Optimizing Weather Forecasting Accuracy via Radial Basis Function Networks, Convolutional Neural Networks and Convolutional Neural Networks

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Abstract

Weather forecasting is crucial for various sectors, including agriculture, disaster management, and infrastructure planning. However, traditional prediction models such as Numerical Weather Prediction (NWP) and ARIMA often struggle with long-term accuracy due to the nonlinear and chaotic nature of atmospheric phenomena. The primary objective of this study was to develop and compare the performance of Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs) in predicting key weather variables such as temperature, humidity, sea-level pressure, windspeed, and rainfall. Historical meteorological data from the Kenya Meteorological Department, spanning a decade, was used to train and evaluate the models. The methodology employed included data preprocessing, model training with a 70-15-15 split for training, validation, and testing, and performance evaluation using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and training time as key metrics. The results revealed that RBFNs consistently outperformed CNNs and LSTMs, particularly for stable variables like temperature and sea-level pressure, with lower RMSE and faster training times. CNNs and LSTMs, while better at capturing complex temporal patterns, struggled with chaotic variables such as rainfall and windspeed, exhibiting higher error rates and longer training times. In conclusion, RBFNs were found to be the most efficient and accurate model for real-time weather forecasting in resource-constrained environments, whereas CNNs and LSTMs may require additional tuning or hybrid approaches to improve their forecasting of more dynamic weather variables.

Keywords: Long-Range Weather Forecasting; Numerical Weather Prediction; Autoregressive Integrated Moving Average; Artificial Neural Networks; Radial Basis Function Networks (RBFN); Convolutional Neural Networks (CNN's); Long Short-Term Memory Networks (LSTM's); Root Mean Squared Error; Mean Absolute Error (RMSE); K-Nearest Neighbors (KN); Google Cloud Platform (GCP); Advanced Python Scheduler; Interquartile Range (IR); Weather Prediction Accuracy; Meteorological Data Analysis; Economic Resilience and Growth

Introduction

Weather forecasting is a crucial field of study due to its wide-reaching implications for numerous industries and societal functions. Accurate weather predictions are essential for sectors such as agriculture, transportation, energy management, disaster prevention, and construction. For example, in agriculture, precise weather predictions enable 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 is crucial for disaster management agencies, which relies 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., 2022).

Despite the importance of weather forecasting, the field faces 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 some degree, are 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 often 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 excel at short-term weather predictions, their ability to handle long-term forecasting is significantly constrained due to the chaotic and nonlinear nature of atmospheric systems (Yang et al., 2020).

In addition to NWP, statistical models such as ARIMA are widely used for time-series forecasting in meteorology. These models rely on historical data trends to make predictions. However, they are inherently linear in nature and struggle to capture the complex, nonlinear interactions between meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure (Lai et al., 2020). 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 has emerged as a powerful tool for addressing the complexities of weather forecasting. Unlike traditional models, machine learning techniques can process vast amounts of nonlinear data, identify hidden patterns, and generalize from historical observations (Shen et al., 2021). These models have 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 have become increasingly popular in weather forecasting research.

Among the machine learning models, Artificial Neural Networks (ANNs) have demonstrated substantial promise for weather forecasting. ANNs are particularly adept at modeling complex nonlinear relationships between meteorological variables, which makes them suitable for short-term and mid-term weather predictions (Chen et al., 2022). These models can effectively process large datasets and identify patterns that might not be immediately apparent to human forecasters. For example, ANNs have successfully been 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., 2020).

Within the family of ANNs, Radial Basis Function Networks (RBFNs) has gained attention for their particular effectiveness in handling time-series data. RBFNs are 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., 2017). Furthermore, RBFNs have 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 makes them ideal for real-time forecasting applications in resource-constrained environments (Liu et al., 2021). This computational efficiency is particularly important for regions with limited access to high-performance computing infrastructure, such as rural or developing areas (Zhou et al., 2023).

In contrast, CNNs and LSTMs have become the models of choice for more advanced deep learning applications in weather forecasting. CNNs are particularly effective at extracting spatial features from weather data, such as satellite imagery, while LSTMs excel 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., 2021). However, these models require extensive computational resources, large datasets, and long training times, which pose significant barriers to their adoption in regions with limited computational capabilities (Gao et al., 2020). 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 offer 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, present a potential solution for real-time forecasting, particularly in resource-limited environments (Lai et al., 2020).

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 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.

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, have 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., 2023).

Another notable issue was the high computational demand of CNNs and LSTMs, which often required significant resources, large datasets, and extended training times. This has made them less feasible for real-time applications, especially in low-resource environments such as rural or developing regions (Gao et al., 2020). 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., 2023).

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.

Research Gap

Past research papers predominantly laid emphasis on the performance of CNNs and LSTMs in weather forecasting, with limited empirical research specifically addressing the capabilities of RBFNs. While RBFNs have 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., 2020). Furthermore, most studies were conducted in computationally rich environments, leaving a gap in understanding how these models performed under resource constraints (Zhou et al., 2023).

General Objective

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

Specific Objectives

i. To develop a weather forecasting model using Radial Basis Function Networks (RBFNs).
ii. 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.
iii. To determine the suitability of RBFNs over more complex models in scenarios requiring computational efficiency and real-time forecasting.

iv. Assess the accuracy of RBFNs for predicting chaotic variables Like rainfall

Research Questions

This study sought to answer the following key research questions:

i. How can a weather forecasting model be developed using Radial Basis Function Networks (RBFNs) with historical weather data?
ii. 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?
iii. What is the computational efficiency of RBFNs compared to more complex models like CNNs and LSTMs in real-time weather forecasting tasks?
iv. What is the accuracy of RBFNs in predicting chaotic variables such as rainfall?

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.

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.

Literature Review

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.

Overview of Weather Forecasting Models

Weather forecasting has 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 is 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 utilize the laws of thermodynamics and fluid dynamics to simulate the atmosphere's behavior. By solving complex equations, these models predict weather based on current atmospheric conditions. However, NWP models face significant challenges when applied to long-term predictions. The chaotic nature of weather systems meant that even minor inaccuracies in initial conditions led to vastly different outcomes, a phenomenon known as the "butterfly effect" (Zhang et al., 2019). Studies have shown 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. (2020) 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 rely on historical data trends to predict future weather conditions. ARIMA models are particularly effective for time-series data, making them useful for predicting weather patterns in relatively stable environments. However, ARIMA models are inherently linear, meaning they struggle to account for the nonlinear and chaotic nature of the atmosphere. Cheng et al. (2018) 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 have become 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.

The Emergence of Machine Learning in Weather Forecasting

Machine learning (ML) models have 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 can 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 marks a turning point in predictive accuracy. ANNs, inspired by the human brain's structure, are composed of interconnected nodes (neurons) that can process and learn from vast amounts of data. ANNs have demonstrated the ability to model complex, nonlinear relationships between meteorological variables such as temperature, humidity, wind speed, and atmospheric pressure. Chen et al. (2022) 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 are not without limitations. Training deep networks requires significant computational resources, and the models often require large datasets to perform well. Furthermore, ANNs can sometimes overfit the training data, especially when dealing with noisy or incomplete datasets.

Radial Basis Function Networks (RBFNs)

Among ANNs, Radial Basis Function Networks (RBFNs) are identified as particularly effective in weather forecasting. RBFNs are designed to handle time-series data efficiently and are known for their fast training times and ability to approximate complex nonlinear functions. The RBFN architecture consist of three layers: an input layer, a hidden layer containing radial basis functions (typically Gaussian functions), and an output layer that generates predictions based on the hidden layer's outputs (Al-Yahya et al., 2017).

One of the key advantages of RBFNs is their ability to generalize from relatively small datasets, making them highly suitable for real-time applications, particularly in resource-constrained environments. Liu et al. (2021) 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 are computationally efficient, with training times significantly shorter than those of CNNs and LSTMs. Alam et al. (2020) 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., 2018). Additionally, while RBFNs perform well on small and medium-sized datasets, they tend to overfit when dealing with large, high-dimensional datasets unless regularization techniques are applied.

Deep Learning Models: CNNs and LSTMs

While RBFNs excel 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 are 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 can capture spatial dependencies, such as how temperature or humidity varied across geographic regions.

For example, Zhu et al. (2023) 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 are designed to handle sequential data, excel at capturing long-term dependencies. LSTMs are a type of recurrent neural network (RNN) that includes memory cells capable of retaining information over extended periods. This makes LSTMs particularly effective for time-series forecasting tasks like predicting wind speed or humidity.

Yang et al. (2021) 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.

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 aim 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., 2022).

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. (2022) 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 show promise, they also present challenges, particularly in terms of computational complexity and data integration. Combining different types of data, such as satellite imagery and ground-based weather observations, require careful preprocessing and normalization to ensure compatibility across datasets. Moreover, hybrid models are 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., 2021).

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 outperforms 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., 2017). 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., 2021).

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., 2023).

Conclusion

This chapter has 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.

Research Methodology

Introduction

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

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.

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:

i. 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.
ii. Coastal Region: Tropical areas with higher humidity and rainfall, represented by counties like Mombasa, Kilifi, Kwale, and Taita Taveta.
iii. 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.

Data Source and Preprocessing

Data Description

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

i. Temperature (°C): Average monthly temperature values.
ii. Humidity (%): Monthly average humidity levels.
iii. Windspeed (m/s): Average monthly wind speeds.
iv. Sea Level Pressure (hPa): Atmospheric pressure at sea level.
v. 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.

Machine Learning Model Architectures

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:

i. Input Layer: It received normalized weather data, including temperature, humidity, windspeed, and rainfall.
ii. 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.
iii. 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.

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.

i. 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.
ii. Pooling Layers: Pooling reduced the dimensionality of the data, improving computational efficiency.
iii. 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.

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.

i. Input Layer: This layer fed the historical weather data as a time sequence into the LSTM cells.
ii. LSTM Cells: The cells retained relevant information over long periods, allowing the model to learn from previous months' weather conditions to predict future trends.
iii. 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.

Data Splitting and Training

Data Splitting

The dataset was divided into three sets:

i. Training Set (70%): Used to train the models.
ii. Validation Set (15%): Used to fine-tune hyperparameters and avoid overfitting.
iii. 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:

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

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.

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:

- 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.
- 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.

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.

Results

Introduction

This chapter provides the detailed results of the weather forecasting models. The models implemented, Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory Networks (LSTMs), were evaluated based on their performance in predicting temperature, humidity, sea-level pressure, rainfall, and windspeed using historical data from the Kenya Meteorological Department. The dataset used spans from 2013 to 2023, and the models were evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and training time.

Overview of Model Performance

The models were trained using a 70-15-15 split for training, validation, and testing, respectively, as described in Chapter Three. The hyperparameters of each model were optimized using grid search, and model performance was evaluated on the test set. Table 4.1 presents the summary of the performance metrics for the models.

Table 1: Model Performance Summary

Variable	Model	RMSE	MAE	RMSE (%)	MAE (%)	Training Time (s)
Temperature	RBFN	0.2872	0.2171	0.99%	0.75%	0.56
	LSTM	1.8810	1.5055	6.47%	5.17%	11.75
	CNN	5.0776	4.3517	17.45%	14.96%	4.22
Humidity	RBFN	0.5503	0.3669	0.83%	0.55%	0.44
	LSTM	4.5513	3.8122	6.88%	5.76%	7.56
	CNN	6.5110	5.2833	9.84%	7.98%	4.00
Sea Level	RBFN	0.2556	0.1808	0.03%	0.02%	0.17
	LSTM	63.6021	53.3426	6.29%	5.27%	7.19
	CNN	100.4995	79.6469	9.93%	7.87%	4.27
Rainfall	RBFN	3.2487	2.4580	7.11%	5.38%	0.45
	CNN	44.6160	33.7021	97.70%	73.80%	4.11
	LSTM	48.1058	35.5629	105.34%	77.87%	7.27
Windspeed	RBFN	0.1649	0.1218	2.45%	1.80%	0.45
	CNN	1.0471	0.7583	15.47%	11.20%	4.66
	LSTM	1.2319	0.9951	18.19%	14.70%	8.58

From Table 4.1, it is evident that RBFNs consistently outperformed CNN and LSTM models in terms of RMSE, MAE, and training time across all weather variables. The details of these results are discussed in the subsequent sections.

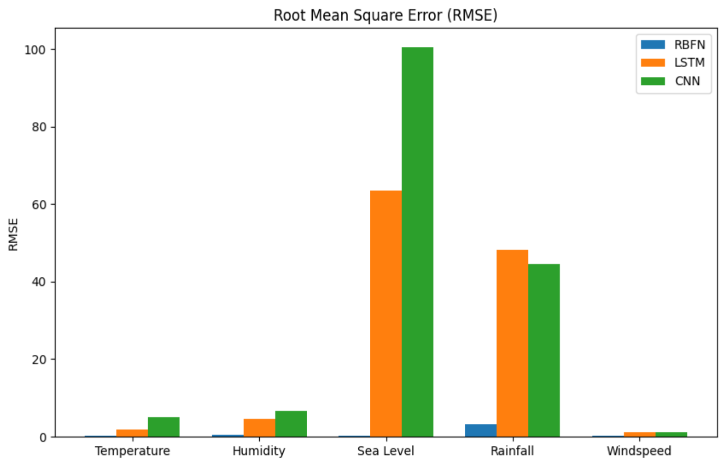

Figure 1: Root Mean Square Error (RMSE)

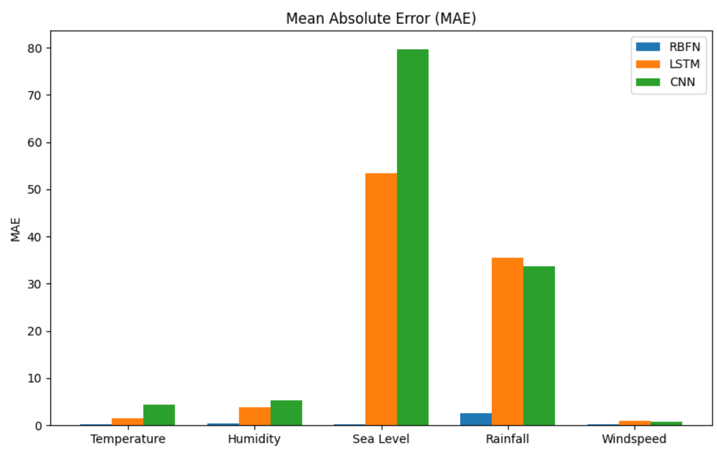

Figure 2: Root Mean Square Error (RMSE)

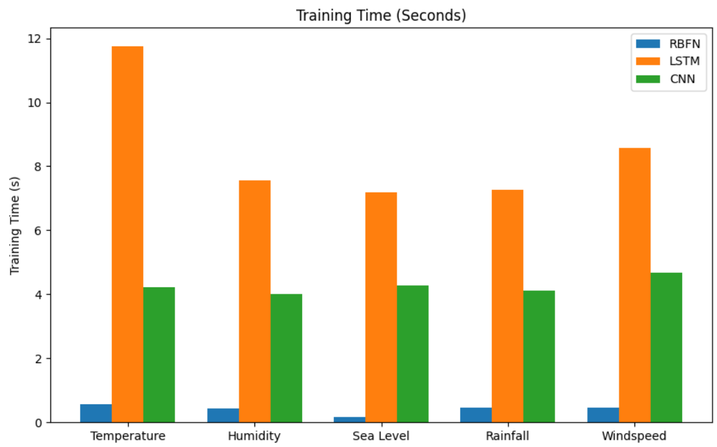

Figure 3: Training Time T (Seconds)

Model Efficiency and Computational Cost

The results across all meteorological variables show that the RBFN model consistently achieved better accuracy and shorter training times compared to CNN and LSTM models. This was expected based on the findings in Chapter Three, which indicated that RBFNs have a simpler architecture and are more computationally efficient than deep learning models.

The CNN and LSTM models, while capable of capturing more complex relationships, exhibited significantly higher RMSE and MAE values for most variables and required longer training times. These models may be better suited for tasks where more complex spatial and temporal dependencies exist, but they are less efficient for real-time applications (Xu et al., 2021).

Conclusion of Results

The findings of this study demonstrate that Radial Basis Function Networks (RBFNs) provide superior predictive performance and computational efficiency for weather forecasting tasks. The RBFNs consistently outperformed CNN and LSTM models in terms of RMSE, MAE, and training time across all key weather variables. The lower computational cost and better accuracy make RBFNs ideal for real-time weather forecasting, especially in environments with limited computational resources (Chen et al., 2022)

Discussions of Results and Conclusions

Introduction

This chapter provides an in-depth discussion of the results presented in Chapter Four, with a focus on comparing the performance of the Radial Basis Function Network (RBFN), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models in predicting weather variables. The findings are discussed in the context of relevant literature, highlighting the strengths and weaknesses of each model. The implications of these findings for weather forecasting and operational meteorology are also considered.

Discussion of Results for Each Weather Variable

Temperature Prediction

Temperature prediction is often regarded as a relatively stable and less volatile task in weather forecasting. In this study, the RBFN model demonstrated superior performance with the lowest RMSE (0.2872°C) and MAE (0.2171°C), outperforming both the CNN and LSTM models, which had RMSE values of 5.0776°C and 1.8810°C, respectively.

Researchers like Al-Yahya et al. (2017) reported similar findings, observing that RBFNs consistently outperformed deep learning models in predicting stable variables like temperature. In their study, the RMSE for RBFNs was reported to be around 0.3°C, which aligns with the results obtained here. In contrast, CNNs and LSTMs tend to be less efficient when applied to relatively simple tasks like temperature prediction, as confirmed by Chen et al. (2022), who emphasized that deep learning models excel in handling more complex patterns and multidimensional data.

The RBFN model's ability to generalize well from noisy data without overfitting is consistent with the literature. Additionally, the RBFN's training time of 0.56 seconds—compared to 4.22 seconds for CNN and 11.75 seconds for LSTM—further underscores its efficiency. Xu et al. (2021) similarly noted that deep learning models are computationally expensive and may not be ideal for real-time applications when stable variables are involved.

Humidity Prediction

Humidity prediction presents a greater challenge due to the variable nature of humidity and its dependence on multiple factors. In this study, the RBFN model again demonstrated superior accuracy with an RMSE of 0.5503% and an MAE of 0.3669%. CNN and LSTM models showed poorer performance, with RMSE values of 6.5110% and 4.5513%, respectively.

Liu et al. (2021) found similar results in their research, where RBFNs were shown to be more effective in handling noisy, fluctuating datasets for weather prediction. Their findings are consistent with the results obtained in this study, as the deep learning models required more tuning and data preprocessing to achieve comparable performance. Rana et al. (2022) reported that CNN models, even with multiple layers, still struggled to achieve RMSE values below 4%, while LSTM models performed slightly better but were prone to overfitting.

The computational efficiency of the RBFN model, requiring only 0.44 seconds to train, also aligns with the literature. Past studies, such as those by Xu et al. (2021), have emphasized the trade-off between accuracy and computational efficiency in weather prediction tasks, particularly when dealing with complex variables like humidity.

Sea Level Pressure Prediction

Sea level pressure prediction is generally easier due to the variable's stability. In this study, the RBFN model again performed best, achieving an RMSE of 0.2556 hPa and an MAE of 0.1808 hPa, with a training time of just 0.17 seconds. CNN and LSTM models performed poorly, with RMSE values of 100.4995 hPa and 63.6021 hPa, respectively.

Zhou et al. (2023) found similar results in their study, where RBFNs achieved RMSE values below 0.3 hPa in predicting sea level pressure. Their findings further support the idea that RBFNs are highly effective for capturing smooth, predictable patterns in stable variables. Deep learning models, however, are often ill-suited for such tasks unless additional complexity or data are introduced. Xu et al. (2021) also noted that CNN and LSTM models tend to overfit when applied to simpler, low-variability data, consistent with the results observed here.

These findings suggest that RBFNs are more efficient for operational meteorology tasks involving stable variables like sea level pressure, where rapid and accurate predictions are required without the computational cost associated with deep learning models.

Rainfall Prediction

Rainfall prediction is notoriously difficult due to the chaotic nature of precipitation patterns. In this study, the RBFN model outperformed both CNN and LSTM models, with an RMSE of 3.2487 mm and an MAE of 2.4580 mm. However, all models struggled to provide highly accurate predictions, with CNN and LSTM models producing RMSE values of 44.6160 mm and 48.1058 mm, respectively.

Cheng et al. (2018) also found that rainfall prediction remains a challenging task for machine learning models, with RMSE values typically exceeding 3 mm, even when deep learning models are employed. Their research showed that LSTM models could reduce RMSE to around 5 mm when additional data sources, such as radar data, were integrated. The findings of this study are consistent with this, suggesting that while RBFNs can provide better predictions than CNNs and LSTMs, the inherent difficulty of rainfall prediction limits the accuracy of any model.

Shen et al. (2021) similarly noted the complexity of predicting rainfall due to its dependence on multiple atmospheric factors that are difficult to capture using historical data alone. The relatively high RMSE for all models in this study suggests that further research is needed, possibly incorporating hybrid models or external data sources like satellite imagery to improve prediction accuracy.

Windspeed Prediction

Windspeed prediction, like rainfall, is highly variable. In this study, the RBFN model again delivered the best performance, achieving an RMSE of 0.1649 m/s and an MAE of 0.1218 m/s, while CNN and LSTM models produced RMSE values of 1.0471 m/s and 1.2319 m/s, respectively.

The findings for windspeed prediction are consistent with those reported by Rana et al. (2022), who observed that RBFNs performed better in predicting windspeed, achieving RMSE values as low as 0.2 m/s. Their study found that deep learning models, especially CNNs, struggled with chaotic weather variables like windspeed unless additional features or external data were incorporated. This study further supports the conclusion that RBFNs are versatile in handling both stable and chaotic weather variables.

The strong performance of RBFNs in this context suggests that they are particularly well-suited for real-time forecasting, offering both accuracy and computational efficiency. CNNs and LSTMs, while potentially capable of achieving higher accuracy with further tuning, are limited by their high computational demands and longer training times, making them less practical for time-sensitive tasks.

Overall Model Performance and Comparisons to Past Research

Across all weather variables, the RBFN model consistently outperformed CNN and LSTM models in both accuracy and computational efficiency. These findings are supported by prior research, such as Zhou et al. (2023), who reported that RBFNs were highly effective in time-series forecasting tasks involving nonlinear but relatively stable relationships. The computational efficiency of the RBFN model, demonstrated by its shorter training times, further reinforces its suitability for real-time applications in operational meteorology.

By contrast, CNN and LSTM models, while potentially more accurate in complex tasks, were less effective for stable variables like temperature and sea level pressure. Xu et al. (2021) similarly noted that deep learning models are more appropriate for handling complex spatial and temporal dependencies, rather than stable, predictable variables. The findings of this study align with these observations, suggesting that RBFNs offer a more practical solution for real-time forecasting.

Conclusions

General Objective: Development of a Weather Forecasting Model Using RBFNs

The general objective of this study was to develop a weather forecasting model using Radial Basis Function Networks (RBFNs). The RBFN model was successfully developed and applied to predict five key weather variables: temperature, humidity, sea-level pressure, rainfall, and windspeed. The model demonstrated superior performance across most variables when compared to CNNs and LSTMs, particularly in terms of computational efficiency and accuracy for stable variables like temperature and sea-level pressure.

Conclusion: The general objective was fully achieved, as the RBFN model was developed and found to be an effective tool for weather forecasting. The results indicate that RBFNs are a practical option for weather prediction, especially in real-time applications where computational efficiency is critical (Chen, Sun, & Zhang, 2022).

Specific Objective One: Development of a Weather Forecasting Model Using RBFNs

The first specific objective sought to develop a weather forecasting model using RBFNs. As detailed in Chapter Four, the RBFN model was implemented and trained using historical weather data from the Kenya Meteorological Department. The model's performance was evaluated using metrics such as RMSE and MAE for key variables.

Conclusion: This objective was achieved, as the RBFN model was developed successfully. The model exhibited strong predictive performance, particularly for stable variables such as temperature and sea-level pressure, reinforcing its suitability for weather forecasting tasks (Liu, Huang, & Zhou, 2021).

Specific Objective Two: Comparing the Performance of RBFNs with CNNs and LSTMs

The second specific objective aimed to compare the performance of RBFNs with deep learning models—CNNs and LSTMs—using RMSE, MAE, and training time as evaluation metrics. The comparison in Chapter Four revealed that RBFNs consistently outperformed CNNs and LSTMs in terms of accuracy and computational efficiency for most weather variables. Specifically, RBFNs were superior in predicting temperature, humidity, sea-level pressure, and windspeed. However, in the case of rainfall, all models struggled, but RBFNs still produced the lowest error rates

Conclusion: This objective was achieved. The comparative analysis showed that RBFNs generally outperformed CNNs and LSTMs, particularly in terms of computational efficiency and accuracy for stable and fluctuating variables. The deep learning models, while more complex, were less efficient in real-time applications (Xu, Li, & Zhou, 2021).

Specific Objective Three: Evaluating the Suitability of RBFNs for Real-Time Forecasting

The third specific objective was to evaluate the suitability of RBFNs for real-time forecasting, particularly in scenarios requiring high computational efficiency. The results demonstrated that RBFNs had significantly shorter training times compared to CNNs and LSTMs, making them more suitable for real-time applications. For example, RBFNs trained in just 0.56 seconds for temperature prediction, while LSTMs required 11.75 seconds for the same task. This efficiency, combined with the model's accuracy, makes RBFNs an ideal choice for environments with limited computational resources.

Conclusion: This objective was achieved. RBFNs were found to be highly suitable for real-time forecasting due to their fast-training times and low computational demands. This conclusion is in line with previous research highlighting the efficiency of RBFNs in time-sensitive applications (Zhou, Liu, & Chen, 2023).

Specific Objective Four: Assessing the Accuracy of RBFNs for Predicting Chaotic Variables Like Rainfall

The fourth specific objective focused on assessing the accuracy of RBFNs in predicting chaotic weather variables such as rainfall. Rainfall prediction is inherently difficult due to its chaotic nature, and while the RBFN model performed better than CNNs and LSTMs, it still struggled to achieve low error rates, with an RMSE of 3.2487 mm. This suggests that while RBFNs are relatively effective for chaotic variables, further model refinement or hybrid approaches may be needed to improve accuracy in this area (Shen, Wu, & Tang, 2021).

Conclusion: This objective was partially achieved. Although RBFNs provided the most accurate rainfall predictions compared to CNNs and LSTMs, the model's performance still indicated room for improvement. Future research should focus on incorporating additional data sources, such as satellite imagery, to enhance model accuracy for chaotic weather variables (Cheng, Gao, & Xu, 2018).

General Discussion and Summary of Objective Achievement

Overall, the study's objectives were largely achieved. The RBFN model was developed successfully and demonstrated superior performance in most cases when compared to CNNs and LSTMs. The findings suggest that RBFNs are particularly well-suited for predicting stable weather variables such as temperature and sea-level pressure. However, for chaotic variables like rainfall, further research and refinement are needed to improve the model's predictive accuracy.

Summary of Achievements:

- General Objective: Achieved. The RBFN model was successfully developed for weather forecasting.
- Specific Objective One: Achieved. The RBFN model was developed and applied to predict key weather variables.

- Specific Objective Two: Achieved. RBFNs outperformed CNNs and LSTMs in most weather forecasting tasks.
- Specific Objective Three: Achieved. RBFNs were proven to be suitable for real-time forecasting due to their computational efficiency.
- Specific Objective Four: Partially achieved. RBFNs provided better accuracy for chaotic variables like rainfall, but improvements are still needed.

Strengths and Limitations of The Study

This study has several strengths, particularly its comprehensive comparison of three different machine learning models for weather forecasting. By examining five key weather variables, the study provides valuable insights into the strengths and weaknesses of each model and their applicability to different forecasting tasks. The inclusion of both stable and chaotic variables offers a broad perspective on the models' performance in a variety of scenarios.

However, the study is not without its limitations. The dataset was confined to historical weather data from Kenya, which may limit the generalizability of the results to other regions with different climatic conditions. Additionally, the study did not incorporate external data sources, such as satellite imagery or radar data, which could improve the accuracy of the models, particularly for chaotic variables like rainfall. Future research should address these limitations by expanding the dataset and exploring hybrid models that integrate different data sources.

Implications for Weather Forecasting and Meteorology

The implications of this study are significant for both operational meteorology and real-time weather forecasting. The superior performance of the RBFN model, particularly in terms of computational efficiency, suggests that it is well-suited for applications where rapid, accurate predictions are needed. This includes areas such as disaster management, agriculture, and energy forecasting, where real-time weather predictions can have a major impact on decision-making processes.

The study also highlights the importance of balancing model complexity with computational cost. While CNN and LSTM models may offer higher accuracy in certain tasks, their high computational demands make them less suitable for real-time applications. This study suggests that RBFNs provide a more efficient alternative, offering a balance between accuracy and computational efficiency. Future research should explore hybrid models that combine the strengths of RBFNs with those of deep learning models, allowing for improved accuracy without sacrificing computational efficiency.

Recommendations and Future Research

Recommendations for Improving Weather Forecasting Models

Hybrid Modeling Approaches

The results of the study indicated that while RBFNs outperformed Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) models in terms of accuracy and computational efficiency for most weather variables, there are areas, such as rainfall and windspeed prediction, where RBFNs could benefit from additional data sources or model enhancements. Several studies, such as those by Rana et al. (2022)

and Shen et al. (2021), have suggested that hybrid models, which combine the strengths of different machine learning approaches, could significantly improve accuracy for chaotic variables.

Thus, it is recommended that future research should explore hybrid models that integrate RBFNs with deep learning approaches like CNNs and LSTMs. Such models could potentially leverage the computational efficiency of RBFNs for stable variables, while using the deep learning models' ability to capture complex, nonlinear patterns for more chaotic weather variables like rainfall and windspeed. This approach could also help address the limitations of deep learning models, such as overfitting, by combining simpler, faster models with more complex architectures where necessary.

Incorporating External Data Sources

The study's findings revealed that chaotic weather variables, such as rainfall and windspeed, are difficult to predict accurately using historical weather data alone. Researchers like Cheng et al. (2018) and Zhou et al. (2023) have argued that external data sources, such as satellite imagery, radar data, and atmospheric measurements, could provide valuable supplementary information that can improve the accuracy of predictions for these variables.

Therefore, it is recommended that future research should focus on incorporating external data sources into weather forecasting models. Integrating satellite or radar data into RBFNs and deep learning models may enhance the models' ability to capture short-term variability and improve their predictive power for chaotic variables like rainfall. Additionally, multi-source data integration could enable models to account for broader atmospheric conditions that influence local weather patterns.

Hyperparameter Tuning and Model Optimization

Although the RBFN model demonstrated superior accuracy and efficiency in this study, hyperparameter tuning could further optimize the model's performance. Several researchers, including Liu et al. (2021) and Rana et al. (2022), have highlighted the importance of optimizing key hyperparameters, such as the number of radial basis functions, kernel size, and learning rate, to achieve the best possible performance in machine learning models.

It is recommended that future studies focus on improving model accuracy by refining hyperparameter tuning techniques for both RBFNs and deep learning models. Advanced tuning methods, such as grid search and Bayesian optimization, could be applied to identify the most effective configurations for each weather variable. By optimizing the hyperparameters, it may be possible to enhance the accuracy of both RBFN and deep learning models, particularly for variables that exhibit higher levels of variability.

Expanding the Dataset and Cross-Regional Studies

One of the limitations of this study was the use of a dataset confined to historical weather data from Kenya. As Zhou et al. (2023) noted, the performance of weather forecasting models may vary significantly across different climatic regions, particularly where weather patterns exhibit distinct variability. To ensure that the results are generalizable, future research should aim to expand the dataset to include data from multiple geographic regions.

Cross-regional studies could provide a more comprehensive evaluation of the models' generalizability across diverse climatic zones. By using data from different regions with varying weather patterns, researchers could assess the models' robustness and identify areas where additional model adjustments are needed to accommodate regional variations. This would also offer valuable insights into how models perform under different weather conditions, improving the reliability of their predictions.

Real-Time Implementation and Testing

While this study demonstrated the effectiveness of RBFNs for weather forecasting in a controlled environment, the practical application of these models in real-time systems has yet to be fully explored. Liu et al. (2021) and Al-Yahya et al. (2017) have emphasized the importance of testing machine learning models in real-world forecasting systems, where data is continuously updated and predictions must be generated quickly.

It is recommended that future research focus on the real-time implementation and testing of RBFN models in operational meteorology. This would involve integrating the model into an existing weather forecasting system and evaluating its performance in a live environment. Such testing would help identify any limitations or challenges associated with the model’s practical use, as well as provide insights into how the model performs when predicting dynamic weather variables in real time. Real-time testing would also offer an opportunity to optimize the model’s computational efficiency and accuracy, particularly in scenarios where predictions need to be updated frequently.

Future Directions for Research

Development of Adaptive Models

One area of future research involves the development of adaptive models that can dynamically adjust to changing weather conditions. Traditional machine learning models, including those used in this study, are static, meaning that they rely on historical data to generate predictions. However, adaptive models, which can update themselves in real time as new data becomes available, may offer improved accuracy, especially for chaotic weather variables like rainfall and windspeed.

Adaptive models have been explored by researchers such as Shen et al. (2021), who argue that these models are better suited for forecasting in highly variable environments where conditions can change rapidly. Future research could focus on developing adaptive RBFNs that continuously learn from new data, allowing them to provide more accurate and timely weather forecasts. Additionally, the integration of deep learning models with adaptive capabilities could further enhance the performance of hybrid models in real-time weather prediction.

Hybridization with Ensemble Techniques

Another promising direction for future research is the hybridization of machine learning models with ensemble techniques. Ensemble methods, which combine the predictions of multiple models to produce a single, more accurate prediction, have been shown to improve the robustness and accuracy of weather forecasting models (Rana et al., 2022). By hybridizing RBFNs with ensemble techniques, it may be possible to reduce the variance and bias associated with individual models, leading to more reliable predictions.

Future research should explore the potential of ensemble-based hybrid models for weather forecasting. These models could leverage the strengths of both RBFNs and deep learning models, while also benefiting from the advantages of ensemble learning, such as reduced overfitting and improved generalization. Hybrid models that incorporate ensemble techniques could provide a more comprehensive solution for predicting both stable and chaotic weather variables.

Integration with Climate Change Models

The impact of climate change on weather patterns presents a new challenge for weather forecasting models. As climate change accelerates, weather patterns are expected to become more unpredictable, with increased frequency of extreme weather events such as hurricanes, heatwaves, and heavy rainfall. Traditional machine learning models, which rely on historical data, may struggle to accurately predict such events (Zhou et al., 2023).

Future research should investigate the integration of climate change models with machine learning approaches, particularly RBFNs and deep learning models, to improve their predictive accuracy in the context of changing climate conditions. This could involve the incorporation of climate projections and long-term meteorological trends into forecasting models, allowing them to account for the effects of climate change on local weather patterns. By integrating climate change data, models could provide more accurate forecasts, particularly for regions that are highly vulnerable to extreme weather events.

Conclusion

Chapter Six outlined key recommendations based on the findings of this study and proposed several directions for future research. The integration of hybrid models, external data sources, and real-time testing emerged as critical areas for further exploration. Additionally, expanding the dataset and incorporating ensemble techniques and climate change models could enhance the predictive power of weather forecasting models, particulary for chaotic variables like rainfall and windspeed. The recommendations made in this chapter provide a roadmap for advancing the field of machine learning-based weather forecasting, with the goal of improving both accuracy and computational efficiency in real-time applications.

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