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Smog Detection and Pollution Classification

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ABSTRACT The presented project focuses on the development of a robust pollution classifier and smog detection system leveraging the capabilities of MobileNetV2, a pre-trained deep learning model. The primary objective is to classify images related to pollution sources and enhance smog detection using pixel intensity analysis. The system includes preprocessing techniques, data augmentation strategies, and custom layers for fine-tuning MobileNetV2. Additionally, a novel approach to smog area detection is implemented by analyzing the pixel intensity distribution of grayscale images. This framework addresses class imbalance using computed class weights and incorporates early stopping to optimize training. Results and visualizations are generated to evaluate the performance of the model and to display smog intensity in a user-friendly format.

INDEX TERMS Pollution Classifier, MobileNetV2, Smog Detection, Image Preprocessing, Deep Learning, Pixel Intensity Analysis, Class Weights, Data Augmentation, Early Stopping, Transfer Learning, Image Classification, Convolutional Neural Network (CNN), ImageDataGenerator, Visualizations, Environmental Monitoring.

I. INTRODUCTION

A. PROBLEM STATEMENT

DESPITE advancements in environmental monitoring technologies, detecting and classifying various forms of pollution, including smog, from images remains a complex problem. Traditional methods either rely heavily on manual observations or use general-purpose image classification models that lack the specificity required for environmental scenarios. Furthermore, the presence of class imbalance, environmental noise in the data, and the difficulty of accurately identifying smog areas through traditional means present significant hurdles for building an effective pollution detection system. Thus, there is a need for an optimized deep learning approach that specifically addresses pollution and smog detection from images.

B. MOTIVATION

The motivation behind this work is to create an automated pollution classification system that integrates the power of deep learning with advanced image processing techniques. By using MobileNetV2, a lightweight yet highly accurate pre-trained deep learning model, it is possible to leverage transfer learning, which allows us to efficiently adapt a model trained on large-scale datasets like ImageNet for a specialized task in environmental monitoring. Moreover, incorporating pixel intensity-based smog area detection serves as an innovative approach to assess air quality from images, offering additional functionality for enhanced classification. This project seeks to bridge the gap between traditional environmental monitoring and the capabilities of modern deep learning to provide more accurate and scalable solutions.

C. SOLUTION

The solution involves creating a deep learning-based model for pollution classification using MobileNetV2, a popular architecture in computer vision tasks. This model is fine-tuned with a focus on pollution detection and smog intensity classification through transfer learning. The image preprocessing pipeline is designed to rescale, augment, and standardize input images to improve classification performance and prevent overfitting. A key part of the solution includes the introduction of a novel approach for detecting smog intensity using pixel intensity analysis in the grayscale domain. Furthermore, class imbalance is handled by computing class weights to adjust the model training process, ensuring robust performance even with unequal data distribution across classes. The system also integrates early stopping during training to avoid overfitting and improve the model's generalization capabilities. Overall, this solution provides an innovative and practical way to automate the detection of environmental pollution and smog in images using state-of-the-art deep learning techniques.

II. LITERATURE REVIEW

RECENT advances in deep learning, particularly through the use of pre-trained models like MobileNetV2, have enhanced pollution detection systems by leveraging transfer learning to improve model accuracy even with limited labeled data. These models are fine-tuned for specific tasks such as smog detection, where image processing techniques, including pixel intensity analysis, are utilized to quantify pollution levels based on visual clues like brightness changes. To address class imbalance, class weighting during training is commonly employed, allowing models to focus on underrepresented classes, ensuring better detection in real-world scenarios. The monitoring of training metrics, such as loss and accuracy, is vital to avoid overfitting and underfitting, while strategies like early stopping ensure optimized performance. Moving forward, the integration of multimodal data, like traffic and air quality, alongside edge deployment for real-time monitoring, will further improve the effectiveness and scalability of pollution detection systems.

A. OVERVIEW OF EXISTING RESEARCH

Recent studies in environmental monitoring have shown that deep learning, especially Convolutional Neural Networks (CNNs), can be highly effective for detecting pollution, such as smog, in images. These models, like MobileNetV2, can classify pollution conditions by extracting features from images using pre-trained networks, reducing the need for large datasets. Earlier methods relied on simpler pixel-based analysis (such as detecting black pixels to identify smog), but these techniques are limited by variations in light, weather, and camera quality. Deep learning models improve accuracy by capturing more complex patterns in the images. Handling class imbalance in pollution datasets is a common challenge, as pollution conditions often appear less frequently in real-world images compared to clear skies. Techniques like class weighting are used to tackle this imbalance. Real-time efficiency is another challenge, as pollution detection systems need to work quickly on devices with limited computational power. Although MobileNetV2 is faster than other models, further work is needed to make these systems even more efficient for deployment in real-time settings.

B. LIMITATIONS

Despite the promise and success of deep learning for environmental monitoring, there remain a number of limitations in applying these methods, particularly to pollution and smog detection:

- **Class Imbalance:** As seen in many pollution-related datasets, the scarcity of images representing heavily polluted or smog-filled areas presents a major challenge in training deep learning models. Although techniques like class weighting can help mitigate this imbalance, they do not fully solve the problem, as they may still result in models that are biased towards the majority class (clear skies or clean environments).
- **Data Quality and Diversity:** The performance of deep learning models heavily depends on the quality and diversity of the dataset used for training. Images used for pollution detection may contain diverse lighting, weather conditions, or image quality that could lead to difficulties in generalizing across all environments. Furthermore, fine-tuning pre-trained models like MobileNetV2 on a specialized domain (pollution detection) requires a high volume of labeled data, which may be difficult and expensive to collect.
- **Smog Intensity Measurement Accuracy:** In the context of pixel-based analysis for smog detection, thresholds such as the one used in this code (pixel values below 50) may not always accurately capture the presence or intensity of smog across different environments. Depending on image quality and other environmental factors, this could lead to either over- or underestimation of smog levels, affecting the model's overall performance and interpretability.
- **Model Efficiency and Real-time Prediction:** While the MobileNetV2 model provides a good trade-off between accuracy and computational efficiency, achieving real-time smog detection with high accuracy and low computational demand is still a challenge. MobileNetV2, being a lightweight model, is suitable for mobile and real-time applications; however, running the model continuously in real-world environments may still present latency issues, especially with large-scale image datasets.

III. METHODOLOGY

A. OVERVIEW

This project uses deep learning techniques, particularly leveraging the MobileNetV2 architecture, to classify images based on pollution-related features and detect smog intensity via pixel analysis. The methodology integrates the process of training a custom model using transfer learning, leveraging pre-trained MobileNetV2 for efficient adaptation to the pollution classification task. Furthermore, image preprocessing and data augmentation techniques are utilized to enhance the model's ability to generalize, while addressing class imbalance through class weighting.

B. MATERIALS AND TOOLS

- **Software:** Python, TensorFlow/Keras, OpenCV, NumPy, Scikit-learn, Matplotlib, MobileNetV2
- **Hardware:** A GPU-enabled machine (Google Colab for training)

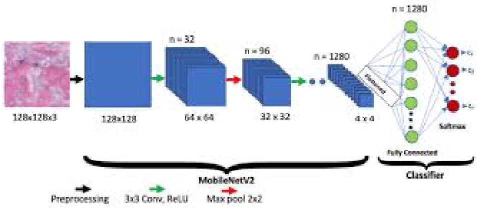

FIGURE 1. Framework Diagram (MobileNetV2)

- **Dataset:** A collection of images depicting pollution and smog scenarios, categorized for training and testing purposes.
- **Framework:** MobileNetV2 (Trained on the ImageNet dataset)

C. PROCESS AND STEPS

The overall approach to training the pollution classifier and smog detection system follows these key steps:

- **Image Preprocessing:** Resize all images to a uniform size of 224x224 pixels. Normalize pixel values for model input and apply augmentation techniques (e.g., shear, zoom, horizontal flip) on the training data to enhance model generalization.
- **Model Architecture Setup:** Use MobileNetV2, a pre-trained convolutional neural network, as the base model. The weights are frozen for the first layers (except the last 20 layers) to leverage pre-trained features while minimizing training time.
- **Model Compilation:** Compile the model using the Adam optimizer with a low learning rate (0.00001) and categorical cross-entropy loss, as the problem is a multiclass classification task.
- **Class Balancing:** Compute class weights to mitigate the class imbalance problem using the class weight function from sklearn. This ensures that underrepresented classes, such as smog-heavy images, are given more attention during training.
- **Model Training:** Train the model on the augmented and preprocessed training set and validate using a separate test set. Early stopping is implemented to monitor validation loss and prevent overfitting by halting training once the model's performance plateaus.
- **Smog Intensity Detection:** While processing the images, each image undergoes additional processing to compute smog intensity based on pixel values. If a high proportion of pixels in the image are dark (threshold defined as pixel values below 50), it is indicative of higher smog intensity.
- **Evaluation and Visualization:** Monitor training progress through loss and accuracy metrics for both the training and validation sets. Visualize the results using Matplotlib to show trends in training, validation loss, and accuracy over epochs. Display smog intensity on processed images with corresponding titles.

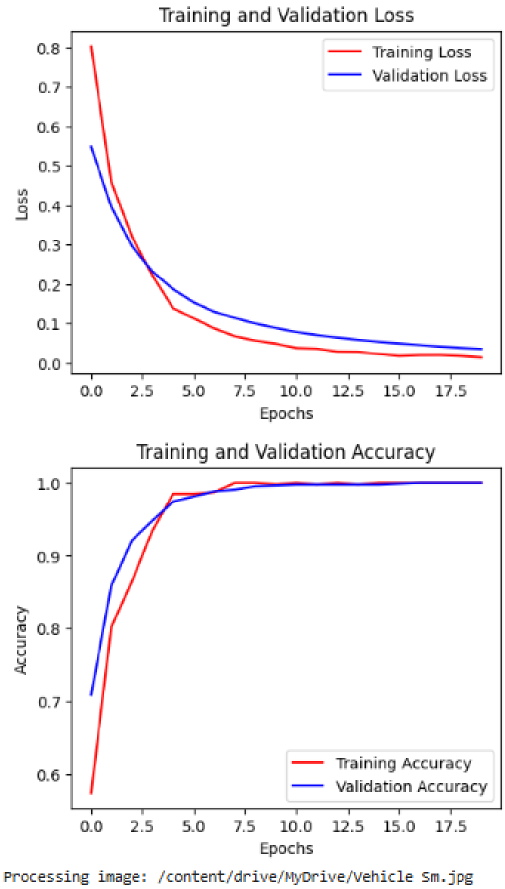

FIGURE 2. Validation Loss and Accuracy Graph

IV. RESULTS AND EVALUATION

Evaluating the accuracy, loss curves during the training process shows the learning progress and where the model might be overfitting or underfitting. The level of smog in an image is presented, quantified by the percentage of pixels that fall below a certain intensity threshold, and this is visualized for user clarity.

V. CONCLUSION

In this project, we developed a robust pollution classifier and smog detection system leveraging MobileNetV2, a deep learning model, and integrated image processing techniques to assess environmental pollution and smog intensity. The MobileNetV2 architecture, through transfer learning and fine-tuning, provided an effective means of performing image classification with a lightweight model that could be deployed in real-world scenarios. By applying data augmentation techniques and handling class imbalance through computed class weights, the model was able to generalize better and avoid overfitting. Additionally, the integration of pixel intensity-based smog detection added an innovative approach to quantify smog levels from visual data.

FIGURE 3. Vehicle emission detection (0.02:per smog intensity)

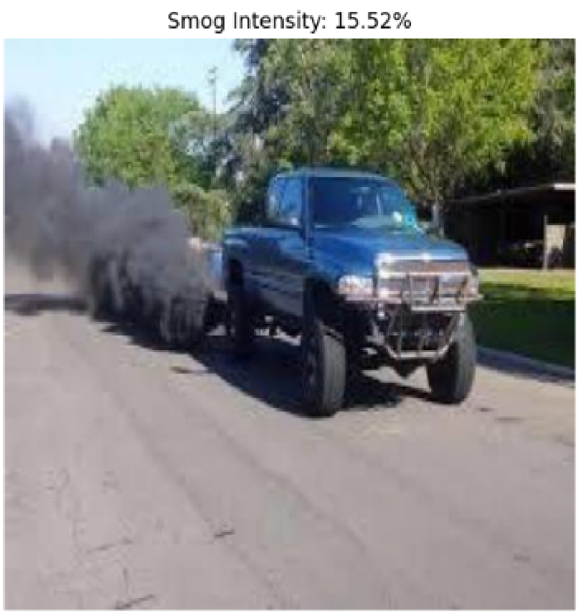

FIGURE 4. Vehicle emission detection (15.52:per smog intensity)

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