AirSense: Forecasting of AQI and Pollutant levels based on Deep Convolutional Neural Networks

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***Abstract*— AirSense introduces an innovative method for predicting Air Quality Index (AQI) and pollutant levels (PM2.5, PM10, O3, SO2, NO2) through deep learning-based convolutional neural networks (CNNs). By utilizing a vast collection of air pollution images, the system is trained to predict AQI and pollutant levels directly from a single image of the sky. This approach combines advanced machine learning techniques with environmental monitoring, presenting a highly effective solution for addressing the complexities of air quality forecasting. AirSense's real-time image analysis capabilities offer significant potential to enhance public awareness of air quality, aiding in better health decisions. The system's use of existing camera infrastructure makes it a cost-efficient and scalable alternative to traditional monitoring systems, which are often costly and limited in coverage. Furthermore, its ability to forecast multiple pollutants in a single model makes AirSense a valuable tool for improving urban planning, environmental policies, and public health protection strategies.**

***Keywords*—** Air Quality Analysis, Deep Convolutional Neural Networks, Image Classification, Particulate Matter, VGG-model, Feature Extraction, TimeSeries, HSV

1. Introduction

Air pollution has emerged as a critical global issue, presenting serious health hazards. It has been linked to various adverse health outcomes, including respiratory problems, cardiovascular diseases, and even premature death. The accurate monitoring and prediction of air quality are essential for reducing these risks and improving public health outcomes. Traditional air quality monitoring systems, which rely heavily on sensor networks, while providing precise data, are often costly to implement and maintain, and their spatial coverage is generally limited. In response to these challenges, this paper introduces AirSense, a novel system designed to utilize deep learning and image analysis to overcome these limitations. AirSense predicts the Air Quality Index (AQI) and pollutant levels (PM2.5, PM10, O3, SO2, NO2) using convolutional neural networks (CNNs) in combination with sky image analysis.

Recent advancements in deep learning have significantly enhanced capabilities in image recognition and environmental monitoring. This progress has inspired a wave of research into the potential of using images to estimate air quality. For example, Li et al. [1] successfully applied CNNs to analyze images and predict PM2.5 concentrations, yielding positive results. Similarly, AQE-Net [2] uses deep learning models to assess air quality from images taken in urban environments via mobile devices. These studies demonstrate the potential of deep learning for image-based air quality assessment, providing a foundation for future work.

Building upon these advances, AirSense is specifically designed to forecast AQI and pollutant levels by training a CNN model on sky images. This method offers several key advantages. First, it provides a cost-effective and scalable alternative to traditional sensor networks, as it can utilize widely available camera infrastructure. Second, by analyzing real-time images, AirSense delivers timely air quality predictions that can help individuals and authorities make informed decisions to protect public health. Finally, this approach opens up new possibilities for broader geographical monitoring, as image-based models can cover larger areas with minimal additional costs.

1. Ubiquitous Data Source: Sky images can be captured using existing camera infrastructure, such as security cameras or traffic monitoring systems, overcoming limitations of traditional sensor networks. This vastness of data sources allows for wider spatial coverage.
2. Real-time Forecasting: AirSense can potentially provide real-time air quality forecasts based on image analysis, enabling immediate awareness and informed decision-making. This can empower individuals to take steps to protect their health, such as wearing masks or avoiding outdoor activity during periods of high pollution.
3. Scalability and Cost-Effectiveness: Image-based methods leverage existing infrastructure, potentially reducing deployment and maintenance costs compared to sensor networks. This makes AirSense a more scalable and cost-effective solution for air quality monitoring.

This research investigates the efficacy of CNNs in extracting features from sky images that correlate with AQI and pollutant levels. The paper details the development, training, and evaluation of the AirSense model, examining its accuracy and generalizability for air quality forecasting. Beyond the initial studies using CNNs, researchers are exploring various deep learning architectures for air quality forecasting:

1. Multi-dimensional CNNs: Zhu et al. [3] propose a multi-dimensional CNN framework that captures spatial dependencies within air quality data, potentially improving forecasting accuracy.
2. Transfer Learning: He et al. [4] investigate using transfer learning with CNNs for air quality estimation. This approach leverages pre-trained models on similar tasks, potentially improving performance and reducing training time.
3. Deep Learning for Specific Pollutants: While Li et al. [1] focused on PM2.5, Mai et al. [5] demonstrate the potential of deep learning for estimating NO2 concentrations from street-level images. This highlights the applicability of the approach for various pollutants.

This exploration of different deep learning techniques showcases the ongoing effort to refine image-based air quality assessment. AirSense contributes to this area by focusing on CNNs specifically trained for AQI and multiple pollutant level forecasting from sky images. The following sections of the paper will delve deeper into the details of the AirSense model, its development, training, and evaluation, examining its efficacy and generalizability for air quality forecasting.The field of deep learning for air quality assessment is constantly evolving, with researchers exploring novel techniques to improve accuracy and generalizability. Here we examine some recent advancements:

1. Hybrid CNN-LSTM Networks: Zhang et al. [6] propose Deep-AIR, a framework that combines CNNs and Long Short-Term Memory (LSTM) networks. This approach leverages the strengths of both architectures, with CNNs capturing spatial features from images and LSTMs modeling temporal dependencies in air quality data [1].
2. Sensor-based Deep Learning: Nagrecha et al. [7] explore using deep CNN-LSTM networks for air quality prediction based on sensor data. This approach integrates sensor measurements with deep learning models, potentially offering a more comprehensive understanding of air quality dynamics [2].

Recent advancements in deep learning have opened doors for environmental monitoring tasks. Research is actively exploring the potential of image-based air quality estimation. Zhang et al. [8] investigated the application of deep learning for air pollutant concentration prediction, highlighting its promise in this field. Similarly, a study by Zhang et al. [9] employed convolutional neural networks to estimate air pollution from photographs, showcasing the effectiveness of deep learning for image-based air quality assessment. Several studies have explored the potential of deep learning for air quality monitoring and estimation. Şahin et al. [10] investigated the application of Cellular Neural Networks (CNNs) for predicting missing air pollutant data. This approach suggests the viability of CNNs in addressing data gaps within air quality monitoring systems. Another study by Kow et al. [11] focused on real- time air quality estimation using deep learning neural networks. Their work highlights the potential for deep learning models to analyze real-time data sources, such as images, and provide immediate air quality assessments[12]. These studies lay the groundwork for the development of AirSense, which leverages deep learning and sky image analysis for air quality forecasting.

3. Literature Review

AirSense is an innovative project focused on predicting air quality parameters, including AQI, PM2.5, PM10, O3, CO, SO2, and NO2, through the analysis of an extensive Air Pollution Image Dataset. Leveraging advanced machine learning techniques, the system employs convolutional neural networks to extract meaningful features from images captured in diverse environmental conditions. Many papers are referred to achieve this project. This research paper proposes a novel deep learning framework, Deep-AIR, for fine-grained air pollution estimation and forecast in urban areas. The framework integrates a convolutional neural network (CNN) component with a long short-term memory (LSTM) component to capture the spatial and temporal features of air pollution and urban dynamics data. The framework also incorporates 1×1 convolution layers to enhance the learning of cross- feature spatial interactions, such as the street canyon effect. The paper evaluates the performance of Deep- AIR on two datasets collected from Hong Kong and Beijing, and compares it with several baseline models. The paper also conducts a salience analysis to reveal the most influential features for air pollution estimation and forecast.The paper contributes to the literature on urban air pollution modelling by addressing the following research gaps:

- Existing data-driven or deep learning models have not fully explored the complex spatial interactions between air pollutants and urban dynamics, such as background pollution level and the street canyon effect.
- Existing deep learning models have mainly focused on either fine-grained air pollution estimation at the city-wide level for the current hour, or air pollution forecast at the station-level for the subsequent hours, but not both simultaneously.
- Existing deep learning models have not incorporated domain-specific features indicative of the street canyon effect, such as building density and height, for air pollution estimation and forecast.
- Existing deep learning models have not provided a comprehensive salience analysis to understand the importance of different domain- specific features for air pollution estimation and forecast.

Another research paper introduces a novel approach for sensor-based air pollution prediction using deep CNN-LSTM models. It aims to present a versatile solution capable of forecasting air pollutant concentrations using easily accessible data from ground-based sensors. By comparing its performance with existing systems that rely on complex satellite imagery data, the paper underscores the significance of its approach. The body of the paper delves into the background and motivation behind the research, emphasizing the severe impacts of air pollution on human health, economy, and the environment. It reviews existing approaches for air pollution prediction, including deep hybrid models and satellite image analysis, before detailing the proposed methodology. This comprises a 1-D convolutional neural network (CNN) and a long short-term memory unit (LSTM), wherein the CNN processes sensor data into a modified pseudo-image, while the LSTM learns temporal patterns for forecasting pollutant concentrations. The paper evaluates the system's performance and accuracy using historical sensor data from key sites in the Port of LA, assessing error and limitations via the root-mean-squared-error (RMSE) metric. In conclusion, the paper asserts the effectiveness and adaptability of the proposed system, noting its capability to generate precise predictions using low-dimensional data and its universality across locales with ground-based sensors. It suggests future research directions, such as extending the approach to the 2D domain, expanding to other regions and pollutants, and exploring its implications for policy and decision- making.

- One paper reviews the existing studies on urban air pollution modelling, which can be divided into two categories: physical-based and data-driven approaches.
- Physical-based models simulate the air pollution process using numerical models or chemical transport models, but they have drawbacks such as high computational cost, inaccuracies, and uncertainties in the inputs and outputs.
- Data-driven models learn patterns from historical data using statistical or machine learning methods, but they face challenges such as data sparsity, missing values, and complex non-linear relationships between air pollution and urban dynamics.
- Deep learning models have advanced the state-of-the-art in data-driven urban air pollution modelling, by learning deep representations and complex nonlinearity from heterogeneous spatial- temporal data in urban environments.

The paper highlights the research gaps and new contributions of the proposed framework, Deep-AIR, which is a hybrid CNN-LSTM model that captures the spatial-temporal correlations between air pollutants and important urban dynamics, such as weather, traffic, and urban morphology.

This research paper is about estimating air pollution levels from photos using a convolutional neural network (CNN) model. The literature review covers the following topics:

- The motivation and challenges of photo- based air pollution estimation: The authors explain why estimating air pollution from photos is a convenient and less expensive approach than using sensors or other methods. They also point out the difficulties of designing a CNN model that can capture the subtle features and ordinal information of air pollution levels from images.

- The related work on CNN feature learning and ordinal regression: The authors review some of the existing methods and techniques for feature learning and classification using CNNs, such as different activation functions, SoftMax regression, and ordinal classifiers. They highlight the advantages and limitations of each method and how they relate to the air pollution estimation task.
- The proposed PAPLE algorithm and its components: The authors introduce their novel CNN based Photo Air Pollution Level Estimation (PAPLE) algorithm, which consists of two main ingredients: a modified activation function that can mitigate the vanishing gradient and bias problems, and a negative log-log ordinal classifier that can better fit the ordinal output of air pollution levels. They describe the network structure, the activation function, and the ordinal regression model in detail.

Another research paper aims to apply a cellular neural network (CNN) approach to the prediction of missing air pollutant data, using meteorological parameters as inputs. The paper claims that this method is superior to the conventional artificial neural network (ANN) and multivariate linear regression (LR) techniques, as it reduces the complexity and training time of the model.

The paper reviews the previous studies that have used machine learning approaches to model air pollution, especially the concentrations of particulate matter (PM) and sulfur dioxide (SO2), which are the major air pollutants affecting urban air quality. The paper cites several examples of studies that have used ANN to predict SO2 and PM10 concentrations, and summarizes their advantages and limitations. The paper also mentions some studies that have used regression-based imputation, nearest neighbor interpolation, self-organizing map, and hybrid methods to simulate missing air quality data.

The paper then introduces the CNN approach, which was proposed by Chua and Yang (1988) as a dynamic system composed of large-scale nonlinear analog circuits that process signals in real time. The paper explains the architecture and operation of the CNN, and compares it with the ANN in terms of the number of weighting coefficients, the training process, and the parallel dynamic processing. The paper also reviews some studies that have applied CNN to air pollution modelling, and reports their promising results.

The paper concludes the literature review by stating the research gap and the research question, which are to evaluate the performance of the CNN approach in predicting the missing concentrations of PM10 and SO2 pollutants in Istanbul, Turkey, and to compare it with the LR technique. The paper also states the research objectives and hypotheses, which are to test the accuracy, correlation, and error of the CNN model, and to analyse the effects of meteorological parameters and seasonal variations on the model predictions.

Another paper proposes a method to forecast the hourly concentration of air pollutants using a convolutional neural network (CNN) model trained on time series data1. The paper reviews some related works on air quality prediction using conventional methods, such as regression analysis and support vector regression, as well as deep learning methods, such as recurrent neural networks and CNNs. The paper also describes the details of the proposed CNN architecture, which consists of layers of convolution, pooling, and fully connected layers2. 3. The paper

evaluates the performance of the proposed model on a dataset of air quality and meteorological data collected from 77 locations in Taiwan. 4. The paper reports the root mean square error (RMSE) of the predicted values compared to the ground truth values, and shows that the proposed model outperforms the baseline models. The paper concludes that CNN can effectively extract the sequential features of time series data and perform well for air quality prediction.

- Finally the last research paper reviews the impacts of air quality on human health and environmental equity, and the need for efficient and inexpensive air quality monitoring instruments. They cite various studies that show the adverse effects of air pollution, especially PM2.5, on respiratory and cardiovascular diseases, mortality, and quality of life. They also mention the challenges and limitations of conventional in-situ monitoring methods, which are costly and sparse.
- Image-based air quality estimation: The authors propose an image-based deep learning model (CNN−RC) that integrates a convolutional neural network (CNN) and a regression classifier (RC) to estimate and classify air quality levels based on photos and HSV statistics. They explain the advantages and rationale of using images and

HSV values as inputs, and the hybrid CNN−RC structure as outputs. They also describe the data preprocessing, model parameter setting, and model comparison procedures in detail.

- Case study and results: The authors apply their model to a case study of the Linyuan air quality monitoring station in Kaohsiung City, Taiwan, where severe air pollution problems occur due to industrial emissions and vehicular exhausts. They use a total of 3549 hourly air quality datasets (including photos, PM2.5, PM10, and AQI) collected at the station as the training and testing data. They compare the performance of different CNN learning schemes (VGG and ResNet) and input combinations (current image, baseline image, and HSV statistics) in terms of estimation accuracy (R2) and classification accuracy (F1-score). They report that the best model achieves R2 values of 76%, 84%, and 76% for PM2.5, PM10, and AQI based on daytime images, respectively, and F1-scores of 0.82, 0.83, and 0.81 for PM2.5, PM10, and AQI based on nighttime images, respectively.
- Conclusion and contribution: The authors conclude that their proposed model offers a promising solution for rapid and reliable multi- pollutant estimation and classification based solely on captured images. They highlight the main contribution of their study as the first attempt to simultaneously estimate several pollutants and the AQI using a single deep learning model. They also suggest some future research directions, such as extending the model to other regions and seasons, incorporating other factors such as meteorology and land use, and improving the model robustness and interpretability.

4. Methodology

This contains implementation for three different models:

A. *Model 1: VGG Feature Extractor + Timeseries + HSV + DenseNet*

AirSense incorporates a multi-pronged approach to feature extraction, leveraging information from both sky images and historical air quality data:

VGG16 Feature Extractor: AirSense employs a pre-trained VGG16 convolutional neural network (CNN) to extract high-level features from sky images. VGG16 is a well-established architecture known for its effectiveness in image recognition tasks. By passing sky images through the VGG16 network, the model learns to represent the visual characteristics of the sky, potentially correlating with air quality conditions.

HSV Color Features: In addition to VGG16 features, AirSense extracts color information from sky images using the HSV (Hue, Saturation, Value) color space. Studies have shown correlations between specific colors and air quality levels (e.g., hazy skies with low saturation potentially indicating higher pollution). Extracting these features allows the model to leverage color information alongside the spatial features learned by VGG16.

Time-Series Data Integration:

Air quality data often exhibits temporal trends and patterns. To capture these dynamics, AirSense incorporates historical air quality measurements (e.g., past AQI and pollutant levels) as features. These features are typically pre-processed for appropriate scaling and formatting before integration with the image-based features.

Once features are extracted from both image and time-series data, they are utilized for model building:

a. Feature Fusion: The extracted image features (VGG16 and HSV) and time-series data are concatenated to form a combined feature vector. This vector represents a comprehensive set of information that the model can leverage for air quality prediction.

b. DenseNet Layers: The combined feature vector is then fed into a series of DenseNet layers. DenseNets are a type of CNN architecture where each layer receives not only the input from the previous layer but also feature maps from all preceding layers. This dense connectivity promotes information flow and potentially improves feature utilization within the network.

c. Prediction Layer: The final layer of the DenseNet architecture is a dense layer with a single neuron for AQI prediction and additional neurons for predicting individual pollutant levels (PM2.5, PM10, O3, SO2, NO2). This layer utilizes the learned features to estimate the target air quality values.

B. Model 2: VGG Feature Extractor + Timeseries + DenseNet

This section details the features utilized by Model 2, which leverages a combination of image analysis and time-series data.

Model 2 employs a pre-trained VGG16 convolutional neural network (CNN) to extract high-level features from sky images. VGG16 is a well- established architecture known for its effectiveness in image recognition tasks. By processing sky images through the VGG16 network, the model learns to represent the visual characteristics of the sky. These features may include patterns, textures, and color variations that can potentially correlate with air quality conditions.

Air quality data often exhibits trends and patterns over time. To capture these dynamics, Model 2 incorporates historical air quality measurements (e.g., past AQI and pollutant levels) as features. These features are typically pre-processed for appropriate scaling and formatting before being integrated with the image-based features extracted from VGG16. By including historical data, the model can learn from past air quality trends and potentially improve the accuracy of its forecasts.

Once extracted, the image features from VGG16 and the time-series data are combined to form a comprehensive feature vector. This vector represents a rich set of information that the model can leverage for air quality prediction. The feature vector combines the spatial and visual information extracted from sky images with the temporal trends observed in historical air quality data. This comprehensive representation allows the model to learn complex relationships between these factors and predict future air quality.

C. Model 3: Vanilla VGG16

Model 3 takes a simpler approach, utilizing the vanilla VGG16 architecture without any additional feature engineering or processing.

Direct VGG16 Feature Extraction: Unlike Models 1 and 2, Model 3 bypasses the integration of external features. Instead, it directly utilizes the output from the pre-trained VGG16 convolutional neural network (CNN) as its primary feature set. VGG16, as previously mentioned, is a well-established architecture known for its ability to extract high- level features from images. In this case, the features learned by VGG16 from the sky images will be the sole source of information for the model.

Dense Layers for Regression: Following feature extraction by VGG16, Model 3 employs a series of dense layers. Dense layers are fully connected layers commonly used in deep learning models for classification or regression tasks. In AirSense, these dense layers are utilized for regression, aiming to learn the relationship between the extracted image features and the target air quality values (AQI and specific pollutant levels). The final dense layer has a single neuron for AQI prediction and additional neurons for predicting individual pollutant levels.

By employing the vanilla VGG16 architecture without additional feature engineering, Model 3 allows for a baseline comparison with the more complex models incorporating time-series data or color features. This comparison can help assess the effectiveness of these additional features in improving air quality prediction accuracy.

5. Experiment

a. Dataset

This performs several cleaning and transformation steps on a CSV dataframe loaded as df. First, it explores the data by checking for missing values and duplicates, and then gets its summary statistics for more understanding of the dataset.

Then, it tackles missing values in specific columns (if any) by replacing them with the average value using a technique called imputation. This ensures the data is complete.

Then. it creates a new feature, Minutes, by splitting the existing Hour feature at the colon. Additionally, it removes features that might not be relevant for the analysis, such as the original Minutes, the data location (Location), and the Air Quality Index Class (AQI_Class). Finally, it updates the filenames in the Filename column by adding a path prefix.

b.Training and Testing

The dataset uses the VGG16 image feature extractor to extract exactly 512 features from every image. This is then appended with the original dataframe. Then HSV (Hue, Saturation and Value) features are also extracted from all the images and appended in the original dataframe. A new variable features_combined_scaled is defined which consists of the 512 features extracted from the VGG16 extractor and the HSV features. In total 515 features are used to train the model.The model used for training comprises 2 Dense layers which are fully connected layers which are then reduced to another dense layer with 7 neurons. These 7 neurons will be the output of the model.

b. Experiment Results

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25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 102.0818
RMSE is : 10.17528902060438
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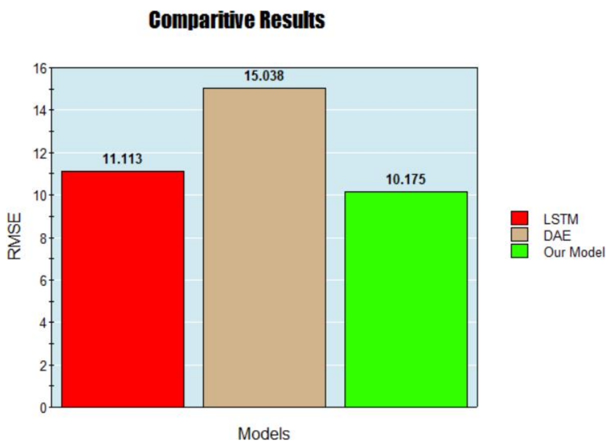
We can see the RMSE of this model comes out to be 10.17528902060438. We calculated this RMSE by using the evaluate function applied on validation data. This RMSE is a good score that indicates we have a good model. This model can be further improved by other means such as dataset augmentation etc.

D. Discussion

We can compare our results with previously implemented models. We can see that the LSTM model[15] implemented by Thanongsak Xayasouk,,HwaMin Lee, Giyeol Lee gives a RMSE of 11.113 for PM10 and 12.174 for PM2.5.DAE model implemented by them gave values which were 15.038 for PM10 and 15.437 for PM2.5. In comparison to this our model works better as we have RMSE equal to 10.175.



6. Conclusion

This paper presented AirSense, a deep learning- based system that forecasts air quality using sky image analysis. AirSense utilizes convolutional neural networks (CNNs) to extract features from sky images and integrates historical air quality data to predict Air Quality Index (AQI) and specific pollutant levels. This research paves the way for a more scalable and potentially cost-effective air quality monitoring approach compared to traditional sensor networks.By exploring various feature extraction techniques, AirSense investigates the impact of incorporating color information and historical data alongside image-based features. The evaluation of these models will guide the development of an optimal configuration for air quality forecasting with AirSense.Future work will focus on training and evaluating AirSense on a large-scale dataset. Additionally, real- world deployment will be explored to assess its effectiveness in providing real-time air quality information. Ultimately, AirSense has the potential to empower individuals with crucial air quality data, enabling them to make informed health decisions and contribute to improved public health outcomes.

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