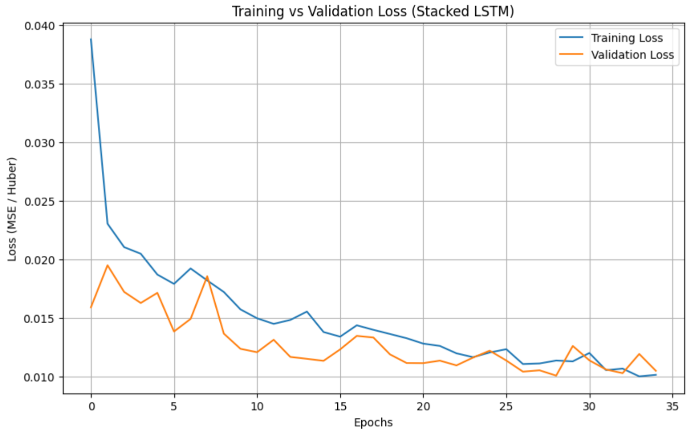
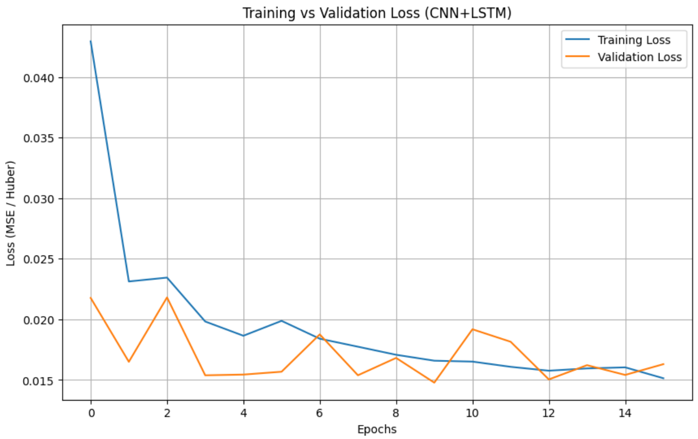
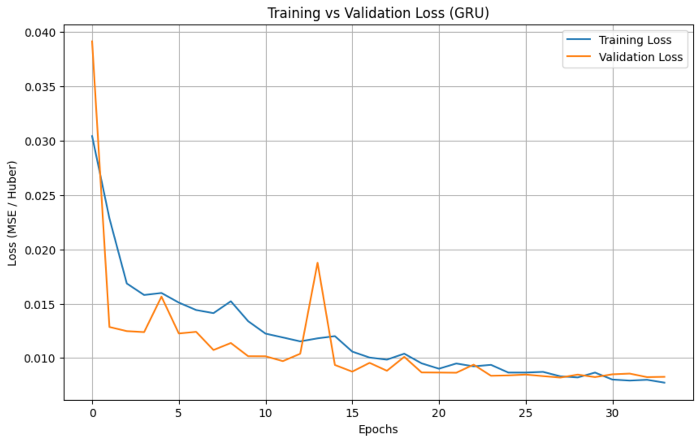
B. Outcome Graphs

1.Training vs Validation Loss Curves







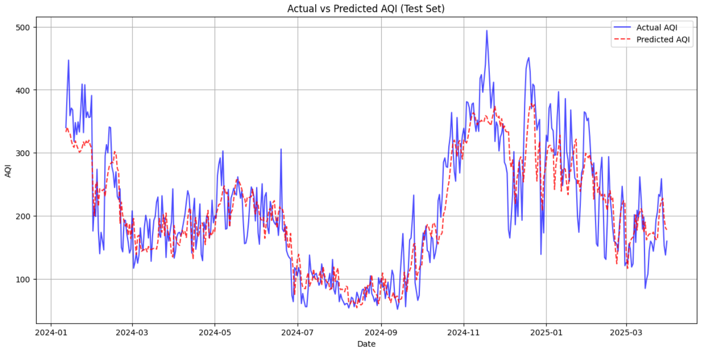


Insights

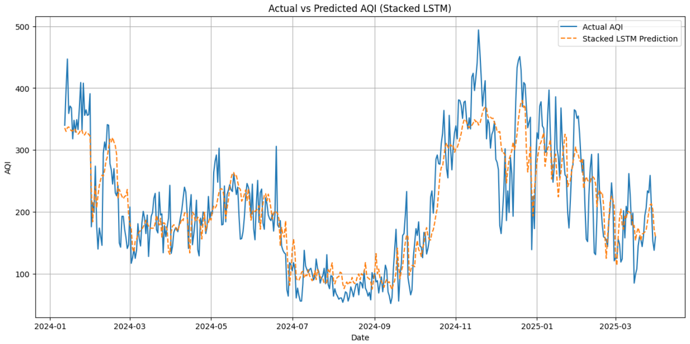
- GRU showed the most stable and smooth convergence, with training and validation loss decreasing consistently.
- LSTM and Stacked LSTM converged well but showed slight fluctuations due to model complexity.
- CNN+LSTM showed higher validation loss and clear signs of overfitting.

Results

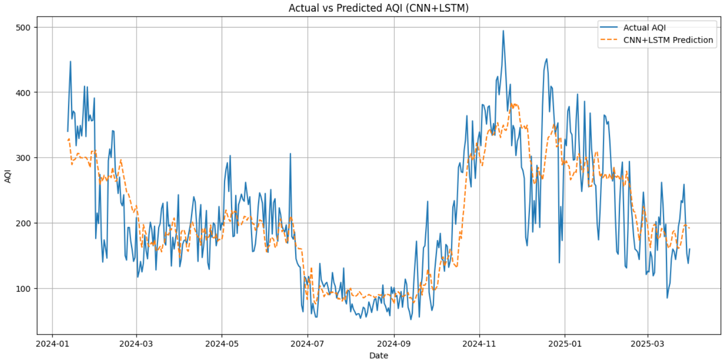
2. Actual vs Predicted AQI Trends



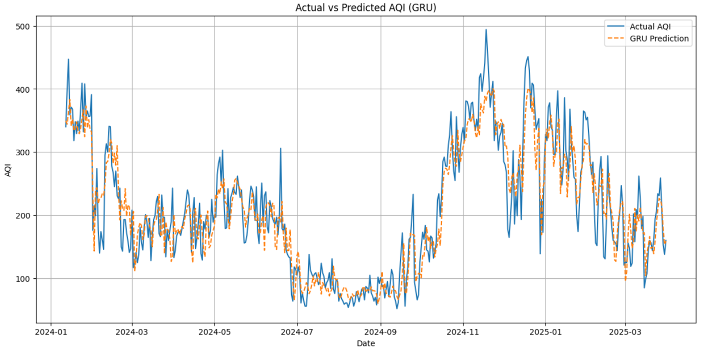
Base LSTM



Stacked LSTM



CNN+LSTM



GRU

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Key Observations

- **GRU** tracks seasonal peaks and daily fluctuations **closest** to the true values.
- **LSTM and Stacked LSTM** correctly capture the general trend but smooth out several sharp peaks.
- **CNN+LSTM** significantly underestimates rapid AQI rises and produces over-smoothed predictions.

Conclusion from Trend Analysis

GRU's predictions best match the *shape*, *timing*, and *magnitude* of AQI variations.

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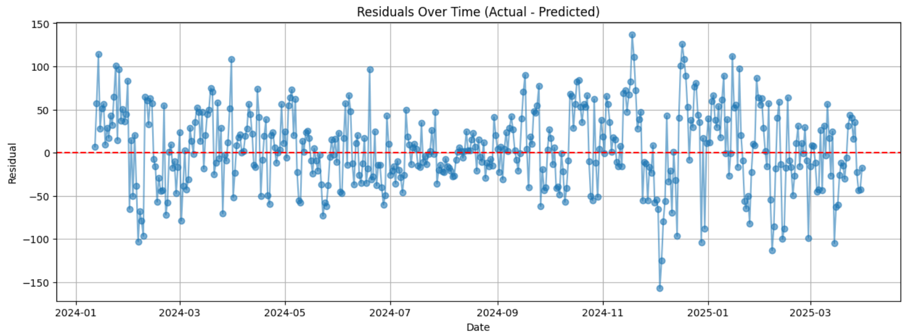
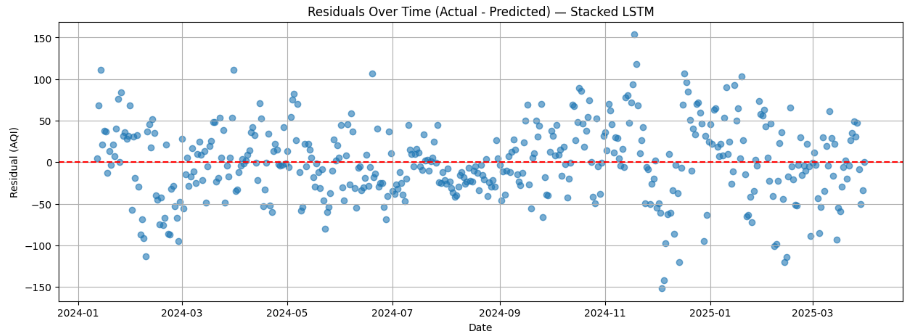
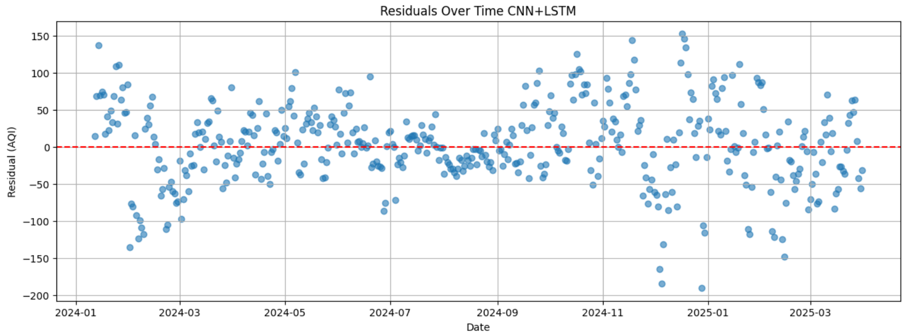
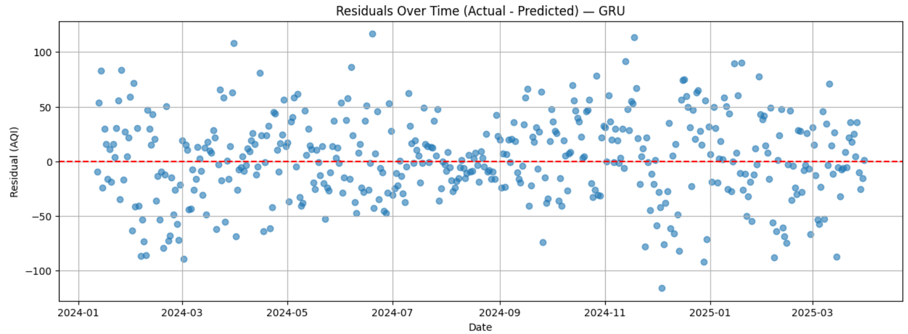
3. Residual Analysis









Insights

- GRU residuals are tightly centered around zero → low bias & low error variance.
- LSTM residuals have moderate spread.
- CNN+LSTM residuals show large deviations, indicating unstable predictions.

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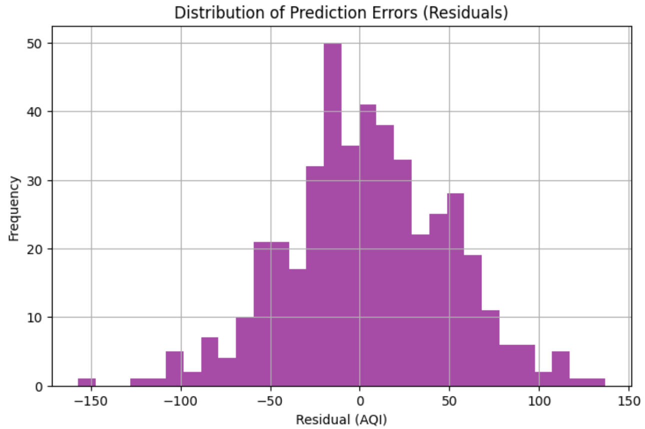
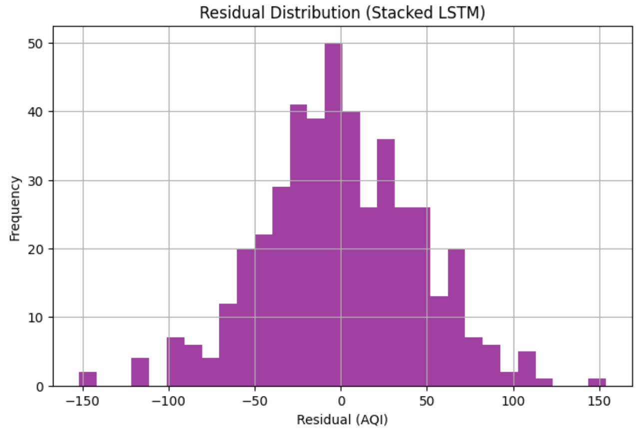
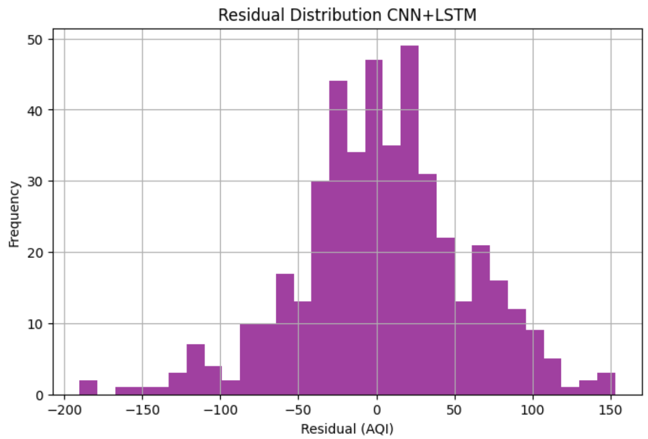
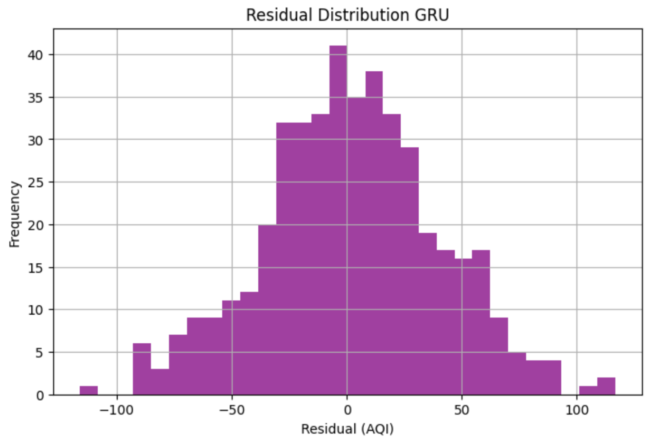
4.Error Distribution









Summary

- GRU errors fall mostly within **±40 AQI points**, much tighter than the other models.
- The distribution is symmetric, indicating consistent performance across conditions.

Results

C. Comparative Studies

A comparative analysis was conducted to identify the best model based on performance metrics, visualization outputs, and temporal pattern learning.

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1. Quantitative Comparison

Model	RMSE ↓	R^2 ↑
Base LSTM	45.42	0.7920
Stacked LSTM	45.22	0.7938
CNN + LSTM	54.45	0.7012
GRU	**38.45**	**0.8510**

Interpretation

- GRU performs the best across both metrics.
- Stacked LSTM provides only marginal improvement over base LSTM.
- CNN+LSTM performs the worst, struggling with rapid AQI fluctuations

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2. Visual Prediction Comparison

Actual vs Predicted Trends

- **GRU** tracks day-to-day AQI trends accurately and adapts well to sudden spikes.
- **LSTM/Stacked LSTM** follow the overall shape but miss sharp peaks.
- **CNN+LSTM** produces overly smooth outputs.

3. Model Complexity & Training Stability

Model	Training Stability	Overfitting Risk	Speed
LSTM	Stable	Moderate	Medium
Stacked LSTM	Less stable	Higher	Slow
CNN+LSTM	Unstable	High	Medium
GRU	**Most stable**	**Low**	**Fastest**

4. Overall Comparison & Final Verdict

Why GRU is the Best Model

- Lowest RMSE
- Highest R^2 score
- Best ability to capture sudden AQI changes
- Least overfitting
- Fastest training
- Handles noisy & volatile time series exceptionally well

Final Selection

GRU is chosen as the final forecasting model due to superior accuracy, robustness, and computational efficiency.

Conclusion

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This project successfully developed a deep learning–based next-day AQI forecasting system for Delhi using LSTM, Stacked LSTM, CNN+LSTM, and GRU models.Through rigorous preprocessing, feature engineering, and time-series modeling, the **GRU model emerged as the most accurate**, achieving **RMSE 38.45** and **R^2 0.851**.The analysis shows that Delhi's AQI is highly volatile but follows short-memory dynamics, making GRU highly suitable due to its simplified gating and strong temporal learning.Engineered features like lag values, rolling means, EWMA, and cyclical encodings significantly boosted model performance. Overall, the system provides reliable next-day AQI forecasts and forms a strong foundation for future environmental prediction systems.

Justification of Objectives

- **Objective 1:** Build a next-day AQI predictor → Achieved using multiple deep learning models.
- **Objective 2:** Perform feature engineering → Completed with lag, rolling mean, EWMA, cyclical features; validated through correlation analysis.
- **Objective 3:** Compare model architectures → All four models evaluated using RMSE, R^2, residuals, and trend analysis.
- **Objective 4:** Identify the best model → GRU selected for highest accuracy and stability.
- **Objective 5:** Provide comprehensive visual evaluation → Achieved through training curves, prediction graphs, residual/error plots, and EDA visuals.

Future Scope

- Extend forecasting horizon to 3–7 days.
- Integrate richer data sources (satellite aerosol data, traffic levels, stubble-burning hotspots).
- Apply advanced tuning techniques (Optuna, Bayesian Optimization).
- Explore modern architectures (Transformers, Temporal Fusion Transformers).
- Deploy a real-time AQI prediction dashboard using FastAPI or Streamlit.

References

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3. “Understanding GRU Networks” – Technical article on gated recurrent units and their applications in sequence modeling.
4. “A Beginner’s Guide to Recurrent Neural Networks (RNNs)” – Online article explaining RNN fundamentals and sequence learning behavior.
5. “Time-Series Forecasting with Deep Learning Models” – Industry article discussing LSTM, GRU, and hybrid models for forecasting.
6. Kaggle & public AQI datasets used for environmental trend analysis.

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Thank You