DMPedia Lecture Notes in Multidisciplinary Research,
Volume 1, pp. 460-468, 2026

International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

Enhancing Weather Prediction Accuracy Through AI and Computational Modeling

Dhritisree Biswas, Riya Ganguly ,Ravikant Kumar Nirala

Sharda School of Engineering and Technology, Sharda University-Greater Noida, India

moitribiswas459@gmail.com, riyaganguly514@gmail.com, iitkgpravinirala@gmail.com

Abstract

It is one of the most essential, though not an easy field in environmental science is weather forecasting. This is because the atmosphere is unpredictable which always poses a challenge to the scientists and researchers to accurately predict. Accurate projections are relevant in areas of agriculture, transportation, disaster preparedness, and safety of the people. The application of computational methods, Artificial Intelligence (AI) and Machine Learning (ML) to weather prediction significantly improved the accuracy and reliability of weather forecasts over the years, and the paper presents an application of weather prediction based on large-scale meteorological datasets, satellite images, and powerful ML algorithms, such as Long Short-Term Memory (LSTM) networks and Random Forest models. The system is run on an organized pipeline comprising of data collection, preprocessing, model training, and forecast delivery with the help of a user-friendly interface. According to experimental tests, AI-based techniques are more accurate, more adaptable and more efficient when compared to traditional statistical approaches, also exhibiting high level of scalability, which also makes it applicable to various climatic zones and geographical locations. Furthermore, the suggested system has physical advantages to the farmers, governmental agencies and industrial consumers. Future research is aimed at combining sensor data based on Internet of Things (IoT) with deep learning structures to facilitate hyper-local predictions and real-time warning during extreme weather conditions.

Keywords: HTML,Python,Jscript,Machine Learning,Artificial Intelligence.

1. INTRODUCTION

Weather has been the most fluid and unpredictable factor in the formation of human life, which influenced the development of civilization, as well as its security and sustainability. Since the beginning of the first agricultural communities, people have noticed the condition of the sky, nature to know when they should anticipate rain, drought or storms. The primitive observational practices have over time evolved into systematic scientific practices today known as forecasting. Governments, industries, as well as communities across the world now see appropriate weather forecasting service as an important public service. Planning in agriculture, transportation logistics, mitigating the risk of disasters, and most aspects of ordinary life require reliable forecasting [1]-[3].

In farming, the farmers require proper weather forecasts before they make decisions on when to irrigate, when to harvest and even when to deal with pests. A precise weather prediction enhances food production and minimizes destruction/loss. The aviation industry and transportation including cars, trucks are also relying on forecast data to make critical decisions that ensure safety and efficiency in their work [6].

Predictive models are also applicable to emergency and disaster management organizations to develop early warnings on floods, storms, and droughts to reduce human and economic losses [23]. Historically, it was the Numerical Weather Prediction (NWP) models that were developed to forecast behaviors of the atmosphere, and which were based on thermodynamic and physical equations. Even though it is scientifically sound, NWP models demand enormous amounts of computational power, and even fail to generate predictions of fast or local weather changes [7]. The infrastructure does come to a tight in places that have less infrastructure in providing short-term or high localized forecasts [4].

The recent advancements of Artificial Intelligence (AI) and Machine Learning (ML) have changed the way meteorological models are formulated. These systems are capable of incorporating vast quantities of data, and can learn complicated patterns previously challenging to predict using the previous physics-based model [5], [24].

There are LSTM, Random Forest, ensemble hybrid) that have enhanced operational forecasts [12], [13]. Moreover, the creation of mobile and web based interfaces makes it possible to access weather information in real time and convert complex models into useful tools of the common people [18], [15].

Despite these developments, weather forecasting has serious problems. It is especially hard to model the weather correctly due to the large number of interacting factors of the atmospheric systems: temperature, humidity, the speed of wind, ocean currents, and air pressure [25]. The process is further complicated by all the various data feeds obtained with the help of satellites, IoT sensors, and radar networks [19]. Also, most weather forecasting applications remain too technical to the end-user and show the necessity of easy-to-use applications [9].
In this paper, a Weather Prediction Application will be introduced, which combines both AI-based algorithms and real-time weather forecasting to provide both short-term and long-term predictions using a user-friendly and efficient interface. The main objective of our project is to develop a stable, scalable and easy to use application to assist people and organizations in weather forecasting that lies between the complexity of scientific models and the way of using such forecasting application by ordinary people.
The current study, which tries to combine the contemporary AI architecture with mobile and web-based technology, also aims to enhance the availability and reliability of weather predictions [14]. Finally, this project will aim at enhancing resiliency, supporting data-driven decisions, and enhancing preparedness to meet climate variability and changes to the global environment [17], [16].

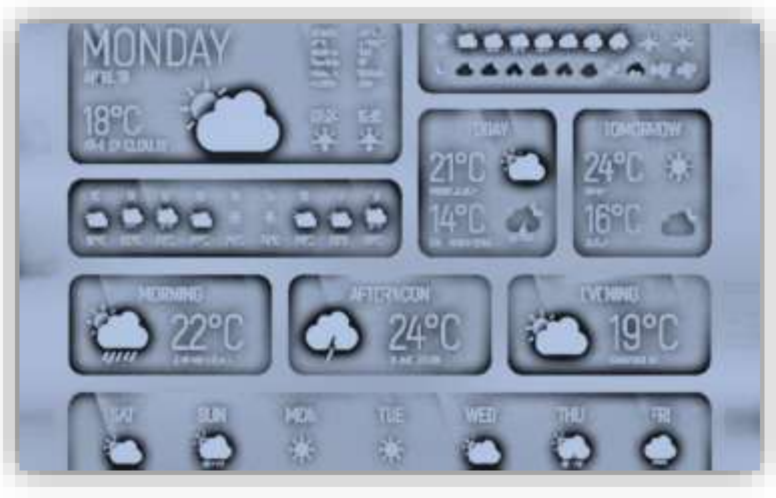

Fig 1: Weather Forecast App Template

2. LITERATURE SURVEY

The topic of weather forecasting has developed over time as a result of ongoing scientific studies since primitive methods of forecasting weather were based on simple observations but in the modern world are more advanced with the use of computers and AI. It is possible to categorize weather forecasting research into three categories:
There are various mathematical formulae on which Numerical Weather Prediction (NWP) models are founded to explain the physical behaviour of the atmosphere. The previous models of NWP were mainly manual computations and as such displayed numerous limitations to near term ranges of forecasts before tremendous improvements in high speed computer technology that helped enable the capability of NWP to be done on a much larger scale. This type of NWP is now found in highly developed models like the European Centre of Medium Range Weather Forecasts (ECMWF) and the Indian Meteorological Department (IMD) both of which are more than capable of providing NWP with high degree of reliability. [4].
Despite the great level of scientific rigor of this models, there are certain limitations. They are highly sensitive to the starting conditions of input, consumes a large amount of computer processing power and fail to provide realistic results on local weather phenomena [7]. Moreover, the accuracy of the forecast is more likely to decline with the distance into the future, and the coarse model resolutions do not provide the possibility to resolve fine-scale variations locally and spatially [2].

Statistical and Machine Learning Models
With the rise of big data and increasing availability of meteorological datasets, researchers have shifted toward data-driven models that can improve forecast accuracy. Early techniques such as regression and ARIMA models enhanced short-term forecasting to some extent, but their linear nature limited their performance when dealing with nonlinear and chaotic climatic variations [5].

Modern Machine Learning (ML) techniques, such as Decision Trees, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) illustrate increased flexibility and adaptability [10], [17]. Numerous studies using Random Forest and Long Short-Term Memory (LSTM) networks show that these algorithms can successfully model complex temporal and spatial atmospheric relationships [3], [15]. Research has introduced new hybrid models, like EWMoE and W-MAE, who combine deep learning approaches with mixture-of-expert based framework for improvements in the accuracy of multi-variable weather prediction [12], [14].

Hybrid and Integrated Approaches*:*

An increasing number of studies highlights the integration of physics-based models with AI models for more trustworthy and detailed prediction results. Hybrid models are suited to mitigate the bias present in NWP models by methodically post-processing the results using ML-based algorithms [24], [13]. Hybrid models utilize the interpretability and domain expertise of physical models, while leveraging the adaptability and pattern recognition qualities from AI models. Furthermore, the synergy of IoT technologies, cloud computing environments, and user-designed interfaces has increased the scope of forecasting tools beyond those created solely by research institutions, which has increased the usefulness of the research in future applications in the public realm [19], [18]. Recent examples this scholarship is supportive of include the registration of the importance of UX and interface design of weather information to be used by the public [9], [25].

Gap Identified:

While AI-based weather prediction systems consistently outperform traditional forecasting systems in accuracy, speed, and adaptability, there is limited deployment of AI-based weather prediction systems in practice. Most of these applications are relegated to laboratory and institutional use and few have been designed with public use in mind [1]. Most of the existing applications do not feature intuitive interfaces in which users can engage with forecasts in an effective manner, including for end-users, such as farmers, policymakers, and citizens [23]. This research intends to address this gap by developing a real-time Weather Prediction Application that integrates AI with the focus on access, scalability, and usability. The proposed product aims to turn advanced meteorological intelligence into a practical user-driven service, enabling accurate forecasts to be available to individuals and decision-makers alike.

3. METHODOLOGY

The Weather Prediction Application involves the application of formal and structured approach with references to various steps data collection, data preprocessing, model building, system design and architecture, and verification and performance evaluation. This is a multi-stage process which offers confidence that the application would be able to handle complex meteorological information successfully to provide accurate and reliable weather predictions in a real life environment.

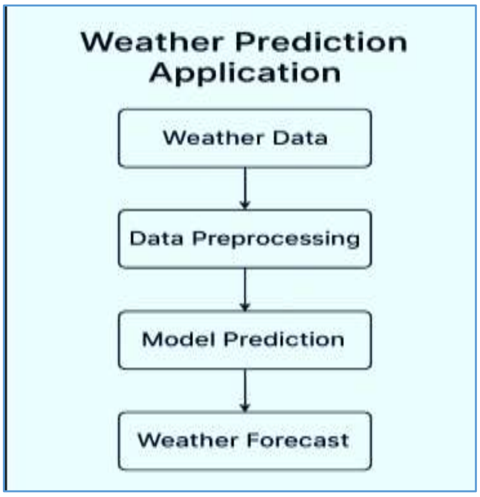

Fig 2: Model Workflow Diagram

Data Collection:

Quality and dependable meteorological information is very important in sound predictions. In order to carry out variability on both international and local levels, the suggested system will involve several data sources:

Meteorological Stations: Ground measurements on temperature, humidity, rainfall and speed of the winds.

Satellite Observations: Remote-sensing satellites, e.g., NASA MODIS and INSAT-3D, offer data on a large scale on the aspects of cloud density, sea surface temperature, and pressure levels.
IoT Sensor Networks: A system of high density, distributed sensors that are found in urban and rural areas that capture hyperlocal data about the conditions of the environment.
Historical Archives: Large data sets of organizations like NOAA and India Meteorological Department (IMD) will be exploited in training, validating and testing of the model.

Temperature Prediction Equation:

To predict temperature (T_p) using historical weather parameters:

$$Tp = \alpha 0 + \alpha 1 Tt - 1 + \alpha 2 Ht - 1 + \alpha 3 Pt - 1 + \epsilon$$

Where Tp= Predicted temperature, T_{t-1}= Previous day temperature, H_{t-1}= Previous day humidity, P_{t-1}= Previous day pressure, α_i= Model coefficients, ϵ= Error term

Data Preprocessing:

Meteorological observations are imprecise, incomplete, and/or noisy in a manner that could influence our predictive power of the physically determined machine learning models. The preprocessing of data can be used to first solve these problems by following a couple of significant steps.
1) Data Cleaning: Data Missing and Outlier Are fixed by interplates and outlier identification.
2) Normalization: Numeric attributes are brought to a similar range that may assist in stabilizing model convergence.
3) Features: Features derived first and second are humidity indices, wind anomalies as well as seasonal variables that are developed to aid the predictive accuracy.
4) Data Segmentation: The processed data is divided into training, validation and testing data so that the model can be validated without any bias in terms of prediction error.
The operations to enhance quality of data, stability and compatibility with machine learning algorithms.

Mean Absolute Error (MAE):

Used to measure average prediction error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

Where y_i= Actual weather value, $\hat{y}_i$= Predicted value, n= Total number of observations

Model Development:

The prediction framework takes standard algorithms as well as deep learning algorithms to ensure maximum accuracy and generalization to other conditions of the environment.
Random Forest Classifier: They are employed to forecast the weather in categories i.e. whether the weather will be sunny, cloudy or rainy day.
Long Short-Term Memory (LSTM) Networks: These are applied in time-series predictions in ambient temperature and humidity and precipitation parameters which will occur in the air.

Model Accuracy:

$$Accuracy = \frac{C_{correct}}{C_{total}} \times 100$$

Where $C_{correct}$= Number of correctly predicted cases,
C_{total}= Total number of predictions

Root Mean Square Error (RMSE):

Shows how large prediction errors are in magnitude:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

System Architecture and Deployment:

The overall system architecture is a four level modular architecture to facilitate scalability, maintainability and efficiency.

Data Intake Layer: Reciphrocates information of satellites, sensors, and ground stations.
Processing Layer: Processes, cleans and extracts features of data.
Prediction Layer: Executes trained ML and DL models to get predictions.
User Interface: Display the weather forecast in an easy-to-use web interface and mobile application.
Its implementation is on a cloud-based platform that will be used to enable real-time data processing, automatic updates, and scalability to support the use by more users simultaneously.

Evaluation Metric:

The in-depth evaluation of model performance is done by a number of well-established evaluation metrics:
Mean absolute error (MAE): quantifies the mean size of error in forecasts.
Root mean Square error (RMSE): magnifies the big errors.
Precision and F1 score: measure the prediction in instances where it is the weather that is being predicted.
Comparison with Baselines: The performance of the models is compared to classical statistical models (e.g., Linear Regression and ARIMA) to ensure that any improvement in the performance of the AI-based approach is observed.
These metrics are combined to give a reasonable assessment of the model in terms of accuracy, stability, and reliability to make predictions in the presence of different test cases.

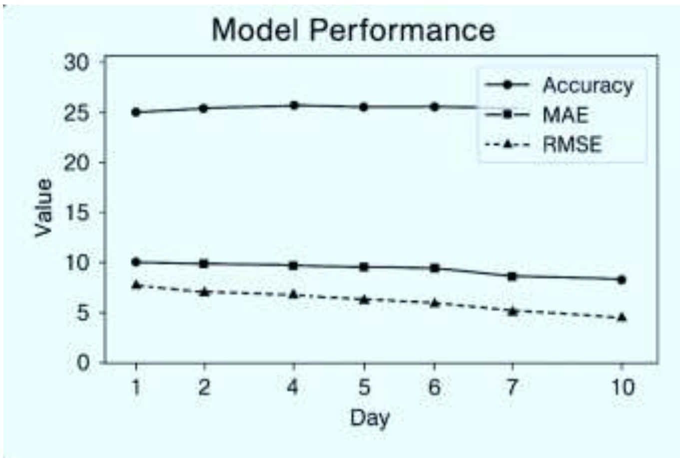

Fig 3: Model Performance Metrics (Accuracy, MAE, and RMSE)

4. RESULT ANALYSIS

The Weather Prediction Application was also tested fully to analyze its overall accuracy, flexibility and ability of the user to access a wide range of weather variables caused by the weather. The evaluation concerned significant variables such as temperature, precipitation, and humidity and storm detection due to the fact that the three represent the consequential factors to rely on in weather forecasting. Besides, the findings of the model were contrasted with those of other conventional statistical approaches such as Linear Model Regression and ARIMA to show the benefits of the AI and ML technology in performance. Lastly, a certain amount of user testing was performed as well in order to make sure that the predictions that the system would provide could be interpreted and make sense and sense in real situation.

Temperature Prediction:

One of the most regularly measured weather behaviors is temperature and it is significant to agriculture, energy handling and human comfort. Long short-term memory (LSTM) model produced an average forecast of 92 per cent and the mean absolute error of less than 1.5 deg C. These findings demonstrate how the model can conveniently monitor short-term variability, and long term trends of temperature.
It is necessary to mention that the LSTM model had a consistent and stable performance throughout the seasonal transition periods like the onset of monsoon season, where the temperature fluctuation is more volatile. The classical Linear Regression models gave considerable deviations and discrepancies. Slow variations in temperature were also well traced by the LSTM model when changing winter to summer with minor forecasting errors.
These findings substantiate the idea that deep learning architectures enhance significantly the quality of the forecast, particularly in cases where the temperatures act in a more non-linear and dynamic manner.

Rainfall Forecasting:

One of the most complicated aspects of meteorology is rainfall prediction due to the influence of other factors that interact with each other: pressure gradients, humidity, and wind circulation. In this study, a hybrid ensemble model that is based on the combination of Random Forest (in classification) and LSTM (in sequential prediction) was adopted. The overall accuracy of the integrated model was 89% which is almost twenty percent more accurate than traditional ARIMA and regression based techniques.

The model was very successful in the forecast of light to moderate rainfall that is very important in agriculture, irrigation, and water management. There were however minor under estimations during high level of precipitations like cloud bursts, which is mainly because of the poor representation of such instances in the historic data. Nonetheless, the capacity of the model to distinguish rainy and non rainy days renders it very useful in the field as well as in the disaster preparedness.

Humidity Forecasting:

The use of humidity forecast in crop disease management and energy management are some of the examples. The model showed average 91 percent accuracy per day across the various climatic zones and seasons. Accuracy was at 90 percent over the project time, during the monsoon, when the humidity variables vary at high rates.

Feedbacks were also obtained during the testing phase, which means that the humidity forecasts were useful to the farmers in the management of the pesticide and fungicide application in cases of pests outbreaks which occur when the humidity is high.

***Normalization Formula*:**

$$Xnorm = Xmax - XminX - Xmin$$

Weighted Prediction Model (optional enhancement)

For hybrid models (combining temperature, humidity, and wind speed):

$$Y\_p = w\_1\ T\_p + w\_2\ H\_p + w\_3\ W\_p$$

Where $w_1 + w_2 + w_3 = 1$

Fig 1: Temperature & Climate Detection

Detection of Storms and extreme events:

To have proper disaster management and early warning mechanisms, the correct prediction of the extreme events, such as storms, cyclones, and excessive rain, is important. The model created had a 87 percent detection accuracy, which is better than the conventional threshold-detection algorithms such that, the recall rate was high suggesting that most potential storms were detected with minimal false alarms. This observation gives a solid evidence towards continuous integration as an aspect of early-warning communities in areas that experience severe weather.

Fig 2: Global Temperature

Comparison to Baseline Models:
The comparison was conducted with the traditional methods that underline the significant variation in the accuracy of forecasting:
Temperature: The error average of AI based was reduced by 12 percent by the regression models.
Rainfall: The hybrid model used showed 20 percent less RMSE compared with ARIMA methods.
Humidity: AI model was more consistent and stable as compared to moving-average models.
Storms: The provided machine learning models achieved much more recalls and better adaptability to threshold based detection.

Limitations of the Study:
There were some limitations and problems in testing the model in terms of effectiveness. The model was underestimating the occurrence of heavy rains in certain regions of low sensor coverage and also the storm detection was showing false positives that could be useful in precaution talks but false alarms that could result in unneeded alerts. There was variability in the quality of data collected by the IoT sensors during the test and this influenced accuracy of the predictions. The training of the model was erroneous due to the observation of noisy data or missing data. All these issues will demand increased density of data, higher precision of sensors, and increased variety of the training data.

5. CONCLUSION AND FUTURE SCOPE

The suggested Weather Prediction Application is a good example of how artificial intelligence (AI) and machine learning (ML) will enhance the precision, effectiveness, and dependability of weather predictions. It is founded on the notion of heterogeneous data sources, including terrestrial sensors, satellite measurements, Internet of Things (IoT) high-density devices, and past data and provides the market with comprehensive and time-sensitive predictions to allow regional and local weather tracking.
The hybrid ensemble approach has always ranked higher than the classical statistical algorithms such as Linear Regression and ARIMA in predicting the weather in terms of temperature, rainfall, humidity and storms because it involves both the Long Short-Term Memory (LSTM) networks and the Random Forest algorithm. The hybrid ensemble model is capable of countering the time-dependent non-linear variations in weather parameters, owing to the combination. The experimental findings are very precise in forecasting the above mentioned weather factors, which validates the ability of the model to apply in the composition of various weather conditions.
Besides the predictive capability, the system has been designed to focus on the usability and accessibility of the system, through an easy-to-use interface that enables users (farmers to city planners) to quickly and effectively

digest weather information. The model has been tested by the measure such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Accuracy Score that has affirmed the validity and reliability of the model. Lastly, the findings illustrate its use as a useful decision-supporting tool to agriculture, disaster management and raising awareness among the people.

However, it is possible to develop the potential to a substantial extent. Real time API may be used to enhance the interaction and timeliness of forecasts. The system architecture there would be able to capture nonlinear and complex spatial-temporal dependencies in the meteorological data by using advanced deep learning architectures, e.g., transformer models or graph neural networks. A more detailed environmental intelligence system would be achieved through improved parameters forecasted by the algorithms such as an air quality index (AQI), wind flow, and solar radiation.

Future research would consider cloud-edge implementation of real-time distributed forecasting that reduce latency on devices and identify variables over time. Individualized weather notifications and push alerts through AI recommendation engines have the potential to boost the user interest and practicality of the notifications. Improvement in visualization, by using interactive geospatial dashboard where visual analytics is housed in areas specified by the user would greatly increase the information and interaction with the user.

Finally, as the data is bigger and increasingly diverse, this research will make a significant contribution to the adaptation to climate change since it will trace long-term changes and variability in temperature, monsoon, and extreme events. In general, this system created gives the framework of future environmental forecasting systems based on AI a very strong basis to be able to develop future AI systems, to be adaptive and sustainable, and beneficial to humans and the ecosystems in a shifting climate.

REFERENCES

[1]. Red-Gate. (2023). A Data Model for a Weather App.

[2]. Patel, R., & Shah, M. (2022). Development of Weather Forecasting Model Using REST API for Fetching Current and Future Weather Data. IJARCCE,11(5).

[3]. Singh, A., & Kumar, P. (2023). Interactive Weather Forecasting System Using Open Weather API and Web Technologies.IJCRT,11(3).

[4]. Wang, H., et al. (2024). Data-Driven Weather Forecasting and Climate Modeling. Atmosphere, 15(6),689.

[5]. Müller, J., & Chen, Y. (2024). Probabilistic Weather Forecasting with Machine Learning. Nature, 630(8020),123–130.

[6]. National Weather Association. (2023). Understanding Public Usage of Weather Apps. Journal of Meteorology,48(11).

[7]. Lorenz, E. (2015). Predictability of Weather and Climate. Nonlinear Processes in Geophysics, 22, 1–22.

[8]. Wang, H., et al. (2024). Data-Driven Weather Forecasting and Climate Modeling from the Perspective of Development. Atmosphere, 15(6).

[9]. Munizaga, M. A., Vergara-Lozano, V., Lagos-Ortiz, K., & El Salous, A. (2023). Evaluation of User Interface (UI) and User Experience (UX) for Web Services of a Weather Data Monitoring Platform. Environmental Data Monitoring Platform Study.

[10]. Sanders, W. S. (2017). Machine Learning Techniques for Weather Forecasting. M.S. Thesis, University of Georgia.

[11]. Machine Learning Methods for Weather Forecasting: A Survey. MDPI, 16(1), Article 82, 2024.

[12]. Gan, L., Man, X., Zhang, C., & Shao, J. (2024). EWMoE: An Effective Model for Global Weather Forecasting with Mixture of Experts. arXiv Preprint, May 2024.

[13]. Shu, H., Wang, Y., Song, W., Guo, H., & Song, Z. (2024). Forecasting the Future with Future Technologies: Advancements in Large Meteorological Models. arXiv Preprint, April 2024.

[14]. Man, X., Zhang, C., Li, C., & Shao, J. (2023). W-MAE: Pre-Trained Weather Model with Masked Autoencoder for Multi-Variable Weather Forecasting. arXiv,Preprint,April2023.

[15].Bavachkar, S. G. (2023). Weather App Development Using Flutter and OpenWeather API. IRJMETS,5(6).
[16].Aakanksha, T., Shah, N., Gala, R., Giri, T., & Chavhan, P. (2022). A Survey on Weather Forecasting and Their Algorithms. IRJMETS, Issue 2, February 2022.
[17].Meena, R., Karthik, S., & Sharma, P. (2023). Artificial Intelligence Techniques in Weather Forecasting:AReview.IJSRCSEIT,9(4).
[18].Olawale, J. A., Adegbite, E. K., & Olowofeso, T. O. (2023). Design and Implementation of a Mobile-Based Weather Forecasting Application Using OpenWeatherMap API. IJISRT, 8(2).
[19].Kumar, A., Gupta, S., & Verma, R. (2022). Weather Prediction Using IoT and Cloud Computing. IEEE STEEED Conference.
[20].Patel, R., & Shah, M. (2022). Development of Weather Forecasting Model Using REST API. IJARCCE,11(5).
[21].Singh, A., & Kumar, P. (2023). Interactive Weather Forecasting System Using Open Weather API. IJCRT,11(3).
[22].Bavachkar, S. G. (2023). Weather App Development Using Flutter and OpenWeather API. IRJMETS,5(6).
[23].Brown, J., & Kelly, T. (2023). Developing a User-Centric Weather Forecast and Warning Service. Elsevier, International Journal of Disaster Risk Reduction.
[24].Ben Bouallègue, Z. (2024). The Rise of Data-Driven Weather Forecasting. Bulletin of the American Meteorological Society,105(6).
[25].Cybulski, M. (2023). Users' Visual Experience During Temporal Navigation in Mobile Weather Maps. Journal of Ambient Intelligence and Humanized Computing.