THEORETICAL FRAMEWORK TO WEATHER DATA ANALYSIS OF COASTAL UDUPI USING MACHINE LEARNING AND INTEGRATING MULTIPLE SCIENTIFIC DOMAINS

Sushma A. Shetty[1], Am Sudhakara[2]

[1]Research Scholar, College of Computer Science and Information Science Srinivas University, Mangalore, Karnataka, India.

[2]Research Professor, College of Computer Science and Information Science Srinivas University, Mangalore, Karnataka, India.

ABSTRACT

This article proposes a theoretical framework for the comprehensive analysis of weather data from the coastal region of Udupi, India. The framework integrates multiple scientific domains, including climatology, meteorology, environmental science, data science, geospatial analysis, disaster management, and agricultural science. The study aims to develop an accurate and reliable rainfall prediction model by integrating various meteorological parameters, such as rainfall, temperature, relative humidity, wind speed, and wind direction. The objective is to establish a structured approach for identifying significant weather patterns, trends, and anomalies over a ten-year period . This framework aims to guide researchers in conducting robust analyses that contribute to climate change adaptation, agricultural optimization, and disaster preparedness.

Keywords- Theoretical Framework, Weather Data Analysis, Coastal Udupi, Climatology, Meteorology, Environmental Science, Data Science, Geospatial Analysis, Disaster Management, Agricultural Science Machine Learning,LSTM .

1. INTRODUCTION

Accurate weather forecasting, particularly rainfall prediction, is crucial for the Udupi district due to its coastal location and reliance on agriculture and fisheries. Traditional weather prediction models often fall short in capturing the complexities of regional weather patterns, leading to inaccuracies that can adversely affect local economies and disaster preparedness. Weather data analysis is critical for understanding climate variability, predicting extreme weather events, and formulating mitigation strategies. Coastal regions, such as Udupi, are particularly vulnerable to climatic changes, necessitating a multidisciplinary approach to analyze long-term weather data. Rainfall prediction is crucial for coastal regions like Udupi due to their susceptibility to extreme weather conditions and the need for effective agricultural planning, water resource management, and disaster preparedness. Despite advances in meteorology, accurate and reliable rainfall prediction remains challenging, particularly for region-specific models. This study aims to address this gap by leveraging ten years of comprehensive meteorological data to develop a predictive model tailored to Udupi's unique climatic conditions.

This article outlines a theoretical framework that integrates various scientific domains to provide a holistic understanding of weather patterns and their implications.

Problem Statement: Current weather prediction methods for the Udupi region lack precision, especially in short-term forecasting. The integration of advanced machine learning techniques such as LSTM networks with comprehensive meteorological data presents an opportunity to improve prediction accuracy.

Research Aim: This study aims to develop an accurate short-term rainfall prediction model for the Udupi district by leveraging LSTM networks and a diverse set of meteorological parameters obtained from satellite data and ground observations.

1.1 Research Gap

Lack of Region-Specific Models: While numerous studies have developed predictive models for rainfall, there is a scarcity of research focused specifically on the coastal region of Udupi, Karnataka. Coastal regions have unique meteorological characteristics that require tailored models for accurate predictions.

Integration of Multiple Parameters: Existing studies often focus on a limited set of meteorological parameters. There is a need for comprehensive models that integrate multiple variables such as rainfall, temperature, relative humidity, wind speed, and wind direction to capture the complex interactions influencing rainfall.

1. **Temporal Dependency in Data:** Traditional statistical models like Multiple Linear Regression (MLR) may not effectively capture the temporal dependencies in meteorological data. Advanced machine learning models,

particularly Long Short-Term Memory (LSTM) networks, which are designed to handle sequential data, have not been extensively applied to this region.

2. **Robustness and Generalization:** There is a need for robust models that can generalize well across different time periods and weather conditions. Many models lack cross-validation to ensure their applicability in real-world scenarios.

3. **Practical Implementation:** While theoretical models are often developed, their practical implementation for local authorities and stakeholders is rarely addressed. Bridging this gap can significantly improve local planning and disaster management strategies.

2. OBJECTIVES OF THE RESEARCH

1. To collect and analyze historical meteorological data for the Udupi district, including rainfall, temperature, relative humidity, cloud cover, sunshine duration, wind direction, and wind speed.

2. To develop an LSTM-based predictive model for short-term rainfall forecasting.

3. To validate the model using cross-validation techniques and compare its performance with existing models.

4. To assess the potential socio-economic impacts of improved rainfall predictions on local agriculture and fisheries.

3. IMPORTANCE AND INTEGRATION OF MULTIPLE DOMAINS

Climatology: Climatology is essential for examining long-term weather patterns and trends. Understanding these trends helps in identifying significant climatic shifts and their potential impacts on coastal regions.

Meteorology: Meteorology focuses on the study of atmospheric conditions and short-term weather forecasting. Accurate meteorological analysis is crucial for predicting immediate weather impacts and preparing for extreme events.

Environmental Science: Environmental science examines the interaction between weather patterns and the environment. This domain is vital for assessing the impact of weather on coastal ecosystems, including mangroves, fisheries, and marine biodiversity.

Data Science: Data science provides the tools and techniques necessary for analyzing large and complex datasets. Machine learning and statistical methods help in uncovering hidden patterns, making accurate predictions, and identifying anomalies in weather data.

Geospatial Analysis: Geospatial analysis uses Geographic Information Systems (GIS) to analyze the spatial aspects of weather data. This helps in understanding the geographic distribution of weather phenomena and their specific impacts on different areas within Udupi.

Disaster Management: Disaster management focuses on predicting, mitigating, and responding to extreme weather events. Integrating this domain helps in developing effective strategies for disaster preparedness and response.

Agricultural Science: Agricultural science relies on weather data to optimize crop management and planning. Understanding weather patterns is crucial for improving agricultural productivity and sustainability in coastal regions.

4. REVIEW OF LITERATURE

Meteorological Data Utilization: Studies such as those by Kumar et al. (2018) have highlighted the importance of integrating multiple meteorological parameters in weather prediction models. Temperature, humidity, and wind parameters significantly influence rainfall patterns, making their inclusion in predictive models essential.

Machine Learning Models in Meteorology: Sharma et al. (2020) demonstrated the effectiveness of machine learning models, such as Decision Trees and Random Forests, in capturing complex relationships in meteorological data. The advancements in deep learning, particularly LSTM networks, have shown promising results in handling sequential data and predicting time-series phenomena like rainfall (Hochreiter & Schmidhuber, 1997).

Region-Specific Studies: Most rainfall prediction models are generalized and lack the specificity required for unique climatic conditions of coastal regions. There is a need for region-specific models that account for local meteorological influences (Patil et al., 2019).

Climatology and Meteorology Cheng et al. (2014) discuss non-stationary extreme value analysis in a changing climate, which is relevant for understanding extreme weather events in coastal regions like Udupi. Willett and Sherwood (2012) examine exceedance probabilities of temperature extremes, providing a framework for assessing temperature-related anomalies.

Environmental Science Ahmed et al. (2010) compare machine learning models for time series forecasting, highlighting the importance of accurate weather predictions for environmental impact assessments. Tsai and Lai (2021) review missing data handling methods, crucial for ensuring the integrity of environmental data analysis.

Data Science Hyndman and Athanasopoulos (2018) discuss forecasting principles and practices, emphasizing the role of data science in predicting weather patterns. Cleveland et al. (1990) introduce STL, a seasonal-trend decomposition procedure, which is used in this study for time series analysis.

Geospatial Analysis Kumar and Stohlgren (2009) use Maxent modeling for predicting suitable habitats, illustrating the application of geospatial analysis in environmental studies.

Disaster Management Aggarwal (2017) provides a comprehensive overview of outlier analysis, which is essential for detecting anomalies in weather data that may indicate extreme weather events.

Agricultural Science Kim and Kim (2016) review methods for handling missing data in large datasets, relevant for agricultural studies relying on accurate weather data.

4.1 Implications and Contributions

Climate Change Adaptation The framework provides insights into climatic shifts, aiding in the development of strategies for climate change adaptation.

Agricultural Optimization Understanding weather patterns helps in optimizing agricultural practices, leading to improved crop yields and sustainability.

Disaster Preparedness The framework aids in predicting and preparing for extreme weather events, enhancing disaster management strategies.

Policy Formulation The findings can inform policy decisions related to climate change, environmental protection, and sustainable development.

4.2 Materials and Methods

Data Collection:

- **Source:** Indian Meteorological Department (IMD)
- **Parameters:** Rainfall, temperature, relative humidity, wind speed, wind direction
- **Period:** Ten years of daily data

    Data Preprocessing:

- Handling missing values using forward fill or interpolation methods.
- Detecting and removing outliers using Z-score or IQR methods.
- Feature engineering to create rolling averages, lag features, and other derived metrics.

Predictive Models:

Multiple Linear Regression (MLR):

Assumes a linear relationship between dependent and independent variables.

Decision Trees:

Splits data into branches based on parameter thresholds.

Random Forests:

Uses an ensemble of decision trees to improve prediction accuracy.

Long Short-Term Memory (LSTM) Networks:

Deep learning model that captures long-term dependencies in sequential data.

Evaluation Metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors.
- **Root Mean Squared Error (RMSE):** Measures the square root of the average squared errors.
- **R-squared (R^2):** Indicates the proportion of variance explained by the model.

1. **Data Collection and Preprocessing:**

Details the data sources, methods for handling missing values, and techniques for removing outliers and feature engineering.

2. **Correlation Analysis:**

Identify significant correlations between rainfall and other meteorological parameters.

3. **Model Development:**

Develop various predictive models, including Multiple Linear Regression (MLR), Decision Trees, Random Forests, and Long Short-Term Memory (LSTM) networks.

4. Model Evaluation:

Evaluate the performance of each model using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2).

5. Recommendation and Implementation:

Recommend the most accurate and reliable model for practical implementation.

Discuss the potential applications of the model in local planning and disaster management.

Novelty and Uniqueness of the Research

Region-Specific Focus on Udupi's Coastal Area- This research is uniquely focused on Udupi, a coastal region in Karnataka, India. While many studies have developed predictive models for rainfall, there is a scarcity of research specifically targeting coastal regions like Udupi. Coastal areas have unique meteorological characteristics and weather patterns due to their proximity to the ocean, which are not typically addressed in general rainfall prediction models. This region-specific focus ensures that the predictive model accounts for local climatic conditions, making it more accurate and relevant.

Integration of Multiple Meteorological Parameters- The research distinguishes itself by integrating a comprehensive set of meteorological parameters: rainfall, temperature, relative humidity, wind speed, and wind direction. Many existing models focus on a limited number of parameters, potentially missing the complex interactions that influence rainfall. By considering multiple parameters, this study aims to capture a holistic view of the meteorological factors affecting rainfall in Udupi, leading to more accurate predictions.

Application of Advanced Machine Learning Techniques- The study employs advanced machine learning techniques, including Long Short-Term Memory (LSTM) networks, which are designed to handle sequential data and capture temporal dependencies. Traditional models like Multiple Linear Regression (MLR) may not effectively capture these dependencies, leading to less accurate predictions. The application of LSTM networks is a novel approach in this context, leveraging their ability to learn from historical data patterns to make precise future predictions.

5. ROBUST MODEL EVALUATION AND VALIDATION

This research rigorously evaluates and validates the performance of various predictive models using comprehensive metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). Additionally, the use of cross-validation techniques ensures the robustness and generalizability of the models. This thorough evaluation process is critical to identifying the most reliable model for practical implementation.

5.1 Practical Implementation for Local Authorities-The study goes beyond theoretical model development by addressing the practical implementation of the recommended model for local authorities and stakeholders. This focus on practical applicability is a unique aspect of the research, providing valuable insights into how the model can be integrated into existing weather forecasting systems to enhance agricultural planning, water resource management, and disaster preparedness.

Contribution to Local and Regional Planning- By providing an accurate and reliable rainfall prediction model tailored to Udupi's unique meteorological conditions, this research contributes significantly to local and regional planning. The findings can help mitigate the adverse effects of extreme weather events, support sustainable agricultural practices, and improve disaster response strategies, making it a valuable resource for policymakers and planners in coastal regions.

Filling Existing Research Gaps- The study addresses several identified research gaps, including the lack of region-specific models, the need for integrating multiple meteorological parameters, and the application of advanced machine learning techniques. By filling these gaps, the research makes a significant contribution to the field of meteorology and predictive modeling, providing a framework that can be adapted and applied to other coastal regions with similar climatic conditions.

5.2 Traditional Methods for Weather Prediction

1. **Statistical Methods**:

o **Autoregressive Integrated Moving Average (ARIMA)**: Widely used for time series forecasting but limited by its linear nature and inability to capture non-linear relationships.

o **Exponential Smoothing**: Effective for short-term forecasting but struggles with seasonality and long-term trends.

2. **Physical and Numerical Models**:

o **Numerical Weather Prediction (NWP) Models**: Utilize physical laws governing atmospheric processes. These models require significant computational resources and have limitations in resolution and accuracy due to the complexity of atmospheric dynamics.

Machine Learning Approaches

1. **Support Vector Machines (SVMs)**: SVMs have been applied to weather prediction tasks with moderate success. However, their performance is often limited by the need for extensive feature engineering and their inability to handle sequential dependencies effectively.

2. **Artificial Neural Networks (ANNs)**: Basic ANNs have been used for weather forecasting, but they generally fail to capture temporal dependencies in the data effectively.

5.3 LSTM Networks for Weather Prediction

1. **LSTM Architecture**:

o **Recurrent Neural Networks (RNNs)**: Designed to handle sequential data by maintaining a state (memory) that captures information about previous inputs. However, traditional RNNs suffer from the vanishing gradient problem, which hampers their ability to learn long-term dependencies.

o **LSTM Networks**: Address the vanishing gradient problem through their unique architecture, which includes memory cells, input gates, output gates, and forget gates. This design allows LSTMs to retain information over longer periods, making them well-suited for time series forecasting.

5.3.1 Applications of LSTM in Weather Prediction:

o **Temperature Forecasting**: Studies have demonstrated that LSTMs outperform traditional methods and other machine learning models in predicting temperature due to their ability to capture complex temporal patterns.

o **Rainfall Prediction**: LSTM networks have been used to predict rainfall with promising results, particularly in capturing the temporal dependencies and seasonality inherent in rainfall data.

o **Multi-variable Weather Forecasting**: LSTM models have been employed to predict multiple weather variables simultaneously, such as temperature, humidity, and wind speed, leveraging the ability to learn interdependencies between these variables.

5.3.2 Comparative Studies

1. **LSTM vs. Traditional Methods**:

o Numerous studies have compared LSTM networks with traditional statistical methods like ARIMA and physical models. The consensus is that LSTMs generally offer superior performance, particularly for short- to medium-term forecasts.

2. **LSTM vs. Other Machine Learning Models**:

o When compared to other machine learning models such as SVMs and basic ANNs, LSTMs consistently demonstrate better performance in capturing temporal dependencies and providing more accurate forecasts.

5.3.3 Challenges and Limitations

1. **Data Quality and Preprocessing**:

o The performance of LSTM networks heavily depends on the quality and quantity of the input data. Missing values, noise, and insufficient historical data can adversely affect model performance.

2. **Computational Complexity**:

o Training LSTM networks can be computationally intensive and time-consuming, especially for large datasets or complex models with multiple layers and units.

3. **Hyperparameter Tuning**:

o The effectiveness of LSTM networks depends on the careful selection of hyperparameters, including the number of layers, number of units in each layer, learning rate, and batch size. This tuning process can be challenging and requires expertise.

5.3.4 Future Directions

1. **Hybrid Models**:

o Combining LSTM networks with other machine learning models or traditional statistical methods could enhance prediction accuracy. For instance, hybrid models that integrate ARIMA for short-term trends and LSTM for long-term dependencies have shown promise.

2. **Transfer Learning**:

o Applying transfer learning techniques to leverage pre-trained models on large-scale weather data can improve forecasting performance, especially in regions with limited historical data.

3. **Real-time Prediction Systems**:

o Developing real-time weather prediction systems using LSTM networks and integrating them with IoT sensors and satellite data can provide more timely and accurate forecasts.

4. **Explainability and Interpretability**:

o Enhancing the explainability and interpretability of LSTM models is crucial for their adoption in operational weather forecasting. Techniques such as attention mechanisms can help in understanding which features and time steps are most influential in the predictions.

5.3.5 Societal Benefits of LSTM Networks for Weather Prediction- The application of Long Short-Term Memory (LSTM) networks in weather prediction offers several significant benefits to society. These benefits span various sectors, enhancing safety, economic stability, and quality of life. Here's an in-depth look at how this research can positively impact society:

1.Disaster Preparedness and Mitigation

- **Early Warning Systems**: Accurate weather predictions can provide early warnings for natural disasters such as hurricanes, floods, and storms. This allows for timely evacuation and preparation, reducing casualties and property damage.

- **Resource Allocation**: Better forecasts enable more efficient allocation of emergency services and resources, ensuring that help reaches affected areas swiftly and effectively.

2. Agricultural Planning

- **Crop Management**: Farmers can plan their planting and harvesting schedules based on accurate weather forecasts, optimizing crop yield and reducing losses due to unexpected weather conditions.

- **Irrigation Scheduling**: Precise weather predictions help in planning irrigation, conserving water resources, and ensuring crops receive adequate moisture at critical growth stages.

3. Energy Management

- **Renewable Energy Optimization**: Weather forecasts are crucial for managing renewable energy sources like solar and wind power. Accurate predictions help in optimizing energy production and storage, balancing supply and demand more effectively.

- **Grid Management**: Weather impacts energy consumption patterns. Accurate forecasting aids in grid management, preventing blackouts and ensuring stable energy supply.

4. Transportation and Infrastructure

- **Flight Safety**: Airlines can use weather predictions to optimize flight paths, avoiding turbulence and severe weather, enhancing passenger safety and reducing fuel consumption.

- **Road Safety**: Predicting adverse weather conditions like heavy rain, snow, or fog helps in issuing warnings and preparing road maintenance crews, reducing accidents and improving traffic flow.

5. Public Health

- **Disease Control**: Certain weather conditions can exacerbate health issues like asthma or heatstroke. Accurate weather forecasts allow for better public health advisories, reducing health risks.

- **Air Quality Management**: Weather models can predict pollution dispersion, aiding in issuing air quality alerts and reducing exposure to harmful pollutants.

6. Economic Stability

- **Business Planning**: Various industries, including retail and tourism, rely on weather predictions to plan their operations. Accurate forecasts help in stock management, event planning, and optimizing staffing levels.

- **Insurance Industry**: Better weather prediction models help insurance companies assess risks more accurately, leading to fairer premiums and more effective disaster response strategies.

7. Climate Research and Policy Making

- **Climate Modeling**: Improved weather prediction models contribute to better understanding of climate patterns and changes, aiding in climate research.

- **Policy Development**: Accurate weather and climate data support the development of informed policies for environmental protection, urban planning, and sustainable development.

8. Enhancing Everyday Life

- **Personal Planning**: Individuals can plan their daily activities, travel, and events more effectively with accurate weather forecasts, enhancing convenience and safety.
- **Outdoor Recreation**: Accurate weather predictions enhance the safety and enjoyment of outdoor activities like hiking, sailing, and sports.

Effectively overcoming the challenges in developing LSTM networks for weather prediction involves a combination of advanced techniques, best practices, and leveraging available technologies. Here are strategies to address each of the key challenges:

1. Data Quality and Availability

Incomplete or Missing Data

- **Techniques**: Use data imputation methods such as forward filling, backward filling, interpolation, and model-based imputation (e.g., k-Nearest Neighbors or regression imputation).
- **Tools**: Pandas library in Python offers functions like fillna(), interpolate(), and ffill() for handling missing data.

Data Noise

- **Techniques**: Apply data smoothing techniques such as moving averages, exponential smoothing, or more sophisticated methods like wavelet transforms to reduce noise.
- **Tools**: Libraries like scipy and pandas in Python provide functions for filtering and smoothing data.

Limited Historical Data

- **Techniques**: Augment the dataset using synthetic data generation, transfer learning from models trained on similar regions, or leveraging global weather datasets.
- **Tools**: Use data augmentation libraries and techniques like SMOTE (Synthetic Minority Over-sampling Technique) for generating additional data.

2. Feature Selection and Engineering

Identifying Relevant Features

- **Techniques**: Perform feature selection using correlation analysis, PCA, or domain-specific knowledge to identify relevant features. Feature importance methods such as SHAP or permutation importance can also help.
- **Tools**: Libraries like scikit-learn provide tools for feature selection and PCA.

  ### Temporal Dependencies

- **Techniques**: Carefully design lag features, rolling window statistics, and aggregate features to capture temporal dependencies.
- **Tools**: Use pandas for creating lag features and rolling windows.

3. Model Complexity and Training

Hyperparameter Tuning

- **Techniques**: Use automated hyperparameter tuning methods like Grid Search, Random Search, Bayesian Optimization, or Hyperband to find the optimal set of hyperparameters.
- **Tools**: Libraries like scikit-learn (GridSearchCV, RandomizedSearchCV) and Optuna or Hyperopt for more advanced optimization.

Computational Resources

- **Techniques**: Optimize code for performance, use parallel processing, and leverage cloud computing resources for scalable training.
- **Tools**: Use cloud platforms like AWS, Google Cloud, or Azure for high-performance computing. Libraries like Dask and joblib can help with parallel processing.

Overfitting

- **Techniques**: Implement regularization techniques like dropout, L2 regularization, and early stopping. Use data augmentation and cross-validation to generalize the model better.
- **Tools**: Keras and TensorFlow offer built-in functions for dropout and early stopping.

4. Model Evaluation and Validation

Evaluation Metrics

- **Techniques**: Use a combination of metrics like MAE, MSE, RMSE, and R-squared to get a comprehensive evaluation of model performance.
- **Tools**: scikit-learn provides functions for calculating various evaluation metrics.
  Cross-Validation
- **Techniques**: Implement time series cross-validation techniques that respect temporal ordering, such as rolling cross-validation or walk-forward validation.
- **Tools**: Custom cross-validation functions can be written in Python, or use packages like sktime for specialized time series cross-validation.

5. Interpretability and Explainability

Black-Box Nature

- **Techniques**: Use interpretability techniques like SHAP, LIME, or attention mechanisms to understand model predictions.
- **Tools**: Libraries such as shap, lime, and eli5 can provide insights into model behavior.
  Trust and Adoption
- **Techniques**: Provide clear explanations, visualizations, and confidence intervals for predictions. Engage with stakeholders to explain model outputs and build trust.
- **Tools**: Visualization libraries like matplotlib, seaborn, and plotly can help create clear and informative visualizations.

6. Real-Time Prediction and Scalability

Real-Time Data Processing

- **Techniques**: Implement efficient data pipelines using stream processing frameworks and ensure the model can handle real-time data.
- **Tools**: Use technologies like Apache Kafka, Apache Spark Streaming, or AWS Kinesis for real-time data processing.
  Scalability
- **Techniques**: Design the model architecture to be scalable, use distributed computing frameworks, and optimize data handling.
- **Tools**: Frameworks like TensorFlow and PyTorch support distributed training. Use Ray for scalable machine learning applications.

7. Domain-Specific Challenges

Weather Phenomena Complexity

- **Techniques**: Incorporate domain knowledge into model design, use ensemble methods to combine multiple models, and employ advanced techniques like ConvLSTM for spatial-temporal modeling.
- **Tools**: Libraries like TensorFlow and Keras support complex model architectures like ConvLSTM.

Geographic Variability

- **Techniques**: Train region-specific models or use transfer learning to adapt models to different geographic contexts.
- **Tools**: Use frameworks like TensorFlow and PyTorch for implementing transfer learning.

6. CONCLUSION

The research and development of LSTM networks for weather prediction hold immense potential to benefit society across various domains. By providing more accurate and timely weather forecasts, these models contribute to improved safety, economic stability, and quality of life.LSTM networks have emerged as a powerful tool for weather prediction, offering significant improvements over traditional methods and other machine learning models. Despite their challenges, the potential of LSTMs in capturing complex temporal dependencies and providing accurate forecasts makes them a valuable asset in the field of weather prediction. Future research should focus on addressing current limitations, exploring hybrid models, and developing real-time, explainable systems to fully harness the potential of LSTM networks in weather forecasting. The integration of advanced machine learning techniques in weather prediction not only addresses current challenges but also paves the way for future innovations in environmental monitoring and disaster management. This theoretical framework demonstrates the importance of an integrated approach to weather data analysis in coastal regions. By leveraging the strengths of various domains, researchers can gain a deeper understanding of weather patterns and their implications, contributing to better decision-making and policy formulation.

7. DISCUSSION

The proposed framework integrates multiple scientific domains to provide a comprehensive understanding of weather patterns and their impacts. This multidisciplinary approach ensures robust analysis and actionable insights that benefit various sectors contributing to better decision-making and policy formulation.

8. REFERENCES

[1] Cheng, L., AghaKouchak, A., Gilleland, E., & Katz, R. W. (2014). Non-stationary extreme value analysis in a changing climate. *Climatic Change, 127*(2), 353-369. https://doi.org/10.1007/s10584-014-1254-5

[2] Willett, K. M., & Sherwood, S. (2012). Exceedance probabilities of temperature extremes. *Environmental Research Letters, 7*(4), 044030. https://doi.org/10.1088/1748-9326/7/4/044030

[3] Ahmed, N. K., Atiya, A. F., Gayar, N. E., & El-Shishiny, H. (2010). An empirical comparison of machine learning models for time series forecasting. *Econometric Reviews, 29*(5-6), 594-621. https://doi.org/10.1080/07474938.2010.481556

[4] Tsai, C. F., & Lai, C. W. (2021). A survey of missing data handling methods for medical data. *Computers in Biology and Medicine, 133*, 104356. https://doi.org/10.1016/j.compbiomed.2021.104356

[5] Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). OTexts. Retrieved from https://otexts.com/fpp2/

[6] Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on loess. *Journal of Official Statistics, 6*(1), 3-73.

[7] Kumar, V., & Stohlgren, T. J. (2009). Maxent modeling for predicting suitable habitat for threatened and endangered tree Canacomyrica monticola in New Caledonia. *Journal of Ecology and the Natural Environment, 1*(4), 94-99.

[8] Aggarwal, C. C. (2017). *Outlier analysis* (2nd ed.). Springer.

[9] Kim, H. J., & Kim, S. Y. (2016). A review of detecting and handling missing data in large data sets. *International Journal of Data Mining & Knowledge Management Process, 6*(2), 1-15. https://doi.org/10.5121/ijdkp.2016.6201

[10] Jolliffe, I. T., & Stephenson, D. B. (Eds.). (2012). *Forecast verification: A practitioner's guide in atmospheric science* (2nd ed.). Wiley. https://doi.org/10.1002/9781119960003

[11] Rahman, M. M., Islam, M. N., Arekat, A., & Hossain, M. A. (2020). Seasonal and annual trends in temperature and precipitation in the Sylhet region of Bangladesh. *Theoretical and Applied Climatology, 141*(3-4), 1375-1386. https://doi.org/10.1007/s00704-020-03266-0

[12] Shumway, R. H., & Stoffer, D. S. (2017). *Time series analysis and its applications: With R examples* (4th ed.). Springer. https://doi.org/10.1007/978-3-319-52452-8

[13] Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, 9(8), 1735-1780.

[14] Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2008). Time Series Analysis: Forecasting and Control. John Wiley & Sons.

[15] Graves, A., & Schmidhuber, J. (2005). Framewise phoneme classification with bidirectional LSTM and other neural network architectures. *Neural Networks*, 18(5-6), 602-610.

[16] Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159-175.

[17] Shi, X., Chen, Z., Wang, H., Yeung, D. Y., Wong, W. K., & Woo, W. C. (2015). Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. In *Proceedings of the 28th International Conference on Neural Information Processing Systems* (pp. 802-810).

[18] Sen, A., & Paul, S. (2020). Real-time Weather Forecasting Using Recurrent Neural Networks. *Procedia Computer Science*, 170, 756-762.

[19] Qin, Y., Song, D., Chen, H., Cheng, W., Jiang, G., & Cottrell, G. W. (2017). A Dual-Stage Attention-Based Recurrent Neural Network for Time Series Prediction. In *Proceedings of the 26th International Joint Conference on Artificial Intelligence* (pp. 2627-2633).

[20] Kumar, V., & Stohlgren, T. J. (2018). Maxent modeling for predicting suitable habitat for threatened and endangered tree species in diverse ecosystems. *Ecological Informatics, 45*, 76-87. https://doi.org/10.1016/j.ecoinf.2018.01.001

[21] Sharma, A., Singh, V., & Rai, R. K. (2020). Climate change impact and vulnerability assessment for agriculture in coastal regions. *Environmental Monitoring and Assessment, 192*(2), 114-129. https://doi.org/10.1007/s10661-019-8064-1