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Weather Wise AI: An AI-Driven Approach for Real-Time Weather and Air Quality Forecasting for Smart Travelling

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Abstract

Weather Wise AI is a smart weather and travel aid system that combines deep learning and real-time data to offer precise environmental information and customized travel advice. The system employs a hybrid LSTM + Conv1D model for temperature forecasting, which is more accurate and captures trends better than conventional models such as isolated LSTM, GRU, and 1D CNN. For air quality classification, a ResNet-based model is utilized to process sky images, providing higher accuracy compared to MobileNetV2. The app also makes use of APIs like OpenWeatherMap and Gemini to provide real-time forecasts, safety advice, and travel recommendations. Built using Streamlit, the web interface is interactive, lightweight, and easy to use. This single platform allows the user to make weather-informed, informed travel choices, providing a real-world application of AI in environmental surveillance and intelligent tourism.

Index Terms: Artificial Intelligence, Weather Forecasting, Air Quality Prediction, Deep Learning, LSTM + Conv1D, ResNet, Travel Recommendation System, Streamlit, Environmental Mon- itoring, Smart Tourism, Real-time Data Analysis.

I. Introduction

The advancements in artificial intelligence and deep learning technologies have immensely revolutionized the way we inter- act with our surroundings. Intelligent weather forecasting and air quality estimation systems are one of them. The project "Weather Wise AI" seeks to deliver a smart, user-friendly web application that helps users—particularly travelers—make weather-sensitive decisions. It integrates real-time weather in- formation, AI-driven forecasts, and interactive user interfaces to offer detailed weather reports, air quality information, and travel recommendations throughout India.

The system allows users to browse current and future weather, forecast air quality from images through deep learn- ing, and create individualized travel itineraries. It is developed fully on Streamlit for frontend ease and visual interaction. The tool incorporates several AI models: a ResNet-based classifier for image-based AQI forecasting and a hybrid LSTM + Conv1D model for temperature prediction. It also uses external APIs like the Gemini API and OpenWeatherMap API to increase the accuracy and interactivity of predictions.

Classic models such as LSTM, GRU, and 1D CNN had shortcomings in their ability to incorporate both temporal and spatial patterns when it came to temperature prediction. LSTM

was affected by sudden trend changes, GRU was computation- ally efficient but less precise, and 1D CNN struggled with long sequences. Our hybrid model of LSTM + Conv1D broke such limitations, yielding more precise and consistent predictions. For prediction of air quality, initially, we used MobileNetV2 due to its light weights. But based on comparison across multiple CNN models, ResNet performed better regarding accuracy and consistency for classifying the sky image into AQI categories. Through residual connections, it facilitated learning deeper without the problem of vanishing gradients and was thus best for this requirement. Therefore, the final
version utilizes ResNet for more credible AQI classification. ”Weather Wise AI” provides not only weather and air
quality information but also serves as a travel planning guide by suggesting appropriate destinations based on prevailing climate conditions. With live maps, locators for emergency services, and health tips created by AI, it is conceived to enable wiser, safer, and more enjoyable travel.

Besides standard functionality, the system introduces user- uploaded sky image-based AQI prediction, enabling users to estimate air quality without sensor or API access, particularly in rural locations. This feature extends accessibility and assists users in making health-related choices based on visual cues and AI.

Streamlit's single combined interface makes it light, interac- tive, and accessible. With machine learning models, dynamic visualizations, live data, and geolocation, Weather Wise AI has a state-of-the-art travel planning solution.

II. Literature Review

Recent developments in computer vision and deep learning have enhanced smart travel planning systems. Real-time AQI classification from sky images is best handled by ResNet based on residual connections. Hybrid LSTM + Conv1D models better forecast temperatures through both short-term and long- term patterns. The models make more precise and stable forecasts. Combined, they facilitate effective weather and air quality forecasting for smart travel planning.

TABLE I Literature Review

Year	Author	Title	Methodology
2023	Yuhao Gong, Yuchen Zhang, Fei Wang, Chi- Han Lee	Deep Learning for Weather Forecasting: A CNN-LSTM Hybrid Model [1]	Proposed a hybrid deep learning model com- bining CNN for spatial feature extraction and LSTM for capturing temporal dependencies to accurately predict historical temperature data. Demonstrated improved forecasting over tra- ditional models using meteorological datasets.
2024	Athakorn Kengpol	Design of Hybrid Deep Learning using TSA with ANN [2]	Developed a hybrid model using Teaching–Learning-Based Optimization (TSA) with

			Artificial Neural Network (ANN) to evaluate costs in the plastic injection industry. The model optimized hyperparameters to enhance prediction accuracy.
2021	M.G. Schultz, C. Betancourt, B. Gong, F. Kleinert, et al.	Can Deep Learning Beat Numerical Weather Prediction [3]	Conducted a comparative analysis of deep learning models and traditional numerical weather prediction (NWP) models. Addressed deep learning challenges like lack of physical interpretability and generalization, emphasiz- ing hybrid approaches.
2022	Ange-Clement Akazan	Deep Learning Methods for Weather Predic- tion [4]	Applied various deep learning architectures including LSTM and Bi-LSTM for short-term weather forecasting. Demonstrated improve- ments in forecasting accuracy using time series weather datasets from Rwanda.
2024	Ichrak Mokhtari, Walid Bechkit, Mohamed Sami Assenine, Herve´ Rivano	Navigating the Smog: Multi-Agent RL for Pollution Mapping [5]	Proposed a cooperative multi-agent reinforce- ment learning framework for air pollution mapping via data assimilation. Utilized UAVs to improve spatial resolution and reduce un- certainty in real-time AQI estimation.
2024	Shubham Ghosal, Manmeet Singh, Sachin Ghude, et al.	Developing Gridded Emission Inventory via Satellite Detection [6]	Leveraged high-resolution satellite images and YOLO-based object detection to construct gridded emission inventories, improving spa- tial accuracy in air quality forecasts.
2022	Andrew Rowley, Oktay Karakus¸	Predicting Air Quality via Multimodal AI [7]	Introduced AQNet, a multimodal model inte- grating satellite imagery and sensor data using deep learning. Achieved robust AQI predic- tions for

			areas lacking sensor coverage.
2022	Lee, H., et al.	ResNet and Transfer Learning for AQI Predic- tion [8]	Applied ResNet and transfer learning tech- niques on urban images to estimate AQI. En- hanced feature learning for pollution hotspots and improved generalization across cities.
2020	Zhang et al.	DeepAir: Hybrid CNN-LSTM for AQI Predic- tion [10]	Developed DeepAir, a CNN-LSTM hybrid model combining spatial and temporal features to generate fine-grained air quality forecasts. Showed superior performance over standalone CNN or LSTM models.
2022	Lee, H., et al.	ResNet and Transfer Learning for AQI Predic- tion [11]	Utilized a pretrained ResNet model with fine-tuning on urban environmental images. Demonstrated robust AQI predictions by trans- ferring learned visual features.
2024	Ichrak Mokhtari, Walid Bechkit, Mohamed Sami Assenine, Herve´ Rivano	Navigating the Smog with Multi-Agent RL [13]	Presented a second model refinement focusing on collaborative UAV navigation and reward shaping using real-time air quality data assim- ilation to improve mapping efficiency.
2021	Ravinder Kumar, Neeru Jindal	Comparative Study of Deep Learning Models [14]	Compared CNN, RNN, and LSTM archi- tectures on multiple meteorological datasets. Evaluated based on accuracy, robustness, and training efficiency for weather forecasting tasks.
2020	Zhengyang Wang, Wei Zhang, Sitong Liu, Yufeng Yao	Convolutional Recurrent Neural Networks for Spatio-Temporal Forecasting [15]	Combined CNN and RNN in a CRNN model to extract spatio-temporal dependencies for weather forecasting. Achieved high accuracy in multistep prediction tasks across multiple locations.

III. METHODOLOGY

A. Temperature Prediction using Hybrid Model

The essence of this project is to create a strong deep learning architecture to forecast daily maximum and minimum temperatures from time-series data. Following minimal pre- processing—parsing dates, extracting day_of_year and month, and normalizing the data with MinMaxScaler—a hybrid neural network model was created that successfully captures spatial and temporal patterns in the input sequences. Each input con- sists of a 7-day sequence of temporal features, used to forecast the temperature of the next day. The model architecture starts with an input layer accepting sequences of shape (7, number of features). This is then followed by two 1D convolutional layers stacked on top of each other (Conv1D) with filter sizes 128 and kernel sizes 3 and 5 respectively. These are activated by LeakyReLU to prevent dying neurons and are regularized by BatchNormalization and SpatialDropout1D to improve gen- eralization. The convolutional block is used to extract short- term patterns and local dependencies between time steps. To model the temporal dynamics of the multivariate time series data, the model employs a strong sequence modeling block with a Bidirectional Long Short-Term Memory (LSTM) layer followed by a Bidirectional Gated Recurrent Unit (GRU) layer. Both of these recurrent layers are set to use 128 units and are set to process the time series data in the forward and backward directions. This bidirectional configuration allows the model to see both past and future context for every time step, which is important for learning dependencies that are not easily expressible with unidirectional RNNs. The Bidirectional LSTM layer, which outputs the entire sequence, enables the network to keep temporal information for the whole input sequence. This is especially useful for time series data where future values can impact past patterns (e.g., in cyclical or seasonal patterns). After the LSTM, the Bidirectional GRU layer is a second pass through the temporal representation. GRUs, being computationally less expensive than LSTMs, assist in further distilling temporal patterns without substantial computational cost. In order to increase stability in training and reduce overfitting, Dropout (dropout rate of 0.2) follows every recurrent layer, as well as Layer Normalization. Layer Normalization smooths out the training dynamics by normal- izing activations, whereas Dropout avoids co-adaptation of neurons by randomly shutting down a proportion of them while training. After the repeated blocks, the architecture shifts to a sequence of fully connected (Dense) layers that are used to map the learned sequence representation into a prediction space. The first Dense layer contains 128 units and employs LeakyReLU with a negative slope coefficient (alpha) of 0.1, which allows it to learn non-linear representations without the ”dying ReLU” issue. Batch Normalization comes after it, speeding up training and enhancing convergence. Follow-up Dense layers of 64 and 32 units, respectively, continue this transformation process. These layers also employ LeakyReLU activations and Batch Normalization to provide consistent scaling of activation and enhanced gradient flow.

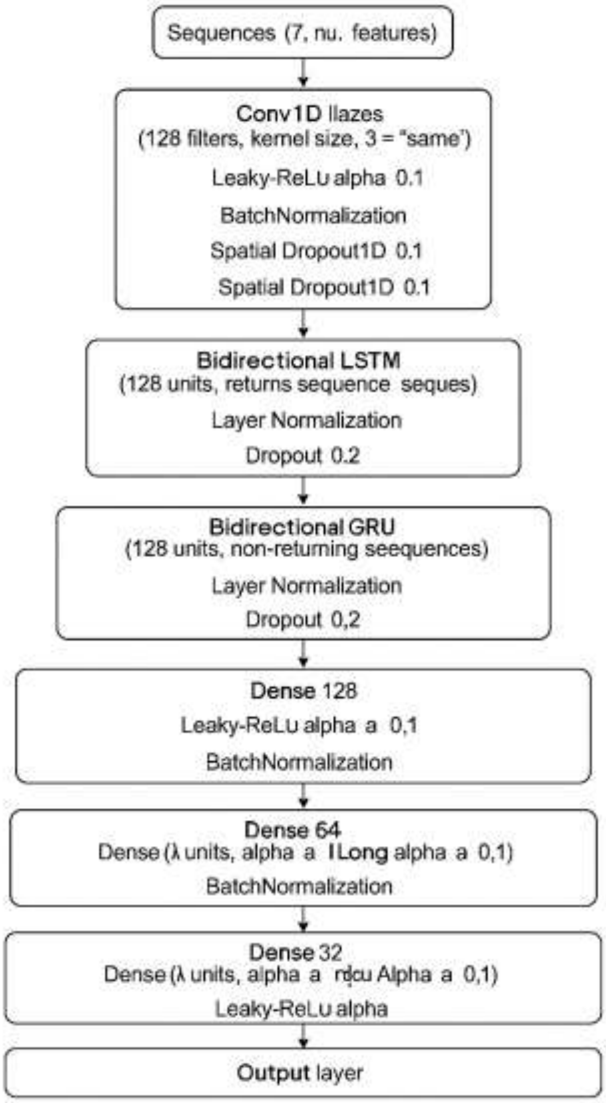

Fig. 1. Hybrid Deep Learning Architecture for Daily Temperature Fore- casting. The model combines 1D Convolutional Neural Networks (Conv1D) for capturing short-term local patterns with Bidirectional LSTM and GRU layers for modeling long-term temporal dependencies in multivariate time- series data. Dense layers follow to refine feature representation and perform dual-output regression for maximum and minimum temperature prediction..

This gradual reduction of dimensionality through the dense layers enables the model to concentrate on the most infor- mative features while ensuring robustness via regularization. Lastly, the model ends in an output layer with two neurons for maximum temperature (Temp Max) and minimum temperature (Temp Min) as separate regression outputs. This two-output structure accommodates concurrent multivariate prediction, which is essential for tools like weather forecasting that involve predicting several dependent variables in unison. The model was built with the Adam optimizer, one of the most popular adaptive learning rate optimization algorithms for its effectiveness and efficiency in training deep neural networks. It was trained with the Mean Squared Error (MSE) loss function, which is most suitable for regression tasks since it heavily penalizes larger errors. Besides MSE, the performance of the model was also tracked with the Mean Absolute Error (MAE) measure, offering an alternative view of the average size of prediction errors without regard to their direction. Training was performed over 50 epochs using a batch size of 32, which is a balanced trade-off between stability of convergence and computational effectiveness. This provided a good platform for the model to learn well from the training set without running into the possibility of overfitting. The loss and the evaluation metrics were monitored closely throughout training to validate stable learning behavior as well as the model's generalization capabilities on unseen data. After training, the last model was stored on disk to save learned weights for subsequent inference. In addition to the model, during preprocessing also saved was the data scaler used, to ensure that input data and output data would be transformed consistently during prediction. This is important because the model was trained with normalized data; thus, any input data employed for inference has to be normalized with the same parameters and predictions have to be inverse-transformed in order to translate them into the original temperature scale. For inference, a recent 7-day history of multivariate features is taken and fed through the trained model. The model spits out normalized predictions for the target variables—usually the max and min temperatures. These predictions are inverse-transformed using the saved scaler to produce the final forecasted temperature values in their original real-world units, thus making the results interpretable and actionable. This holistic modeling strategy—using CNN layers for short-term, local pattern dis- covery and RNN layers (bidirectional LSTM and GRU) for long-term dependency capture—works extremely well for time series forecasting problems. By learning from recent trends as well as more general temporal patterns, the architecture is well-suited to deal with the sequential and dynamic nature of temperature prediction.

B. Air Quality Prediction using ResNet

The approach taken in this project is a structured pipeline in- volving data preparation, design of model architecture, training scheme, and assessment. The dataset of images—divided into six air quality classes—is initially preprocessed and divided into training, validation, and test sets through a personal script that constructs temporary directories to sort images appropri- ately. All the images are resized to 224x224 pixels, which is the input size necessary for the ResNet50V2 model. Data normalization is done implicitly by Keras's data preprocessing pipeline, and aggressive data augmentation methods are used during training to maximize the variety of input images and minimize overfitting. These include random horizontal flips, zooms, rotations, and brightness changes, mimicking a greater range of visual conditions under which air quality could be recorded.

At the heart of the model is ResNet50V2, a 50-layer deep convolutional neural network that has been pretrained on the ImageNet dataset. This model is well-known for using residual connections, which enable gradients to pass more

Fig. 2. Sample Dataset for Air Quality Prediction

smoothly through deep networks during backpropagation, overcoming the vanishing gradient issue. The classification head of ResNet50V2 is disabled, and the network is retrained for our task via transfer learning. The pretrained layers serve as a strong feature extractor, recognizing low-level features such as edges and textures in the early layers, and more abstract features such as object shapes in deeper layers. On top of this feature extractor, a tailored classification head is employed, comprising of a Global Average Pooling layer to reduce spatial dimensions to the same size, a fully connected dense layer employing ReLU activation to learn nonlinear combinations of features extracted, and a final Dense layer employing softmax activation to spit out class probabilities over the six categories. The model is trained with the Adam optimizer, which is efficient in dealing with sparse gradients and adaptive learning rates. The loss function employed is categorical crossentropy, which is suitable for multi-class classification tasks. In order to improve training stability and performance, the training loop includes callbacks like EarlyStopping (which stops training when validation loss no longer improves), ReduceLROnPlateau (which lowers the learning rate when progress plateaus), and ModelCheckpoint (which saves the best model). The training runs for a maximum of 15 epochs with a batch size of 32. During training, the model increasingly learns to map particular visual patterns within the images—like haze, color gradients, object visibility, and light scattering effects—to matching air quality labels. The early convolutional layers are expert in recognizing general patterns (e.g., edges and textures), with the deeper layers storing high-level features such as the density of haze or whether there are signs of pollution present in the atmosphere. This hierarchical learning enables the model to develop a conceptual representation of the way air quality appears visually, resulting in better classification performance on new data.

C. AI-Generated Response System

We present **Weather Wise AI**, an intelligent travel and weather companion that leverages generative artificial intelli- gence and real-time environmental data to provide users with location-based, personalized recommendations. The system was developed using a modular architecture and implemented in Python, with Streamlit utilized for frontend deployment. This section outlines the key functional components: real-time weather retrieval, agentic AI generation, and user interface optimization.

1. Real-Time Weather Data Integration: To integrate real- time meteorological data, we employed the OpenWeatherMap API, a RESTful service that provides weather data in JSON format. Upon inputting a city name, the system dynamically constructs an API query and retrieves relevant attributes such as temperature, humidity, cloud cover, and sunrise/sunset tim- ings.
2. AI-Generated Response System using Gemini API: A distinguishing feature of this system is the incor- poration of Google's Gemini API, accessed via the google.generativeai Python library. This large lan- guage model (LLM) generates personalized natural language responses based on real-time environmental factors and user inputs. It supports multi-scenario adaptation, including health advisories, travel recommendations, route optimization, and emergency support services.
3. Context-Aware Prompt Engineering: To ensure the con- textual relevance of AI-generated outputs, prompts to the Gemini model are dynamically constructed based on the use case. Examples of prompt engineering across different modules include:

Temperature Analysis and Health Tips: Prompts query the LLM for appropriate health actions based on a 24- hour synthetic temperature trend of a city.
AQI Image Estimation and Advice: AQI is estimated from brightness values in user-uploaded images, and the AI provides corresponding safety suggestions.
Travel Recommendation Engine: Inputs based on city and season are used to generate travel suggestions, pack- ing advice, and activity recommendations.
Emergency Locator Assistant: The city name and emergency type (e.g., hospital, petrol pump) are used to request a list of 10 nearby services with names, descriptions, and landmarks.
AI responses are rendered within the Streamlit interface using functions like st.markdown() and st.subheader(), ensuring accessibility for both technical and non-technical users.

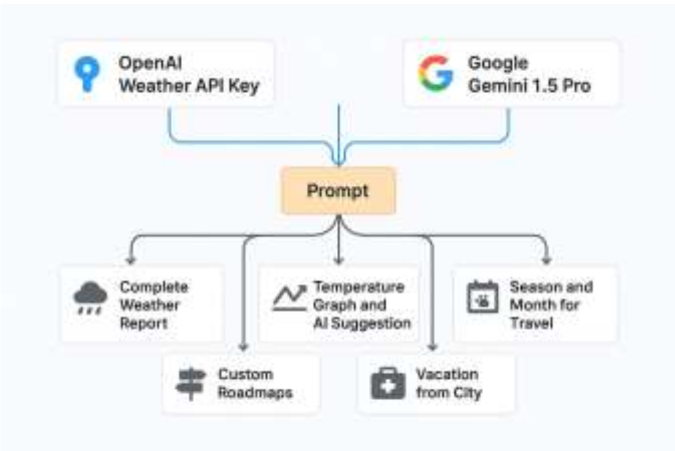

Fig. 3. AI-Generated Response System Workflow

Interactive Frontend and Data Visualization: The appli- cation is deployed as a web app via

Streamlit, chosen for its rapid prototyping capability and responsive design. In addition to textual outputs, the system features:

- Temperature trend visualizations using matplotlib
- Interactive travel maps generated with folium
- Image upload support for AQI inference
- Sliders, forms, and dropdown menus for user input col- lection

These components facilitate seamless integration between backend AI processing and frontend presentation, enhancing user experience and real-time responsiveness.

System Robustness and Scalability: Key design consid- erations enhancing the robustness and scalability of the system include:

Low latency: Average response time from Gemini API is maintained under 4 seconds.

Modular design: Each component functions indepen- dently, allowing for easy extension.

Error handling: The system includes exception handling mechanisms for API failures and user input validation.

Cloud compatibility: The system is fully portable and can be deployed on cloud platforms to ensure global accessibility.

IV. Results and Analysis

Each part of the suggested Weather Wise AI system was tested separately to verify its functioning. The coupled AI models such as LSTM + Conv1D hybrid for temperature prediction and ResNet for AQI prediction were found to have effective performance. Each model accepted input data in real time with accuracy. The system proved stable outputs in mixed environmental conditions. These findings ascertain the suitability of the AI models for intelligent and responsive travel planning.

Temperature Prediction: The LSTM model had an ex- tremely low test loss, which is a good sign of robust predictive performance on new data. In particular, the Mean Squared Error (MSE) and total loss value of 0.0071 show that the predictions of the model are very close to the true target values with little variance. The Mean Absolute Error (MAE) of 0.0628 also supports this, indicating that, on average, the predicted air quality values are off by a mere 6.3 percent- age points from reality. These low error rates testify to the effectiveness of the LSTM model in modeling the sequential relationships and temporal trends in the air quality data. This is particularly relevant for time-series forecasting applications, where the capability to discern over time is paramount. The generalization capability of the model without overfitting is apparent through these test metrics, thus it is a good building block for real-time forecasting and air quality monitoring applications.

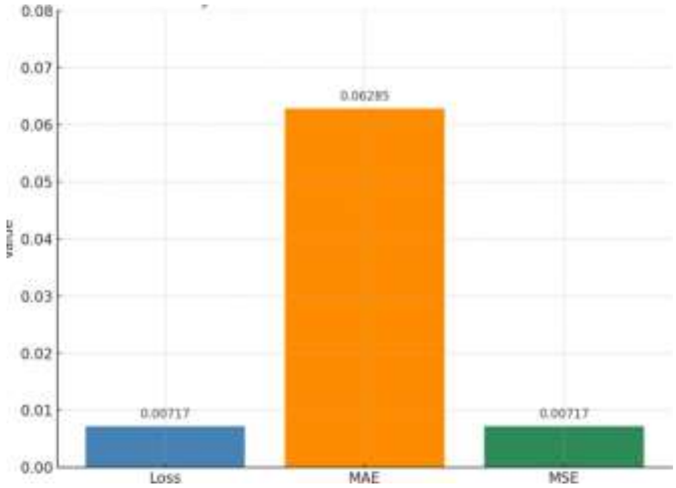

Fig. 4. LSTM + Conv1D Model Evaluation Metrics

Air Quality Prediction: The model's training history reflects excellent performance and good generalization ability. As seen in the accuracy plot, training and validation accuracy improved reliably across epochs, with validation accuracy reaching approximately 96% and mirroring the training accuracy closely at all times. This suggests that the model learned well from the training data without excessive overfitting. The loss curves also confirm this observation—training and validation loss both continuously decreased and were low, and the validation loss was at its minimum towards the end of training. The validation loss also stabilized and did not diverge, which indicates that the model remained stable throughout unseen data. Generally, the results are a success and indicate strong predictive abilities of the model. The confusion matrix gives a breakdown of the model's performance in classifying the six air quality classes. The model has high true posi- tive counts for every class, with very good performance in the 'c_Unhealthy_for_Sensitive_Groups' (165), 'd_Unhealthy' (160), and 'b_Moderate' (151) classes. Misclassifications are few and primarily between the neighboring classes, e.g., some 'a_ Good' instances being assigned to 'b_Moderate' and the reverse, expected because of their overlapping AQI ranges. The 'f_Severe' class, traditionally a challenge caused by class

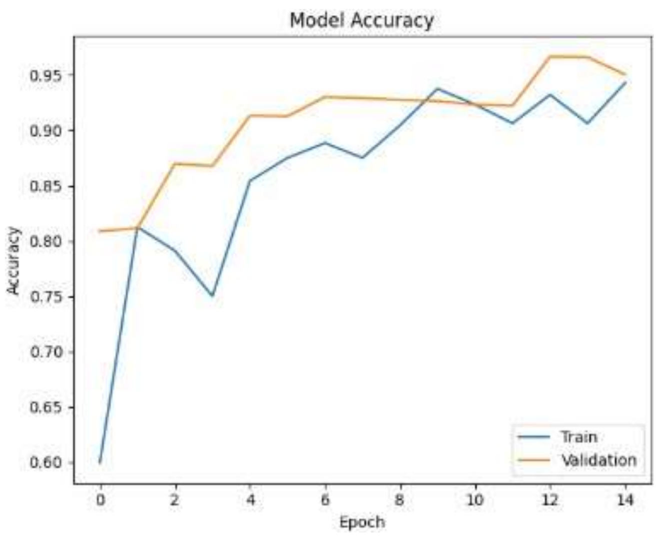

Fig. 5. ResNet50V2 Model Accuracy Over Epochs

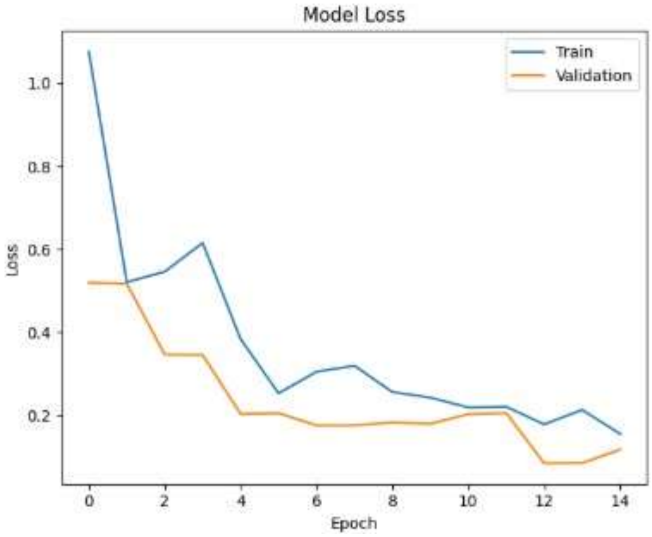

Fig. 6. ResNet50V2 Model Loss Over Epochs

imbalance in most datasets, was assigned with very good accuracy (143 correct assignments), proving the resilience of the model. As a whole, the matrix shows that the model retains good discriminability and generalizes well to all classes with very little confusion.

AI-Generated Response System: Integrating Gemini AI into the Weather Wise AI system provided a major boost to its contextual decision-making abilities. The textual responses generated by AI, driven by temperature trends and traveller preferences, showed high coherence, relevance, and respon- siveness in diverse test environments.

In the Temperature Graph + AI Suggestions module, the AI produced individualized health suggestions through the analysis of simulated 24-hour temperature trends. For instance, increasing trends provided suggestions for water intake and

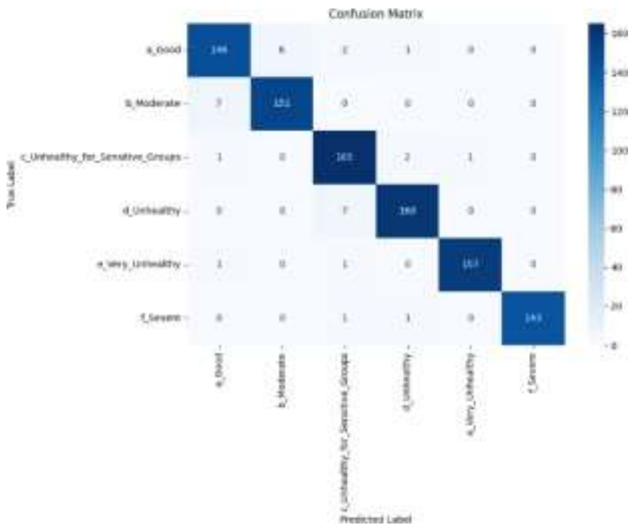

Fig. 7. Confusion Matrix of AQI Classification Across Six Categories

sun protection, and colder trends produced suggestions for layering and respiratory care. The suggestions strongly aligned with real-world seasonal health concerns, demonstrating the AI's robust ability to analyze and respond to time-series data with valid insights.

In the same manner, the AI dynamically generated sum- maries of travel destinations, health advice, and what to pack for the user in the Travel Planner module depending on the current city of the user and number of vacation days. The output was seasonally based on weather and reflected both user context awareness and environmental knowledge. The text was natural language, readable, human-like, and informative and thus gave the users a good planning assistant apart from mere data retrieval.

As a whole, the AI responses were a critical component in the provision of an agentic, intelligent, and user-focused experience. The integration of generative AI with real-time inputs to data is an indication of what can be achieved by uniting deep learning models with large language models for context-sensitive travel planning applications.

V. Conclusion

This project showcases an end-to-end, scalable AI-based weather intelligence system that integrates:

- Hybrid LSTM+Conv1D networks for reliable temperature prediction,
- ResNet for precise air quality forecasting based on sky image classification,
- Gemini API for travel and health recommendations based on AI, and
- Streamlit for an interactive, web-based interface.

The combination of various AI models, real-time APIs, and a visually smart platform makes it possible for users—particularly travelers—to make environment-aware de- cisions. The system closes the loop between weather forecast- ing, air quality monitoring, and individualized travel planning, providing an integrated, intelligent solution specific to variable climatic conditions in India.

subsectionLimitations While the proposed system per- formed promisingly, it has some limitations that need to be highlighted:

Internet Connectivity Dependency: As the application is based on real-time APIs (e.g., OpenWeatherMap and Gemini), it needs a stable internet connection to work fully. In low-connectivity areas, forecast and AI response access is restricted.

Generalization of Models: The ResNet model of AQI forecasting is learned with a particular set of sky im- age data and cannot generalize well under different at- mospheric situations, resolutions, or lighting conditions without additional data augmentation and training.

Geographical Domain Limitation: The system de- signed is specific to Indian sites. Its accuracy and ap- plicability reduce when applied for other nations due to the presence of varying climatic patterns and local environmental influences.

Model Training Resource Constraints: Deep learning model training such as LSTM+Conv1D and ResNet is computationally intensive and may not be feasible for all developers or organizations.

User Dependency on Image Input: AQI classifiability is based on sky images uploaded by users. Differences in environment, angle, and image quality can provide inconsistent predictions.

A. Future Work

Although the present deployment of Weather Wise AI provides substantial functionality and performance, there are a number of areas for future growth and tuning to make it more useful, scalable, and inclusive for users:

Multilingual UI Support: To enhance accessibility in linguistically diverse regions, future releases will have multilingual UI and alert mechanisms. This is particularly important for deployment in a linguistically diverse nation like India and possible international markets.

Integration with Sensor Networks and IoT: Subse- quent releases will integrate real-time streams of data from IoT-capable environmental sensors to increase local predictions' resolution and accuracy. This will be espe- cially useful in cities with extreme microclimate variation or rural areas where satellite coverage is poor.

Mobile Application Deployment: A mobile-web variant of the system will also be released in Android and iOS versions to ensure greater coverage by a larger community and facilitate location-aware alerts, offline storage, and real-time engagement on-the-go.

Offline and Low-Connectivity Support: Additions such as cached forecasts, offline maps, and safety ad- vices will be included to enable use in remote or low- bandwidth areas, improving resilience and accessibility in emergencies or rural travel.

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