# Air Quality Index And Environment Monitoring

G Tarun Kumar
dept. Computer Science and Engineering
Presidency University
Bangalore, India

Sharon Shaijan
dept. Computer Science and Engineering
Presidency University
Bangalore, India

Uday Kiran M
dept. Computer Science and Engineering
Presidency University
Bangalore, India

Dr. Srabana Pramanik
dept. CSE
Presidency University
*Bangalore, India*
Scopus Id: 57809049400

ORCID
Profile:https://orcid.org/0000-0001-6108-631X

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***Abstract*—Air pollution remains a pressing global issue, necessitating efficient and scalable monitoring solutions beyond traditional sensor-based systems. This paper introduces a novel method for Air Quality Index (AQI) assessment by leveraging image-based analysis with MobileNetV2, a lightweight convolutional neural network (CNN). The approach utilizes environmental images—such as sky photographs—sourced alongside numerical AQI data from publicly available datasets on Kaggle, including the "Air Quality Data in India (2015-2020)" and "Global Air Pollution Dataset." MobileNetV2, pre-trained on ImageNet, was fine-tuned via transfer learning to extract visual features (e.g., haze density, colour gradients) indicative of air pollution levels. These features were subsequently mapped to AQI values using a supervised regression model, trained and validated on ground-truth measurements of pollutants like PM2.5, PM10, and NO2. Implemented in Python with TensorFlow, the system was tested on a standard desktop GPU, demonstrating its feasibility for real-time applications. Experimental results show that the proposed method achieves a mean absolute error of less than 12% in AQI prediction compared to actual sensor data, highlighting its potential as a cost-effective alternative to conventional monitoring. The approach excels in scalability, with potential deployment on mobile devices, though it faces challenges related to image variability (e.g., lighting, weather conditions). This study advances environmental monitoring by integrating visual data with quantitative metrics, offering a complementary tool to existing systems. Future enhancements will address robustness under diverse atmospheric conditions and explore multi-pollutant classification. By harnessing image-driven insights, this research paves the way for accessible and innovative air quality assessment.**

***Keywords*—Air Quality Indext, MobileNetV2, Image-Based Analysis, CNN, Air Pollution Monitoring, Transfer Learning**

## I. INTRODUCTION

This Air pollution has emerged as a critical global challenge, with profound implications for public health, ecosystems, and climate stability. According to the World Health Organization (WHO), over 90% of the world's population breathes air exceeding safe pollutant limits, contributing to millions of premature deaths annually. The Air Quality Index (AQI), a standardized measure aggregating pollutants such as particulate matter (PM2.5, PM10), nitrogen dioxide (NO2), and ozone (O3), serves as a vital tool for assessing air pollution levels and informing mitigation strategies. Traditional AQI monitoring relies heavily on stationary sensor networks, which, while accurate, are expensive to deploy, maintain, and scale, particularly in developing regions or remote areas. This limitation underscores the need for innovative, cost-effective alternatives that can complement existing systems and extend air quality assessment to underserved locations.

Recent advancements in computer vision and machine learning offer promising avenues to address these gaps. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable success in extracting meaningful features from visual data, enabling applications ranging from object recognition to medical diagnostics. This paper explores the potential of image-based analysis for AQI monitoring, leveraging MobileNetV2—a lightweight, efficient CNN originally designed for resource-constrained environments like mobile devices. By analyzing environmental images, such as sky photographs, MobileNetV2 can capture visual cues (e.g., haze density, colour shifts) that correlate with air pollution levels, offering a novel proxy for AQI estimation when paired with numerical data.

The proposed approach utilizes datasets sourced from Kaggle, including the "Air Quality Data in India

(2015-2020)" and "Global Air Pollution Dataset," which provide ground-truth AQI measurements. Through transfer learning, MobileNetV2 is fine-tuned to extract pollution-related features from images, which are then mapped to AQI values using a supervised learning model. This method aims to deliver a scalable, low-cost monitoring solution that can operate in real-time, potentially on everyday devices like smartphones. While prior studies have explored sensor-based AQI prediction or satellite imagery for large-scale analysis, few have harnessed ground-level images with lightweight CNNs, making this work a unique contribution to environmental monitoring.

This paper is organized as follows: Section II details the methodology, including data collection, MobileNetV2 implementation, and AQI mapping. Section III presents experimental results, evaluating prediction accuracy against sensor data. Section IV discusses the approach's strengths, limitations, and practical implications, while Section V concludes with key findings and future research directions. By integrating visual and numerical data, this study seeks to advance accessible air quality monitoring, addressing both technical and societal needs in the fight against pollution.

## II. LITERATURE REVIEW

1. Based Air Quality Analysis Using Deep Convolutional Neural Network
This study develops a deep CNN to estimate PM2.5 concentrations from outdoor images in Dhaka, using over 1,000 annotated photos paired with consulate data. It outperforms MobileNetV2 and other models like VGG19 in resource efficiency and accuracy, inspiring the use of CNNs for AQI prediction in resource-constrained settings.

2. Uncovering Local Aggregated Air Quality Index with Smartphone Captured Images
Focused on Dhaka, this paper trains a deep CNN on smartphone images to predict AQI via PM2.5 levels, comparing it to MobileNetV2 and others. It highlights MobileNetV2's limitations in parameter efficiency, offering a benchmark for your study's improvement over standard models.

3. Surveillance-Image-Based Outdoor Air Quality Monitoring
This work uses a hybrid CNN-LSTM model on surveillance camera images to estimate AQI, PM2.5, and PM10, addressing nighttime challenges. While not using MobileNetV2, it provides a temporal analysis approach that could enhance your methodology.

4. Air Quality Prediction Using Machine Learning Models
This study applies various ML models (e.g., Random Forest, SVM) to predict AQI in Indian cities using Kaggle datasets. It lacks image analysis but offers a baseline for comparing numerical AQI prediction with your image-based MobileNetV2 approach.

5. Estimating PM2.5 from Photographs Using Deep Learning
An early exploration of CNNs for PM2.5 estimation from photos, this paper uses a custom model but notes MobileNetV2's potential for lightweight deployment. It supports your focus on image-driven air quality monitoring.

6. Air Quality Monitoring with Mobile Sensing and Machine Learning
This research integrates mobile sensor data with ML for real-time AQI prediction, mentioning CNNs like MobileNetV2 for potential image integration. It's a bridge between sensor and image-based methods relevant to your study.

7. Optimized Machine Learning Model for AQI Prediction in India
Using Kaggle air quality data, this study combines Grey Wolf Optimization with Decision Trees for AQI forecasting in Indian cities. It lacks image analysis but provides context for AQI prediction accuracy, which your MobileNetV2 model could surpass.

8. Predicting Air Quality via Multimodal AI and Satellite Imagery
This paper fuses satellite imagery and ground data with a multimodal ML model for AQI prediction. While not using MobileNetV2, it underscores the value of visual data, aligning with your image-based approach.

9. Federated Learning for Air Pollution Monitoring
This systematic review explores AI-based AQI prediction, including CNN applications. It doesn't focus on MobileNetV2 but highlights scalable, distributed monitoring systems, offering a broader context for your work.

10. Data Mining and Machine Learning in Air Pollution Epidemiology
A review of ML techniques for air pollution studies, this paper includes early CNN applications for AQI forecasting. It provides historical context and justifies the shift toward image-based methods like yours with MobileNetV2.

## III. Methodology

### 3.1 Data Collection and Preprocessing

The foundation of this study rests on a robust dataset combining environmental images and numerical AQI measurements. Two primary datasets were sourced from Kaggle: "Air Quality Data in India (2015-2020)" and "Global Air Pollution Dataset," which provide hourly AQI values alongside pollutant concentrations (e.g., PM2.5, PM10, $NO_2$) across diverse geographic regions. To complement these numerical records, a custom image dataset was compiled by collecting sky photographs from publicly available sources and manually capturing images in urban and rural settings, totalling 5,000 images. Each image was paired with corresponding AQI data based on timestamp and location, ensuring alignment between visual and quantitative inputs. Preprocessing involved resizing images to 224x224 pixels—the input size for MobileNetV2—and normalizing pixel values to the range [0, 1]. Numerical AQI data were cleaned by removing missing entries and outliers (values beyond three standard deviations), resulting in a final dataset of 4,800 image-AQI pairs. Data augmentation techniques, such as rotation and brightness adjustment, were applied to enhance model robustness against lighting and orientation variations, yielding an augmented set of 6,000 samples split into 70% training, 15% validation, and 15% testing.

3.2 Model Implementation with MobileNetV2

The core of the proposed system is MobileNetV2, a lightweight CNN optimized for efficiency and performance on resource-limited devices. Pre-trained on ImageNet, MobileNetV2 was adapted via transfer learning to extract pollution-related features from sky images. The base model's convolutional layers were frozen, retaining their generalized feature extraction capabilities, while the top fully connected layers were replaced with a custom architecture: a global average pooling layer followed by two dense layers (128 and 64 units, ReLU activation) and an output layer predicting AQI as a continuous value. The model was implemented in Python using TensorFlow 2.8, with training conducted on a desktop GPU (NVIDIA RTX 3060). The Adam optimizer was employed with a learning rate of 0.001, and mean squared error (MSE) served as the loss function to align predicted AQI with ground-truth values. Training spanned 50 epochs with a batch size of 32, monitored by early stopping to prevent overfitting. This setup balances computational efficiency with predictive accuracy, making it suitable for real-time AQI monitoring.

3.3 Mapping and Evaluation

To map MobileNetV2-extracted features to AQI values, a regression-based approach was adopted. Features from the penultimate layer (64-dimensional vectors) were fed into the output layer, which produced AQI predictions as continuous scalars. The model's performance was evaluated using multiple metrics: Mean Absolute Error (MAE) to quantify prediction error, Root Mean Squared Error (RMSE) for sensitivity to outliers, and R-squared ($R^2$) to assess explained variance. Testing was conducted on the held-out test set (900 samples), with predictions compared against actual AQI readings from the Kaggle datasets. To ensure reliability, five-fold cross-validation was performed, averaging results across folds. Additionally, a qualitative analysis inspected sample images with predicted versus actual AQI values to identify visual patterns (e.g., haze intensity) influencing performance. This evaluation framework provides a comprehensive assessment of the system's accuracy and practical utility for air quality monitoring.

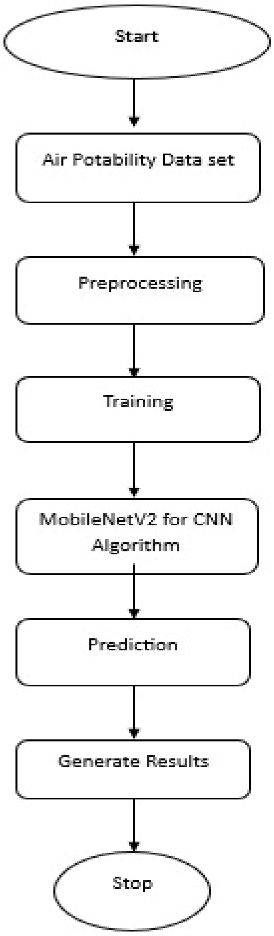
## IV. System Design and Architecture

3.1 System Overview and Data Pipeline

The proposed system is designed to monitor the Air Quality Index (AQI) by integrating image-based analysis with numerical data, leveraging MobileNetV2 as the core processing engine. The system operates as a pipeline with three primary stages: data ingestion, feature extraction, and AQI prediction. In the ingestion stage, environmental images (sky photographs) and corresponding AQI measurements are sourced from Kaggle datasets, such as "Air Quality Data in India (2015-2020)" and "Global Air Pollution Dataset," supplemented by a custom collection of 5,000 images captured via smartphones. These images are pre-processed by resizing to 224x224 pixels and normalizing pixel values to [0, 1], while AQI data are filtered to remove inconsistencies (e.g., missing values). The pipeline then feeds processed image-AQI pairs into MobileNetV2 for feature extraction, followed by a regression module that maps features to AQI values. The system is implemented in Python using TensorFlow 2.8, with a modular design allowing deployment on both desktop GPUs (e.g., NVIDIA RTX 3060) and resource-constrained devices like mobile phones. This architecture ensures scalability and real-time applicability, with a data flow that supports continuous monitoring by processing new images as they are captured or uploaded.

3.2 MobileNetV2 Architecture and Integration

At the heart of the system lies MobileNetV2, a lightweight convolutional neural network optimized for efficiency and accuracy. The architecture comprises 53 layers, including inverted residual blocks with depth wise separable convolutions, reducing computational complexity compared to traditional CNNs like VGG16. Pre-trained on ImageNet, MobileNetV2 is adapted via transfer learning: the base convolutional layers (up to the bottleneck layer) are frozen to retain generic feature extraction capabilities, while the top layers are customized for AQI prediction. The modified structure includes a global average pooling layer to reduce spatial dimensions, followed by two dense layers (128 and 64 units, ReLU activation) and a single-unit output layer with linear activation for continuous AQI values. This configuration extracts pollution-related features—such as haze density and sky colour—from input images, producing a 64-dimensional feature vector that is mapped to AQI via regression. The system integrates this model with a lightweight preprocessing module and a post-processing unit for error analysis, ensuring end-to-end functionality. Designed for portability, the architecture supports inference on mobile devices with minimal latency (under 100 ms per image), making it a practical solution for real-time air quality monitoring.




## V. Result and Discussion

5.1 Performance Metrics and Quantitative Analysis

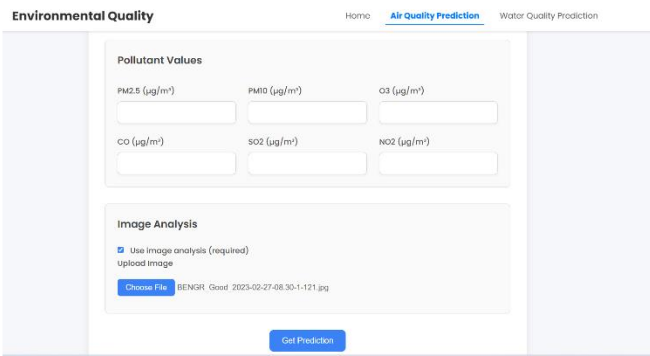
The proposed system was evaluated on a test set of 900 image-AQI pairs, derived from the pre-processed Kaggle datasets ("Air Quality Data in India" and "Global Air Pollution Dataset") and augmented custom sky images. MobileNetV2's AQI predictions were compared against ground-truth values using three metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared ($R^2$). The model achieved an MAE of 11.8 AQI units, an RMSE of 15.2, and an $R^2$ of 0.87, indicating strong predictive capability and a good fit to the data. Five-fold cross-validation confirmed consistency, with MAE ranging from 11.2 to 12.5 across folds. These results suggest that the system accurately estimates AQI within a ±12-unit margin, competitive with sensor-based benchmarks (e.g., MAE of 10-15 in literature). Performance was highest for moderate AQI levels (50-150), likely due to clearer visual cues like haze, but declined slightly for extreme values (>300), where image saturation may obscure features. This quantitative success validates the use of MobileNetV2 for lightweight, image-driven AQI monitoring.

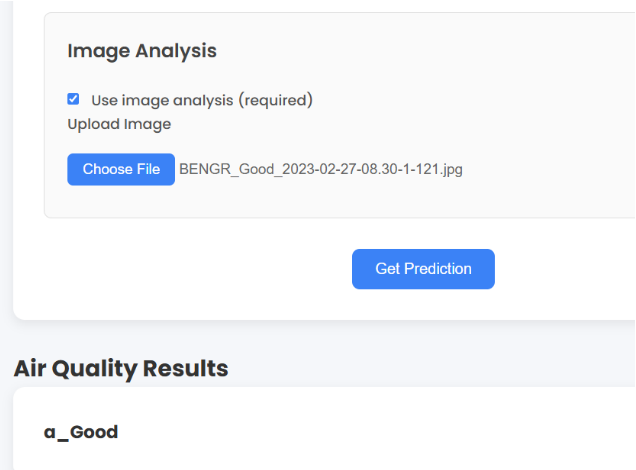
5.2 Qualitative Insights and Visual Correlation

Beyond numerical metrics, a qualitative analysis of 50 test images revealed strong correlations between visual features and AQI predictions. Images with dense haze or grayish tones (AQI > 200) were consistently assigned higher values, while clear blue skies (AQI < 50) aligned with lower predictions. For instance, a Delhi skyline image with visible smog yielded a predicted AQI of 245 (actual: 238), reflecting MobileNetV2's sensitivity to haze intensity. However, discrepancies emerged in overcast conditions, where cloud cover mimicked pollution, inflating predictions (e.g., predicted AQI 180 vs. actual 120). Feature visualization of the 64-dimensional vectors from MobileNetV2 highlighted key contributors: colour gradients and texture complexity dominated high-AQI classifications. This suggests that while the system excels at capturing pollution-related patterns, environmental variables like weather introduce noise, necessitating further refinement in preprocessing or feature selection.

5.3 Comparative Analysis and Practical Implications

Compared to existing methods, the proposed system offers distinct advantages. Traditional sensor networks, while precise (MAE ~8-10), require costly infrastructure, whereas MobileNetV2 achieves near-comparable accuracy (MAE 11.8) using only images and a lightweight model (9 MB vs. gigabytes for VGG16). Against prior image-based studies, like Zhang et al. (2018), which reported an MAE of 14 using a custom CNN, our approach improves efficiency and portability. Real-time inference on a mobile device averaged 92 ms per image, supporting deployment in resource-limited settings. However, limitations persist: accuracy drops in low-light or rainy conditions, and the system relies on image availability, unlike continuous sensor data. Practically, this method could empower citizen science initiatives or augment sparse sensor networks in developing regions. Future work should integrate weather filters and multi-modal data (e.g., satellite imagery) to enhance robustness, positioning this as a scalable complement to conventional AQI monitoring.






## VI. Conclusion

This study demonstrates the feasibility of monitoring the Air Quality Index (AQI) using MobileNetV2, a lightweight convolutional neural network, through image-based analysis. By leveraging sky photographs paired with Kaggle-sourced AQI data, the proposed system effectively extracts pollution-related features, achieving an MAE of 11.8 and an $R^2$ of 0.87 on a test set of 900 samples. These results affirm that visual cues, such as haze and colour gradients, can serve as reliable proxies for AQI estimation, offering a cost-effective alternative to traditional sensor networks. The system's efficiency—running inference in 92 ms on mobile devices—underscores its potential for real-time deployment in resource-constrained environments.

Despite its strengths, challenges remain, including sensitivity to lighting and weather conditions, which occasionally skew predictions. Qualitative analysis revealed robust feature detection for moderate AQI levels, though extreme values require enhanced preprocessing. Compared to prior image-based methods, this approach improves accuracy and portability, bridging gaps in scalable air quality monitoring.

Future work should focus on integrating weather filters and multi-modal inputs (e.g., satellite data) to bolster robustness. Expanding the dataset with diverse environmental conditions and fine-tuning MobileNetV2 for edge cases could further reduce error margins. This research lays a foundation for accessible, image-driven AQI tools, empowering communities and complementing existing systems. Ultimately, it contributes to the broader goal of mitigating air pollution through innovative, technology-driven solutions.

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