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Air Pollution Checker Using Image Processing

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Abstract— **In this paper we present a new method to visualize air pollutant through image processing. In order to achieve a realistic effect, we further enhance thus above obtained images in spatial domain. In the proposed method we map the densities of air pollutants to different gray levels, and visualize them by blending those gray levels with background images. The proposed method can visualize large-scale air pollution data from different viewpoints in real time and provide the resulting image with any resolution theoretically, which is very important and favorable for the Internet transmission.**

Keywords: Machine Learning; Air Pollution; Air Pollution Prediction,images

I. INTRODUCTION

Air pollution has become a major issue of modern metropolis because of industrial emissions and increasing urbanization along with traffic jams and heating/cooling of buildings. Monitoring urban air quality is therefore required by municipalities and by the civil society. Air pollution affects human health dramatically. According to World Health Organization (WHO), exposure to air pollution is accountable to seven million causalities in 2012.In 2013; the International Agency for Research on Cancer (IARC) classified particulate matter, the main component of outdoor pollution, as carcinogenic for humans.

Air pollution has become a major issue of modern metropolis, where the majority of world population lives, and adding industrial emissions to the consequences of an ever denser urbanization. As a consequence, the reduction of pollutant emissions is the main aim of many sustainable development efforts, in particular those of smart cities. The main reason for air quality damage is due to the smoke exhaust from industries, pollution generated by power plants and the smoke exhaust from various vehicles. Industrial revolution made humans to advance further into twenty first century. Due to rapid increase in the industries pollution increased. The other reason for the air pollution is vehicles which emits smokes. These smokes accumulate in the environment and cause a serious effect to human beings, damages the ozone layer. This project focuses on air pollution monitoring through image processing. Polluted images are obtained from the environment. These images are compared with the other image which is pollution free. From those images diffusion process is done and ratio factor is obtained from the images. Proposed system works well for higher noise level, which is one of the advantages of the project. Another advantage is Fair noise illumination analysis.

II. RELETED WORK

Air pollution is a modern-day curse, which is an outcome of expanding urbanization and industrialization. It does, however, evolve with interesting transitions in line with economic, technological, and political change. So, to disseminate the impact, the detection of pollution is necessary at the very first place. In “Air Quality Monitoring System Based on Image Processing and Wireless Sensor Networks” addressed how to design and implement an air quality monitoring system that combines image processing. Also this paper presents a comprehensive system that captures images of the environment, processes them todetect pollutants, and communicates this data. ” Air Quality Monitoring and Control System Based on IoT and Image Processing” this paper introduces a smart system that collects data from various sensors, including cameras.The paper “Real-Time Air Quality Monitoring using UAVs and Image Processing” explores the deployment of UAVs equipped with cameras to capture images from different altitudes.The paper presents a method for detecting and quantifying air pollutants using convolutional neural networks (CNNs) applied to image data. The approach shows promise in urban air quality monitoring. The method can help in real-time monitoring and has potential applications in smart cities.The paper “Integration of Satellite Imagery for Regional Air Pollution Assessment.” investigates the integration of satellite imagery and ground-based sensor data for regional air quality assessment. The study demonstrates the feasibility of monitoring large areas. This paper focuses on the combination of satellite imagery with traditional air quality monitoring data.

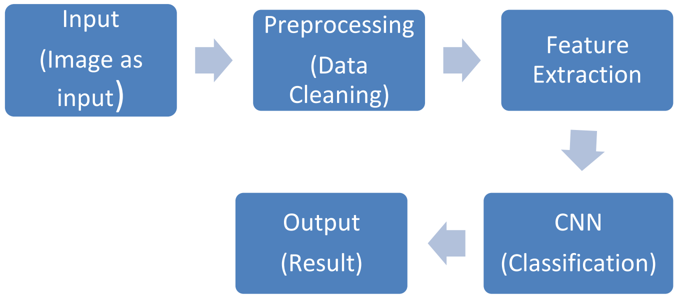

Fig.1 Main components of processing pipeline.

III. PROPOSED SOLUTIONS

A. *Image Preparation*

Image Acquisiton :Set up cameras or sensors to capture images of the environment.Ensure that the cameras are placed in strategic locations to cover the area of interest.We may also collect data from satellites or aerial platforms for a broader perspective.Image Preprocessing: Image preprocessing is essential to enhance the quality of the captured images and remove noise. Common preprocessing steps include:

Noise reduction: Apply filters (e.g., Gaussian or median filters) to remove noise.Image enhancement: Adjust contrast, brightness, and sharpness for better visibility.

Image registration: Align images if you're using multiple cameras or sources.Image Segmentation: Segment the images to identify region of interest (ROI) related to air pollution. For air pollution, this may include identifying smoke, dust, or other pollutants in the image.Common segmentation techniques include thresholding, edge detection, and contour detection.Feature Extraction:Extract relevant features from the segmented regions to quantify pollution levels. These features could include color intensity, particle size, or texture characteristics.Convert the extracted features into numerical data for analysis.Image Classification:Use machine learning or deep learning models to classify the extracted features into different pollution levels (e.g., low, moderate, high).Train your model with labeled data to make predictions about airquality based on extracted features. .Data Integration:Combine image data with other relevant data sources, such as meteorological data, geographical information, or historical pollution data, to improve the accuracy of your air pollution predictions.

Visualization:Present the air quality information in a user-friendly way, such as interactive maps, real-time dashboards, or historical trend graphs.Use visualization techniques to display pollution levels in a comprehensible manner to end-users Real-Time Monitoring:Implement real-time monitoring and update the air pollution status regularly based on newly acquired images.Use alarms or notifications to alert authorities or the public when pollution levels reach dangerous thresholds.Calibration and Validation:Regularly calibrate and validate your system by comparing its predictions with ground-based air quality measurements or other established sources of air quality data.Maintenance and Improvement:Continuously monitor the performance of your system and make improvements as necessary. This may include updating image processing algorithms, retraining machine learning models, or expanding the sensor network.

B. *Feature Extraction Techniques*

Feature extraction for an air pollution checker using image processing is a critical step in analyzing images to assess air quality. It involves identifying and quantifying relevant characteristics or patterns in images that are indicative of air pollution levels. The extracted features provide valuable information for assessing and monitoring air quality. Here's an overview of feature extraction for this purpose. Feature extraction is a process in which relevant information is distilled from images to represent key characteristics related to air pollution. The goal is to transform raw image data into a more compact and meaningful form that can be used for analysis and decision-making.Common types of features used in air pollution monitoring through image processing include color-based features, texture features, particle size distribution, edge features, shape features, statistical features, intensity-based features, frequency domain features, spatial distribution features, motion features, histogram-based features, and deep learning features.Color-based features involve analyzing color properties in images, such as color histograms, color moments, and color correlations. Changes in color composition may indicate the presence of pollutants.Texture features focus on textural patterns within the image and can be extracted using methods like Gabor filters, local binary patterns (LBP), and gray-level co-occurrence matrices (GLCM). These features capture textural variations that may result from air pollution.

Particle size distribution features are important for quantifying the size and shape of particles in the air. Features related to particle count, size distribution, and concentration can be indicative of air quality.Edge features help detect boundaries and edges within the image. Parameters such as edge density, length, and sharpness can provide information about the presence of pollutants.Shape features quantify the shapes of pollution-related regions. For instance, circularity, elongation, or aspect ratio may be relevant depending on the type of pollutants being monitored.Statistical features involve the calculation of statistical properties like mean, variance, skewness, and kurtosis for pixel intensity values within pollution-related regions.Intensity-based features analyze pixel intensity values within regions of interest. These features can include the mean, standard deviation, or median intensity and can provide insights into air quality.

Frequency domain features involve the analysis of image data in the frequency domain. Techniques like Fourier or wavelet transforms can help identify pollution-related patterns or oscillations.cSpatial distribution features assess the spatial layout of pollution-related regions within the image. Characteristics such as centroids, spatial density, and spatial correlation can be informative for air quality assessment.

Motion features are relevant in videos or time-lapse sequences, where changes in pollution concentration over time can be observed. These features may include motion vectors, flow fields, and optical flow analysis. Histogram-based features analyze histograms of various image properties, such as gradients, edges, or color channels. Deviations from expected distributions may indicate the presence of pollution. Composite features involve combining multiple individual features using mathematical operations or feature vectors to create a comprehensive set of information for pollution assessment.

Deep learning features are derived from deep neural networks, where features can be extracted from intermediate layers (e.g., convolutional feature maps) or using pre-trained models for feature extraction.The choice of features depends on the specific pollutants being targeted and the characteristics of the image data. It often requires a combination of domain expertise, experimentation, and data-driven approaches to select the most informative features for air pollution monitoring. These extracted features serve as input data for machine learning or statistical models, allowing for accurate predictions and real-time air quality assessment.

C. CNN Algorithm

A Convolutional Neural Network (CNN) algorithm for an air pollution checker using image processing is a sophisticated deep learning approach that plays a crucial role in the assessment and monitoring of air quality based on image data. The key objective of this algorithm is to automatically and accurately classify and quantify air pollution levels by leveraging the inherent features present in the images. The process begins with data collection and preprocessing. A dataset of images representing diverse air quality conditions is compiled and appropriately labeled to reflect the pollution levels they represent. These images may be captured by monitoring cameras placed in different locations to capture a wide range of environmental scenarios. Image preprocessing techniques are then applied to enhance the quality and consistency of the images. This may involve noise reduction, contrast adjustment, and image calibration to ensure that the input data is in optimal condition for analysis. The heart of the CNN algorithm lies in its architecture design. The CNN model is meticulously crafted to facilitate the recognition of relevant features and patterns within the images that are indicative of varying pollution levels. The architecture typically comprises convolutional layers that serve as feature extractors. These layers apply convolutional filters to the input images, allowing them to identify patterns, edges, textures, and shapes that are relevant to air pollution. This feature extraction process is critical for capturing the distinguishing characteristics of pollutants in the environment.

Subsequently, the training phase is initiated, during which the CNN model learns to identify and understand the visual cues associated with air pollution. Backpropagation and gradient descent algorithms are employed to fine-tune the model's parameters and minimize classification errors. The training dataset, consisting of labeled images, is used to teach the model to make accurate predictions about air quality based on visual information. The model adjusts its internal representations and connections to optimize its performance. The feature extraction process is not limited to the convolutional layers. The intermediate layers within the CNN also play a vital role as feature extractors. These layers automatically learn and extract features such as edges, textures, and object shapes from the input images, enabling the model to capture a wide range of visual characteristics related to pollution. The extracted features are then used for subsequent classification.

Classification is another key aspect of the CNN algorithm. The fully connected layers in the network are responsible for the classification task. They take the features extracted by the convolutional layers and make predictions regarding the air pollution levels depicted in the input images. The output layer of the network typically contains as many nodes as there are pollution level classes, such as low, moderate, and high. Through the activation of these nodes, the model assigns an appropriate pollution level to each input image.To facilitate the learning process, a loss function is used to measure the disparity between the model's predictions and the actual pollution levels provided in the training dataset. Optimization techniques, such as stochastic gradient descent (SGD) or Adam, are employed to minimize this loss and adjust the model's parameters. The optimization process fine-tunes the model's internal representations to enhance its predictive capabilities.

The CNN model is subsequently validated and tested using separate datasets. Validation assesses the model's performance and generalization capabilities, ensuring that it can make accurate predictions on new, unseen data. The testing phase evaluates the model's effectiveness in providing real-time assessments of air quality based on images captured by monitoring cameras. This deployment phase involves real-time monitoring, visualization of results, and potentially alert notifications to inform stakeholders of air quality conditions. In an environment where air quality conditions can change dynamically, the CNN algorithm is subject to continuous improvement. Model performance is continuously monitored, and updates or retraining may be necessary to adapt to changing data distributions, environmental conditions, and evolving pollution patterns. This iterative approach ensures that the air pollution checker remains accurate and reliable in its assessments and contributes significantly to environmental monitoring and pollution management efforts.

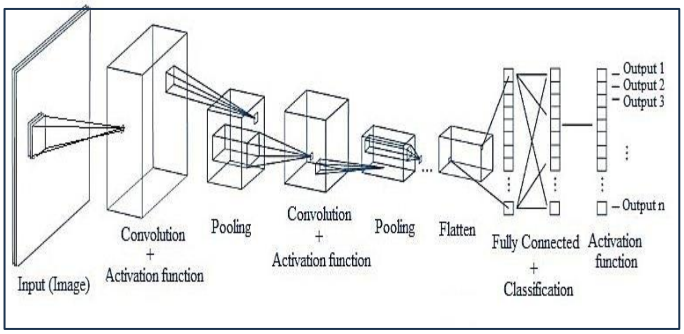

Fig.2 Neural network with many convolutional layers

IV. CONCLUSION AND FUTURE WORK

This article examines the open question of whether it is possible to understand air quality, and in particular air pollution levels, through visual information. As a result of analysis and consideration, the following conclusions are drawn. First, traditional image quality evaluation methods, especially objective measurement indicators of image haze characteristics and deep learning methods, can reflect air quality to some extent and are as effective or more effective than subjective indicators. Second, the proposed air pollution assessment method, namely fastDBCP, is faster and has better correlation with air quality indicators than previous methods, so it can be applied to customized air pollution monitoring systems.

Third, the presented new indicators can be integrated into real air pollution warning systems to warn of worsening air pollution, drizzle monitoring for autonomous driving, tornado monitoring for weather forecasting, or It could be used for wildfire prediction for disaster warning. Of course, our current research still leaves much room for improvement. For example, fast DBCP cannot be validated against other databases because no other publicly available datasets with both subjective image measurements and air quality metrics are found. Additionally, we would like to apply our metrics to video surveillance systems. However, there are currently few databases for evaluating the quality of outdoor images and videos in foggy weather [45], and no data are provided on air quality indicators. Future research should discover and build outdoor image or video databases that provide more accurate air quality metrics. This will allow us to verify the performance of fast DBCP on these datasets and demonstrate or verify the internal relationship between air quality and vision and its mechanisms.

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