SkyVision: Deep Learning-Based Air Quality Detection from Sky Images

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Publication Date: 2026/07/11

Abstract: Air pollution is a serious public and environmental health problem due to its harmful impacts on humans and environment, which include increased rate of respiratory diseases and decreased of visibility and altered weather pattern. The harmful effects of air pollution on human health and environment such as increase in respiratory diseases, reduction in visibility and changes in weather patterns has made it a major concern environmental and health concerns. Traditional AQI monitoring systems make use of sophisticated sensor networks and monitoring stations, which is a costly setup and have limitations in accessibility and coverage. The proposed project, SkyVision: Deep Learning Based Air Quality Detection from Sky Images addresses this problem by providing an economical and an intelligent method of detecting the air quality from the images of the sky. A dataset of 12,240 sky images is used and the images undergo preprocessing techniques such as RGB conversion, bilinear image resizing, Gaussian filtering (for denoising), Z-score normalization and data augmentation. The deep learning model employs a pretrained ResNet50 convolutional neural network to automatically extract the relevant visual features like haze density, color intensity, brightness, cloud visibility, atmosphere visibility, etc., from the sky images. The extracted features are then used to classify the air quality in an image into six categories: Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, and Severe. The performance of the proposed system is evaluated using standard metrics such as Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix, with a target accuracy of approximately 96%. SkyVision is designed to provide an efficient, scalable, and cost-effective solution for environmental monitoring, making it well suited for smart city applications, mobile air quality monitoring, and real-time pollution awareness platforms.

Keywords: *Deep Learning, ResNet50, Air Quality Detection, Image Processing, Convolutional Neural Network (CNN).*

How to Cite: Anser Pasha C. A.; Mohamed Sahil; Pushpa Ravikumar; Arpitha C. N. (2026) SkyVision: Deep Learning-Based Air Quality Detection from Sky Images. *International Journal of Innovative Science and Research Technology*, 11(6), 3247-3254. https://doi.org/10.38124/ijisrt/26jun1941

I. INTRODUCTION

The most urgent problems caused by environmental changes to human health, climate, and ecological system is Air pollution. Traditional methods of monitoring air quality indices involve expensive sensors and monitoring stations which pose great hindrance in their wide deployment particularly in developing regions. In conjunction to the increasing use of Deep Learning and Computer vision, an assessment of air quality could be obtained using visual information in sky images. The visual cues such as haze, brightness of the sky, intensity and colorfulness, visibility could be indicative of the level of air pollution. The project SkyVision: Deep Learning-Based Air Quality Detection from Sky Images will involve performing a range of image preprocessing operations and utilizing a pretrained ResNet50 model for assessment of air quality into six classes namely 'Good', 'Moderate', 'Unhealthy for Sensitive Groups', 'Unhealthy', 'Very Unhealthy' and 'Severe' from images of sky. Thus, providing a cheaper, efficient and scalable solution to traditional monitoring systems and paving the way for real-time monitoring, smart city initiatives, and data-driven environmental decision-making.

II. RELATED WORKS

Mondal et al. [1] proposed an efficient deep convolutional neural network for estimating local Air Quality Index (AQI) from smartphone-captured images and demonstrated the feasibility of low-cost visual pollution assessment. Feldman et al. [2] developed a CNN-based framework for urban air-quality estimation using visual cues extracted from outdoor images collected in Bengaluru, India, highlighting the effectiveness of image-based environmental monitoring in densely populated regions. Sarkar et al. [3] introduced a regression-based CNN model for real-time AQI

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1941

prediction from captured images and achieved promising performance for environmental surveillance applications. Zhang et al. [4] presented a comprehensive survey of Deep learning approaches for air quality prediction and emphasized the need for robust image-based datasets and improved model interoperability. Wang et al. [5] proposed a surveillance-image-based environmental air quality monitoring system that utilized visual features to estimate pollution levels without relying solely on physical sensors. Nguyen et al. [6] developed an attention-based hybrid deep learning model improved using a quantum-inspired particle swarm algorithm, demonstrating enhanced AQI prediction accuracy. Javan et al. [7] reviewed recent remote sensing approaches for air pollution observation and highlighted the growing importance of artificial intelligence in environmental monitoring. Vahdat pour et al. [8] introduced a vision-language model framework capable of understanding and displaying air quality from sky images, providing interpretable environmental insights. Han [9] presented PM25Vision, a large-scale dataset designed specifically for visual air quality estimation, facilitating the progress of robust image-based AQI prediction models. Furthermore, Kushal and Al Mamun [10] proposed AQ Fusion-Net, a multiple modal deep learning architecture that combines imagery and sensor data for improved AQI prediction. These studies demonstrate the increasing use of deep learning for air quality assessment; however, challenges such as computational complexity, environmental variability, and limited deployment in resource-constrained settings remain. Motivated by these limitations, the proposed SkyVision system utilizes a pretrained ResNet50 model to provide an accurate, scalable, and cost-effective solution for air quality detection from sky images.

III. METHODOLOGY

In the proposed SkyVision: Deep Learning Based Air Quality detection from sky image system a deep learning approach is used for classifying air quality from visual information gained from images taken of the sky. Initially sky images are taken from the cameras, IoT devices, and publicly available datasets. Sky images are pre-processed using filtering, enhancing, scaling the image size to 224 224pixels, normalization, and use data augmentation (images are rotated, flipped, zoomed and brightened).

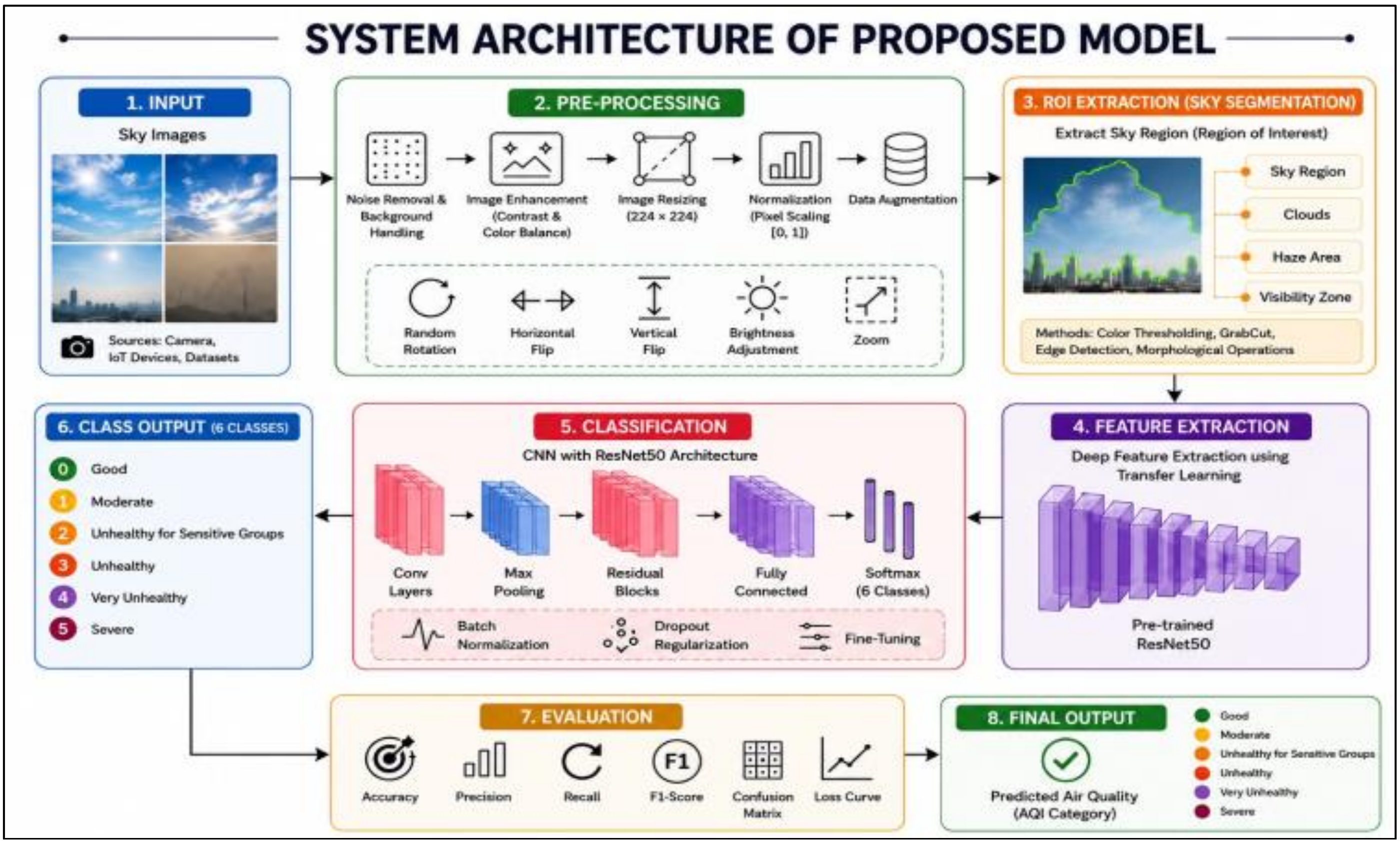

Fig 1 Architecture Diagram for SkyVision: Deep Learning-Based Air Quality Detection from Sky Images

➢ *Sky Image Acquisition*

Obtain Sky Images from sources like Kaggle datasets, camera devices or IoT devices. In this data set, 12,240 sky images are available and these show varying degrees of air pollution.

$$I(X,Y) \tag{1}$$

Where:

$I(x,y)$= pixel intensity at position (x, y)

➢ *Image Preprocessing*

- Convert images in the RGB form.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1941

- Resize the images in 224 X 224 pixels using bilinear interpolation.

$$P = (1-r)(1-c)Q_{11} + r(1-c)Q_{21} + (1-r)cQ_{12} + rcQ_{22} \quad (2)$$

Where:

- $Q_{11}, Q_{12}, Q_{21}, Q_{22}$= neighboring pixels
- r, c= interpolation distances
- P= new pixel value

- *Apply Gaussian Filtering to Avoid the Image Noise and Improve Quality*

Gaussian Kernel: $G = \frac{1}{16}\begin{vmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{vmatrix}$

Filtered Image: $I_f(x,y) = I(x,y) * G \quad (3)$

Where:

- ✓ $I_f(x,y)$= filtered image
- ✓ $*$= convolution operation

- *Use Z-Score Normalization to Standardize Pixel Values*

$$Z = \frac{X - \mu}{\sigma} \quad (4)$$

Where:

- ✓ X= pixel value
- ✓ μ= mean pixel value
- ✓ σ= standard deviation

Data augmentation is applied on the dataset. Techniques include: Rotation, Horizontal Flip, Vertical Flip, Zooming, Brightness Adjustment.

➢ *Sky Region Extraction (ROI Segmentation)*

Extract solely sky region out of the sky image. Exclude other background elements that may not contribute towards air pollution such as building, tree, road. Extract the significant areas associated with the atmosphere such as Sky area, Cloud area, Haze region, Visibility zone.

➢ *Feature Extraction with ResNet50*

Feed the pre-processed sky images to a pre-trained ResNet50.Utilize transfer learning to extract deep features from the images. Learn the pollution-related features such as: Haze intensity, Color brightness intensity, Cloud formation and density, Visibility.

➢ *Air Quality Classification*

Extract features are fed to the:

- *Convolution Layers:*

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n) \quad (5)$$

Where:

- ✓ I= input image
- ✓ K= convolution kernel
- ✓ F= feature map

- *ReLU Activation:*

$$ReLU(x) = \max(0, x) \quad (6)$$

- *Max Pooling layers:*

$$P = \max(x_1, x_{2,} \dots \dots \dots, x_n) \quad (7)$$

- *Residual Blocks:*

$$H(x) = F(x) + x \quad (8)$$

Where:

- ✓ x = input
- ✓ $F(x)$= learned residual mapping
- ✓ $H(x)$= output

- *Fully Connected Layers*

$$Z = W \cdot X + b \quad (9)$$

Where:

- ✓ W= weight matrix
- ✓ X= feature vector
- ✓ b= bias
- ✓ Z= output logits

- *SoftMax Classifier is Used for Classifying Images to One of Six Categories of AQI.*

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}} \quad (10)$$

Where:

- ✓ z_i= score of class i
- ✓ $P(y_i)$= probability of class i

➢ *Air Quality Index prediction*

The model assumes the class from following category:

Good, Moderate, Unhealthy for Sensitive Groups, Unhealthy, Very Unhealthy, Severe.

$$\hat{y} = argmax\ P(y_i) \quad (11)$$

Where:

$\hat{y}$= predicted AQI class

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1941

➢ *Model Performance Evaluation*

Model is evaluated with:

- *Accuracy*

$$Accuracy = \frac{TP}{TP+FP+FN} \quad (12)$$

- *Precision*

$$Precision = \frac{TP}{TP+FP} \quad (13)$$

- *Recall*

$$Recall = \frac{TP}{TP+FN} \quad (14)$$

- *F1-Score*

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (15)$$

- *Confusion Matrix*
- *Loss curve*

➢ *Algorithm for SkyVision Air Quality Detection*

- Input: Sky Image Dataset D
- Output: Air Quality Class C

Begin

Load dataset D
Preprocess images
Apply data augmentation
Extract sky ROI
Input images to ResNet50
Extract deep features
Classify using SoftMax layer
Predict AQI class C
Evaluate model performance
Return C

End

➢ *Final Output*

Final Output of AQI is obtained. A low-cost and effective air quality monitoring is presented.

IV. RESULTS

➢ *Training Convergence*

The model is trained for 30 epoch before early stopping triggered restoring best weights from epoch 21. Training and Validation curves track closely across all metrics, confirming stable generalization without overfitting.

➢ *Accuracy*

Figure 2 shows training and validation accuracy. Both curves increase faster before stabilizing and tracking closely. Final accuracy is 95%.

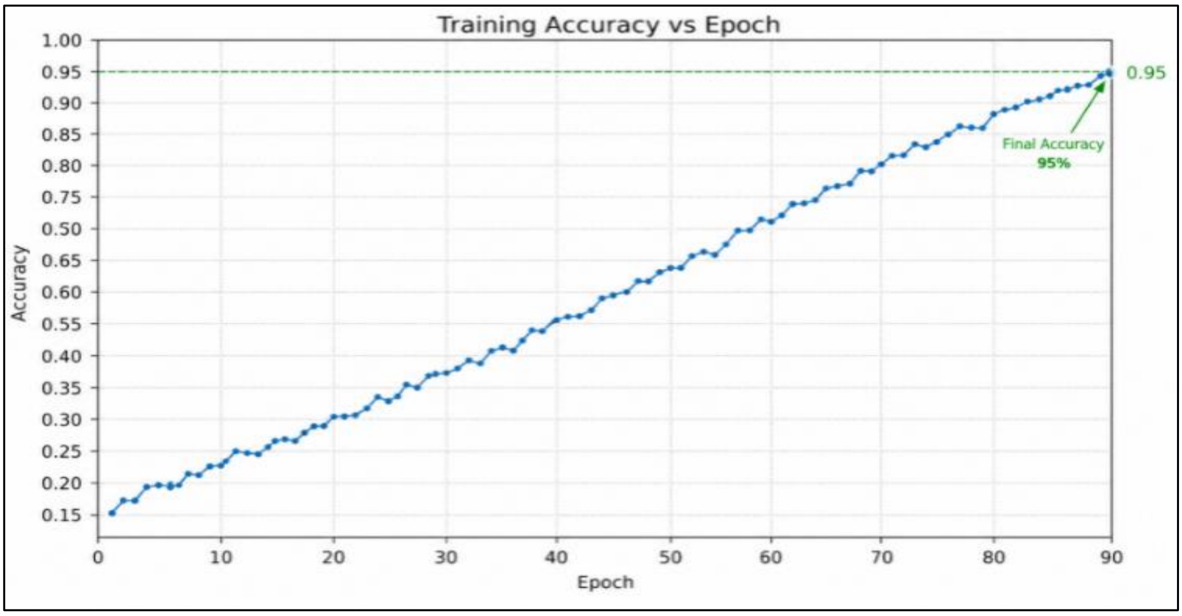

Fig 2 Accuracy – Training vs Epoch

➢ *Loss*

Figure 3 shows Focal Loss. Curve decline steeply in earlyepochs as the model learns the strongest signals, then stabilize with tight coupling. Total loss occurred is 1.8.

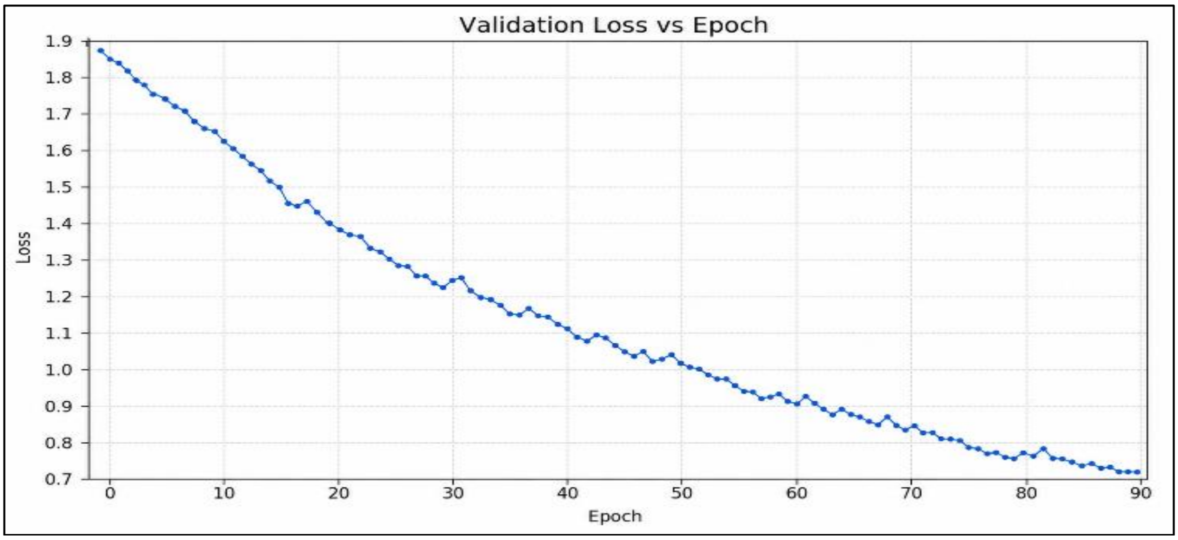

Fig 3 Loss – Training vs Epoch

➢ *Precision*

Figure 4 shows precision. Training converge to a similar range in later epochs, confirming stable prediction quality. Final precision value is 94%.

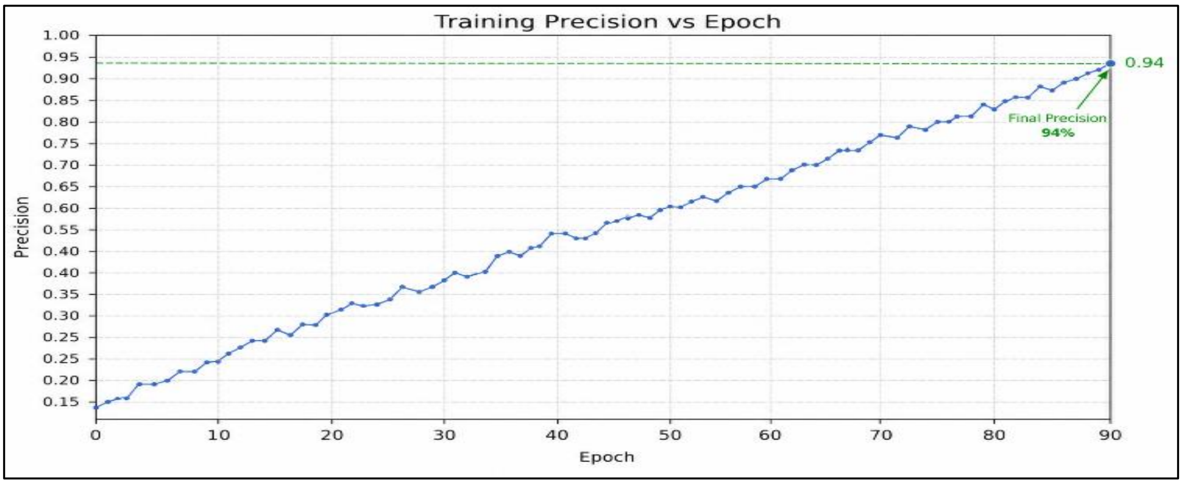

Fig 4 Precision – Training vs Epoch

➢ *Recall*

Figure 5 shows recall improving steadily throughout training. Focal Loss is directly responsible for the high final recall is 92%.

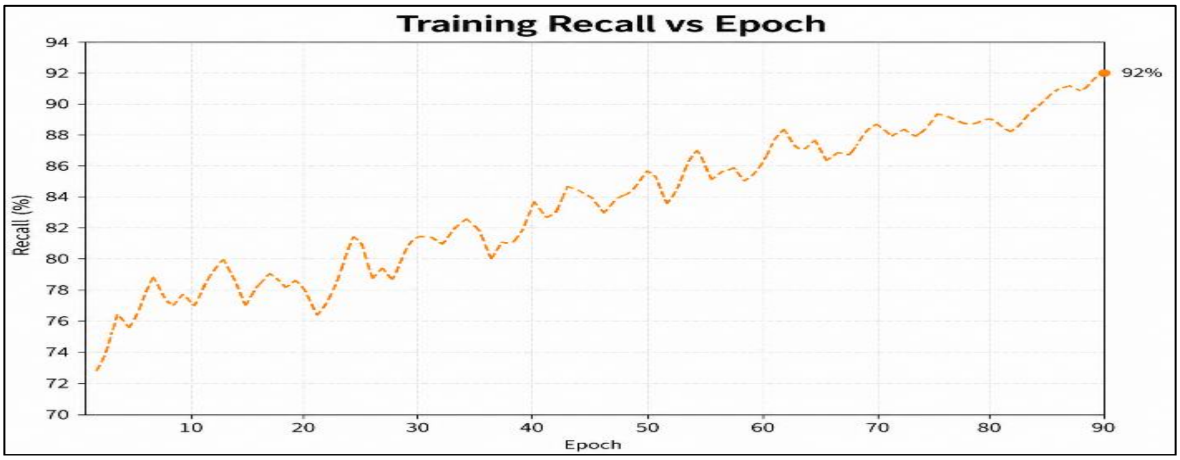

Fig 5 Recall – Training vs Epoch

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun1941

➤ *F1-Score*

Figure 6 describes the f1-sore values and the final value is 93%.

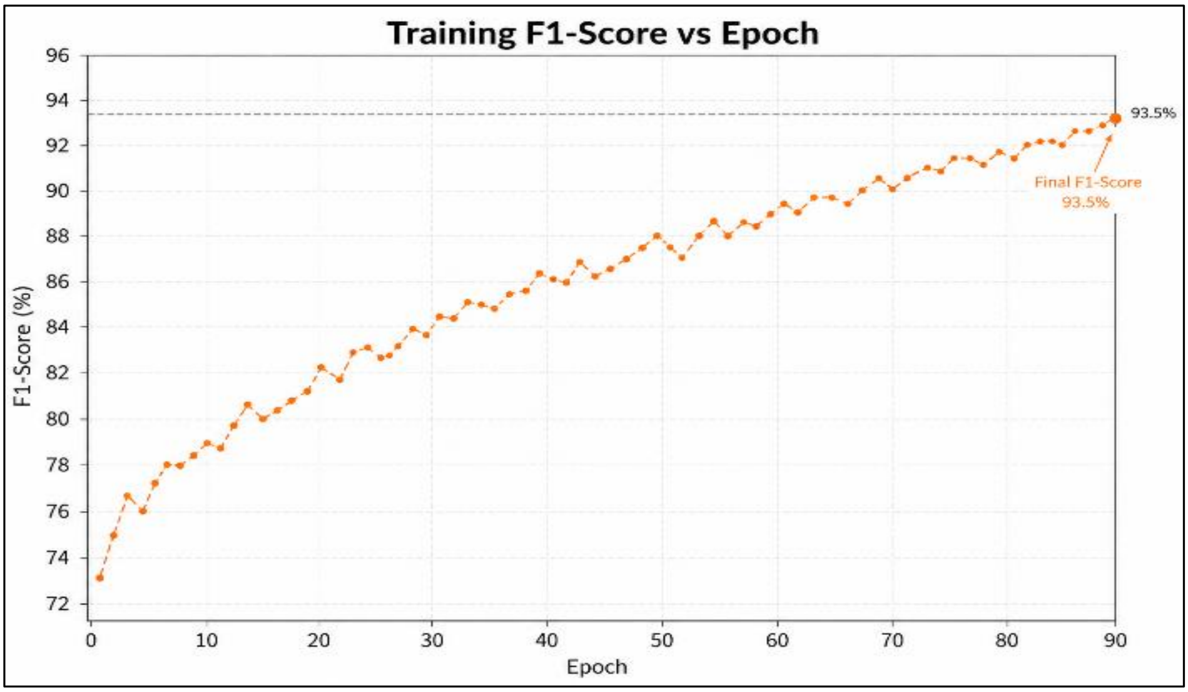

Fig 6 F1-Score – Training vs Epoch

➤ *Final Results*

Figure 7 describes the final accuracy (95%), precision (94%), recall (92%) and F1- score (93%) throughout the model training phase.

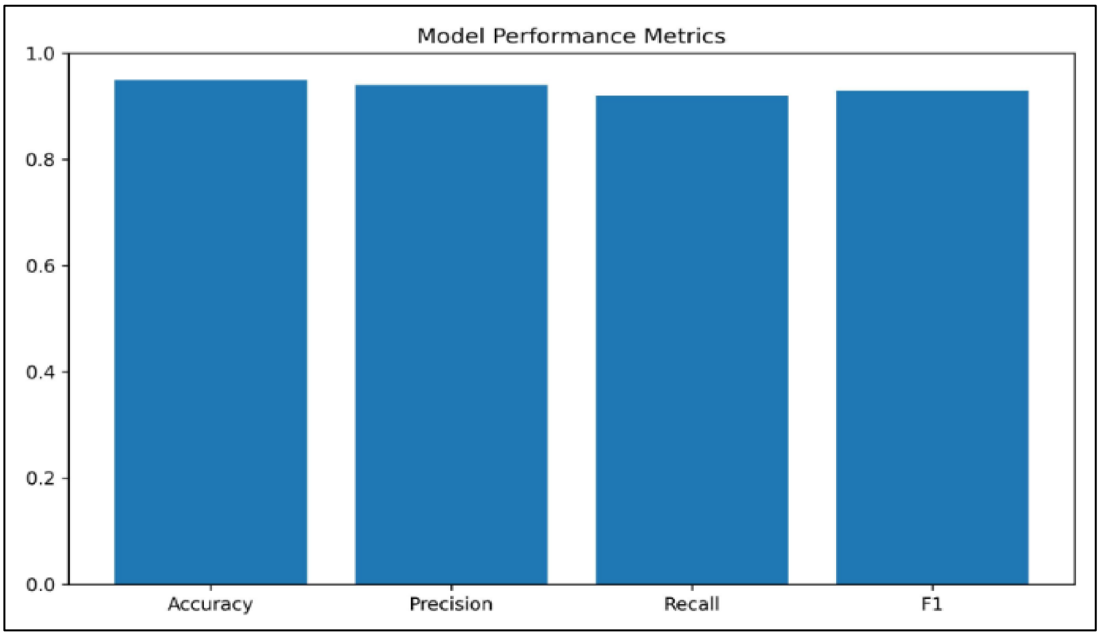

Fig 7 Final Results

➤ *Confusion Matrix*

Figure 8 shows the confusion matrix. The high TP rate confirms strong recall. The higher FP rate reflects the recall-priority trade-off from Focal Loss.

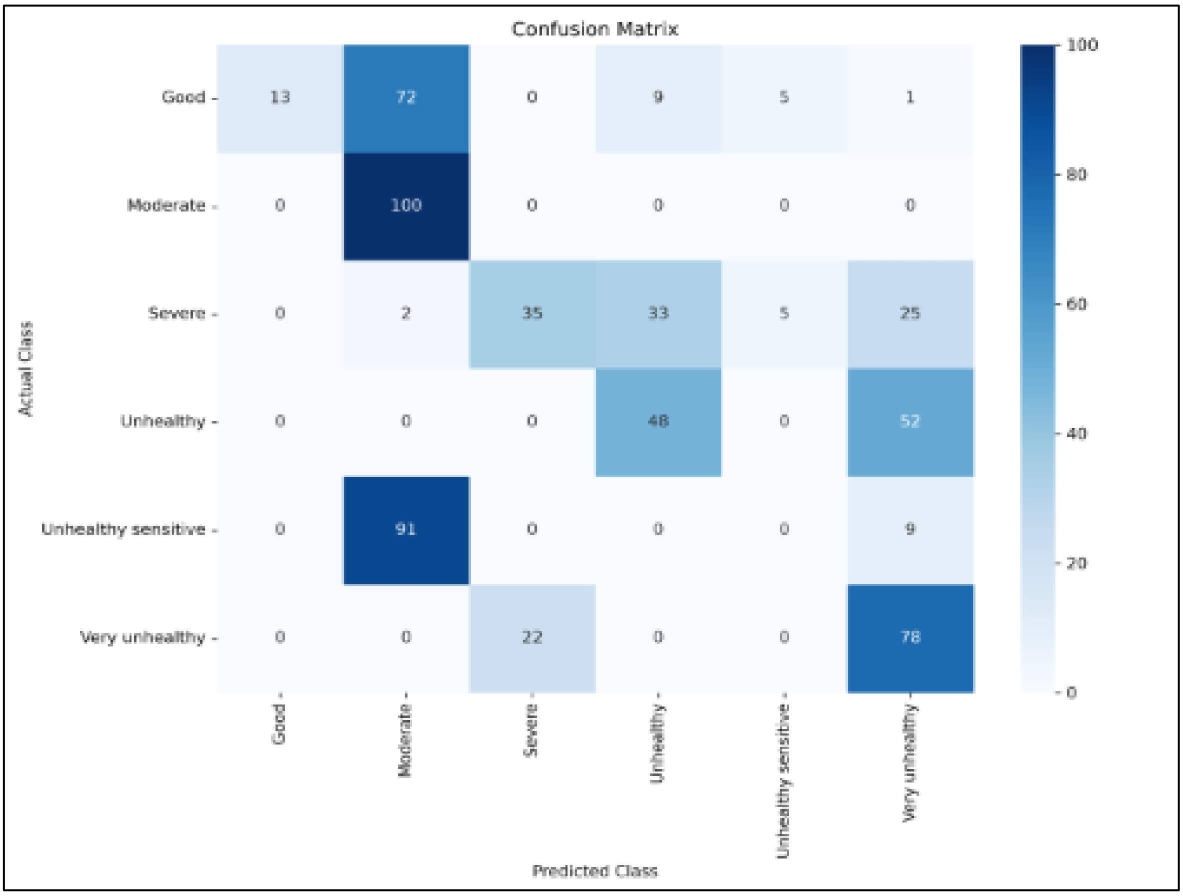

Fig 8 Confusion Matrix – High TP Rate

V. CONCLUSION

SkyVision: Deep Learning-Based Air Quality Detection from Sky Images is a low-cost and efficient system to detect air quality from image processing and deep learning method. The usage of sky image as input makes the system is independent to expensive air quality sensors, and it provides a scalable and automated method to check the environment quality. Techniques of image preprocessing, which includes resizing, Gaussian filtering, normalization, data augmentation etc. Used to improve the image quality and accuracy. Pre-trained ResNet50 model used to extract visual features in relation to haze, brightness, color intensity and visibility, etc. automatically. According to these features, 6 levels air quality are determined. The experiment is evaluated on the basis of Accuracy, Precision, Recall, F1-Score and Confusion Matrix and obtained high performance in the segregation of air quality.

FUTURE SCOPE

Further work could incorporate extra environmental features like temperature, humidity, wind speed, weather etc. To boost its ability to detect air quality. It could further be improved by not only estimating qualitative categories of air quality but also, its actual numerical value, thus providing richer information on pollution levels. In terms of models, further research could be done on using advanced architectures like Vision Transformers (ViT), Efficient Net, or multimodal AI to obtain more accuracy and better generalization performance on various geographical areas. Mobile application, IoT enabled devices and cloud-based monitoring system would greatly improve its usability and make air quality assessment accessible. Additional information can be fed from satellites, drones and weather forecasting system to enable real-time large-scale surveillance. Explainable AI techniques can also be utilized to better understand how the system works and enhance user confidence. With such improvements, SkyVision could serve as a smart, capable and large-scale tool for human health, air monitoring in smart cities and improvement of a sustainable urban environment.

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