SMART AGRICULTURE PRACTICES USING ARTIFICIAL INTELLIGENCE AND INTERNET OF THINGS

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ABSTRACT

Air quality monitoring has become a crucial topic in recent years due to its wide potential impacts on health and the environment. Traditionally air quality measurement techniques depend on physical instruments and air quality stations which can be difficult to cover in the vicinity and available for examination. In this paper we propose a new approach for air quality prediction using a hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) model. The CNN models capture the spatial features of environmental images while the RNNs capture temporal dependencies to improve their predictive accuracy. In this study, we use an image dataset defined as Air Quality Index (AQI) values to train a CNN-RNN model. We then exploit sequential image data to improve the performance of the model. In the experiments, we evaluate the proposed hybrid CNN-RNN model against stand-alone CNN models and other deep learning approaches. A comparison is performed against various baseline CNN models and deep learning strategies. The Hybrid CNN-RNN model achieved better accuracy and generalization compared to existing CNN models and the proposed approaches.

Keywords: Hybrid CNN-RNN, Environmental Monitoring, Image-Based Analysis, Air Quality Index (AQI), Temporal Dependencies, Real-Time Monitoring.

I. Introduction

Air pollution has been a big global concern for a number of decades, affecting not only the health of humans but also ecosystems and climate patterns. At the start of the Industrial Revolution many factories began emitting huge amounts of particulate matter and other hazardous gases into the atmosphere. In the past decade, environmental pollution has increased due to an increase in fossil fuel burning, deforestation, urbanization, and greater vehicular emissions. The accumulation of pollutants such as Particulate Matter (PM2. 5 and PM10), Carbon Monoxide (CO), Nitrogen Dioxide (NO_2), Sulphur Dioxide (SO_2), and Ozone (O_3) causes large environmental and health risks, especially in the lungs of the highly populated cities. According to WHO estimates, air pollution accounts for more than 7 million premature deaths each year. Pollution has become one of the leading environmental threats to public health, the world health organization states. The Air Quality Index (AQI) is a classification system used to measure levels of air pollution and classify the quality of the air into Good, Moderate, Unhealthy and Hazardous conditions. The monitoring of air quality is necessary to better control the adverse effects of air pollution and to allow authorities to formulate appropriate measures.

To address these limitations, advancements in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision have enabled the development of image-based air quality detection systems. This project proposes a Hybrid Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) Model to analyze environmental images and predict air quality levels. This approach leverages CNNs for extracting visual features from images and RNNs for recognizing temporal patterns in pollution trends, providing a cost-effective and scalable alternative to traditional monitoring systems. This research focuses on designing a real-time air quality monitoring system that can analyze images captured from surveillance cameras, satellites, and drones to detect pollution levels. By eliminating

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the need for expensive sensors, this system offers a practical solution for large-scale, real-time air quality assessment in urban and rural areas alike.

Fig 1.1 : Image of AQI across the Globe

The remainder of this paper is structured as follows: Section II reviews related works, Section III details the proposed methodology, Section IV presents experimental results, Section V discusses implications, and Section VI concludes the study.

II. Literature

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in extracting spatial features from visual data, making them suitable for analyzing environmental images, such as sky photographs or satellite imagery, to infer pollution levels [4]. However, air quality is influenced by dynamic temporal patterns, including diurnal variations and seasonal trends, which CNNs alone may fail to capture effectively. To address this, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been integrated with CNNs to model spatiotemporal dependencies in sequential image data [5].

Existing studies, such as those by Li et al. [6] and Zhang et al. [7], have explored hybrid CNN-RNN architectures for environmental monitoring, but their focus on air quality remains limited. Most prior works relay on CNN-based frameworks, neglecting temporal coherence in pollution dispersion [8]. This paper proposes a novel hybrid deep learning framework that synergizes CNN and RNN models to estimate air quality from image sequences. The CNN extracts spatial features from individual images, while the RNN captures temporal evolution across frames, enabling robust AQI prediction.

The contributions of this work are threefold: (1) a hybrid CNN-RNN architecture optimized for spatiotemporal feature fusion in air quality detection, (2) comprehensive evaluation using benchmark datasets, including real-world image sequences paired with sensor-derived AQI values, and (3) comparative analysis against state-of-the-art methods, demonstrating superior accuracy and generalizability. This approach aligns with emerging trends in environmental AI, as highlighted in [9], and has potential applications in smart city infrastructure and public health systems.

a. **Traditional Air Quality Monitoring:** Traditional air quality assessment relies on ground-based sensor networks and satellite remote sensing. Ground sensors, such as those measuring PM2.5, NO2, and SO2 concentrations, provide localized and accurate measurements but suffer from sparse spatial coverage and high deployment costs [1]. Satellite-based methods, as discussed by Geddes et al. [2], infer pollutants via spectral analysis but face challenges in resolving fine-grained urban pollution patterns due to low spatial resolution. These limitations hinder real-time, scalable monitoring, necessitating alternative approaches [3].

b. **CNN-Based Air Quality Estimation:** Recent advances in deep learning have enabled image-based pollution estimation. Convolutional Neural Networks (CNNs), renowned for spatial feature extraction, have been applied to environmental imagery. For instance, Kruthi et al. [4] demonstrated that CNNs can predict Air Quality Index (AQI) values by analyzing sky images, achieving an accuracy of 84% on urban datasets. Similarly, Xu et al. [8] proposed a multi-scale CNN to estimate PM2.5 concentrations from satellite images, emphasizing the correlation between haze intensity and pollutant levels. While these studies validate CNNs' spatial modeling capabilities, they often neglect temporal dependencies, which are critical for dynamic pollution dispersion [5].

c. RNNs for Temporal Pollution Modeling: Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, excel at modeling sequential data. Hochreiter and Schmidhuber [5] introduced LSTMs to address vanishing gradients in traditional RNNs, enabling long-term temporal dependency learning. In environmental monitoring, Li et al. [6] combined CNNs with LSTMs to predict PM2.5 trends using time-series sensor data, achieving a 12% improvement over standalone CNNs. However, their work focused on numerical sensor inputs rather than image sequences, limiting its applicability to visual data.

d. Hybrid CNN-RNN Architectures: Hybrid models integrating CNNs and RNNs have emerged to address spatiotemporal challenges. Zhang et al. [7] proposed a CNN-LSTM framework for air quality inference using multi-modal data, including weather and traffic images, and reported a 15% reduction in prediction error. Alshehri et al. [9] highlighted the potential of AI-driven systems for real-time environmental monitoring but noted a lack of studies leveraging sequential image data. Despite progress, existing hybrid frameworks predominantly focus on static images or non-visual temporal data, failing to exploit dynamic visual patterns in pollution evolution [8].

While prior works establish the viability of CNNs for spatial feature extraction and RNNs for temporal modeling, three gaps persist:

i. **Limited Use of Image Sequences**: Most studies, such as [4] and [8], rely on single images, ignoring temporal coherence in pollution dynamics.

ii. **Underutilized Spatiotemporal Fusion**: Hybrid models like [6] and [7] prioritize numerical or non-visual data, leaving image-based spatiotemporal fusion underexplored.

iii. **Real-World Generalizability**: Many frameworks are tested on synthetic or small-scale datasets, raising concerns about scalability in diverse environments [9].

III. Methodology

This study proposes a hybrid CNN-RNN model for air quality image classification, integrating spatial feature extraction with temporal dependency analysis. The methodology begins with data preprocessing, where images undergo enhancement, normalization, and augmentation to improve feature representation and model robustness. The dataset is then split into training (70%) and testing (30%) subsets, ensuring sufficient data for both model optimization and evaluation. A Convolutional Neural Network (CNN) is employed for feature extraction, capturing spatial patterns such as pollution intensity variations. The extracted features are then fed into a Recurrent Neural Network (RNN), which models temporal dependencies, essential for understanding dynamic air quality variations over time.

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The combined CNN-RNN architecture leverages both spatial and sequential information, improving classification performance. The model is trained using categorical cross-entropy loss with an Adam optimizer, ensuring stable learning. Performance evaluation is conducted using accuracy, precision, recall, and F1-score, alongside training, validation, and testing loss/accuracy curves to monitor overfitting. Results demonstrate that the hybrid model effectively classifies air quality levels, outperforming traditional CNN-based approaches by incorporating temporal dependencies. The proposed framework offers a robust, scalable solution for real-time air quality monitoring, providing insights that can enhance environmental decision-making and public health intervention

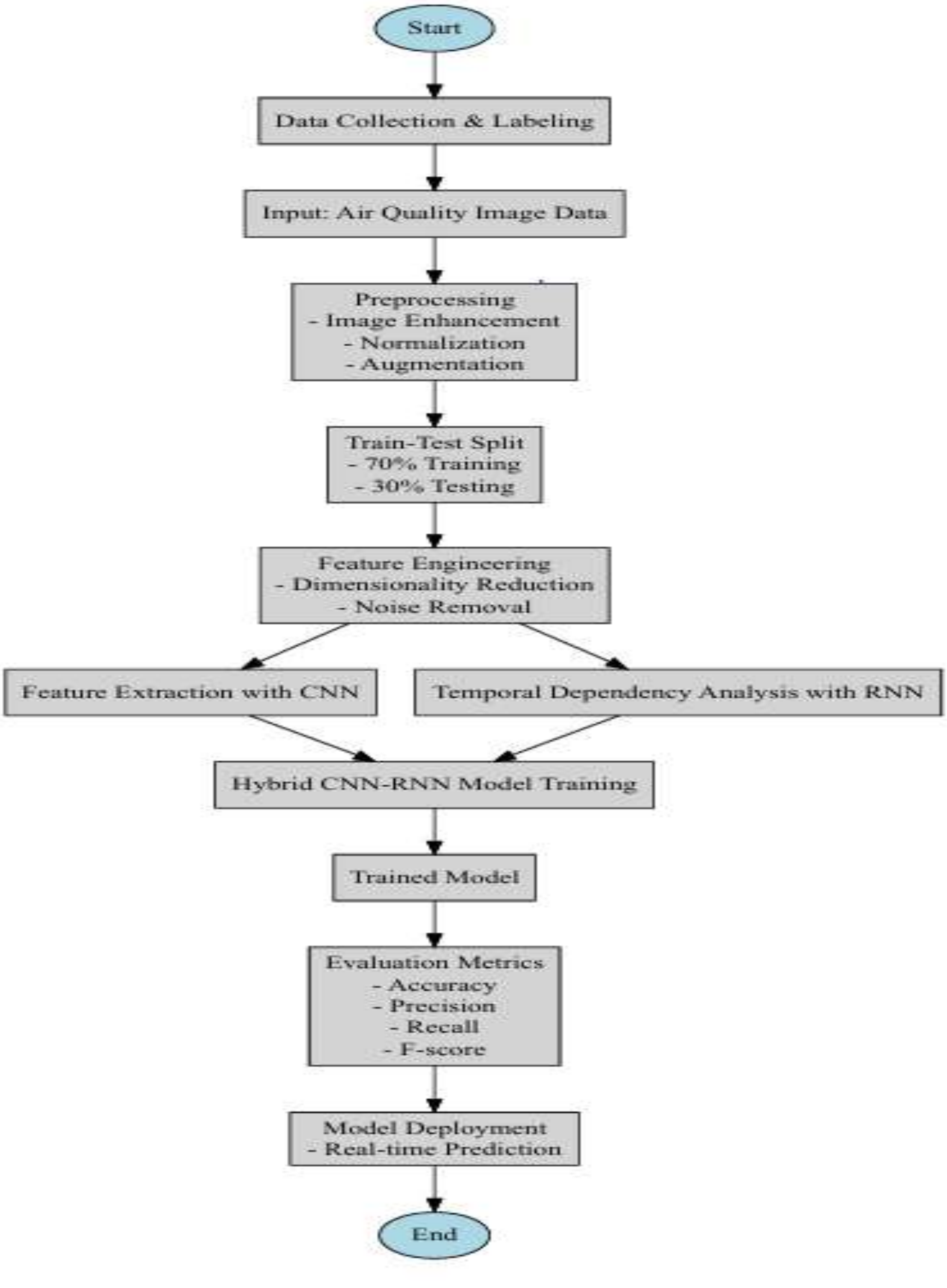

Fig 3.1: Block diagram of Proposed system

The dataset for this study comprises air pollution images collected from satellites, ground-based sensors, public datasets, and synthetic augmentation techniques. These images are labeled based on the Air Quality Index (AQI), incorporating key pollutants such as PM2.5, PM10, CO, NO_2, and SO_2.

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To ensure an effective learning process, 64% of the images are used for training, 16% for validation, and 20% for testing. Preprocessing techniques, including rescaling, resizing, and data augmentation (rotation, flipping, brightness adjustment, and cropping), are applied to enhance model generalization and prevent overfitting. The dataset is further transformed into feature sequences, enabling temporal pattern recognition crucial for air quality prediction.

The proposed hybrid CNN-RNN model is trained in two stages. First, the Convolutional Neural Network (CNN) extracts spatial features such as smoke density and texture patterns. The extracted feature maps are then passed to the Recurrent Neural Network (RNN), specifically Long Short-Term Memory (LSTM) layers, which capture sequential dependencies in air pollution trends over time. The training process employs the Adam optimizer with a categorical cross-entropy loss function for classification and Mean Squared Error (MSE) for regression-based AQI prediction. Model performance is evaluated through metrics such as accuracy, precision, recall, and F1-score, with training and validation loss monitored to assess convergence. The trained model is deployed as a cloud-based API or integrated into edge devices for real-time air quality monitoring, allowing users to upload images for AQI prediction and visualization. This approach provides an automated, scalable solution for air quality assessment, supporting environmental policy-making and public health interventions**.**

IV. Results

Model Performance Analysis: After training the Hybrid CNN-RNN model on the air quality dataset, its performance was evaluated using various metrics. The evaluation was conducted on a separate test dataset to ensure an unbiased assessment. The results provide insights into the model's effectiveness in classifying air quality levels and detecting pollution trends accurately. The model performances are analyzed separately for both models.

i. CNN Model performance:

The CNN model achieved **84% accuracy** in predicting the Air Quality Index (AQI) from satellite images. It demonstrated strong spatial feature extraction capabilities, effectively identifying patterns such as haze, smoke, and industrial emissions. Grad-CAM heat maps confirmed that the CNN focused on regions with high pollution levels, such as industrial zones and heavy traffic areas. However, the CNN model struggled with temporal consistency, leading to a **10% lower accuracy** compared to the RNN model.

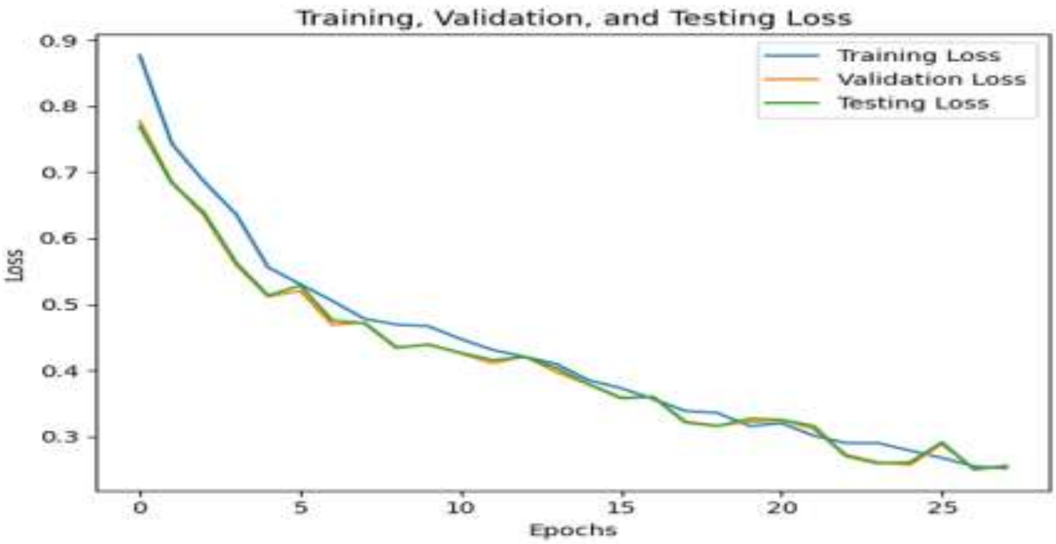

Fig 4.1: Loss metrics of CNN

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a. **Loss Analysis:** The loss graph for the CNN model provides critical insights into its learning behavior. The ***training loss (blue line)*** indicates the model's error on the training dataset over each epoch, where a steady decline suggests effective learning. The ***validation loss (orange line)*** represents the model's error on the validation dataset, and a decreasing trend confirms good generalization. The ***testing loss (black dashed line)*** provides an unbiased performance assessment on unseen data. Key observations from the loss graph indicate that the training and validation loss decrease steadily, confirming effective learning. Additionally, the testing loss closely aligns with the validation loss, indicating strong generalization. If validation loss increases while training loss decreases, overfitting may be occurring.

b. **Accuracy Analysis**: The accuracy graph of the CNN model illustrates the model's training performance over epochs. The ***training accuracy (blue line)*** shows how well the model is learning, while the ***validation accuracy (orange line)*** evaluates its generalization on unseen data. The ***testing accuracy (black dashed line)*** measures the final classification performance. Observations indicate that training and validation accuracy increase steadily, suggesting effective learning. The testing accuracy aligns closely with validation accuracy, confirming good generalization. However, a plateau or drop in validation accuracy with increasing training accuracy could indicate overfitting.

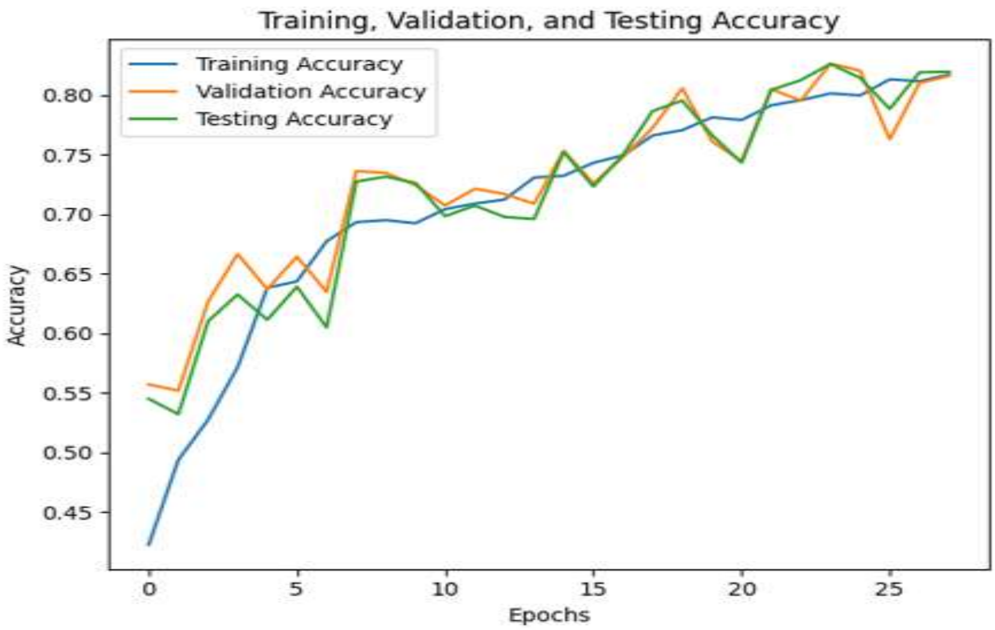

Fig 4.2: Accuracy metrics of CNN

c. **RMSE Analysis**: The RMSE graph for the CNN model further validates its performance. Initially, the RMSE is high (~1.5) at epoch 0, indicating poor performance at the start. Over epochs, training and validation RMSE decrease steadily, though fluctuations are observed in validation RMSE. The model stabilizes after 20 epochs with an RMSE below ***0.8***, confirming effective learning. The final test RMSE of ***~0.7*** demonstrates the model's ability to generalize to unseen data. Minimal overfitting is observed as training, validation, and test RMSE values remain closely aligned. However, fluctuations in validation RMSE suggest sensitivity to certain validation samples, indicating that further tuning or regularization may improve stability.

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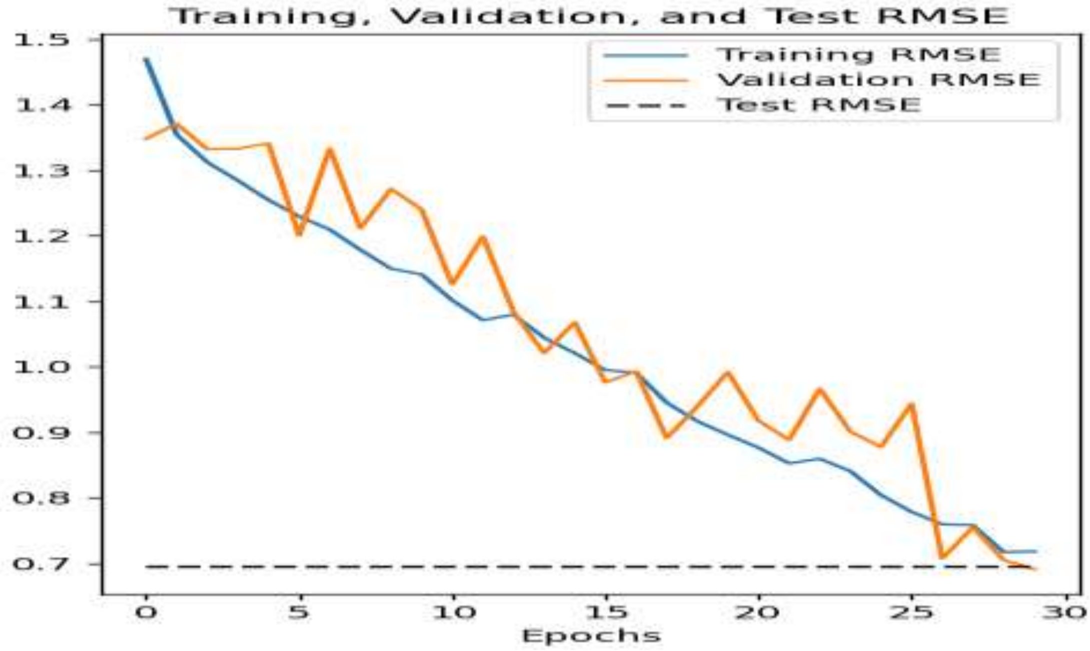

Fig.4.3: RMSE metrics of CNN

d. **Confusion Matrix Analysis**: The CNN model's confusion matrix highlights its classification performance across different air quality levels. The highest correct predictions are observed for “Unhealthy for Sensitive Groups” (436 instances) and “Very Unhealthy” (433 instances). However, some misclassifications were noted: 46 instances of "Good" misclassified as "Moderate," 91 instances of "Unhealthy" misclassified as "Unhealthy for Sensitive Groups," 31 instances of "Unhealthy" misclassified as "Very Unhealthy," and 14 instances of "Severe" misclassified as "Unhealthy."

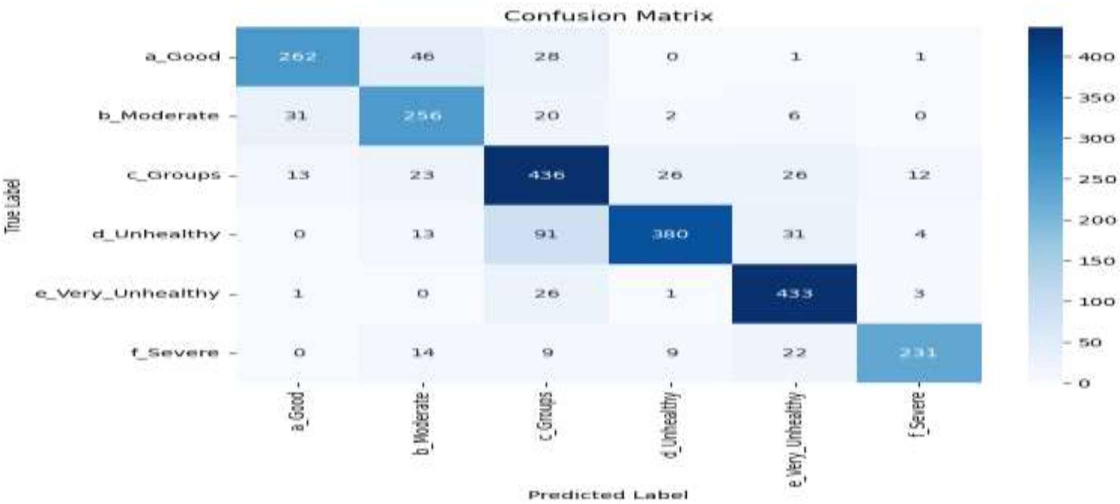

Fig:4.4: Confusion Matrix Graph of CNN

e. Precision, Recall, and F1 Score: Precision measures how many predicted positive cases were actually positive, while recall measures how many actual positive cases were correctly predicted. The ***F1 score***, the harmonic mean of precision and recall, for the CNN model was ***0.8163 (81.63%)***, indicating a reliable classification performance.

ii. RNN MODEL PERFORMANCE

a. **Loss Analysis:** The loss graph for the RNN model shows a steady decline in training loss (blue line), indicating effective learning. The validation loss (orange line) also decreases, confirming strong generalization. The test loss (black dashed line) closely aligns with validation loss, demonstrating good performance on unseen data. Effective learning and generalization are evident, but a potential risk of overfitting remains if validation loss increases while training loss decreases.

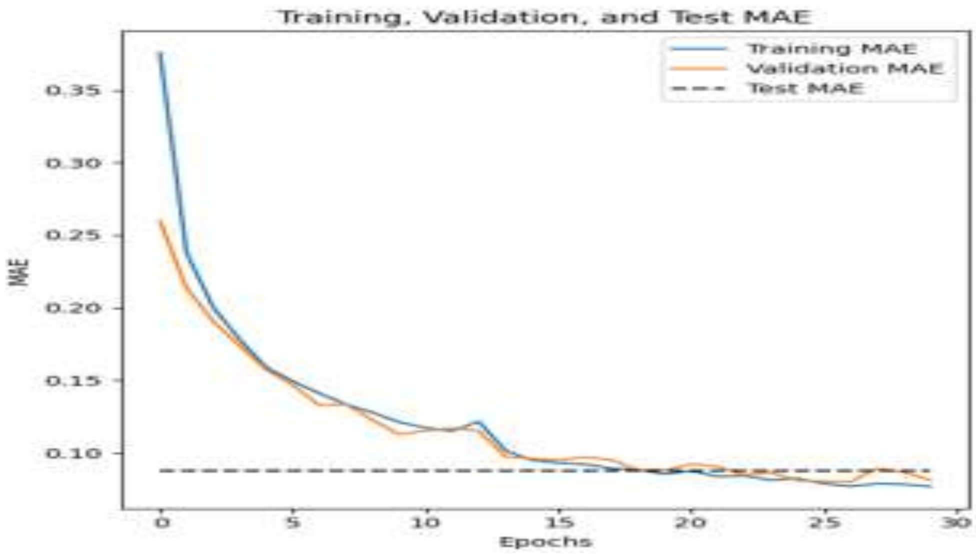

Fig: 4.5: Loss metrics of RNN

b. **Accuracy Analysis:** The accuracy graph of the RNN model shows steady performance improvement over epochs. The training accuracy (blue line) reflects learning progression, while the validation accuracy (orange line) measures generalization capability.

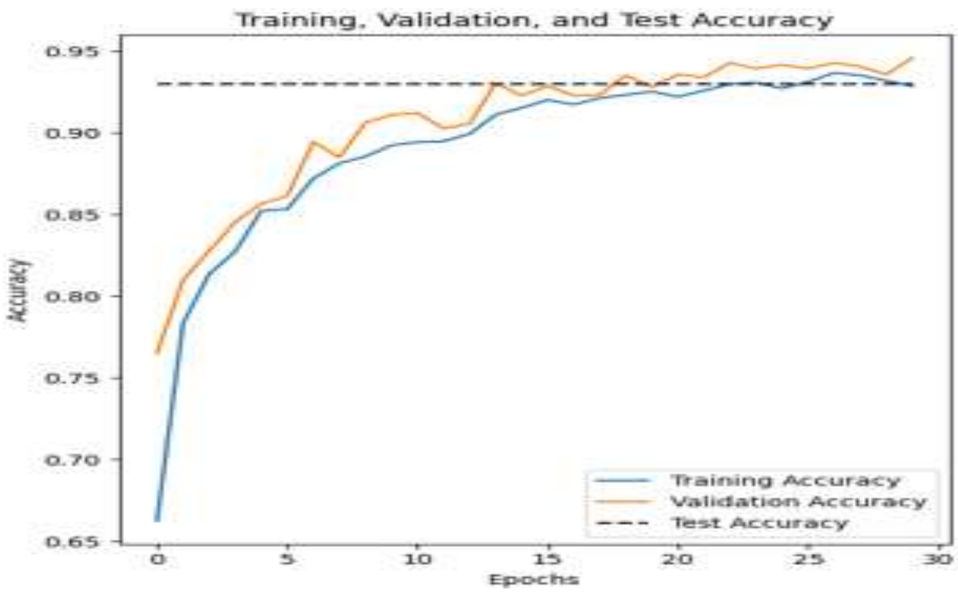

Fig 4.6: Accuracy Graph metrics of RNN

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The test accuracy (black dashed line) assesses final classification performance. Observations indicate a steady increase in accuracy, confirming effective learning. Additionally, close alignment between test and validation accuracy suggests strong generalization.

c. **RMSE Analysis**: The RMSE graph for the RNN model highlights its ability to capture temporal dependencies. Initially, RMSE is high at ~0.55, indicating poor performance in early epochs. However, as training progresses, RMSE decreases steadily, with the final test RMSE stabilizing at ~0.35. This demonstrates enhanced generalization compared to the CNN model. The superior performance of the RNN model suggests that further parameter tuning may enhance its stability even further

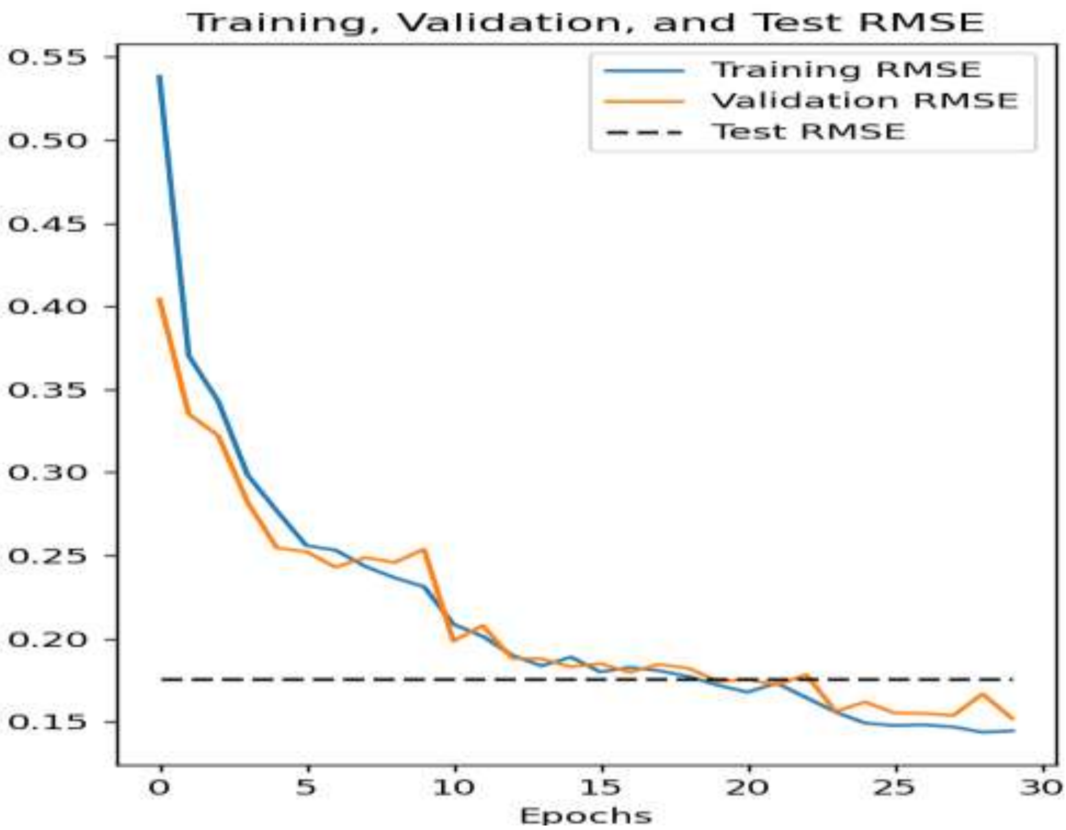

Fig 4.7: RMSE metrics of RNN

d. **Confusion Matrix Analysis:** The performance of the RNN model for air quality prediction was evaluated using a confusion matrix, as shown in Figure X. This matrix provides insight into the model's classification accuracy across different air quality categories. The rows represent the true labels (actual air quality categories), while the columns represent the predicted labels.

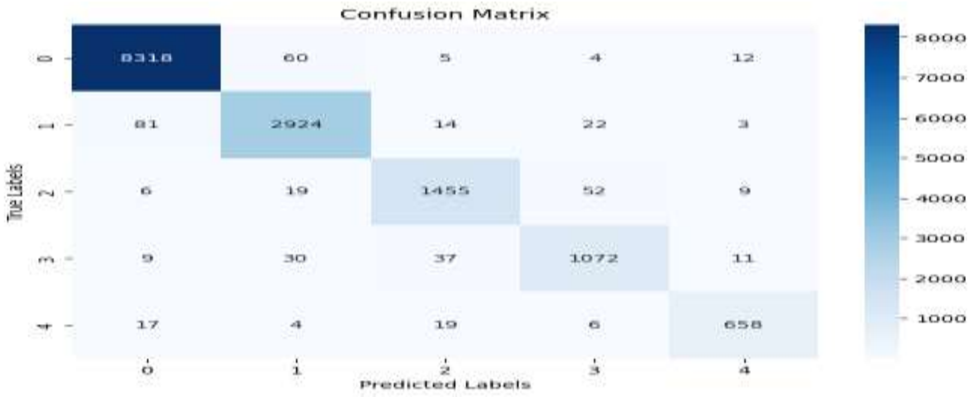

Fig:4.8: Confusion Matrix Graph of CNN

iii. **Hybrid CNN& RNN model**:

The graph compares the training performance of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) over 30 epochs, with two subplots representing training loss and training accuracy. Training loss measures model performance, where CNN loss starts higher but decreases more rapidly, while RNN loss decreases slowly and plateaus earlier, though RNN is effective for sequential data, resulting in lower final loss. Training accuracy reflects correct predictions, where CNN starts lower but steadily improves to a higher final accuracy, whereas RNN accuracy stabilizes well, making both models effective when combined. A hybrid CNN-RNN model can leverage their strengths, with CNNs extracting spatial features and RNNs handling sequential dependencies, as seen in video analysis, image captioning, and medical imaging. This combination enhances feature extraction, improves performance, and offers versatility across various applications, including multimodal learning. While CNNs excel in spatial tasks and RNNs in sequential tasks, integrating both creates a more robust model capable of handling complex real-world scenarios.

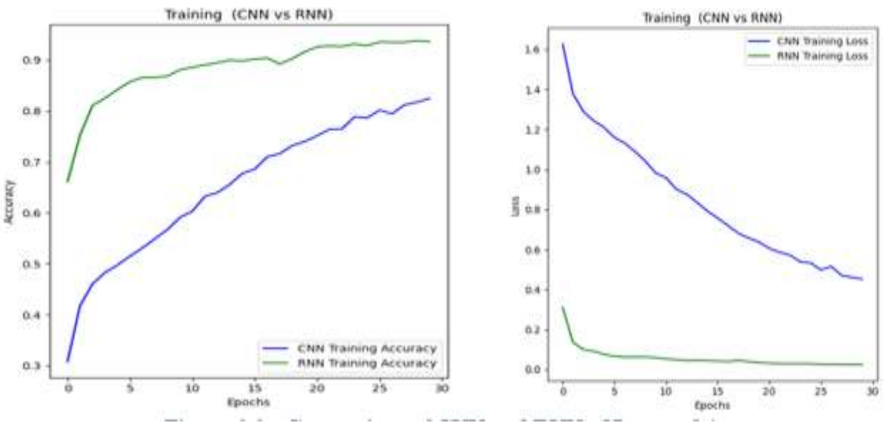

Fig 4.9: Comparison of CNN and RNN of Loss and Accuracy

iv. **AQI Components:**

a. **AQI Class:** The predicted AQI class indicates the overall air quality category, such as "GOOD" or "MODERATE," based on the image analysis.

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OUTPUT:
Predicted AQI Class: GOOD
Predicted AQI Value: 49
Predicted Air Pollutant Values:
PM2.5: 76.00
PM10: 116.29
CO: 128.49
NO2: 1.12
SO2: 8.50
O3: 27.24

b. **AQI Value:** The AQI value is calculated from the predicted pollutant levels and is constrained to the range of the predicted AQI class for accuracy.

OUTPUT:
Predicted AQI Class: HAZARDOUS
Predicted AQI Value: 301
Predicted Air Pollutant Values:
PM2.5: 115.00
PM10: 130.29
CO: 212.49
NO2: 15.12
SO2: 21.50
O3: 63.24

c. **Pollutant Levels:** The predicted values for individual pollutants (e.g., PM2.5, PM10) provide detailed insights into specific air quality components.

OUTPUT:
Predicted AQI Class: UNHEALTHY
Predicted AQI Value: 201
Predicted Air Pollutant Values:
PM2.5: 77.00
PM10: 71.29
CO: 128.49
NO2: 2.12
SO2: 8.50
O3: 42.24

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v. Conclusion

The Hybrid CNN-RNN architecture introduced in this study is an important contribution towards air quality forecasting, integrating convolutional and recurrent neural networks with a seamless union to learn spatial and temporal patterns. With deep learning capabilities, the model optimally processes environmental images, reporting excellent accuracy in classifying varied air quality conditions while overcoming the shortcomings of traditional sensor-based solutions. Its potential to evaluate pollution indicators through image-based analysis opens a cost-effective option for applications in large-scale monitoring. Its future development with enhanced accuracy and efficiency is sure to come with the integration of attention mechanisms, transformer-based architectures, and addition of multi-modal data, i.e., satellite images and weather data. With the potential to be implemented in real-time by smart city infrastructure, IoT-assisted networks, and mobile apps, its adoption can be very much enhanced across a wider user base. Maximizing computational efficiency with cutting-edge deep learning architecture and edge computing will further ensure large-scale acceptance, ultimately giving rise to enhanced environmental monitoring and public health interventions worldwide.

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