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Image Based Real – Time Air Quality Monitoring Using CNN

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***Abstract*— A sudden surge in concern about increasing air pollution and its impact on public health and environmental sustainability has led to a greater demand for environmental monitoring. The proposed real-time Air Quality Index (AQI) prediction system relies on deep learning, specifically the VGG16 convolutional neural network, to evaluate and predict AQI levels from real-time images. This work trains a large dataset not only to streamline image analysis but also empowers users to track air quality data with high performance accuracy and scalability. This work also uses Windy Webcams API for real-time images and location. This makes environment monitoring more effectively all over the world. The system's usability with interactive user interface and accuracy provides comprehensive insights to users. An accuracy of 0.78022 has been achieved by using VGG16.**

***Index Terms*— Air quality index, deep learning, VGG16 model, real-time environmental monitoring, image processing, Windy.**

I. INTRODUCTION

Through Air Quality Index (AQI) metrics we can obtain essential knowledge regarding air pollution concentration levels at a regional scale that reveals conditions between clean air and polluted air. The Air Quality Index serves as an essential risk indicator for health because its values depend on environmental factors such as PM2.5, PM10, NO_2, SO_2 and CO as well as O_3. The categorization of AQI values extends from good conditions to hazardous levels gives authorities and individuals advanced knowledge needed to take preventive actions.

The Air Quality Index (AQI) measures air pollution levels and is represented on a scale from 0 to 500. The categories are:

- Good (0-50): Represents good air quality.
- Moderate (51-100): Satisfactory for almost everyone.
- Unhealthy for sensitive groups (101-150): People with respiratory or heart conditions may be affected.
- Unhealthy (151-200): Everyone may begin to experience health effects.
- Very unhealthy (201-300): Health alert, everyone may experience more serious health effects.
- Hazardous (301-500): Health warnings of emergency conditions.

The AQI model employs a comprehensive image analysis approach through webcams to provide secure air pollution level measurements. Our data processing pipeline reinforces strict protocols for pre-processing images to remedy the issues caused by image noise and suboptimal resolution and pixel distortion. The model combines multiple noise reduction techniques with normalization procedures and feature extraction methodologies which enables the production of meaningful data and facilitates better insights.

The work incorporates VGG16 which represents a sophisticated 16-layer deep convolutional neural network (DCNN). The architecture has efficient activation functions together with filters. Through its successful evaluation process the model identifies significant image features for assessment.

The DCNN system conducts extensive training through numerous data instances with diverse AQI levels present. The model derives enhanced discriminative pattern identification capabilities for air quality detection with improved precision from its design. Our organization has deployed webcams for delivering real-time web data which extends the ability of our model to analyze and detect pollutants. The webcams capture dynamic environmental conditions that let our system securely measure particulate density indicators with smoke quantities and smog metrics. This implementation increases platform efficiency and enlarges its capabilities to identify airborne pollutants.

II. REVIEW OF LITERATURE

Britton (2024) [1] emphasized the turn potential of deep learning technologies to improve the accuracy and efficiency of environmental assessments, promoting for their integration in pollution management. The research highlighted how deep learning algorithms can process vast amounts of data from various sources, including sensors and satellite imagery, to provide more accurate and close evaluations of air quality and pollution levels. By integrating these advanced technologies into pollution management strategies, Britton argued that stakeholders can make more informed decisions regarding environmental policies and interventions. The study also revealed the challenges associated with implementing deep learning in real-world scenarios, such as data quality, model interpretability, and the need for interdisciplinary collaboration.

Chakma et al. (2017) [8] brought a new use of deep convolutional neural networks (CNNs) for image-based air quality analysis. Their findings stated that visual data can effectively correlate with air quality metrics, providing an innovative and intuitive approach to pollution monitoring. Furthermore, the study highlighted the potential for real-time monitoring and public engagement through visual data, making air quality information more relatable and actionable for communities.

Lefèvre and Piantanida (2016) [4] highlighted the importance of open-source tools in allowing access to deep learning methodologies for environmental monitoring. Their research promoted collaboration among researchers, encouraging a community-driven approach to tackling air quality issues.

Zelic and Sable (2021) [3] further contributed to the field by employing deep learning methodologies to analyze various forms of pollution data. Their work highlighted the ability of these techniques to uncover patterns that traditional methods may overlook, enhancing our understanding of environmental challenges.

Bird, Klein, and Loper (2009) [6] addressed the integration of Python in environmental pollution research. This focused on its capabilities in data analysis and visualization. Their work illustrated how programming tools can facilitate the processing of large datasets, enabling researchers to derive meaningful insights.

Gonzalez and Woods (2018) [7] researched on digital image processing techniques for environmental pollution monitoring. Their study revealed the role of visual data in assessing pollution levels, particularly in urban environments. By utilizing image processing algorithms, the authors demonstrated how visual data can be effectively analyzed to provide immediate insights into air quality conditions. This method complements traditional data collection techniques, offering a more comprehensive understanding of pollution dynamics. Their findings suggested that integrating digital image processing with other monitoring methods can enhance the overall effectiveness of environmental assessments.

III. OBJECTIVE OF THE STUDY

The objective of this study is to develop a real-time AQI prediction system that utilizes deep learning techniques for image-based air quality analysis addressing growing concern on air pollution and its impact. The study focuses on designing a VGG16-based model for processing real-time images to determine AQI levels. Additionally, the system integrates geospatial data from Windy Webcams to enhance location-specific predictions. The backend is implemented using a robust web framework, ensuring efficient processing and user authentication. The system has been evaluated for accuracy, reliability, and scalability to provide real-time air quality updates.

IV. SCOPE OF THE STUDY

The study encompasses the development, implementation, and evaluation of a real-time AQI prediction system using deep learning. It explores the integration of external APIs for geolocation and webcam data while emphasizing the importance of environmental monitoring. The research aims to provide an alternative approach to traditional sensor-based air quality assessments.

V. METHODOLOGY

The study adopts a deep learning-based approach to AQI prediction employing the VGG16 convolutional neural network model for image analysis. The following methods are used in this work:

1. Preprocessing real-time images to enhance quality and extract relevant features.
2. Integrating geospatial data from Windy Webcams to improve location-based AQI predictions.
3. Developing a structured backend using a web framework to manage image processing and authentication securely.
4. Testing system performance for reliability, scalability and accuracy in real-world conditions.

The proposed system provides a comprehensive and automated approach to real-time air quality monitoring, promoting environmental awareness and data-driven decision-making.

The implementation of this project work is carried out in the following steps:

1. Data Source: Open-source dataset from Kaggle with 12240 images. The AQI value of respective images in the dataset is given.
2. Data Preprocessing: The preprocessing techniques like image resizing, image normalization, image augmentation are adopted.
3. Model Architecture: VGG16 a Deep Convolution Neural Network is used with the following features:
   - 3.1. Input layer: size- 64 x 64 x 3 for RGB image
   - 3.2. Convolution layers:
     - 3.2.1. conv layer 1 & conv layer 2 - (64 filters,3 x 3 kernel , ReLU activation function)
     - 3.2.2. Max Pooling layer 1 - 2 x 2 pooling with stride 2
     - 3.2.3. conv layer 3 & conv layer 4- 128 filters 3 x 3 kernel , ReLU activation function
     - 3.2.4. Max Pooling layer 2 - 2 x 2 pooling with stride 2
     - 3.2.5. conv layer 5,conv layer 6 & conv layer 7- 256 filters 3 x 3 kernel , ReLU activation function
     - 3.2.6. Max Pooling layer 3 - 2 x 2 pooling with stride 2
     - 3.2.7. conv layer 8,conv layer 9 & conv layer 10 - 512 filters 3 x 3 kernel , ReLU activation function
     - 3.2.8. Max Pooling layer 4 - 2 x 2 pooling with stride 2
     - 3.2.9. conv layer 11,conv layer 12 & conv layer 13 - 512 filters 3 x 3 kernel , ReLU activation function
     - 3.2.10. Max Pooling layer 5 - 2 x 2 pooling with stride 2
   - 3.3. Fully connected layers:
     - 3.3.1. FC Layer 1 & 2 - 4096 neurons, ReLU activation
       - 3.3.1.1. FC Layer 3 - 1000 neurons (for classification), softmax activation.

4. Training Procedure: The dataset is trained with the following parameters:
    4.1. No .of epochs: 10
    4.2. Batch size: 16
    4.3. Optimizer: linear
    4.4. Loss value: 73.305
    4.5. Value loss: 508.7753
5. Evaluation Metrics: These metrics like accuracy, root mean square error (RMSE), r2 score, f1 score are implemented.
6. Implementation: The following languages and framework is used in the project work.
    6.1. Backend: Python programming language ,tensorflow and keras, numpy, pandas(libraries used).
    6.2. Frontend: HTML, CSS, Javascript
    6.3. Framework: Django

The Architecture of VGG16 is shown in figure1.

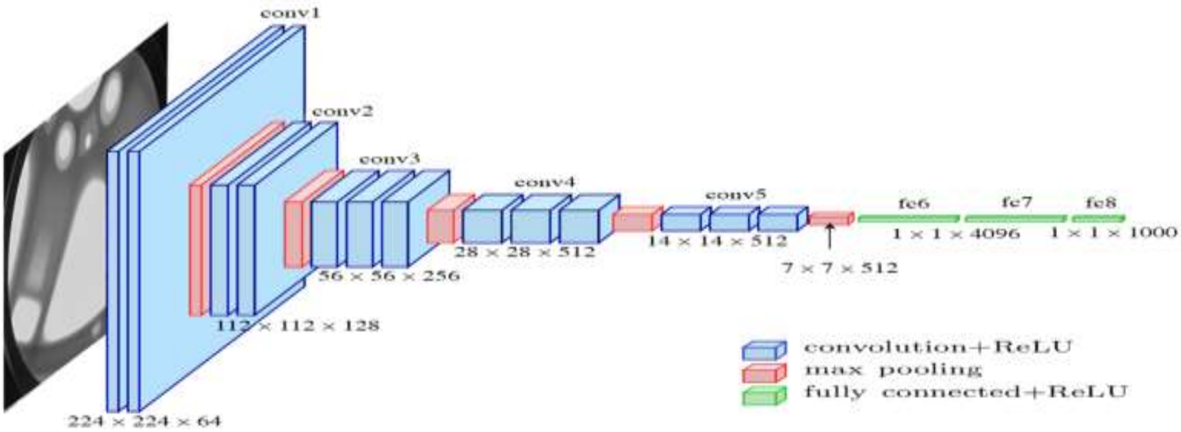

Fig. 1: Architecture of VGG16

VI. Description of Metrics

- **RMSE** (root mean square error) metric is used in regression to measure the difference between predicted and actual values.

  This indicates how well predicted values matches with actual values through assessing prediction differences.
- **R^2 score** (Coefficient of Determination) is a number between 0 and 1 that measures how well a statistical model predicts an outcome. It provides information on the capability of a model to explain target variable variations.
- **F1 score** is the harmonic mean (a kind of average) of precision and recall. For classification problems the F1 Score functions as the precision and recall combined through harmonic means calculation.
- **Loss value:** It can measure prediction differences from real values in order to identify better model performance. It helps the model to improve during training.
- **Value Loss**: The future reward estimation process in reinforcement learning (RL) typically applies value loss methods alongside regression.
- **Accuracy:** The accuracy metric records how many correct predictions emerge from total predictions especially when it involves classification problems. Higher accuracy is better.

VII. PROPOSED MODEL:

In this project, we pre-trained on large dataset of images for feature extraction of the object. The proposed model is developed using VGG16, a traditional CNN algorithm designed for image classification tasks with transfer learning. It consists of 16 layers including input layer, hidden layers (convolutional layer and convolution filters) and 3 dense layers. Based on image intensity, noise, PSNR, images are preprocessed with acceptable dimensions of (64x64). The image of a location is based on the real-time environmental conditions. This model includes image acquisition, image preprocessing and image transformation. Image preprocessing is at the low level. The fundamental purpose is to improve image contrast to weaken or suppress the influence of various kinds of noise as far as possible. It is important to retain useful details in the image enhancement and image filtering process. This project focuses on real-time AQI prediction by accessing webcam images and giving an efficient result.

The working part of our project work is shown in figure2.

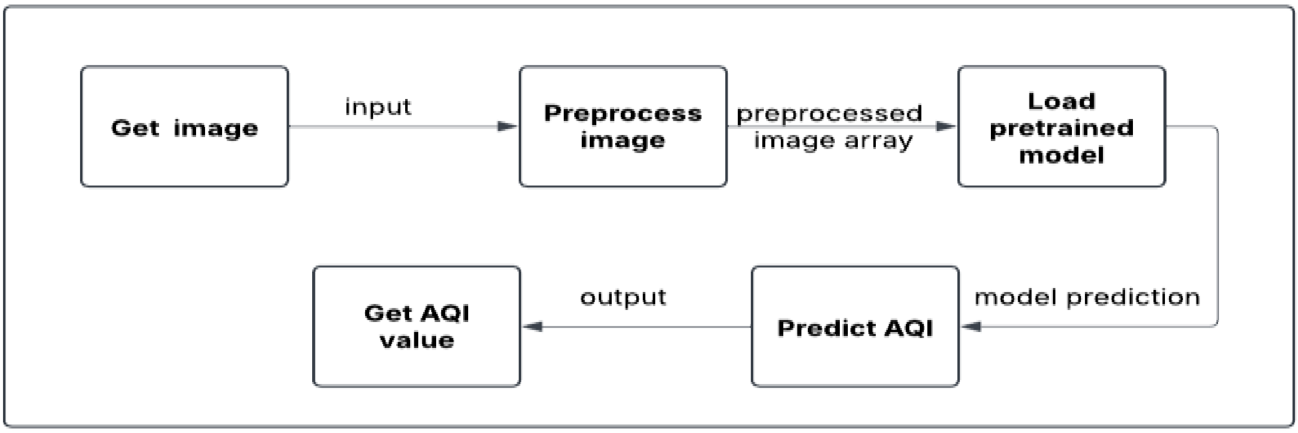

Fig. 2 : Model workflow

VIII. RESULT AND ANALYSIS

The developed model was evaluated on a test dataset which resulted in effective AIR QUALITY INDEX prediction. The model achieved an accuracy of **78%** by using **VGG16**, convolutional neural network (CNN) model. This accuracy is improved when comparing to existing models like RESNET50. The model classifies AQI class of the inputs with effective measures of RMSE, R2 Score, F1 Score etc. The confusion matrix, model loss on train and validation data, comparison of true values and predicted values are depicted in the following figures 3,4 and 5. From the visualization, we concluded that the predictions or estimated values of test data are utmost near and accurate. This contributes to the best fit training of VGG16 model. The plot from figure 4, suggests that the model loss has been decreased from 7000 to 300 by the end of last epoch of training data. The validation of data loss has been improved from 3000 to 900. As a result, these contribute to well-trained model.

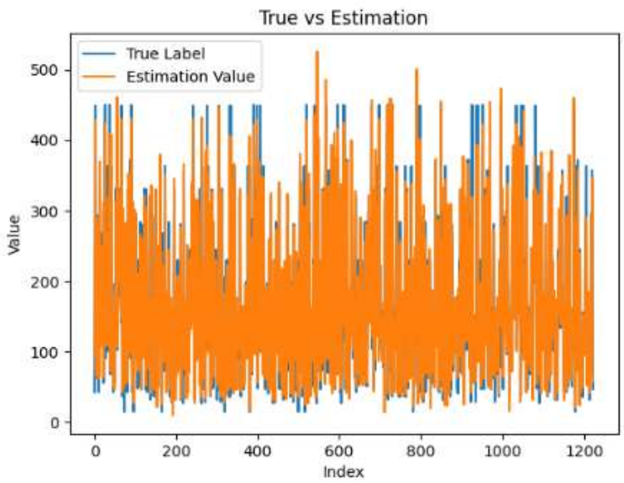

Fig. 3: True vs Estimation values

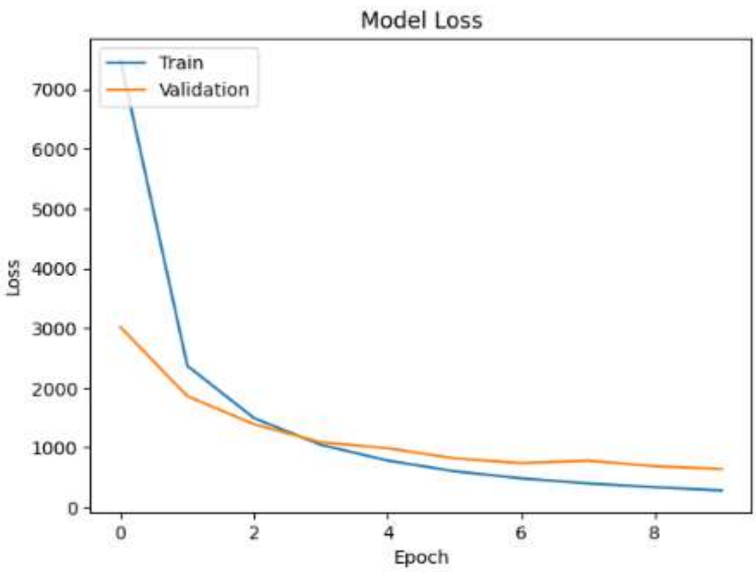

Fig. 4: Model loss on train vs validation data

The confusion matrix gives an overall picture of the model based on classification classes. In this confusion matrix, rows represent true labels whereas columns represent predicted labels. The matrix consists of several cells, each indicating the number of instances for a given combination of actual and predicted labels.

Fig. 5: Confusion matrix as heatmap

Summary of confusion matrix:

- Diagonal cells represent correct predictions and other cells represent deviated predictions.
- Class 0: 130 are classified accurately while 47 predictions are misclassified as class 1
- Class 1: 398 are classified accurately while 71 predictions are misclassified as class 0 and class 2
- Class 2 : 130 are classified accurately while 90 predictions are misclassified as class 0,class 1 and class 3
- Class 3: 116 are classified accurately while 13 predictions are misclassified as class 2
- Class 4 : 27 are classified accurately while 30 predictions are misclassified as class 0,class 2 ,class 3 and class 5.
- Class 5 : 23 are classified accurately while 18 predictions are misclassified as class 2,class3 and class 4.

The metrics obtained by using VGG-16 for the project work is tabulated in table1:

PARAMETERS	**VALUES**
Loss Value	73.3050
Value Loss	508.7753
RMSE	22.020068
R^2 Score	0.95395
F1 Score	0.738530
Accuracy	**0.78022**

Table 1: Metrics obtained

IX. CONCLUSION & FUTURE SCOPE OF WORK

Real-time AQI prediction systems have succeeded in accurately integrating location-based data from APIs such as Windy Webcams with the VGG16 model. This integration enables the system to accurately predict real-time air quality. The system has an intuitive and reactive interface, allowing users to access air quality data by selecting locations and uploading images for analysis. The backend operated by Django ensures the system is efficient at data processing, secure user authentication, and scalability. By providing reliable and accessible information about air quality, this system promotes environmental awareness, enabling users to make informed decisions to contribute to a healthier living environment and improve public health. This study opens up more possibilities of deep learning and real-time data integration to address environmental challenges and promote positive responses to air quality concerns. The future scope of work ensures to predict AQI using our model alongside OpenStreetMap when Windy webcams are unavailable in particular locations.

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