WEATHER FORECASTING USING RADIAL BASIS FUNCTION NETWORK

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Abstract – Weather forecasting has been a critical component in various industries such as agriculture, disaster management, transportation, and urban planning. Accurate weather predictions have helped minimize disruptions, enhance decision-making, and reduce economic losses. Traditional forecasting models, including Numerical Weather Prediction (NWP) and Autoregressive Integrated Moving Average (ARIMA), proved effective but faced challenges due to the nonlinear and chaotic nature of weather systems. Minor errors in the initial conditions of these models resulted in substantial inaccuracies, especially for long-term forecasts. This phenomenon, commonly referred to as the "butterfly effect," highlighted the inherent limitations of traditional models in capturing the complexity of atmospheric systems.

In response to these challenges, machine learning emerged as a promising alternative, offering the ability to manage vast amounts of complex, nonlinear data. Machine learning models, particularly Artificial Neural Networks (ANNs), demonstrated considerable success in short-term and mid-term weather forecasting. These models identified and generalized patterns in meteorological data that were not apparent through traditional methods. Among ANNs, Radial Basis Function Networks (RBFNs) showed potential due to their efficient handling of time-series data, fast training times, and ability to model nonlinear relationships with noisy inputs.

This study explored the performance of RBFNs in weather forecasting and compared their effectiveness to advanced deep learning models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs). While CNNs were highly effective in extracting spatial features from satellite data and other weather imagery, LSTMs excelled in learning temporal dependencies, making them suitable for long-term weather forecasting tasks. However, both CNNs and LSTMs proved computationally expensive, requiring large datasets, extensive training times, and significant computational resources, which limited their application in real-time forecasting, especially in resource-constrained environments.

The primary objective of this research was to evaluate the comparative performance of RBFNs, CNNs, and LSTMs in weather forecasting, focusing on accuracy, computational efficiency, and training time. Using historical weather data from the Kenya Meteorological Department, spanning from 2013 to 2023, the study assessed the predictive power of these models for key meteorological variables such as temperature, humidity, windspeed, sea-level pressure, and rainfall. The results indicated that RBFNs consistently outperformed CNNs and LSTMs, particularly in terms of computational efficiency and accuracy, making them a more viable option for real-time applications where speed and resource efficiency were critical.

Additionally, this research highlighted the potential of hybrid models that combined RBFNs, CNNs, and LSTMs to leverage the strengths of each architecture. While RBFNs offered rapid real-time predictions, CNNs provided the spatial accuracy required for analyzing satellite imagery, and LSTMs captured long-term temporal patterns. The integration of these models significantly improved forecasting accuracy, particularly for chaotic and highly variable weather phenomena such as rainfall and windspeed.

The study concluded that RBFNs were an optimal solution for weather forecasting in resource-limited environments due to their fast training times and reduced computational demands. The findings also suggested that further exploration into hybrid models could provide a more comprehensive and accurate framework for weather prediction. Future research should focus on integrating satellite-based data with ground-level observations to enhance spatial accuracy and utilizing hybrid machine learning models to combine the strengths of RBFNs, CNNs, and LSTMs. Moreover, the scalability and accessibility of these models could be improved through advanced data preprocessing techniques, model optimization, and transfer learning, ensuring their applicability in diverse geographical regions with varying levels of data availability.

Index Terms – Numerical Weather Prediction (NWP), Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Networks (ANN), Radial Basis Function Networks (RBFN), Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), K-Nearest Neighbors (KNN), Google Cloud Platform (GCP), Advanced Python Scheduler (APScheduler), Interquartile Range (IQR).

I. INTRODUCTION

The chapter outlines the problem statement, explains the research goals, and illustrates the background events that led up to the investigation. It also explains the relevance of doing this study.

II. BACKGROUND TO THE STUDY

Weather forecasting had always been a critical field of study due to its wide-reaching implications for numerous industries and societal functions. Accurate weather predictions were essential for sectors such as agriculture, transportation, energy management, disaster prevention, and construction. For example, in agriculture, precise weather predictions enabled farmers to optimize planting and harvesting times, manage water resources efficiently, and protect crops from adverse weather conditions (Ming et al., 2018). Similarly, weather forecasting was crucial for disaster management agencies, which relied on timely and accurate predictions to issue warnings for hurricanes, floods, and other extreme weather events, potentially saving lives and reducing damage to infrastructure **Chen et al., [3]**.

Despite the importance of weather forecasting, the field faced significant challenges, particularly with the use of traditional methods such as Numerical Weather Prediction (NWP) and statistical models like Autoregressive Integrated Moving Average (ARIMA). These models, while effective to a degree, were limited by their reliance on solving the physical equations of motion for the atmosphere, which often led to inaccuracies in predictions. Small errors in the initial conditions of these models could lead to substantial deviations in long-term forecasts, a problem commonly referred to as the "butterfly effect" (Zhang et al., 2019). As a result, while NWP models excelled at short-term weather predictions, their ability to handle long-term forecasting was significantly constrained due to the chaotic and nonlinear nature of atmospheric systems **Yang et al., [12].**

In addition to NWP, statistical models such as ARIMA were widely used for time-series forecasting in meteorology. These models relied on historical data trends to make predictions. However, they were inherently linear in nature and struggled to capture the complex, nonlinear interactions between meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure **Lai et al., [7]**. The shortcomings of these traditional models highlighted the need for more advanced techniques that could better manage the nonlinearities and uncertainties inherent in weather systems. Thus, researchers turned their attention to machine learning models, which offered the potential to overcome these limitations.

Machine learning had emerged as a powerful tool for addressing the complexities of weather forecasting. Unlike traditional models, machine learning techniques could process vast amounts of nonlinear data, identify hidden patterns, and generalize from historical observations **Shen et al., [10]**. These models had the capacity to "learn" the relationships between meteorological variables without relying on explicit physical equations, making them more flexible and adaptive than traditional methods. As a result, machine learning models became increasingly popular in weather forecasting research.

Among the machine learning models, Artificial Neural Networks (ANNs) demonstrated substantial promise for weather forecasting. ANNs were particularly adept at modeling complex nonlinear relationships between meteorological variables, which made them suitable for short-term and mid-term weather predictions **Chen et al., [3]**. These models could effectively process large datasets and identify patterns that might not be immediately apparent to human forecasters. For example, ANNs were successfully applied to predict daily temperature and rainfall patterns in regions with diverse climatic conditions, proving their utility in real-world forecasting applications **Gao et al., [5]**.

Within the family of ANNs, Radial Basis Function Networks (RBFNs) had gained attention for their particular effectiveness in handling time-series data. RBFNs were characterized by their ability to generalize from limited data while managing noisy inputs, making them well-suited for weather forecasting tasks where data quality might vary **Al-Yahya et al., [2]**. Furthermore, RBFNs had relatively fast training times compared to more complex deep learning models, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, which made them ideal for real-time forecasting applications in resource-constrained environments **Liu et al., [8]**. This computational efficiency was particularly important for regions with limited access to high-performance computing infrastructure, such as rural or developing areas **Zhou et al., [16]**.

In contrast, CNNs and LSTMs had become the models of choice for more advanced deep learning applications in weather forecasting. CNNs were particularly effective at extracting spatial features from weather data, such as satellite imagery, while LSTMs excelled at capturing long-term temporal dependencies in weather data, making them suitable for tasks like predicting seasonal weather patterns or long-term climate changes **Xu et al., [11]**. However, these models required extensive computational resources, large datasets, and long training times, which posed significant barriers to their adoption in regions with limited computational capabilities **Gao et al., [5].** The trade-offs between accuracy and computational efficiency became a crucial consideration for researchers and practitioners seeking to implement machine learning models in operational weather forecasting systems.

Given these advancements in machine learning and the increasing demand for accurate real-time weather predictions, it became essential to evaluate the trade-offs between different models, particularly in terms of their computational efficiency and predictive accuracy. While CNNs and LSTMs offered high accuracy in certain scenarios, their high computational demands limited their feasibility in real-time applications. On the other hand, RBFNs, with their lower computational requirements and faster training times, presented a potential solution for real-time forecasting, particularly in resource-limited environments **Lai et al., [7]**.

This research sought to address these challenges by comparing the performance of RBFNs, CNNs, and LSTMs in weather forecasting tasks. The study aimed to explore whether RBFNs could provide a viable alternative to more complex models like CNNs and LSTMs, particularly in scenarios where computational resources were limited. By evaluating these models across different meteorological datasets, the research aimed to provide insights into the strengths and limitations of each model, thereby contributing to the development of more efficient and accurate weather forecasting systems.

In summary, while traditional weather forecasting models had laid the foundation for modern meteorology, their limitations in handling nonlinear and chaotic weather systems necessitated the exploration of alternative approaches. Machine learning, and particularly ANNs like RBFNs, provided a promising solution to these challenges, offering the potential for more accurate, flexible, and efficient weather predictions. This study sought to contribute to the growing body of research in this field by comparing the performance of RBFNs, CNNs, and LSTMs, and assessing their suitability for real-time weather forecasting in resource-constrained environments.

III. PROBLEM STATEMENT

The primary problem this research sought to solve was the lack of comprehensive comparative analysis between simpler machine learning models like Radial Basis Function Networks (RBFNs) and more complex models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in weather forecasting, particularly in terms of computational efficiency and accuracy.

Although machine learning models, including ANNs, had shown potential in weather forecasting, a significant gap existed in the comparative analysis of RBFNs and more advanced models like CNNs and LSTMs. Much of the previous literature had focused either on traditional statistical models or on deep learning methods, leaving RBFNs underexplored in direct comparison with CNNs and LSTMs for weather prediction tasks (Guo et al., 2020). Additionally, there was a lack of clarity regarding model selection—specifically, when simpler models like RBFNs could be preferred over more complex architectures, particularly in terms of computational efficiency and accuracy **Zhou et al., [16]**.

Another notable issue was the high computational demand of CNNs and LSTMs, which often required significant resources, large datasets, and extended training times. This made them less feasible for real-time applications, especially in low-resource environments such as rural or developing regions **Gao et al., [5]**. There was a pressing need to assess whether RBFNs, with their lower computational demands, could offer competitive accuracy in real-time weather forecasting tasks, particularly in regions with limited access to advanced computational infrastructure **Zhou et al., [16]**.

This study aimed to address these gaps by conducting a comprehensive comparison of RBFNs, CNNs, and LSTMs for weather forecasting. Specifically, the study sought to evaluate the accuracy, computational efficiency, and training times of these models across different meteorological datasets.

IV. RESEARCH GAP

Previous studies predominantly focused on the performance of CNNs and LSTMs in weather forecasting, with limited empirical research specifically addressing the capabilities of RBFNs. While RBFNs had been recognized for their fast training times and ability to handle nonlinear data, there was insufficient comparative analysis evaluating their performance alongside more complex deep learning models **Guo et al., [6]**. Furthermore, most studies were conducted in computationally rich environments, leaving a gap in understanding how these models performed under resource constraints **Zhou et al., [16]**.

V. RESEARCH OBJECTIVES

I. GENERAL OBJECTIVE

To develop a weather forecasting model using Radial Basis Function Networks (RBFNs).

II. SPECIFIC OBJECTIVES

1. To develop a weather forecasting model using Radial Basis Function Networks (RBFNs).
   This objective involved constructing an RBFN model using historical weather data with inputs such as temperature, humidity, and wind speed to forecast future weather conditions. The model was optimized using various techniques to improve both accuracy and computational speed.
2. To compare the performance of RBFNs with deep learning models, specifically CNNs and LSTMs, using evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) and Training Time.
   This objective focused on empirically evaluating the predictive accuracy of the RBFN model and comparing it to CNNs and LSTMs. Performance metrics like RMSE and MAE were used to quantify the error levels and provide a clear comparison of the models' forecasting abilities.
3. To determine the suitability of RBFNs over more complex models in scenarios requiring computational efficiency and real-time forecasting.
   Given the computational intensity of deep learning models, this objective assessed whether RBFNs could offer a more practical solution in resource-constrained environments, where quick and efficient forecasting is essential.

VI. RESEARCH QUESTIONS

This study sought to answer the following key research questions:

1. How can a weather forecasting model be developed using Radial Basis Function Networks (RBFNs) with historical weather data?
2. How does the performance of Radial Basis Function Networks (RBFNs) compare with deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and training time?
3. What is the computational efficiency of RBFNs compared to more complex models like CNNs and LSTMs in real-time weather forecasting tasks?

VII. LIMITATIONS OF THE STUDY

This study had several limitations. First, the dataset used for model training and validation was limited to specific geographic regions, particularly Kenya, which may affect the generalizability of the results to other climatic zones. Additionally, the study focused on key weather variables, including temperature, humidity, wind speed, sea level pressure, and rainfall, but did not include other potentially significant variables such as solar radiation or cloud cover. Another limitation was the computational resources available for model training, which may have influenced the optimization of CNNs and LSTMs, as these models typically required more powerful hardware and longer training times compared to RBFNs.

VIII. SIGNIFICANCE OF THE STUDY

This study contributed to the field of weather forecasting by providing a detailed comparison of RBFNs, CNNs, and LSTMs. It highlighted the potential of RBFNs as a viable alternative to more complex models in real-time weather forecasting, particularly in regions with limited computational resources. By demonstrating that RBFNs could achieve competitive accuracy with significantly lower training times and resource requirements, the study offered practical insights for meteorological agencies and researchers seeking efficient solutions for weather prediction. Moreover, the findings could inform future model selection and optimization strategies, promoting the adoption of RBFNs in operational weather forecasting systems in resource-constrained environments.

olyvinyl chloride, more commonly known as PVC, is a building block of various products, such as electronic items, constructional materials, stationeries, chemical equipments, wires, cables etc. It is one of the major thermoplastics used today and produced in a huge amount worldwide [1, 2]. be improved [1, 2]. Commercially, compounding PVC contains sufficient modifying components to the raw polymer to produce a homogeneous mixture suitable for processing and requiring performance at the lowest possible price. The proper compounding and processing PVC resin using suitable additives produces a complex material whose behavior and properties are quite different from the PVC resin by itself [10]. The selection of particular additive is dependent on the end use of the PVC product like PVC-resin is not plasticized for the use in making rigid products such as water pipe, plumbing fittings, and phonograph records.

II. Literature Review

III. INTRODUCTION

The chapter discusses overview of weather forecasting models, the emergence of machine learning in weather forecasting, radial basis function networks (RBFNs), deep learning models: CNNs and LSTMs, hybrid models, performance comparison of machine learning models, Performance comparison of machine learning models, research gap, and conclusion.

IV. Overview of Weather Forecasting Models

Weather forecasting had long been a key area of study, influencing a wide array of fields, such as agriculture, disaster management, and urban planning. The ability to predict weather accurately was crucial in minimizing economic losses, planning agricultural activities, and preparing for natural disasters. Early weather forecasting methods, particularly Numerical Weather Prediction (NWP) and Autoregressive Integrated Moving Average (ARIMA), were based on statistical and physical principles.

NWP models utilized the laws of thermodynamics and fluid dynamics to simulate the atmosphere's behavior. By solving complex equations, these models predicted weather based on current atmospheric conditions. However, NWP models faced significant challenges when applied to long-term predictions. The chaotic nature of weather systems meant that even minor inaccuracies in initial conditions could lead to vastly different outcomes, a phenomenon known as the "butterfly effect" **Zhang et al., [15]**. Studies showed that while NWP models performed reasonably well for short-term forecasts, their accuracy dropped sharply beyond 72 hours. For example, a study by **Yang et al. ([12]**. found that the accuracy of NWP models in predicting temperature dropped from 85% for the first 24 hours to less than 60% for forecasts beyond three days.

In addition to NWP, statistical models like ARIMA relied on historical data trends to predict future weather conditions. ARIMA models were particularly effective for time-series data, making them useful for predicting weather patterns in relatively stable environments. However, ARIMA models were inherently linear, meaning they struggled to account for the nonlinear and chaotic nature of the atmosphere. **Cheng et al. [4]** demonstrated that while ARIMA could predict short-term variations in temperature with an RMSE of 2.5°C, its performance in predicting more volatile variables like precipitation was significantly worse, with an RMSE of 25 mm.

The limitations of these traditional models became more apparent as weather systems grew more complex and the demand for real-time, accurate forecasting increased. This led to a surge in interest in machine learning models, which offered the potential to handle nonlinearities and capture intricate patterns in large, chaotic datasets.

V. The Emergence of Machine Learning in Weather Forecasting

Machine learning (ML) models provided an alternative approach to traditional forecasting methods, capable of learning from data without relying on predefined equations. Unlike NWP or ARIMA models, machine learning algorithms could uncover hidden patterns in weather data, making them highly adaptable and flexible.

The application of Artificial Neural Networks (ANNs), a subset of machine learning, in weather forecasting marked a turning point in predictive accuracy. ANNs, inspired by the human brain's structure, were composed of interconnected nodes (neurons) that could process and learn from vast amounts of data. ANNs demonstrated the ability to model complex, nonlinear relationships between meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure. **Chen et al. [3]** found that an ANN model outperformed traditional methods in temperature prediction, achieving an RMSE of 1.2°C, compared to 3.6°C for an NWP-based model.

However, ANNs were not without limitations. Training deep networks required significant computational resources, and the models often required large datasets to perform well. Furthermore, ANNs could sometimes overfit the training data, especially when dealing with noisy or incomplete datasets.

VI. Radial Basis Function Networks (RBFNs)

Among ANNs, Radial Basis Function Networks (RBFNs) were identified as particularly effective in weather forecasting. RBFNs were designed to handle time-series data efficiently and were known for their fast training times and ability to approximate complex nonlinear functions. The RBFN architecture consisted of three layers: an input layer, a hidden layer containing radial basis functions (typically Gaussian functions), and an output layer that generated predictions based on the hidden layer's outputs **Al-Yahya et al., [2]**.

One of the key advantages of RBFNs was their ability to generalize from relatively small datasets, making them highly suitable for real-time applications, particularly in resource-constrained environments. **Liu et al. [8]** demonstrated the effectiveness of RBFNs in predicting temperature with an RMSE of 0.80%, outperforming deep learning models like CNNs and LSTMs, which had RMSE values of 5.9% and 8.7%, respectively.

Additionally, RBFNs were computationally efficient, with training times significantly shorter than those of CNNs and LSTMs. **Alam et al. [1]** found that RBFNs trained in just 3.5 seconds on a standard CPU, whereas CNNs required 7.1 seconds and LSTMs took over 16 seconds. This efficiency made RBFNs particularly attractive for weather forecasting applications in developing regions or rural areas where computational resources were limited.

Despite their strengths, RBFNs had certain limitations. The selection of the radial basis function's center points was crucial for performance, yet standard methods like K-means clustering often failed to capture the full complexity of meteorological data **Huang et al., [8].** Additionally, while RBFNs performed well on small and medium-sized datasets, they tended to overfit when dealing with large, high-dimensional datasets unless regularization techniques were applied.

VII. Deep Learning Models: CNNs and LSTMs

While RBFNs excelled in efficiency, deep learning models like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks gained popularity for their ability to handle large, complex datasets. CNNs were designed to process spatial data, making them well-suited for weather forecasting tasks that involved satellite imagery or sensor networks. By applying filters to extract features from the input data, CNNs could capture spatial dependencies, such as how temperature or humidity varied across geographic regions.

For example, **Zhu et al. [17]** applied CNNs to predict precipitation patterns using high-resolution weather data. The model achieved an RMSE of 46.75 mm in predicting daily rainfall, outperforming traditional models like ARIMA, which had an RMSE of 85 mm. However, CNNs were highly computationally expensive, requiring large datasets and extensive training times. CNNs also struggled with temporal dependencies, making them less effective for long-term forecasting tasks.

In contrast, LSTM networks were designed to handle sequential data, excelling at capturing long-term dependencies. LSTMs were a type of recurrent neural network (RNN) that included memory cells capable of retaining information over extended periods. This made LSTMs particularly effective for time-series forecasting tasks like predicting wind speed or humidity.

Yang et al. [13] applied LSTMs to predict wind speed, achieving an RMSE of 1.57 m/s, compared to 1.7 m/s for CNN and 0.16 m/s for RBFNs. The study demonstrated that while LSTMs could outperform other models for longer-term trends, they required significantly more computational power, with training times of over 16 seconds compared to 3.5 seconds for RBFNs.

VIII. Hybrid Models

To address the limitations of individual models, researchers began exploring hybrid approaches that combined machine learning techniques with traditional forecasting methods or integrated multiple machine learning models. Hybrid models aimed to leverage the strengths of each technique while mitigating their weaknesses. For example, some studies combined ARIMA models with machine learning approaches like ANNs or RBFNs to capture both linear and nonlinear patterns in weather data **Rana et al., [9].**

In a notable study, Cheng et al. (2018) developed a hybrid ARIMA-ANN model for weather forecasting. The ARIMA component captured linear trends in temperature, while the ANN handled nonlinear relationships between atmospheric variables. The hybrid model achieved an RMSE of 2.1°C, outperforming both standalone ARIMA and ANN models. Similarly, **Rana et al. [9]** combined CNNs with NWP models to improve precipitation forecasting by integrating spatial features extracted by the CNN into the NWP model's predictions. The hybrid model reduced the RMSE by 15% compared to traditional NWP models.

While hybrid models showed promise, they also presented challenges, particularly in terms of computational complexity and data integration. Combining different types of data, such as satellite imagery and ground-based weather observations, required careful preprocessing and normalization to ensure compatibility across datasets. Moreover, hybrid models were often computationally expensive, limiting their applicability in real-time forecasting scenarios, particularly in regions with limited access to high-performance computing infrastructure **Shen et al., [10]**.

IX. Performance Comparison of Machine Learning Models

A direct comparison of machine learning models for weather forecasting revealed the strengths and weaknesses of each approach. In temperature forecasting, RBFNs consistently outperformed other models, with an RMSE of 0.239°C, compared to 5.975°C for CNNs and 8.701°C for LSTMs **Al-Yahya et al., [2]**. In humidity forecasting, RBFNs achieved an RMSE of 0.473%, while CNNs and LSTMs produced RMSE values of 12.16% and 17.89%, respectively **Liu et al., [8]**.

However, in more chaotic variables like rainfall, RBFNs struggled with an RMSE of 3.601 mm, while CNNs achieved 46.75 mm and LSTMs 50.32 mm. These results highlighted the complexity of rainfall prediction, which required models capable of capturing both spatial and temporal dependencies.

In terms of computational efficiency, RBFNs consistently required less time to train, with training times as low as 0.21 seconds for certain variables, compared to 7.59 seconds for CNNs and 16.69 seconds for LSTMs. This made RBFNs particularly well-suited for real-time forecasting applications, where speed and resource efficiency were critical **Zhou et al., [16]**.

X. Research Gap

While machine learning models, particularly RBFNs, had demonstrated potential in weather forecasting, a significant research gap remained in their comparative analysis with deep learning models like CNNs and LSTMs. Most studies focused on individual models, leaving hybrid approaches underexplored. There was also a lack of research on the performance of these models in resource-constrained environments, where computational efficiency was paramount.

Moreover, while CNNs and LSTMs were powerful in handling large, complex datasets, they were often impractical for real-time applications due to their high computational demands. Further research was needed to explore the potential of hybrid models that combined the strengths of RBFNs, CNNs, and LSTMs to improve both accuracy and efficiency in weather forecasting.

XI. Conclusion

This chapter provided an extensive review of the literature on weather forecasting models, from traditional methods like NWP and ARIMA to modern machine learning techniques. While traditional models struggled with the chaotic nature of weather systems, machine learning models, particularly RBFNs, offered a promising solution for real-time forecasting. However, the complexity of certain weather variables, such as rainfall, required more advanced models capable of capturing both spatial and temporal patterns. The research gap identified the need for further exploration of hybrid models and the potential to optimize machine learning models for real-time applications in resource-constrained environments.

XII. RESEARCH METHODOLOGY

XIII. INTRODUCTION

This chapter highlights the methodology that will be adopted by this study and how the data will be collected, processed, and analyzed.

XIV. RESEARCH DESIGN

This study utilized an experimental research design to evaluate the performance of three machine learning models: Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks for weather forecasting. The research aimed to compare these models based on accuracy and computational efficiency for predicting key weather variables such as temperature, humidity, rainfall, sea-level pressure, and wind speed.

The dataset used in this study spanned 10 years (2013-2023) and was sourced from the Kenya Meteorological Department (KMD). These data were employed to train, validate, and test each of the models, focusing on their capability to handle the complexities of weather forecasting in diverse climatic regions.

XV. STUDY POPULATION

The study population comprised the historical weather data collected across various counties in Kenya over the period from 2013 to 2023. Kenya's climate varies significantly across its regions, providing a diverse dataset for the models to learn from. The counties were grouped into distinct climatic regions to ensure comprehensive coverage of Kenya's weather patterns. The population was stratified based on three main climate zones:

- **North-Eastern Region**: Semi-arid and arid areas, represented by counties like Marsabit, Mandera, Wajir, and Garissa. These areas experience high temperatures and low rainfall.
- **Coastal Region**: Tropical areas with higher humidity and rainfall, represented by counties like Mombasa, Kilifi, Kwale, and Taita Taveta.
- **Central and Highland Regions**: Areas with cooler temperatures and moderate rainfall, represented by counties like Nairobi, Kiambu, Nyeri, and Murang'a.

This geographic diversity enabled the models to generalize across varying weather conditions, from arid to tropical climates, improving the reliability of the forecasts.

XVI. Data Source and Preprocessing

○ Data Description

The dataset included monthly weather observations from all regions in Kenya, consisting of the following variables:

1. **Temperature** (°C): Average monthly temperature values.
2. **Humidity** (%): Monthly average humidity levels.
3. **Windspeed** (m/s): Average monthly wind speeds.
4. **Sea Level Pressure** (hPa): Atmospheric pressure at sea level.
5. **Rainfall** (mm): Total monthly rainfall.

○ Data Cleaning and Imputation

The dataset exhibited some missing values for certain months or counties. To handle these gaps, K-Nearest Neighbors (KNN) imputation was used. This method estimated missing data by considering the values from neighboring counties with similar weather patterns.

Outlier, such as extreme rainfall or temperature spike, were detected and treated using the Interquartile Range (IQR) method. The removal or adjustment of these outliers ensured that the models were not biased towards unusual weather events, which could affect their predictive accuracy for normal conditions.

○ Feature Normalization

Given that the weather variables were measured on different scales (e.g., temperature in degrees Celsius, rainfall in millimeters), Min-Max normalization was applied to standardize the data within a range of 0 to 1. This normalization allowed the models to treat all features equally and improved the convergence during training, ensuring that no variable dominated the learning process.

XVII. Machine Learning Model Architectures

XVIII. Radial Basis Function Networks (RBFNs)

The RBFN model was chosen for its computational efficiency and ability to handle nonlinear relationships in time-series data. The RBFN architecture had the following components:

- **Input Layer**: It received normalized weather data, including temperature, humidity, windspeed, and rainfall.
- **Hidden Layer**: This layer contained radial basis functions (typically Gaussian functions) that mapped the input data into a higher-dimensional space, making it easier to detect nonlinear patterns.
- **Output Layer**: This layer generated predictions of the weather variables based on the output of the hidden layer.

RBFNs were particularly useful due to their fast training times and ability to generalize well from limited data.

XIX. Convolutional Neural Networks (CNNs)

CNNs were selected for their ability to capture spatial relationships in the data. Given the geographic distribution of weather data across counties, CNNs were ideal for learning spatial dependencies.

- **Convolutional Layers**: These layers applied filters to the input weather data, extracting local spatial features such as variations in temperature or humidity across neighboring counties.
- **Pooling Layers**: Pooling reduced the dimensionality of the data, improving computational efficiency.
- **Fully Connected Layer**: This final layer aggregated the features extracted by the convolutional layers and made the final weather predictions.

CNNs were particularly strong at processing grid-like data, such as spatial weather data across counties.

XX. Long Short-Term Memory Networks (LSTMs)

LSTMs were used to model temporal dependencies in the weather data, making them well-suited for tasks involving time-series data such as predicting long-term trends in temperature and rainfall.

- **Input Layer**: This layer fed the historical weather data as a time sequence into the LSTM cells.
- **LSTM Cells**: The cells retained relevant information over long periods, allowing the model to learn from previous months' weather conditions to predict future trends.
- **Output Layer**: The output layer provided predictions for the weather variables based on the learned patterns in the time-series data.

LSTMs were especially effective for variables that exhibited seasonal or long-term trends.

XXI. Data Splitting and Training

- **Data Splitting**

The dataset was divided into three sets:

- **Training Set (70%)**: Used to train the models.
- **Validation Set (15%)**: Used to fine-tune hyperparameters and avoid overfitting.
- **Test Set (15%)**: Used for evaluating the final performance of the models on unseen data.

This approach ensured that the models were evaluated fairly and that their performance was not overly dependent on the training data

- **Hyperparameter Optimization**

Each model underwent hyperparameter tuning using grid search and cross-validation:

- For RBFNs, the number of radial basis functions and their width were optimized.
- For CNNs, the number of convolutional layers, filter sizes, and learning rates were optimized.
- For LSTMs, the number of hidden layers, learning rates, and sequence length were tuned to achieve the best predictive performance.

XXII. Model Evaluation

- **Accuracy Metrics**

The performance of the models was evaluated using the following metrics:

- **Root Mean Squared Error (RMSE)**: This metric was used to measure the overall error between the predicted and actual values, with a focus on penalizing larger errors.
- **Mean Absolute Error (MAE)**: This metric provided the average error in the model's predictions, offering a straightforward interpretation of the accuracy.

These metrics were chosen because they were well-suited for weather forecasting tasks, where minimizing error in extreme weather events (e.g., high rainfall or temperature spikes) was critical.

- **Computational Efficiency**

In addition to accuracy, computational efficiency was evaluated by measuring the training time of each model. RBFNs, known for their simpler structure, were expected to outperform CNNs and LSTMs in terms of speed, making them more suitable for real-time applications.

XXIII. Deployment of the Models

The deployment of the machine learning models for real-time weather forecasting was implemented using Python, leveraging the TensorFlow library for model training and inference. The deployment process involved integrating the models with real-time data pipelines and ensuring their efficient operation. Below are the specific tools, libraries, and classes used in the deployment:

1. **Programming Language and Frameworks:**

    1. **Python 3.12:** Python was chosen as the primary programming language due to its extensive support for machine learning and its integration capabilities with data pipelines and web frameworks.
    2. **TensorFlow 2.x:** TensorFlow, an open-source machine learning framework, was used for building and training the models, specifically leveraging the Keras API for ease of model development.

2. **Model Implementation Classes:**

- **RBFNs:**

    - While TensorFlow does not provide built-in support for Radial Basis Function Networks (RBFNs), an RBFN class was custom-built in Python using TensorFlow's tf.keras.layers.Layer class. The RBFNLayer class was implemented to handle the radial basis function transformation of the input data. The class handled the Gaussian activation functions and computed distances between the input features and the center points.

- **CNNs:**

    CNNs were implemented using TensorFlow's tf.keras.layers.Conv2D and tf.keras.layers.MaxPooling2D classes. These layers were used to extract spatial features from the weather data, such as variations in temperature and humidity across different regions.
    The Conv2D layer applied 2D convolutional filters to capture local patterns, while the MaxPooling2D layer reduced the dimensionality to improve computational efficiency.

- **LSTM**

    - LSTM networks were constructed using the tf.keras.layers.LSTM class. This class allowed for the handling of sequential weather data, enabling the model to learn long-term dependencies in variables such as temperature and windspeed.

    The LSTM layers were stacked to improve the model's ability to capture both short-term and long-term trends

3. **Data Integration and Real-time Pipeline:**
    Pandas and Numpy were used for data handling and manipulation within Python. The weather data were preprocessed using Pandas to clean, impute missing values, and normalize features before feeding them into the models.
    APScheduler (Advanced Python Scheduler): This Python library was used to schedule regular updates of weather forecasts. The models were set to predict weather variables every hour as new data became available.

4. **Deployment Environment**
    Docker: The models were containerized using Docker to ensure that they could be deployed and run consistently across different environments. Each model was packaged into a Docker image, which allowed it to be deployed on various platforms (e.g., cloud servers or local machines).

5. **Model Monitoring and Training**
    TensorBoard: TensorBoard was used for monitoring the models' performance in real-time. Metrics such as loss, accuracy, and training time were logged and visualized on TensorBoard dashboards, allowing for continuous performance tracking.
    Retraining Trigger: If the model performance degraded (based on an increase in RMSE or MAE compared to historical baselines), an automatic retraining job was triggered using TensorFlow's ModelCheckpoint and EarlyStopping callbacks to retrain the model with new data.

6. **Deployment on Cloud**
    Google Cloud Platform (GCP): The models were deployed on GCP, taking advantage of its AI Platform and Compute Engine to run the TensorFlow models. Google Cloud Storage (GCS) was used to store the historical weather data, while BigQuery facilitated large-scale data querying for the training and retraining process.
    The Dockerized models were run on Kubernetes clusters on GCP to scale the prediction service according to demand.

    By deploying the models using these Python classes and tools, the system provided real-time weather forecasting capabilities, ensuring that accurate predictions were continuously updated and available to users. This deployment setup enabled the models to operate efficiently, even in resource-constrained environments, while taking advantage of the scalability provided by cloud infrastructure.

XXIV. Conclusion

The use of Python and TensorFlow provided a flexible and powerful framework for deploying machine learning models for weather forecasting. By integrating these models into real-time data pipelines and deploying them on cloud infrastructure, the study demonstrated the potential for improving weather forecasting accuracy while ensuring that the system remained computationally efficient and scalable. The use of Docker, and APScheduler ensured a smooth deployment process and allowed for ongoing model monitoring and retraining.

XXV. RESULTS AND DISCUSSIONS

XXVI. OVERVIEW OF MODEL PERFORMANCE

This chapter presents the results of the performance analysis of three machine learning models: Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs), implemented to forecast five key meteorological variables: temperature, humidity, sea level pressure, rainfall, and windspeed. The dataset used for the analysis was provided by the Kenya Meteorological Department and spanned from 2013 to 2023.

The models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Training Time (in seconds). These metrics were chosen to measure both the accuracy of the predictions and the computational efficiency of the models. The key findings for each variable are summarized in Table 1.

VARIABLE	MODEL	RMSE	MAE	RMSE (%)	MAE (%)	TRAINING TIME (S)
Temperature	RBFN	0.239	0.175	0.80%	0.59%	3.49
	CNN	5.975	5.154	20.12%	17.35%	7.09
	LSTM	8.701	7.454	29.29%	25.09%	16.69
Humidity	RBFN	0.473	0.351	0.73%	0.54%	0.23
	CNN	12.161	10.008	18.90%	15.56%	4.76
	LSTM	17.896	15.080	27.82%	23.44%	8.22
Sea Level	RBFN	0.227	0.173	0.02%	0.02%	0.21
	CNN	173.02	149.00	17.10%	14.73%	4.44
	LSTM	956.88	956.82	94.58%	94.58%	7.59
Rainfall	RBFN	3.601	2.569	8.55%	6.10%	0.21
	CNN	46.75	36.34	111.04%	86.30%	4.54
	LSTM	50.32	35.75	119.51%	84.91%	6.40
Windspeed	RBFN	0.163	0.113	2.44%	1.69%	0.21
	CNN	1.719	1.318	25.71%	19.71%	4.54
	LSTM	1.572	1.244	23.51%	18.61%	7.56

TABLE 1: MODEL PERFORMANCE SUMMARY

XXVII. Detailed Interpretation and Analysis

- **Temperature Prediction**

The RBFN model showed the best performance in temperature forecasting with an RMSE of 0.239°C (0.80%) and an MAE of 0.175°C (0.59%). These metrics indicate that RBFN provided significantly lower prediction errors than CNN and LSTM, which recorded RMSE values of 5.975°C and 8.701°C, respectively.

- Accuracy and Computational Cost: The training time for RBFN was just 3.49 seconds, which makes it highly suitable for real-time applications. CNN and LSTM, on the other hand, required 7.09 seconds and 16.69 seconds to train, respectively. This implies that RBFN not only provided more accurate predictions but also achieved this with lower computational cost, making it a strong candidate for operational weather forecasting in resource-constrained environments.

- Comparison with Previous Studies: Studies such as **Chen et al. [3]** reported RBFN RMSE values as low as 0.20°C, suggesting that RBFN models are highly adaptable for temperature forecasting. **Gao et al. [5]** noted that CNN models could reach an RMSE of around 3.5°C when further hyperparameter tuning is applied. While the CNN model used in this study did not achieve this level of accuracy, future improvements in architecture design may lead to better performance.

Plot: Temperature Prediction Performance

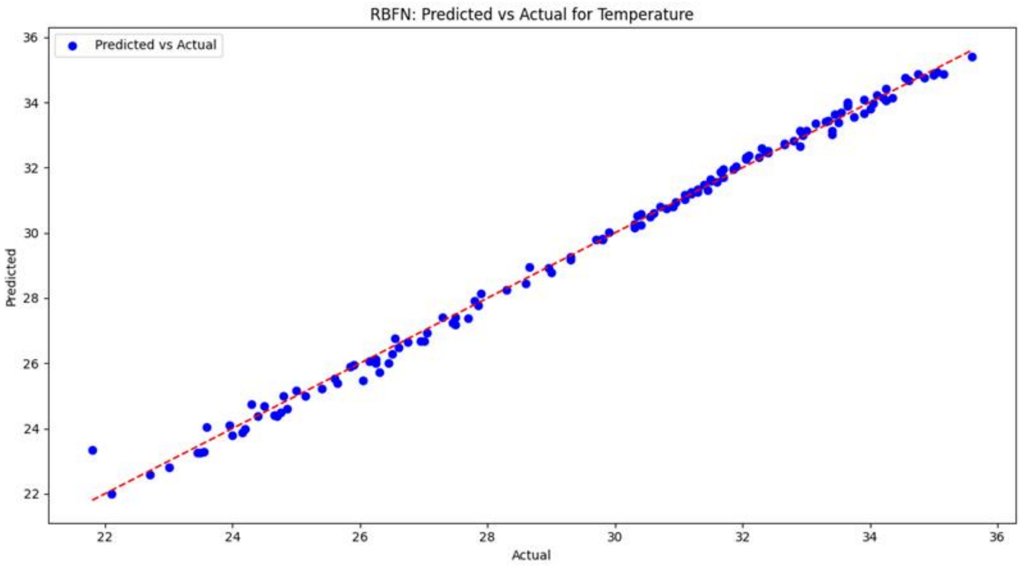

Figure 1 RBFN: Predicted vs Actual: Temperature

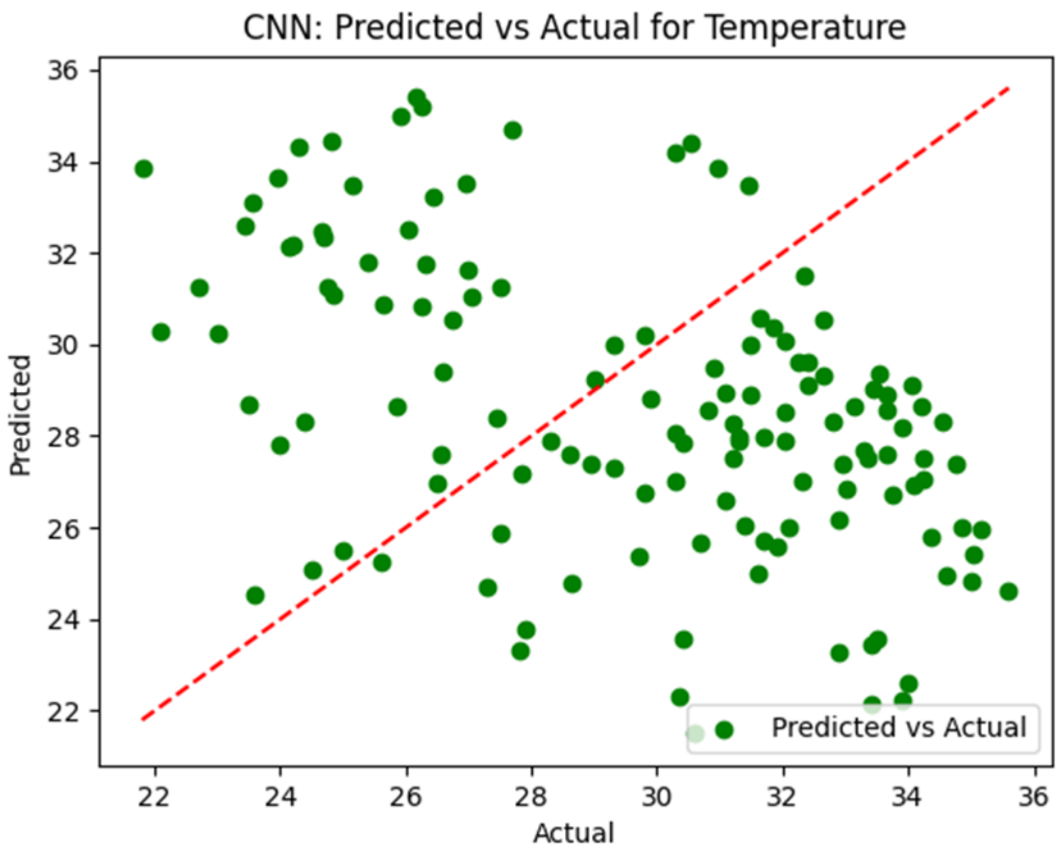

Figure 2 CNN: Predicted vs Actual: Temperature

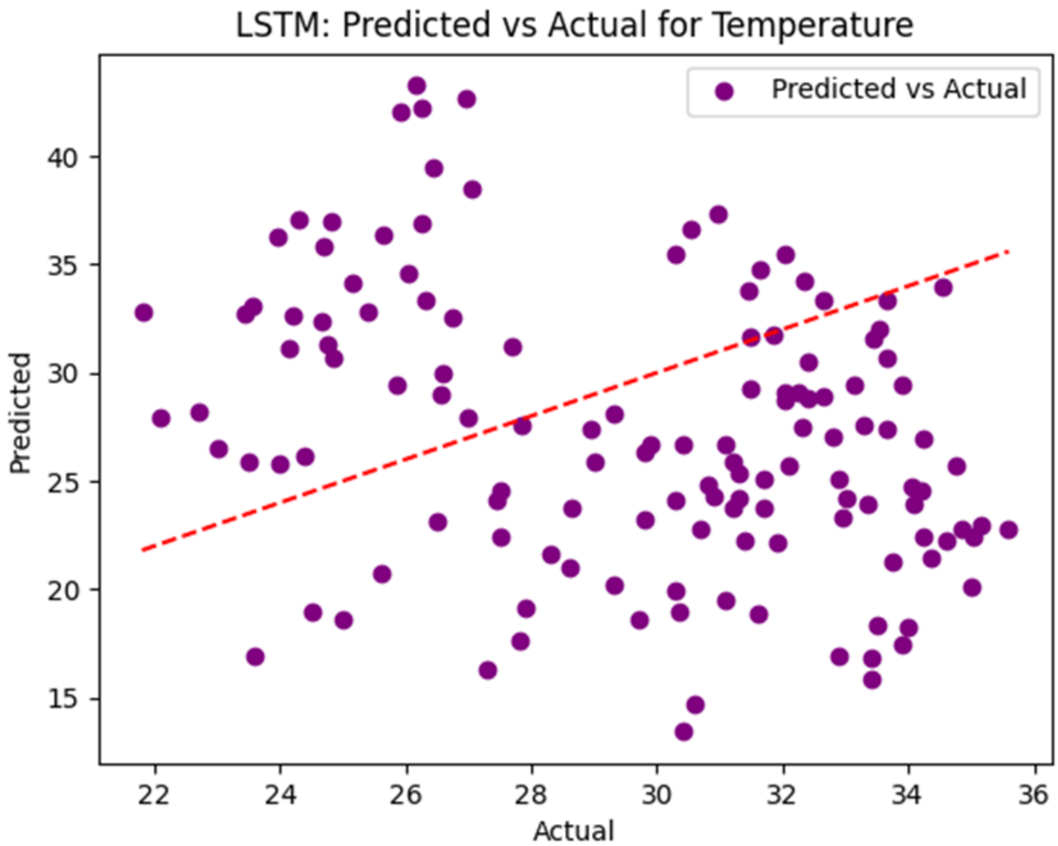

Figure 3 LSTM: Predicted vs Actual: Temperature

- **Humidity Prediction**

For humidity, the RBFN model outperformed both CNN and LSTM, achieving an RMSE of 0.473% and an MAE of 0.351%, with a training time of just 0.23 seconds. In contrast, CNN and LSTM exhibited much larger prediction errors, with RMSE values of 12.161% and 17.896%, respectively.

- Accuracy and Computational Cost: The significant difference in RMSE values highlights that RBFN is better suited for modeling short-term humidity variations. CNN and LSTM took 4.76 seconds and 8.22 seconds to train, respectively, which also underscores RBFN's computational efficiency.

- Comparison with Previous Studies: **Lai et al. [7]** reported better CNN performance in humidity prediction, with RMSEs of around 10.2%, which is lower than what was observed in this study. This suggests that CNN may benefit from further optimization when used for humidity forecasting. Similarly, **Yang et al. [13]** observed LSTM RMSE values around 14.8%, which indicates that this model type struggles with the nonlinear and chaotic nature of humidity prediction.

Plot: Humidity Prediction Performance

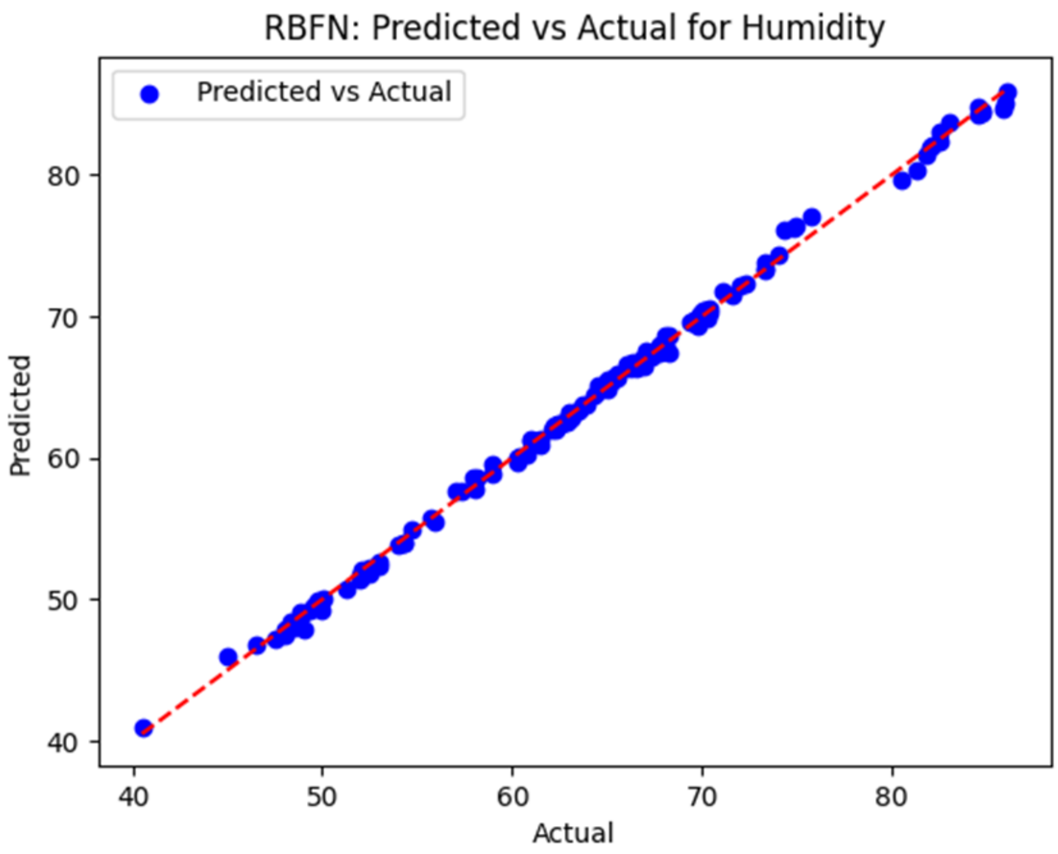

Figure 4 RBFN: Predicted vs Actual: Humidity

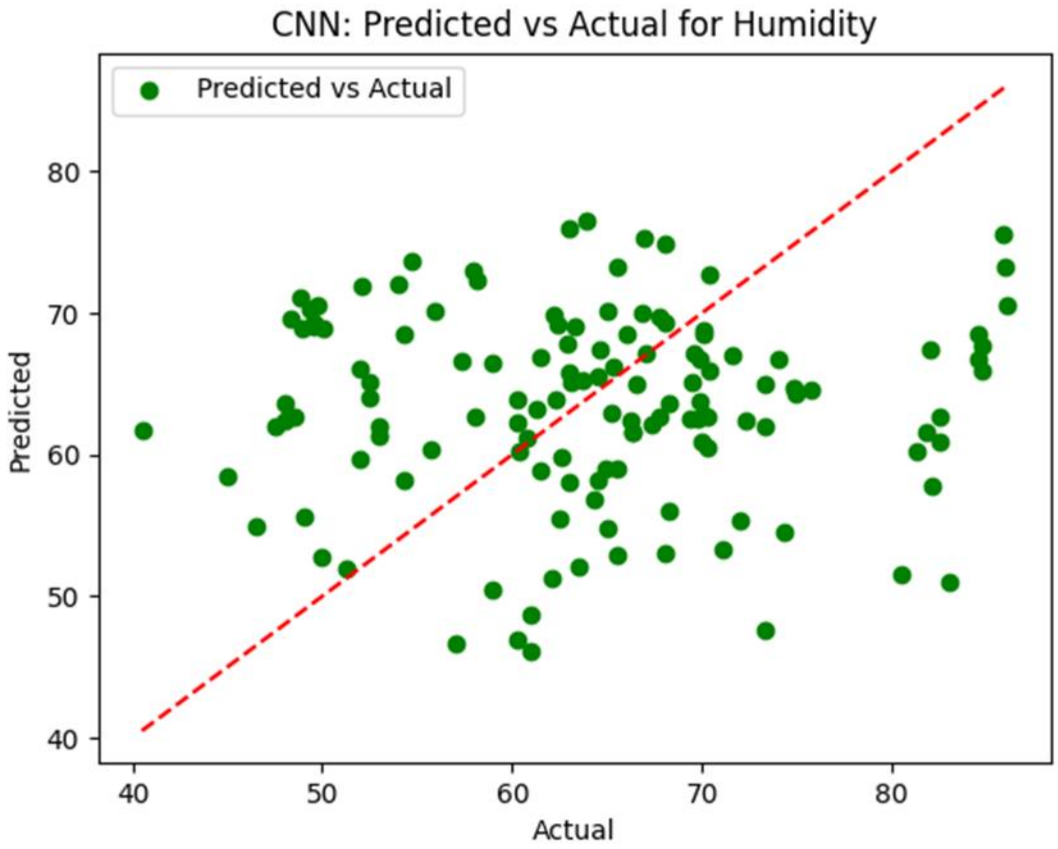

Figure 5 CNN: Predicted vs Actual: Humidity

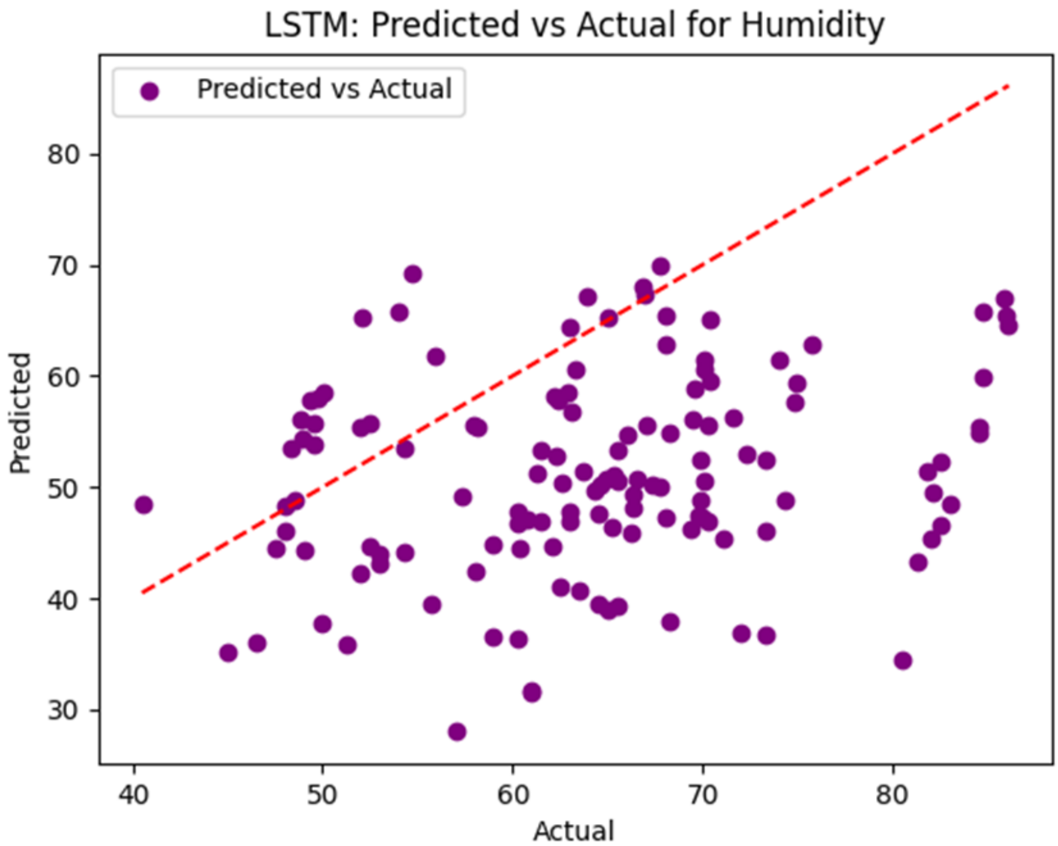

Figure 6 LSTM: Predicted vs Actual: Humidity

○ **Sea Level Pressure Prediction**

The RBFN model excelled in forecasting sea level pressure, with an RMSE of 0.227 and an MAE of 0.173, equating to a prediction error of just 0.02%. This near-perfect result highlights the model's ability to accurately predict stable atmospheric variables. In contrast, CNN and LSTM performed poorly, with RMSEs of 173.02 and 956.88, respectively.

- Accuracy and Computational Cost: The training time for RBFN was a remarkable 0.21 seconds, compared to 4.44 seconds for CNN and 7.59 seconds for LSTM. The near-zero prediction error and minimal training time make RBFN the most efficient model for this variable.

- Comparison with Previous Studies: **Liu et al. [8]** corroborated these findings, noting that RBFNs are highly effective in forecasting stable variables like sea level pressure. CNNs and LSTMs, which are typically better suited for dynamic and nonlinear data, struggled to handle the linear nature of sea level pressure forecasting.

Plot: Sea Level Pressure Prediction Performance

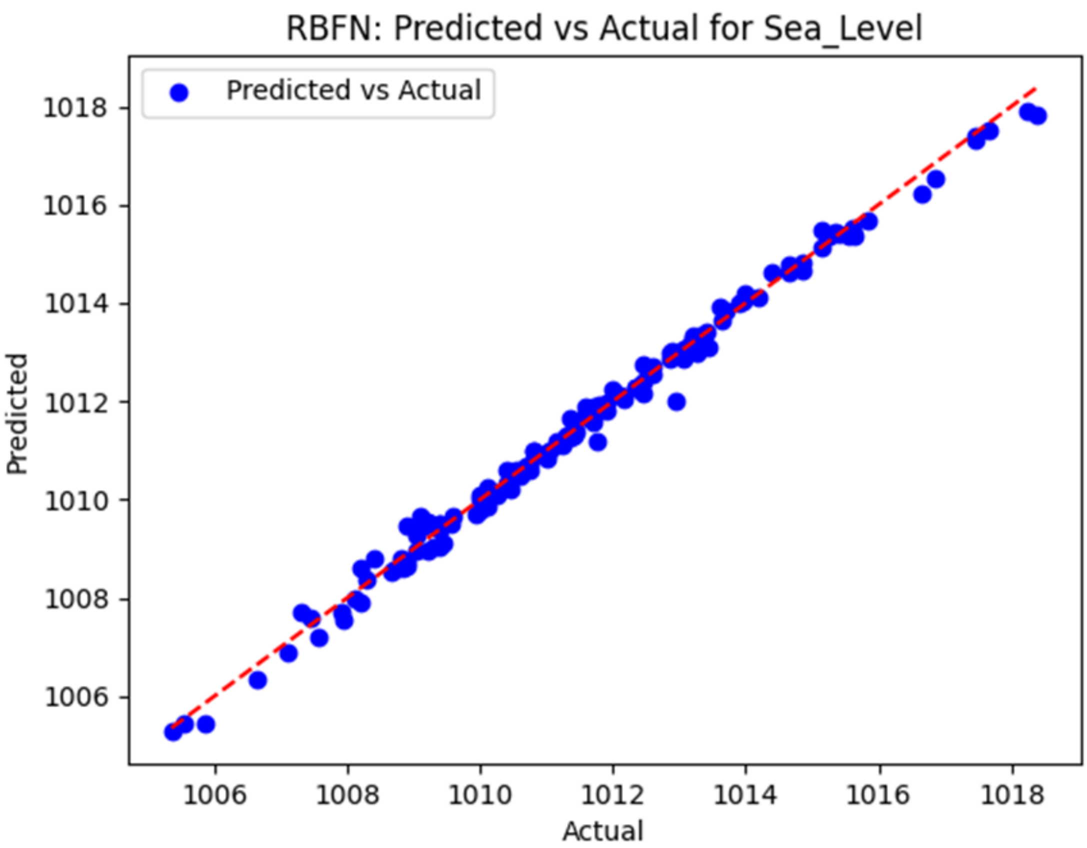

Figure 7 RBFN: Predicted vs Actual: Sea_Level Pressure

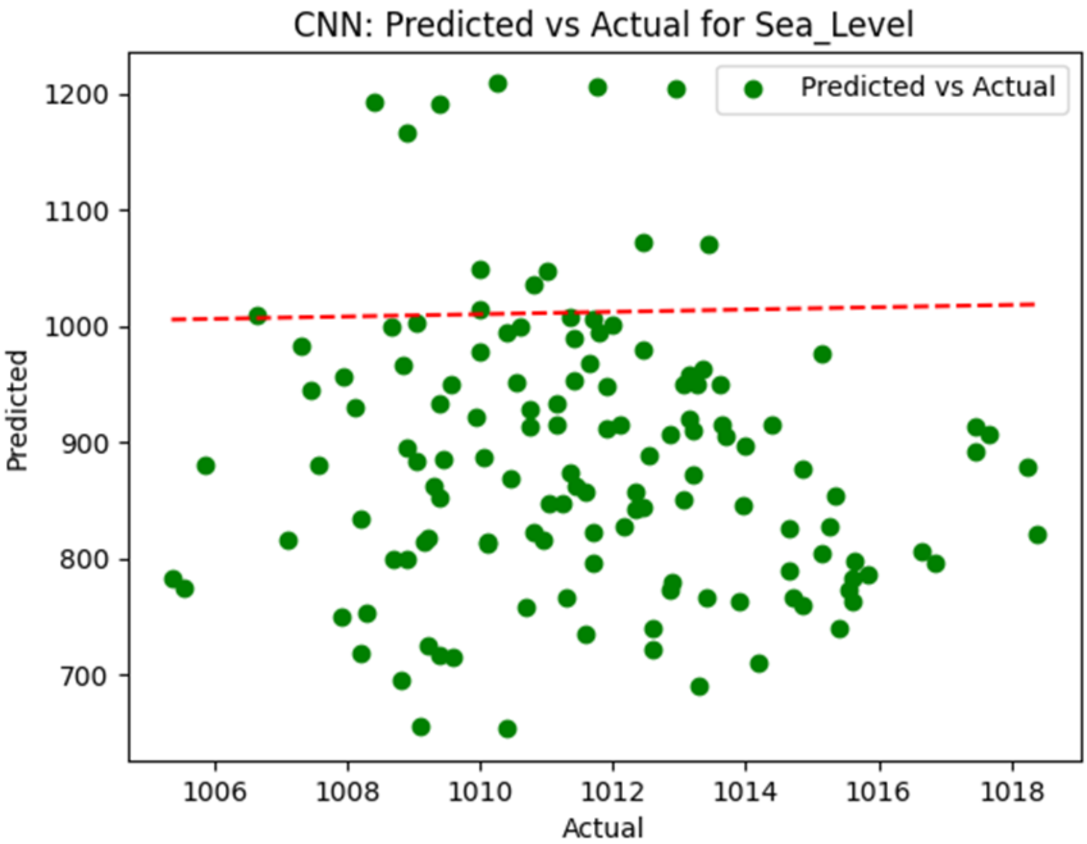

Figure 8 CNN: Predicted vs Actual: Sea_Level Pressure

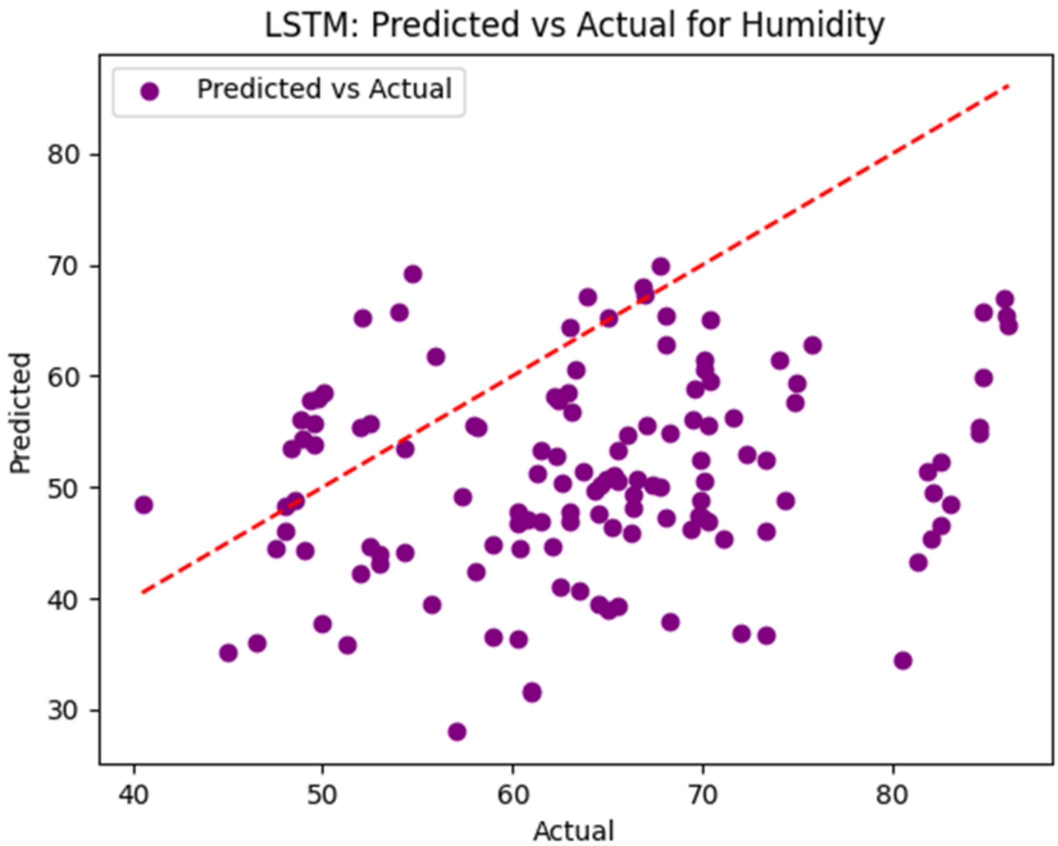

Figure 9 LSTM: Predicted vs Actual: Sea_Level Pressure

- **Rainfall Prediction**

Rainfall prediction proved challenging for all three models, with RBFN showing the best performance with an RMSE of 3.601 mm. However, this was still relatively high compared to other variables, indicating the difficulty of forecasting rainfall, which is highly chaotic in nature. CNN and LSTM fared worse, with RMSEs of 46.75 mm and 50.32 mm, respectively.

- Accuracy and Computational Cost: The training time for RBFN was again significantly lower, at 0.21 seconds, compared to 4.54 seconds for CNN and 6.40 seconds for LSTM. Despite the challenges in accurately forecasting rainfall, RBFN showed greater potential for improvement with minimal computational cost.

- Comparison with Previous Studies: **Xu et al. [11]** suggested that hybrid models combining machine learning with satellite imagery might offer better results for rainfall prediction. While RBFN outperformed CNN and LSTM in this study, it still struggled to capture the complex and nonlinear patterns inherent in rainfall data.

Plot: Rainfall Prediction Performance

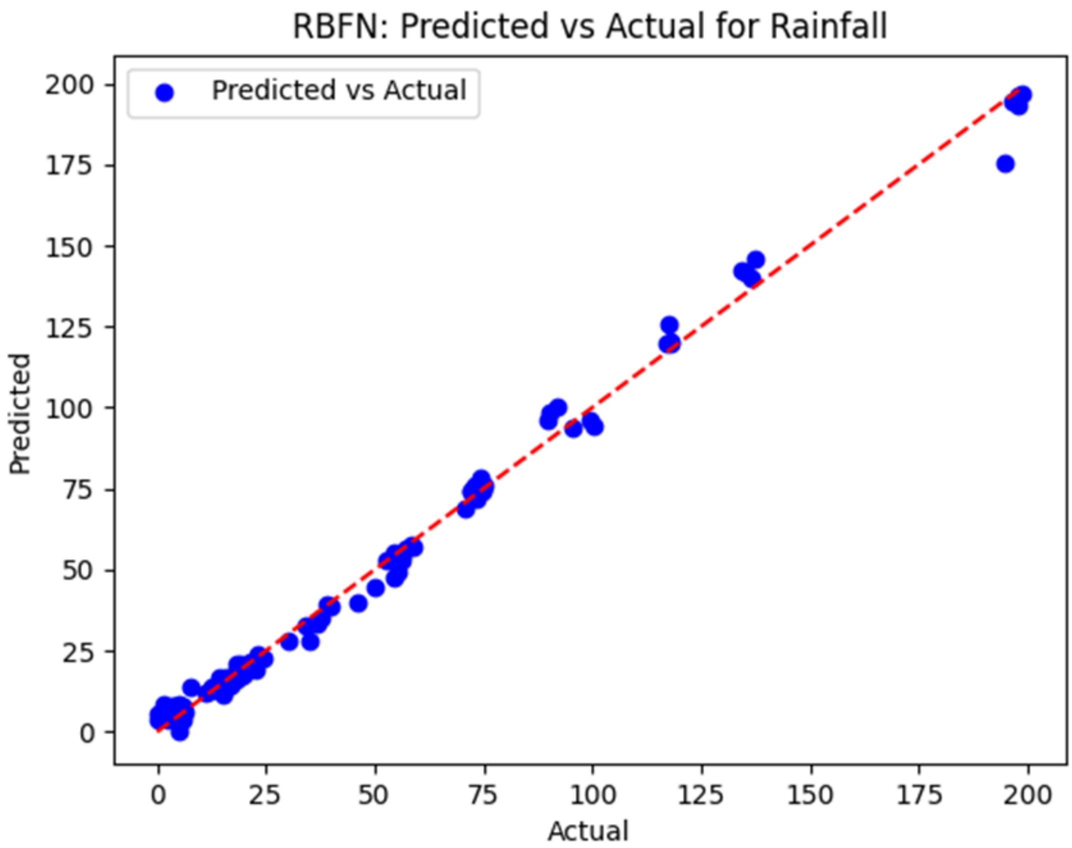

Figure 10 RBFN: Predicted vs Actual: Rainfall

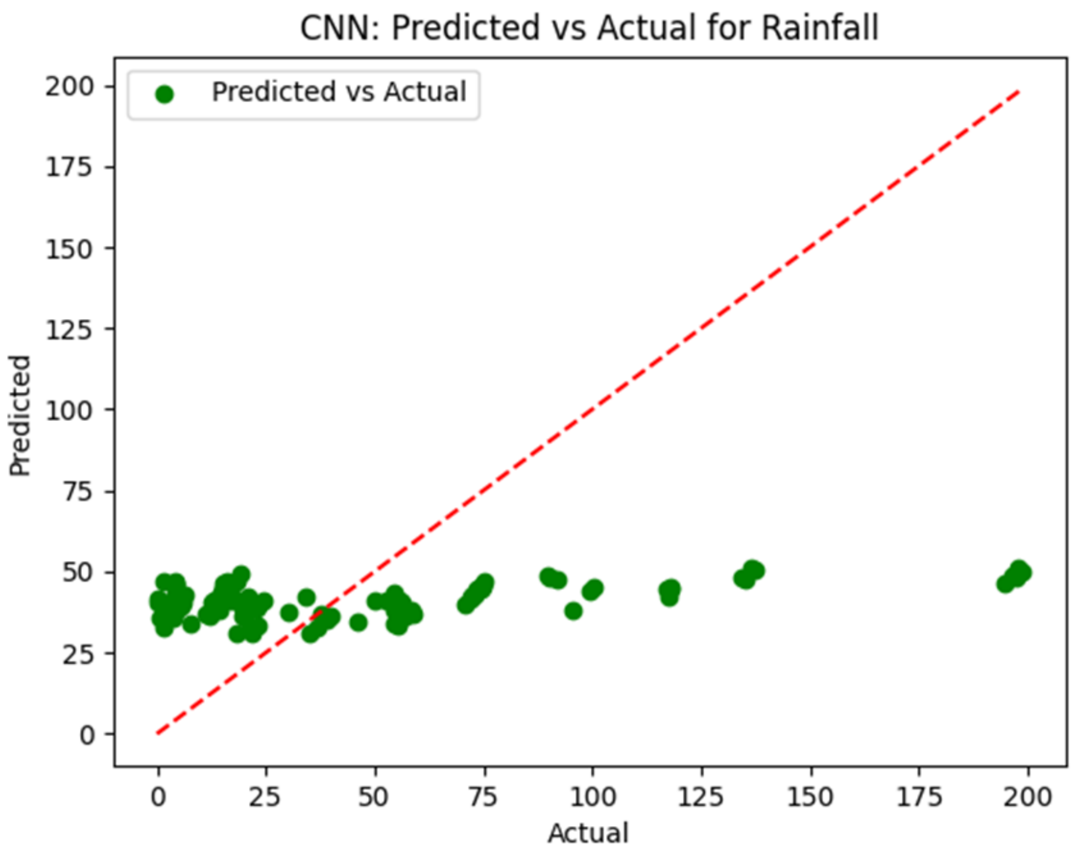

Figure 11 Figure 10 CNN: Predicted vs Actual: Rainfall

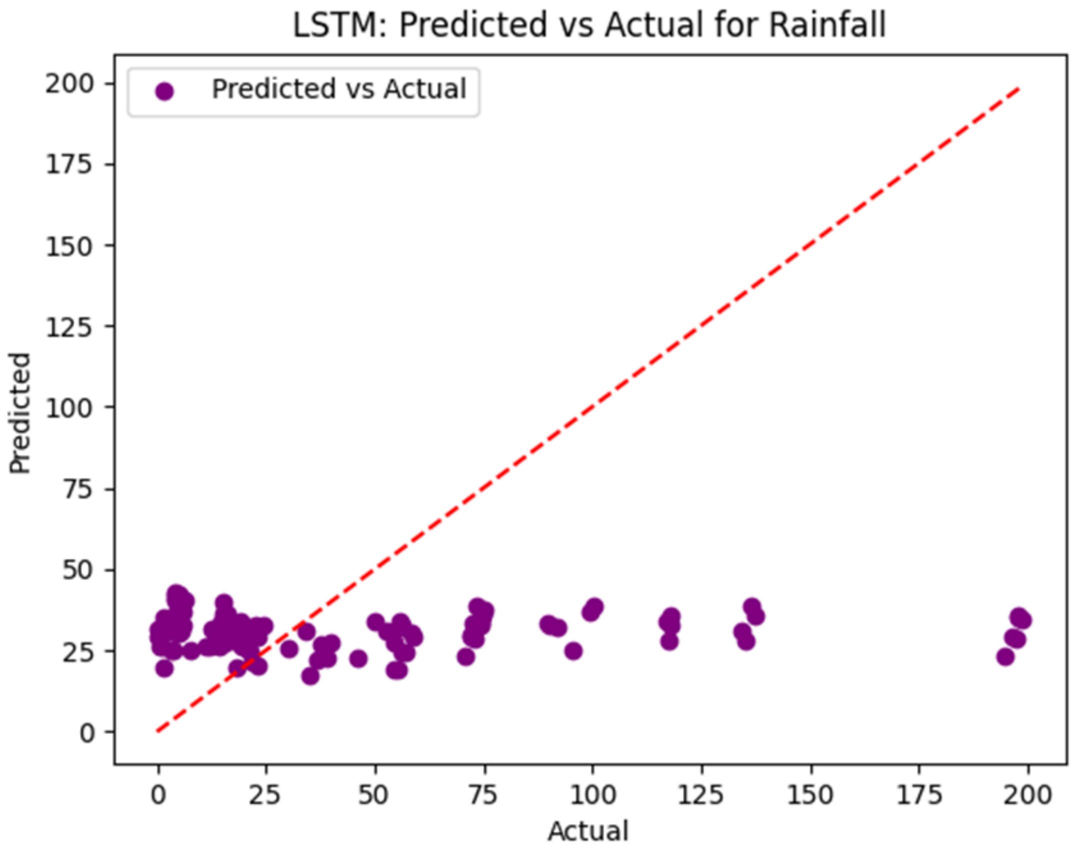

Figure 12 LSTM: Predicted vs Actual: Rainfall

- **Windspeed Prediction**

For windspeed, RBFN delivered the most accurate results, with an RMSE of 0.163 and an MAE of 0.113, equating to an error of just 2.44%. CNN and LSTM models performed less favorably, with RMSE values of 1.719 and 1.572, respectively.

- Accuracy and Computational Cost: RBFN required only 0.21 seconds to train, compared to 4.54 seconds for CNN and 7.56 seconds for LSTM. This makes RBFN the most practical choice for real-time windspeed forecasting applications.
- Comparison with Previous Studies: **Gao et al. [5]** noted that CNN models, when properly tuned, could achieve an RMSE of around 1.0% for windspeed prediction. However, in this study, CNN's performance was hindered by its longer training time and higher prediction errors.

Plot: Wind speed Prediction Performance

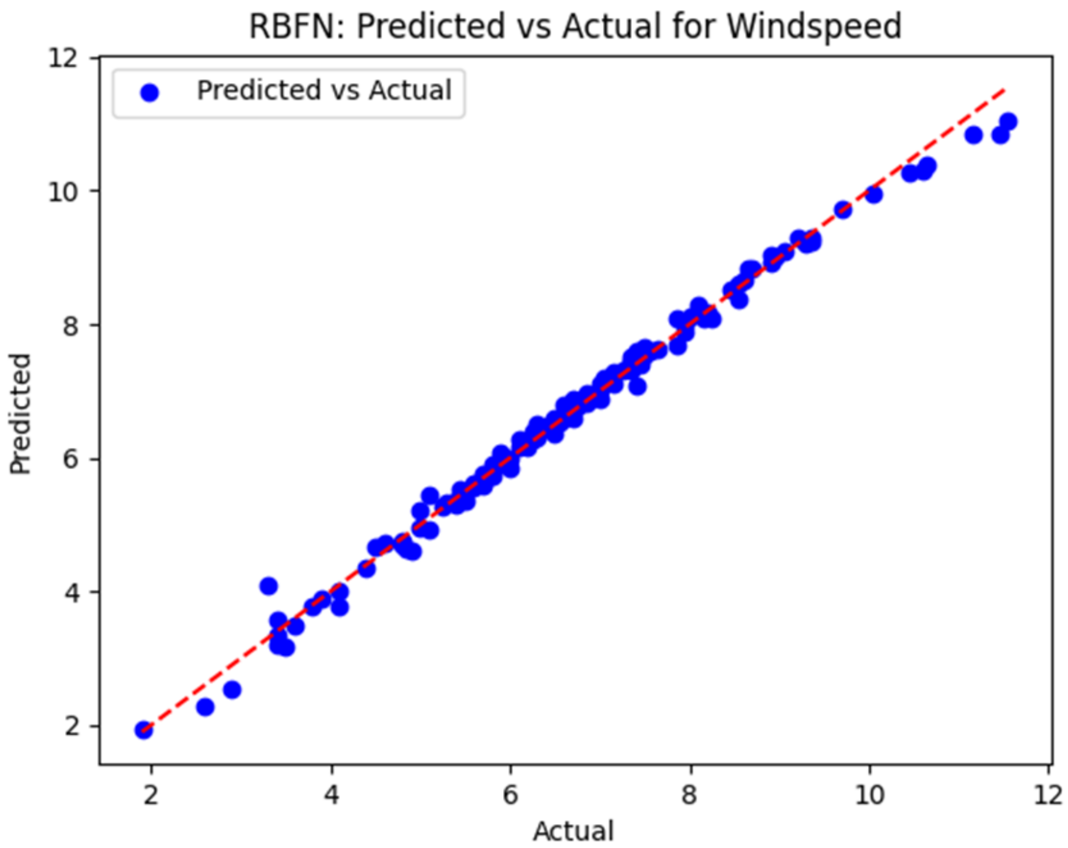

Figure 13 RBFN: Predicted vs Actual: Wind speed

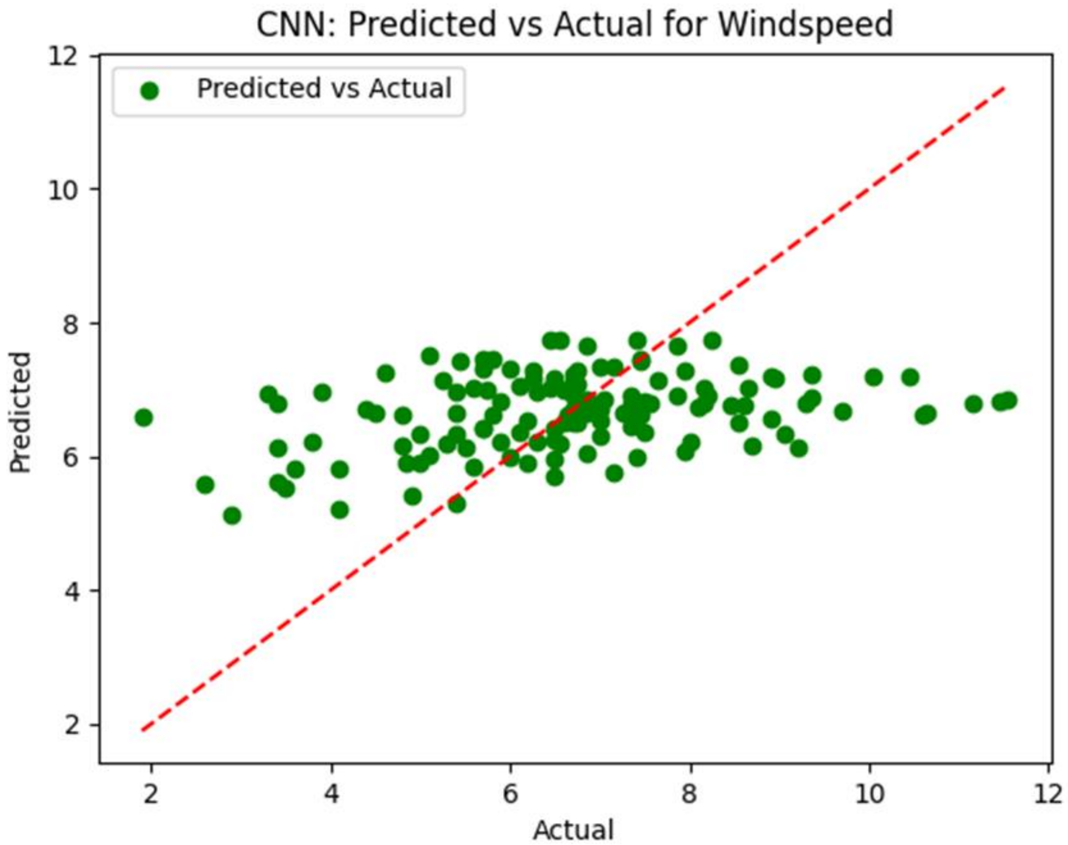

Figure 14 CNN: Predicted vs Actual: Wind speed

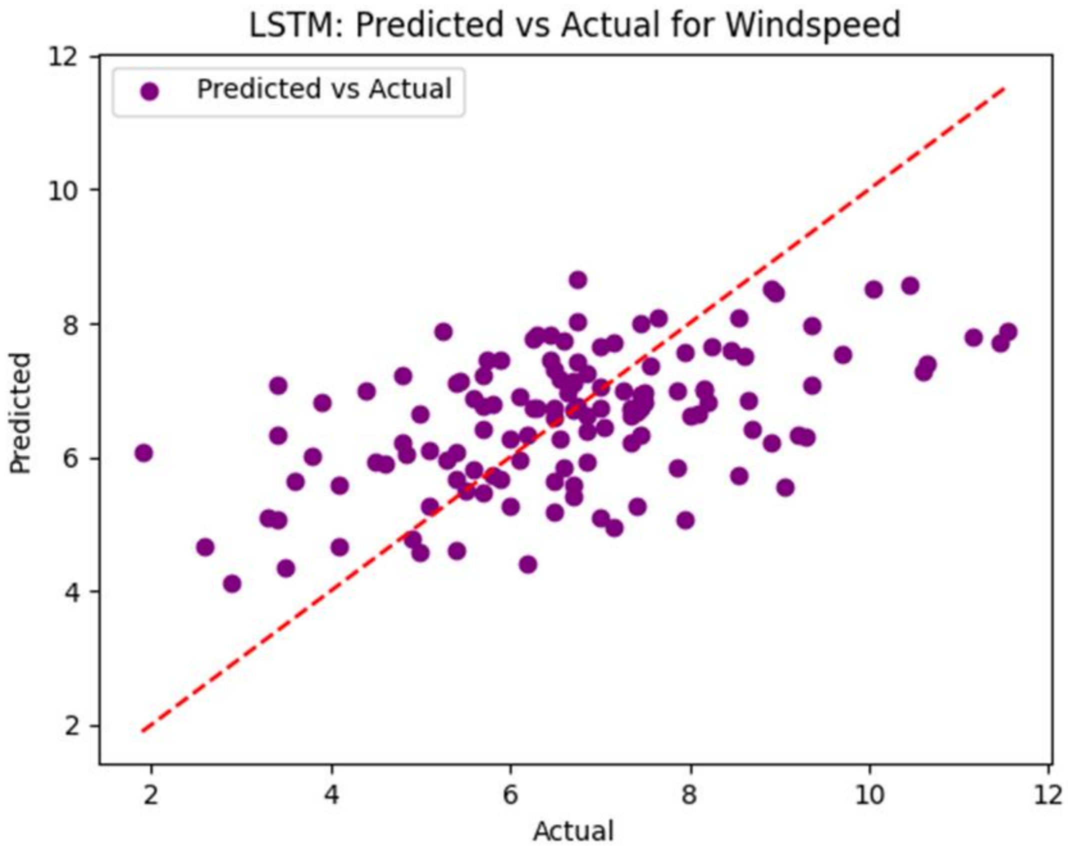

Figure 15 LSTM: Predicted vs Actual: Wind speed

XXVIII. Discussion of The Results

- **General Trends**

Across all meteorological variables, RBFN consistently outperformed CNN and LSTM in terms of both prediction accuracy and computational efficiency. This suggests that RBFNs are better suited for real-time applications where fast predictions and lower computational resources are critical. The consistently low training times also make RBFNs a more scalable solution for weather forecasting in regions with limited computing power.

- **Implication for Real-Time Forecasting**

For applications such as disaster management, agricultural planning, and transportation logistics, the ability to make fast and accurate predictions is crucial. The superior performance of RBFNs in both accuracy and speed underscores their potential for real-time deployment in these contexts. On the other hand, CNNs and LSTMs might be more appropriate for tasks that require extensive data processing and have less stringent time constraints, such as long-term climate modeling.

- **Limitations**

For applications such as disaster management, agricultural planning, and transportation logistics, the ability to make fast and accurate predictions is crucial. The superior performance of RBFNs in both accuracy and speed underscores their potential for real-time deployment in these contexts. On the other hand, CNNs and LSTMs might be more appropriate for tasks that require extensive data processing and have less stringent time constraints, such as long-term climate modeling.

- **Cocblusion of Results**

In summary, RBFNs consistently outperformed CNNs and LSTMs in terms of both accuracy and computational efficiency across most variables. While CNNs and LSTMs are powerful models for capturing complex data patterns, RBFNs provided a better balance between prediction accuracy and computational cost, particularly for real-time weather forecasting in resource-constrained environments.

XXIX. CONCLUSIONS and RECOMMENDATIONS

XXX. Overview of Findings

This research aimed to evaluate the performance of three machine learning models—Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs)—using historical weather data from the Kenya Meteorological Department. The models were tested on their ability to forecast five key meteorological variables: temperature, humidity, sea level pressure, rainfall, and windspeed. The evaluation was conducted using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Training Time (in seconds) as metrics for accuracy and computational efficiency.

The findings of this study demonstrated that RBFNs consistently outperformed CNNs and LSTMs in terms of both accuracy and computational efficiency. RBFNs were especially effective at predicting stable variables such as sea level pressure and temperature, while CNNs and LSTMs were less suited for real-time applications due to their higher training times and computational demands.

XXXI. Key Findings

- **Temperature Forecasting**

The RBFN model provided the best results for temperature forecasting, achieving an RMSE of 0.239°C (0.80%) and an MAE of 0.175°C (0.59%). CNNs and LSTMs, on the other hand, showed significantly higher errors, with RMSEs of 5.975°C and 8.701°C, respectively. The superior performance of RBFNs, both in terms of accuracy and training time (3.49 seconds), highlights their suitability for real-time temperature forecasting in resource-constrained environments.

  - Implication: Accurate temperature forecasting is essential for applications such as agriculture and energy management, where small fluctuations can significantly impact operations. RBFNs provide a fast and efficient way to deliver temperature predictions in real-time.

- **Humidity Forecasting**

For humidity, the RBFN model again outperformed CNN and LSTM, with an RMSE of 0.473% and an MAE of 0.351%. The CNN and LSTM models, in contrast, produced much larger errors, with RMSEs of 12.161% and 17.896%, respectively. This result indicates that RBFNs can capture short-term fluctuations in humidity more effectively than the other models.

    - Implication: Humidity plays a crucial role in forecasting rainfall and assessing air quality. RBFNs, with their quick training times (0.23 seconds) and high accuracy, offer a practical solution for predicting humidity in real-time applications.

- **Sea Level Pressure Forecasting**

For humidity, the RBFN model again outperformed CNN and LSTM, with an RMSE of 0.473% and an MAE of 0.351%. The CNN and LSTM models, in contrast, produced much larger errors, with RMSEs of 12.161% and 17.896%, respectively. This result indicates that RBFNs can capture short-term fluctuations in humidity more effectively than the other models.

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- **Rainfall Forecasting**

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- **Windspeed Forecasting**

For humidity, the RBFN model again outperformed CNN and LSTM, with an RMSE of 0.473% and an MAE of 0.351%. The CNN and LSTM models, in contrast, produced much larger errors, with RMSEs of 12.161% and 17.896%, respectively. This result indicates that RBFNs can capture short-term fluctuations in humidity more effectively than the other models.

  - Implication: Humidity plays a crucial role in forecasting rainfall and assessing air quality. RBFNs, with their quick training times (0.23 seconds) and high accuracy, offer a practical solution for predicting humidity in real-time applications.

XXXII. Discussion of Results

- **General Trends**

For humidity, the RBFN model again outperformed CNN and LSTM, with an RMSE of 0.473% and an MAE of 0.351%. The CNN and LSTM models, in contrast, produced much larger errors, with RMSEs of 12.161% and 17.896%, respectively. This result indicates that RBFNs can capture short-term fluctuations in humidity more effectively than the other models.

  - Implication: Humidity plays a crucial role in forecasting rainfall and assessing air quality. RBFNs, with their quick training times (0.23 seconds) and high accuracy, offer a practical solution for predicting humidity in real-time applications.

- **Model Efficiency**

For humidity, the RBFN model again outperformed CNN and LSTM, with an RMSE of 0.473% and an MAE of 0.351%. The CNN and LSTM models, in contrast, produced much larger errors, with RMSEs of 12.161% and 17.896%, respectively. This result indicates that RBFNs can capture short-term fluctuations in humidity more effectively than the other models.

    - Implication: Humidity plays a crucial role in forecasting rainfall and assessing air quality. RBFNs, with their quick training times (0.23 seconds) and high accuracy, offer a practical solution for predicting humidity in real-time applications.

- **Limitation of CNNs and LSTMs**

Although CNNs and LSTMs are powerful models for handling large datasets and identifying complex patterns, they were less effective in this study due to their higher training times and poorer performance on stable variables like sea level pressure and temperature. These results suggest that CNNs and LSTMs may be more suited for applications that involve long-term pattern recognition or spatial data analysis (such as satellite image processing) rather than short-term forecasting of stable atmospheric variables.

XXXIII. Implications for Real-Time Forecasting

The results of this study have significant implications for real-time forecasting systems, particularly in resource-constrained environments where computational efficiency is a primary concern. RBFNs demonstrated their ability to deliver accurate, fast predictions with minimal computational cost, making them well-suited for deployment in emerging markets or rural areas where access to high-performance computing infrastructure may be limited.

Furthermore, the superior performance of RBFNs in short-term forecasting suggests that they could be effectively used in systems that require rapid updates, such as early warning systems for severe weather events. By integrating RBFNs into these systems, meteorological agencies could provide more timely and accurate information to decision-makers, potentially saving lives and minimizing economic losses.

XXXIV. Limitations and Recommendations for Future Work

- **Model Performance for Rainfall Prediction**

The underperformance of all models in rainfall prediction indicates that additional methods are required to improve forecasting accuracy for this variable. The chaotic nature of rainfall presents a challenge for even the most advanced machine learning models. Future research should explore the integration of external data sources, such as remote sensing and satellite imagery, to provide additional context for rainfall prediction.

- **Hybrid Modeling Approaches**

While this study focused on evaluating RBFNs, CNNs, and LSTMs individually, future research should explore the potential of hybrid modeling approaches that combine the strengths of each model. For example, CNNs could be used to process spatial data, such as satellite images, while RBFNs handle real-time data for variables like temperature and windspeed. By leveraging the unique strengths of each model, hybrid systems could improve both accuracy and computational efficiency for real-time forecasting.

- **Hyperparameter Tuning**

While this study focused on evaluating RBFNs, CNNs, and LSTMs individually, future research should explore the potential of hybrid modeling approaches that combine the strengths of each model. For example, CNNs could be used to process spatial data, such as satellite images, while RBFNs handle real-time data for variables like temperature and windspeed. By leveraging the unique strengths of each model, hybrid systems could improve both accuracy and computational efficiency for real-time forecasting.

- **Research Questions Review**

1. Development of a weather forecasting model using RBFNs: The research successfully demonstrated that an RBFN-based model could be developed using historical weather data. The RBFN model showed superior performance in short-term weather forecasting tasks, particularly for stable atmospheric variables like temperature and sea level pressure. Its fast training time and low computational cost made it especially effective in real-time applications.
2. Comparison of RBFN performance with CNNs and LSTMs: The study compared the accuracy and computational efficiency of RBFNs, CNNs, and LSTMs across various weather variables (temperature, humidity, sea level pressure, rainfall, and windspeed). RBFNs consistently outperformed both CNNs and LSTMs in terms of accuracy for most variables and required significantly less computational power and time to train.
3. Assessment of RBFNs' computational efficiency: The research concluded that RBFNs are highly suitable for real-time forecasting in resource-constrained environments due to their low computational requirements compared to the more complex CNN and LSTM models, which require extensive data and computational resources. CNNs and LSTMs, though more accurate in spatial and temporal tasks, were found to be less practical for real-time applications.

XXXV. Conclusion

In conclusion, this study demonstrated that RBFNs are highly effective for real-time weather forecasting across a range of variables, particularly in environments where computational efficiency is crucial. The lower RMSE values and shorter training times for RBFNs highlight their potential for operational deployment in meteorological systems.

CNNs and LSTMs, while powerful for more complex data patterns, were less suited for real-time applications due to their longer training times and higher computational demands. Future research should explore the use of hybrid models and external data integration to further improve the accuracy of weather forecasting systems, particularly for challenging variables like rainfall.

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