WEATHER FORECASTING USING RADIAL BASIS FUNCTION NETWORK

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J562/21312/2021

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RESEARCH PROJECT DOCUMENTATION SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF SCIENCE IN COMPUTER SCIENCE IN THE SCHOOL OF PURE AND APPLIED SCIENCES OF KENYATTA UNIVERSITY

May 2025

DECLARATION

This research project documentation is my original work and has not been presented for an award of degree or any other award in any other university.

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DEDICATION

I wholeheartedly dedicate this research project documentation to my family, whose unwavering financial and emotional support has been instrumental throughout this journey. Your belief in me has been my greatest source of strength and motivation.

ABSTRACT

Weather forecasting plays a vital role across sectors such as agriculture, disaster management, transportation, and urban planning. While traditional models like Numerical Weather Prediction (NWP) and Autoregressive Integrated Moving Average (ARIMA) have been instrumental, they often fall short in handling the nonlinear and chaotic nature of atmospheric systems, especially in long-term predictions. This study addresses these limitations by applying and evaluating the performance of machine learning models—Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs)—using a decade-long dataset (2013–2023) obtained from the Kenya Meteorological Department, encompassing temperature, humidity, rainfall, sea-level pressure, and windspeed. Data preprocessing involved K-Nearest Neighbours (KNN) imputation and Min-Max normalization. Models were developed using TensorFlow in Python, optimized through grid search, and deployed via Docker containers on Google Cloud Platform to simulate operational forecasting conditions. Comparative analysis showed that RBFNs outperformed CNNs and LSTMs across all variables, achieving the lowest Root Mean Squared Error (e.g., 0.239°C for temperature versus 5.975°C and 8.701°C for CNN and LSTM, respectively) and the fastest training time, making them highly suitable for real-time forecasting in resource-constrained environments. Hybrid models combining RBFNs with CNNs and LSTMs showed improved accuracy, particularly for complex variables like rainfall. These findings suggest that RBFNs, either standalone or in hybrid configurations, provide an efficient, scalable, and accurate alternative for operational weather forecasting. The study concludes by recommending further exploration of hybrid model integration and the incorporation of satellite imagery to enhance spatial resolution.

ACKNOWLEDGEMENT

I extend my sincere gratitude to my supervisor, **Dr. Abraham Matheka**, for his invaluable guidance, constructive feedback, and unwavering support throughout the course of this research. His expertise and mentorship have been instrumental in shaping this work.

I am also deeply thankful to my family and friends for their constant encouragement, patience, and support during this academic journey.

A special note of appreciation goes to the **Kenya Meteorological Department** for providing the historical weather data that formed a critical foundation for this study.

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ACRONYMS /ABBREVIATIONS

NWP: Numerical Weather Prediction

ARIMA: Autoregressive Integrated Moving Average

ANN: Artificial Neural Networks

RBFN: Radial Basis Function Networks

CNN: Convolutional Neural Networks

LSTM: Long Short-Term Memory Networks

RMSE: Root Mean Squared Error

MAE: Mean Absolute Error

KNN: K-Nearest Neighbors

GCP: Google Cloud Platform

APScheduler: Advanced Python Scheduler

IQR: Interquartile Range

CHAPTER ONE

1.1 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.

1.2 Background of the Study

Weather forecasting is a foundational component of modern planning, risk management, and operational efficiency across a variety of sectors worldwide, including agriculture, aviation, disaster management, water resource planning, and urban development. Accurate and timely weather forecasts are critical for minimizing economic losses, safeguarding lives, and optimizing national productivity (Shen et al., 2021). Globally, meteorological agencies utilize a range of forecasting systems that blend observational data, physics-based simulations, and increasingly, artificial intelligence methods to predict atmospheric behaviour.

In Kenya, the Kenya Meteorological Department (KMD) plays a significant role in national climate monitoring and weather forecasting. As the official government agency mandated with providing meteorological and climate services, KMD is responsible for issuing daily forecasts, severe weather alerts, and long-term climate outlooks. Its services support vital sectors such as smallholder agriculture—where weather variability can severely impact livelihoods—and disaster preparedness, especially in regions prone to droughts, floods, or tropical storms. The department maintains a nationwide network of ground-based weather stations and collaborates with international organizations such as the World Meteorological Organization (WMO) to ensure data interoperability and standards compliance.

Despite the importance of KMD's services, challenges persist. The diversity of Kenya's climate zones—from arid northern regions to humid coastal areas—demands forecasting tools that are both spatially and temporally adaptive. Traditional models, such as Numerical Weather Prediction (NWP) and Autoregressive Integrated Moving Average (ARIMA)**,** have proven effective to a certain extent but struggle to accommodate the nonlinear and chaotic nature of atmospheric processes. Small deviations in initial conditions can lead to large errors in predictions, especially over extended periods—an issue commonly referred to as the **"butterfly effect"** (Zhang et al., 2019; Yang et al., 2020). Furthermore, statistical models like ARIMA, though suitable for short-term linear forecasting, fall short when addressing complex, multi-variable weather systems (Lai et al., 2020).

To address these limitations, researchers globally have turned to machine learning (ML)**,** which offers robust alternatives capable of handling nonlinear relationships and learning from large volumes of data without relying on predefined physical equations (Chen et al., 2022). In Kenya, the integration of ML into meteorological services is still emerging, constrained by limited computational infrastructure and a lack of tailored evaluation studies focused on regional performance.

Radial Basis Function Networks (RBFNs)**,** a type of Artificial Neural Network (ANN), have been identified as promising candidates for weather forecasting due to their fast-training times, capacity to handle nonlinear time-series data, and minimal computational requirements (Al-Yahya et al., 2017). However, comprehensive studies comparing their performance to advanced models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM**)** networks in real-world forecasting applications remain scarce.

This study aims to bridge that gap by evaluating the performance of RBFNs, CNNs, and LSTMs in forecasting key meteorological variables using historical data from the Kenya Meteorological Department. While the focus is national, the implications of the findings are global—particularly for developing countries and low-resource settings where real-time forecasting is crucial but constrained by technical limitations. By contributing to the understanding of efficient model selection for operational meteorology, the study provides insights that are both locally relevant and globally applicable**.**

1.3 Problem Statement

Despite significant advances in weather forecasting, the task of accurately predicting atmospheric conditions remains a complex and unresolved challenge due to the chaotic, nonlinear nature of weather systems (Zhang et al., 2019). Traditional forecasting methods such as Numerical Weather Prediction (NWP) and statistical models like Autoregressive Integrated

Moving Average (ARIMA) rely on physical equations and linear assumptions, which often lead to substantial prediction errors—especially for long-term forecasts (Yang et al., 2020; Lai et al., 2020). These limitations are particularly problematic in regions like Kenya, where accurate and timely weather forecasts are crucial for sectors such as agriculture, disaster preparedness, and infrastructure planning.

Recent developments in machine learning (ML) have shown promise in improving the accuracy and efficiency of weather forecasting. Models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been successfully applied to capture spatial and temporal patterns in meteorological data (Chen et al., 2022; Xu et al., 2021). However, these models are computationally intensive and require large datasets and powerful hardware—resources that are often unavailable in developing regions or real-time operational settings (Gao et al., 2020; Zhou et al., 2023).

Radial Basis Function Networks (RBFNs), a class of Artificial Neural Networks (ANNs), offer a potentially effective and efficient alternative due to their ability to handle nonlinear data with reduced computational overhead (Al-Yahya et al., 2017). However, there is a notable research gap in systematically comparing RBFNs to more complex deep learning models like CNNs and LSTMs within the context of weather forecasting. Specifically, it remains unclear whether RBFNs can provide comparable forecasting accuracy while offering advantages in speed and computational efficiency.

This research aims to address this gap by evaluating the performance of RBFNs in weather forecasting and comparing them with CNNs and LSTMs using historical weather data from Kenya. The study investigates whether RBFNs can serve as a viable alternative for real-time forecasting in environments with limited computational resources. By doing so, it seeks to inform model selection strategies that balance accuracy with operational feasibility in meteorological applications.

1.4 Research Objectives

1.4.1 General Research Objective

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

1.4.2 Specific Research Objectives

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

1.5 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?

1.6 Limitations of the Study

Every research undertaking faces certain constraints that influence the scope, methodology, and interpretation of findings. This study, which evaluated the performance of machine learning models—Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNN's), and Long Short-Term Memory networks (LSTMs)—in weather forecasting, encountered several anticipated limitations. The researcher identified these early in the process and implemented strategies to mitigate their potential impact.

1.6.1 Geographical and Climatic Scope of Data

The primary dataset used in this study was obtained from the Kenya Meteorological Department (KMD) and covered weather records from 2013 to 2023. While this dataset was rich in temporal breadth, it was geographically constrained to Kenyan counties, which posed a challenge in terms of generalizability to other climatic zones. To mitigate this, Kenya's diverse climatic regions (semi-arid, tropical, and highland) were treated as distinct subpopulations, allowing the model to be evaluated across a wide range of microclimates within the country. This approach aimed to improve the robustness and applicability of the models to other regions with similar weather dynamics (Xu et al., 2021).

1.6.2 Missing and Noisy Data

Historical weather datasets often contain missing records or anomalies due to equipment malfunctions, transmission errors, or environmental disturbances. To address this, the study employed K-Nearest Neighbours (KNN) imputation to fill in missing values and the Interquartile Range (IQR) method to detect and correct outliers. These preprocessing techniques ensured that the training data were dependable and reduced the risk of bias in model performance (Liu et al., 2021).

1.6.3 Limited Computational Resources

Training deep learning models such as CNN's and LSTMs typically demands high-performance computing infrastructure, which was not readily available for this research. This constraint could have affected the degree of hyperparameter tuning and model optimization achievable. To overcome this, cloud-based platforms—specifically Google Cloud Platform (GCP)—were used to supplement local computational capabilities, and efficient training strategies such as early stopping and batch normalization were implemented to conserve resources (Zhou et al., 2023).

1.6.4 Model Generalization and Overfitting Risk

Given the nonlinear nature of weather data, there was a risk of overfitting—especially with deep learning models like LSTMs. The researcher addressed this by employing cross-validation techniques and using separate validation datasets during training. Regularization methods were also incorporated to improve the generalization capability of the models (Gao et al., 2020).

1.6.5 Variable Selection Limitation

The study focused on five key weather variables—temperature, humidity, rainfall, sea-level pressure, and windspeed. However, other important meteorological parameters such as solar radiation, cloud cover, and evapotranspiration were excluded due to data unavailability. While this restricted the model's holistic understanding of atmospheric dynamics, the selected variables were sufficient to assess the models' core forecasting performance. Future research could address this gap by integrating satellite-derived and remote sensing data to enhance model inputs (Zhu et al., 2023).

1.7 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.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Weather forecasting has long been an essential domain of scientific inquiry, influencing critical sectors such as agriculture, aviation, disaster preparedness, public health, and energy planning. The growing unpredictability of climate patterns due to global warming has heightened the demand for more accurate, scalable, and reliable forecasting methods. Traditionally, numerical weather prediction (NWP) models and statistical methods such as Autoregressive Integrated Moving Average (ARIMA) have formed the backbone of operational forecasting systems. While these models are grounded in physical atmospheric principles and historical trends, they often falter in capturing the nonlinear, chaotic, and multivariate nature of atmospheric systems, especially in data-scarce or resource-constrained environments (Zhang et al., 2019; Yang et al., 2020).

In response to these limitations, the last two decades have witnessed a surge in the application of machine learning (ML) and deep learning techniques to weather forecasting. These models offer data-driven alternatives capable of identifying complex, hidden patterns in high-dimensional meteorological datasets without relying on rigid physical equations (Chen et al., 2022). Among these, Radial Basis Function Networks (RBFN’s), Convolutional Neural Networks (CNN’s**)**, and Long Short-Term Memory (LSTM) networks have gained prominence due to their respective strengths in modelling nonlinear relationships, spatial dependencies, and temporal sequences (Al-Yahya et al., 2017; Xu et al., 2021).

This chapter reviews the theoretical underpinnings and empirical applications of these models in weather forecasting. It begins by outlining the foundational principles of weather prediction and the evolution from traditional to AI-driven models. It then explores key studies on RBFNs, CNNs, and LSTMs, comparing their methodological approaches, performance outcomes, and practical limitations. Special attention is given to literature evaluating model performance in diverse climatic settings and operational constraints similar to those in Kenya and other Sub-Saharan African contexts.

Furthermore, this chapter identifies critical gaps in the existing body of research, particularly the lack of comparative analyses that benchmark RBFN's against deep learning counterparts using real-world datasets. It highlights how most existing studies are concentrated in highly instrumented environments—such as North America, Europe, and China—leaving a void in the empirical understanding of how these models perform in low-infrastructure, high-variability settings like Kenya (Zhou et al., 2023). This literature review thus provides the conceptual and empirical foundation upon which the current study is built.

2.2 Theoretical Framework

The theoretical framework for this study is anchored in the interdisciplinary convergence of atmospheric science, nonlinear systems theory, and machine learning, particularly focusing on the modelling of complex time-series data for predictive analytics. The theoretical basis is divided into two core domains: chaos theory and dynamical systems in weather, and computational learning theory as applied through neural network architectures.

2.2.1 Chaos Theory and Weather Forecasting

Weather systems are inherently nonlinear and chaotic, governed by complex partial differential equations that exhibit extreme sensitivity to initial conditions—a phenomenon widely known as the butterfly effect (Lorenz, 1963). This means that even minor inaccuracies in input measurements can lead to exponentially divergent forecast outcomes, especially over extended time horizons. Traditional models like Numerical Weather Prediction (NWP) often struggle to manage these instabilities due to their deterministic structure and dependence on finely tuned physical equations (Zhang et al., 2019).

Chaos theory provides a conceptual lens to understand why traditional linear models fall short in modelling meteorological phenomena. It supports the need for adaptive, data-driven modelling systems capable of capturing hidden nonlinearities without assuming pre-set functional forms (Yang et al., 2020). This understanding forms the rationale for adopting artificial intelligence (AI) techniques in weather forecasting.

2.2.2 Artificial Neural Networks (ANNs) and Learning Theory

The mathematical foundation of neural networks lies in computational learning theory, which explores how algorithms can learn mappings from input to output spaces through exposure to labelled examples. In the context of weather forecasting, this involves learning a functional approximation from historical meteorological variables to future atmospheric conditions.

This study is underpinned by three major neural architectures:

- **Radial Basis Function Networks (RBFNs)**: Based on kernel methods, RBFNs use radial basis (Gaussian) activation functions to interpolate the relationship between inputs and outputs. RBFNs are theoretically supported by Cover's Theorem, which states that a nonlinear transformation of input space into a higher-dimensional feature space increases the likelihood of linear separability (Broomhead & Lowe, 1988). This makes them suitable for modelling moderately nonlinear processes like daily weather variations with low computational cost (Al-Yahya et al., 2017).

- **Convolutional Neural Networks (CNN's)**: Rooted in the theory of shared weights and spatial feature extraction, CNNs are designed to model local dependencies across spatial dimensions. Originally proposed for image processing, CNNs are now widely used in climate science to detect spatial patterns such as pressure ridges and storm fronts (Zhu et al., 2023). Their theoretical advantage lies in translation invariance and hierarchical abstraction, making them effective in forecasting tasks involving gridded weather data.

- **Long Short-Term Memory Networks (LSTMs)**: LSTMs are an extension of Recurrent Neural Networks (RNNs), specifically designed to capture long-term dependencies in sequential data. They are built on the principles of gated memory units, which control the flow of information through forget, input, and output gates (Hochreiter & Schmidhuber, 1997). In weather forecasting, LSTMs are well-suited to learn seasonal and temporal dynamics, such as El Niño–Southern Oscillation cycles or monsoon patterns (Chen et al., 2022).

2.2.3 Model Selection Theory

The study also aligns with the bias-variance trade-offs in machine learning theory. RBFN's, being simpler models, may have higher bias but lower variance, offering faster training and better generalization on small or moderately complex datasets. CNN's and LSTMs, being deep models, may offer lower bias but risk high variance—leading to overfitting, especially in resource-constrained contexts with limited data or compute power (Gao et al., 2020).

This trade-off provides a theoretical justification for empirically comparing these models in a real-world context like Kenya, where data sparsity and computational constraints are operational concerns.

This theoretical framework establishes the rationale for selecting and comparing RBFNs, CNNs, and LSTMs in forecasting applications. It also highlights the necessity of moving beyond physical models to learned representations that are scalable, adaptive, and suited to chaotic systems like the atmosphere.

2.3 Empirical Review

This section reviews empirical studies that have applied machine learning (ML) techniques—particularly Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs)—to weather forecasting. The review focuses on research that assesses forecasting accuracy, computational efficiency, and applicability across different climatic and geographic contexts. It also highlights how these findings support or contrast with the current study's methodology and objectives.

2.3.1 Radial Basis Function Networks (RBFNs) in Weather Forecasting

Radial Basis Function Networks (RBFNs) have been increasingly explored in recent years for their ability to efficiently model nonlinear time-series data with low computational overhead. Al-Yahya et al. (2017) applied RBFNs to temperature forecasting in Saudi Arabia and found that the model achieved faster convergence and lower Root Mean Squared Error (RMSE) than traditional multilayer perceptrons (MLPs). The study concluded that RBFNs are well-suited for real-time systems where both speed and interpretability are necessary.

Similarly, Liu et al. (2021) conducted a comparative analysis of RBFNs, Support Vector Regression (SVR), and LSTMs for temperature and humidity forecasting in rural China. RBFNs achieved an RMSE of 0.80% in temperature predictions—lower than the 5.9% and 8.7% recorded for CNNs and LSTMs, respectively. The study emphasized the model's scalability and suitability for deployment in low-resource regions.

However, limitations were noted. RBFNs tend to perform sub-optimally in highly chaotic or multi-modal datasets without adequate tuning of the number of RBF centres or kernel bandwidth.

Despite this, their lightweight architecture and fast training make them ideal for operational environments with constrained infrastructure, such as many regions in Africa.

2.3.2 Convolutional Neural Networks (CNNs) in Spatial Weather Prediction

Convolutional Neural Networks (CNNs), though originally developed for image processing, have been increasingly applied in spatial weather modelling. Chen et al. (2022) utilized CNNs to predict rainfall in Taiwan using high-resolution radar images and gridded data. The model outperformed baseline statistical models, particularly in identifying storm onset and spatially distributed rainfall intensity. The authors highlighted CNNs' ability to preserve spatial correlations that are often lost in traditional models.

Another study by Zhu et al. (2023) developed a hybrid CNN-LSTM model for typhoon trajectory forecasting. While the CNN handled spatial encoding, the LSTM managed temporal sequencing. The model demonstrated powerful performance in multi-step forecasting scenarios, reducing average trajectory error by 18% compared to LSTM-only baselines.

However, CNNs are computationally intensive and require large, labelled datasets to generalize well. This makes them less ideal in contexts with limited data availability or computational infrastructure, as noted by Gao et al. (2020). In many African contexts, such computational requirements pose a barrier to real-time deployment.

2.3.3 Long Short-Term Memory Networks (LSTMs) in Temporal Forecasting

LSTMs are a subclass of recurrent neural networks (RNNs) optimized for modelling sequential dependencies in time-series data. Their memory cell architecture allows them to capture long-term dependencies, making them particularly effective in weather forecasting where seasonal and periodic trends exist.

Yang et al. (2020) used LSTM models to predict temperature and precipitation in northern India. The LSTM outperformed traditional ARIMA and feedforward neural networks, particularly in long-range forecasts. The authors attributed the improved accuracy to the model's capacity to retain relevant temporal features over long sequences.

In another study, Xu et al. (2021) deployed an LSTM model for hourly rainfall forecasting in Southern China. The LSTM model produced reliable short-term forecasts and demonstrated resilience to input noise, especially when trained on 10+ years of historical data. However, the model exhibited longer training times and required more hyperparameter tuning compared to shallow models like RBFNs.

Despite their strength in capturing temporal dynamics, LSTMs are prone to overfitting in small datasets and require extensive preprocessing to yield optimal results. Their deployment is also constrained by their higher computational cost, which can hinder real-time usage in low-resource environments.

2.3.4 Comparative and Hybrid Approaches

Some empirical studies have explored hybrid or comparative frameworks to combine the strengths of different models. Cheng et al. (2018) proposed an ARIMA-ANN hybrid model for rainfall forecasting, finding that the hybrid model improved both accuracy and stability across forecast horizons. However, the approach lacked flexibility when applied to multivariate forecasting tasks involving more than one weather variable.

Zhou et al. (2023**)** conducted a comparative study between RBFNs, CNNs, and LSTMs in forecasting windspeed and sea-level pressure. The study found that while CNNs and LSTMs offered powerful performance in high-resolution datasets, RBFNs outperformed them in terms of training time and adaptability, especially in data-constrained environments. These results support the findings of this study, which positions RBFNs as a viable alternative for operational meteorology in developing regions.

2.3.5 Empirical Studies in African Contexts

There is a notable lack of empirical machine learning research in weather forecasting based on African data. Most reviewed studies are concentrated in Asia, Europe, and North America. A few African studies include:

- Mwangi et al. (2019), who applied artificial neural networks to rainfall prediction in Kenya using data from the Kenya Meteorological Department. While promising, the study used shallow ANNs and did not explore modern architectures such as RBFNs or LSTMs.

- Abate et al. (2020) evaluated LSTM models for rainfall forecasting in Ethiopia and found them more accurate than linear regression models. However, the study lacked comparative benchmarking against simpler architectures like RBFNs.

This gap underscores the importance of the present study in extending empirical insights into low-resource, climate-vulnerable settings, where the need for accurate and efficient forecasting is critical but understudied.

2.3.6 Empirical Studies in Africa and Developing Regions

While machine learning techniques have gained widespread attention in weather forecasting, their application in Africa and other developing regions remains comparatively limited. Much of the global literature has focused on high-income countries with dense weather station networks, reliable internet infrastructure, and access to high-performance computing resources. By contrast, African meteorological systems face challenges such as sparse data availability, infrastructural limitations, and a lack of localized algorithm development, which have constrained the growth of AI-based weather forecasting research in the region (World Meteorological Organization [WMO], 2020).

Despite these constraints, a few significant studies have emerged. Mwangi et al. (2019**)** applied a basic artificial neural network (ANN) model to forecast monthly rainfall in Kenya using historical data from the Kenya Meteorological Department. The ANN achieved moderate accuracy but lacked the complexity needed to capture nonlinear seasonal transitions. The study acknowledged the limitations of shallow models and suggested the need to explore more advanced architectures like RBFNs or LSTMs. However, it also highlighted challenges such as missing data, poor resolution, and underinvestment in data infrastructure, which hindered more ambitious model designs.

In Ethiopia, Abate et al. (2020) implemented LSTM models for short-term rainfall forecasting in the central highlands. The models outperformed classical regression and support vector approaches, especially in capturing seasonal rainfall peaks. However, the study also noted the computational demands and training instability of LSTMs, especially when operating without access to GPU acceleration. The authors recommended that future research explore lightweight architectures that require less training time and perform well with noisy or incomplete data—an argument strongly aligned with the inclusion of RBFNs in this study.

Mansour et al. (2021) conducted a hybrid model study in Nigeria, integrating ARIMA with ANN to predict humidity and temperature variations across Lagos State. The model showed improved short-term prediction compared to ARIMA alone but struggled with complex, multivariable forecasting scenarios. The researchers highlighted a key barrier in developing regions: data interoperability. Many African meteorological departments still rely on analogue data collection methods or incompatible digital formats, limiting the development of integrated machine learning solutions.

Beyond Africa, in South Asia and Southeast Asia, more robust studies have demonstrated both the potential and limitations of AI in developing contexts. Karim et al. (2020) in Bangladesh used an LSTM-CNN hybrid model to predict flood-prone rainfall using satellite-derived data and found it significantly better than traditional forecasting. While promising, the study emphasized that such success relied heavily on access to satellite imagery and consistent sensor data, which are not yet universally accessible in Sub-Saharan Africa.

A major commonality in empirical studies across developing regions is the limited access to rich datasets. Many rely on daily or monthly observations from a few stations, compared to the high-resolution, gridded data available in Europe, North America, or China (Gao et al., 2020). The lack of data density undermines the training and generalization capacity of deep learning models like CNNs and LSTMs. Additionally, high computational costs and limited local technical expertise present further barriers to widespread adoption of AI in weather forecasting (Zhou et al., 2023).

Interestingly, few if any studies have directly compared lightweight neural models such as RBFNs with deep learning alternatives in African settings. Most studies have focused either on single-model performance or hybrid approaches, without benchmarking computational efficiency or real-time suitability—factors that are crucial in operational meteorology in developing countries. This underscores a significant research gap, which the present study aims to fill by conducting a controlled performance comparison between RBFNs, CNNs, and LSTMs using Kenyan meteorological data.

Moreover, little emphasis has been placed on model deployment and usability, which are vital components of practical forecasting systems. Even when models are trained successfully, few studies document the transition to real-time deployment or cloud-based scalability—often due to the absence of digital transformation strategies within national meteorological agencies (WMO, 2020).

In summary, empirical research in Africa and other developing regions has demonstrated the potential of machine learning in weather forecasting but has been constrained by:

- Sparse and low-resolution data,
- Limited access to computing infrastructure,
- Lack of local model evaluation and benchmarking,
- Underdeveloped data ecosystems, and
- Weak support for model deployment and integration.

By addressing these constraints through a comparative evaluation of three models under real-world data conditions in Kenya, the present study contributes new empirical insights to the global body of knowledge, while also offering regionally relevant recommendations for AI-driven weather forecasting in developing contexts.

2.4 Rationale for the Present Study

Despite significant advancements in the application of machine learning to weather forecasting, a persistent gap exists in comparative evaluations between simpler models such as Radial Basis Function Networks (RBFNs) and more complex deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks (Chen et al., 2022; Xu et al., 2021; Zhou et al., 2023). While numerous studies have demonstrated the individual strengths of these models—such as CNNs for spatial pattern recognition and LSTMs for temporal sequence learning—they are often limited by high computational costs, extended training times, and infrastructure demands that reduce their viability in real-time forecasting, particularly in low-resource settings (Chen et al., 2022; Xu et al., 2021).

Conversely, RBFNs have shown considerable promise in modelling nonlinear time-series data due to their fast convergence, minimal computational requirements, and competitive accuracy in variables like temperature and humidity (Al-Yahya et al., 2017; Liu et al., 2021). However, there remains a lack of empirical research comparing RBFNs directly against CNNs and LSTMs within a unified framework using real-world, geographically diverse datasets—particularly in Sub-Saharan African contexts like Kenya, where data heterogeneity and infrastructural limitations are more pronounced (Zhou et al., 2023).

Additionally, while hybrid models—such as ARIMA-ANN integrations—have shown improved performance in certain cases (Cheng et al., 2018), there is a notable absence of research exploring hybridization strategies involving RBFNs and deep learning models. Most available literature is also concentrated in data-rich environments like North America, Europe, and East Asia, which limits the generalizability of their findings to African forecasting systems (Zhou et al., 2023; Mwangi et al., 2019; Abate et al., 2020).

To address this empirical and methodological gap, the present study conducts a structured comparative performance analysis of RBFNs, CNNs, and LSTMs using a ten-year dataset from the Kenya Meteorological Department (2013–2023). The models are evaluated based on forecasting accuracy, training time, and computational efficiency to determine their real-time suitability in resource-constrained operational settings. By emphasizing practical deployment considerations and investigating hybrid potentials, this study contributes to evidence-based model selection strategies and paves the way for scalable, efficient, and context-sensitive forecasting solutions in developing regions.

2.5 Summary and Research Gap

2.5.1 Summary of Literature Reviewed

This chapter has examined the theoretical and empirical foundations of weather forecasting using machine learning models, with a particular focus on Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs).

From a theoretical perspective, weather forecasting is characterized by nonlinear dynamics, chaotic behaviour, and multivariate dependencies that challenge traditional statistical and physics-based models (Zhang et al., 2019; Lorenz, 1963). In this context, machine learning offers an adaptable alternative that allows models to learn complex spatiotemporal relationships from historical data, especially when physical laws become analytically intractable.

The review demonstrated that RBFNs have shown high efficiency and adequate accuracy for moderately nonlinear problems. Their lightweight architecture makes them well-suited for low-resource operational environments, though they can struggle with deep temporal forecasting if not properly optimized (Al-Yahya et al., 2017; Liu et al., 2021).

CNNs, widely used for image and spatial data processing, have shown promise in weather forecasting tasks that rely on satellite images or grid-based weather observations. Their ability to capture spatial patterns—such as pressure gradients or storm clusters—has made them a popular choice in highly instrumented countries, though they require large datasets and substantial computational resources (Chen et al., 2022; Zhu et al., 2023).

LSTMs, built to handle sequential data, have demonstrated powerful performance in long-range weather prediction, particularly in capturing seasonality and periodicity. However, they are computationally intensive and susceptible to overfitting when trained on sparse or noisy datasets—conditions that are typical in many developing regions (Xu et al., 2021; Yang et al., 2020).

Furthermore, a review of hybrid approaches showed benefits from model integration (e.g., CNN-LSTM, ARIMA-ANN) but revealed that few studies evaluate these models head-to-head in a structured, controlled experiment using the same dataset and evaluation criteria.

The empirical literature from Africa and other developing regions remains sparse. While some research has explored ANN and LSTM-based forecasting in Ethiopia, Nigeria, and Kenya, these efforts have largely used shallow architectures or single-model trials, without rigorous benchmarking or deployment strategies. Additionally, most studies do not address operational constraints such as data sparsity, model training time, or system scalability—factors essential for effective forecasting in national meteorological departments (Mwangi et al., 2019; Abate et al., 2020; Mansour et al., 2021).

2.5.2 Research Gap

A review of existing literature reveals significant strides in the application of machine learning to weather forecasting. However, a consistent theme across multiple studies is the lack of comprehensive comparative evaluations between simpler models like Radial Basis Function Networks (RBFNs) and more complex deep learning architectures such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks—especially in the context of computational efficiency and real-time applicability.

Empirical studies have explored the individual strengths of these models. For instance, Chen et al. (2022) demonstrated the effectiveness of CNN's and LSTMs in capturing spatial and temporal dependencies, respectively, but noted their high computational costs. Xu et al. (2021) emphasized that deep learning models, while accurate, demand significant data preprocessing, training time, and computing power, which limits their practicality in real-time forecasting, particularly in low-resource settings.

On the other hand, RBFNs have shown promising results in modelling nonlinear time-series data with relatively fast training times and lower resource requirements (Al-Yahya et al., 2017; Liu et al., 2021). For example, Liu et al. (2021) reported that RBFNs achieved an RMSE of 0.80% in temperature forecasting, outperforming CNNs and LSTMs, which had RMSEs of 5.9% and 8.7%, respectively. Yet, there is limited empirical work comparing RBFNs directly against CNNs and LSTMs within a unified experimental framework, especially using data from real-world, geographically diverse environments like Kenya.

Moreover, while hybrid models that integrate multiple machine learning techniques have been explored—such as the ARIMA-ANN model proposed by Cheng et al. (2018)—there is insufficient focus on combining RBFN's with deep learning methods to leverage their complementary strengths. Additionally, many prior studies are based on data from highly instrumented regions such as North America, Europe, or China, leaving a gap in understanding how these models perform in data-scarce, resource-constrained environments (Zhou et al., 2023).

This study addresses this gap by conducting a comparative performance analysis of RBFNs, CNNs, and LSTMs using historical weather data from the Kenya Meteorological Department, spanning 2013 to 2023. The research specifically focuses on evaluating each model's forecasting accuracy, training time, and computational efficiency, providing new insights into their suitability for real-time deployment in regions with limited computational infrastructure.

By filling this empirical and methodological void, the study contributes to model selection strategies for operational forecasting and lays the groundwork for future research into hybrid systems optimized for both accuracy and efficiency.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter outlines the research methodology employed to achieve the study's objectives of evaluating and comparing the forecasting performance of Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks using meteorological data from Kenya. The methodology describes the research design, target population, data sources, preprocessing techniques, model architectures, evaluation metrics, and deployment strategies. It also explains the rationale behind the selection of each methodological component, ensuring that the research process aligns with both the research questions and the context of real-time weather forecasting in resource-constrained environments.

Machine learning-based forecasting requires a methodological framework that balances experimental rigor, data fidelity, and computational feasibility (Shen et al., 2021). Given the nonlinearity and chaotic nature of meteorological systems, the chosen methods needed to support flexible modelling, allow performance benchmarking, and ensure generalizability across variable climate conditions. This chapter provides a detailed explanation of how these goals were achieved through a structured and reproducible approach.

3.2 Research Design

This study adopted a comparative experimental research design, which is suitable for evaluating machine learning algorithms under controlled conditions. This design facilitates objective performance comparison by applying the same dataset and evaluation metrics to different algorithms and observing how each model responds to the same forecasting task. According to Gao et al. (2020), experimental designs are essential in machine learning research as they help isolate the impact of specific model configurations on predictive performance.

The primary goal of this research was to determine whether RBFNs could serve as a viable alternative to more computationally intensive deep learning models like CNNs and LSTMs in real-time weather forecasting scenarios. As such, the design involved:

- Constructing and training each of the three models using identical datasets,
- Evaluating model performance using common statistical metrics—Root Mean Squared Error (RMSE)**,** Mean Absolute Error (MAE)**,** and training time**,**
- Analysing the models' suitability for operational deployment in environments with limited computational resources.

The comparative experimental design also supports internal validity, ensuring that observed performance differences are due to model characteristics rather than extraneous factors such as data variability or preprocessing inconsistencies (Zhou et al., 2023). Additionally, it allows for replicability, a crucial component in computational science (Chen et al., 2022).

The decision to compare RBFNs against CNNs and LSTMs stems from the gap identified in the literature: while RBFNs are known for their fast training and generalization capabilities (Al-Yahya et al., 2017), very few studies have empirically compared them against more complex models using real-world meteorological data. This study aims to fill that gap by applying a design that aligns with best practices in empirical algorithmic research and by grounding the model evaluation in a real-world forecasting context.

3.3 Data Collection Instruments

The primary data collection instruments used in this study were digital weather observation systems and meteorological databases maintained by the Kenya Meteorological Department (KMD). The data were obtained in structured digital formats (CSV and Excel), allowing for systematic analysis and easy integration with machine learning pipelines.

The choice of secondary data from a reputable government agency was justified for several reasons:

1. **Credibility and Reliability**: KMD follows international standards set by the World Meteorological Organization (WMO) for data collection and station calibration, ensuring high-quality and validated datasets (Zhou et al., 2023).
2. **Temporal and Spatial Coverage**: KMD's dataset spans over a 10-year period (2013–2023) and includes measurements from diverse climate zones across Kenya. This provided a rich and varied data source for model training and evaluation.

3. **Real-world Relevance**: Using operational data enhances the external validity of the models, making them more applicable to live forecasting systems, which aligns with the practical goals of this study (Shen et al., 2021).

The tools used for accessing and preparing the data included:

- **Microsoft Excel** and **Google Sheets**: For initial exploration and manual cleaning of anomalies.
- **Python (Pandas and NumPy)**: For programmatic preprocessing, normalization, and integration with model training pipelines.
- **KMD APIs and FTP access**: Where available, API endpoints were used to fetch station-level updates in real-time formats, simulating operational deployment environments.

These instruments enabled structured, scalable, and repeatable data handling workflows, essential for ensuring data consistency and model reproducibility in machine learning research (Gao et al., 2020).

3.4 Sampling Technique

The study employed a stratified purposive sampling technique to ensure that the machine learning models were trained and tested on data from distinct climatic zones across Kenya. Stratification was based on regional climate categories defined by KMD and supported by global climate classification systems such as the Köppen-Geiger scheme.

Three major climate zones were identified and used as strata:

1. **Arid and Semi-Arid Regions** – Represented by counties such as Mandera and Marsabit.
2. **Humid Tropical Coastal Regions** – Including Mombasa, Kwale, and Kilifi.
3. **Temperate Highland Regions** – Such as Nairobi, Nyeri, and Murang’a.

Justification for stratified purposive sampling:

- **Ensures representation of climatic diversity**: This increases the model’s generalizability across different weather regimes, a key factor in national-scale weather forecasting (Lai et al., 2020).

- **Improves model robustness**: Training across diverse conditions helps avoid overfitting to specific weather patterns or regions (Guo et al., 2020).
- **Data sufficiency**: Each stratum contained counties with complete data records over the 10-year period, meeting the minimum data quality threshold required for deep learning models (Chen et al., 2022).

  Within each stratum, counties with consistent and complete records were selected purposefully. This approach ensured that the models were trained on high-integrity data while still reflecting the full range of Kenya's climatic variability. Although not probabilistic, purposive sampling is justified in computational research where the goal is model performance under specific, real-world conditions, not population estimation (Liu et al., 2021).

3.5 Study Population

The study population consisted of historical weather data collected across multiple counties in Kenya by the Kenya Meteorological Department (KMD) between 2013 and 2023. Kenya's unique geographical diversity—ranging from arid northern regions to humid coastal zones and highland areas—offered a rich dataset with substantial climatic variability. This diversity made the dataset particularly suitable for evaluating the models' generalization capabilities under heterogeneous weather conditions (Lai et al., 2020).

The population was stratified into three main climate zones to ensure coverage of different weather regimes:

1. **North-Eastern Region** (Arid and Semi-Arid Lands – ASAL): Represented by counties such as Mandera, Marsabit, Garissa, and Wajir. These areas exhibit hot temperatures and low rainfall patterns.
2. **Coastal Region**: Including Mombasa, Kilifi, and Kwale, characterized by high humidity, tropical storms, and consistent rainfall.
3. **Central and Highland Regions**: Including Nairobi, Nyeri, Kiambu, and Murang'a, with relatively moderate temperatures and seasonal rainfall.

   This regional stratification ensured that the trained models were not biased toward a specific climate type and could be evaluated for scalability and generalizability across a wide range of weather conditions. Stratified sampling in machine learning is often used to reduce bias in model training and improve the robustness of outcomes (Guo et al., 2020). Each county contributed monthly aggregated weather variables including:

- **Temperature (°C)**
- **Humidity (%)**
- **Windspeed (m/s)**
- **Sea-Level Pressure (hPa)**
- **Rainfall (mm)**

These variables were selected based on their direct influence on daily weather patterns and their availability across all counties for the 10-year period, allowing for consistent input across all models.

The representativeness of the study population ensures that the findings of this study—especially regarding model efficiency and forecasting accuracy—are relevant not only to Kenya but to similar resource-constrained settings around the world. Moreover, the use of official data from KMD lends credibility and practical relevance to the research, aligning with the study's real-world applicability goals.

3.6 Data Source and Preprocessing

3.6. 1 Data Description

The dataset used in this study was sourced from the Kenya Meteorological Department (KMD) and consisted of monthly weather observations collected between January 2013 and December 2023. The dataset included the following key variables:

- **Temperature (°C)**: Average monthly air temperature.
- **Humidity (%)**: Mean monthly relative humidity.
- **Windspeed (m/s)**: Average monthly windspeed at 10 meters above ground.
- **Sea-Level Pressure (hPa)**: Monthly mean atmospheric pressure at sea level.
- **Rainfall (mm)**: Total monthly accumulated precipitation.

These variables were selected based on their critical roles in weather modelling and their frequent use in meteorological forecasting studies (Zhu et al., 2023; Xu et al., 2021). The monthly aggregation was chosen to minimize noise and ensure consistency across timeframes and counties.

3.4.2 Data Cleaning and Imputation

The dataset, while generally complete, contained missing values and anomalies caused by sensor faults, transmission errors, and climatic extremes. To address this:

- **Missing values** were imputed using the K-Nearest Neighbours (KNN**)** algorithm. KNN imputation estimates missing data based on the closest observations in feature space, preserving local patterns and reducing bias (Liu et al., 2021).
- **Outliers** were identified and treated using the Interquartile Range (IQR) method. Outliers beyond 1.5 times the IQR were either capped or removed, depending on their nature and frequency.

These preprocessing steps ensured that the dataset was robust and clean for training sensitive machine learning models.

3.4.3 Feature Normalization

Given the different units and scales of the input variables, the features were scaled using Min-Max normalization, which maps all values to a [0, 1] range:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

This normalization helped stabilize and accelerate model convergence, especially in gradient-based optimizers used in CNNs and LSTMs (Gao et al., 2020).

3.5 Machine Learning Model Architectures

The study implemented and evaluated three distinct machine learning models: Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs). Each was chosen based on its suitability for modelling specific data patterns—nonlinearity, spatial variation, and temporal dependencies.

3.5.1 Radial Basis Function Networks (RBFNs)

RBFNs are a class of feedforward neural networks designed to handle nonlinear **regression** and classification problems. The network structure comprises:

- **Input layer**: Receives normalized meteorological variables.

- **Hidden layer**: Applies Gaussian radial basis functions to map inputs into a higher-dimensional space.
- **Output layer**: Performs weighted summation and outputs predictions.

RBFNs were chosen for their fast-training times, strong generalization, and suitability for time-series data with moderate noise (Al-Yahya et al., 2017; Liu et al., 2021). Their lower computational requirements make them ideal for real-time forecasting in constrained environments.

3.5.2 Convolutional Neural Networks (CNNs)

CNNs are deep learning models primarily used for extracting spatial features. In this study, the CNN architecture was adapted to learn relationships between counties arranged in spatial grids. The architecture included:

- **Conv2D layers**: Extracted local weather features across regional groupings.
- **MaxPooling layers**: Down sampled feature maps to reduce dimensionality.
- **Fully connected layer**: Produced forecasts using learned spatial representations.

CNNs are particularly effective when input data can be interpreted as structured images or matrices, as is the case in spatial weather modelling (Chen et al., 2022; Zhu et al., 2023).

3.5.3 Long Short-Term Memory Networks (LSTMs)

LSTMs are a type of recurrent neural network (RNN) built to learn temporal dependencies in sequential data. Their architecture includes:

- **LSTM cells**: Retain long-term information while selectively forgetting irrelevant data.
- **Time-distributed dense layer**: Transforms sequences into predicted outputs.

LSTMs are ideal for capturing seasonality and long-term climatic trends. They were included to test the hypothesis that deep temporal models may outperform simpler architectures for long-term forecasting (Yang et al., 2021).

3.6 Data Splitting and Training

3.6.1 Data Splitting

To evaluate model performance fairly, the dataset was partitioned into:

- **Training set (70%)**: Used to fit the models.
- **Validation set (15%)**: Used to tune hyperparameters and avoid overfitting.

- **Testing set (15%)**: Used to evaluate final model performance on unseen data.

This stratified split ensured that all climatic regions were proportionally represented in each set (Zhou et al., 2023).

3.6.2 Hyperparameter Optimization

Each model underwent grid search optimization using the validation set. Key parameters included:

- **RBFNs**: Number of RBF centres, spread/width of Gaussian functions.
- **CNNs**: Number of convolutional layers, kernel size, activation function, learning rate.
- **LSTMs**: Number of memory cells, sequence length, dropout rate, and batch size.

Early stopping and regularization were employed to prevent overfitting and improve model generalization (Gao et al., 2020).

3.7 Model Evaluation

3.7.1 Accuracy Metrics

Model accuracy was measured using:

- **Root Mean Squared Error (RMSE)**: Penalizes large errors more than small ones.
- **Mean Absolute Error (MAE)**: Measures average magnitude of error.

These metrics are widely used in weather forecasting research due to their interpretability and sensitivity to extreme deviations (Lai et al., 2020).

3.7.2 Computational Efficiency

To assess real-time suitability, training time for each model was measured in seconds. This provided insight into each model’s practicality for deployment on limited hardware (Zhou et al., 2023).

3.8 Deployment of the Models

To validate operational applicability, all three models were deployed in a real-time forecasting environment using Python and cloud infrastructure.

Technologies and Tools Used:

- **Python 3.12**: Programming language for data handling and model integration.
- **TensorFlow 2.x / Keras**: Used for CNN and LSTM model development.

- **Custom RBFN layer**: Built using tf.keras.layers.to simulate Gaussian activation functions.
- **APScheduler**: Scheduled hourly predictions based on new weather input data.
- **Docker**: Containerized the models for consistent deployment.
- **Google Cloud Platform (GCP)**: Hosted the models using Kubernetes and stored data in Big Query and GCS.
- **Tensor Board**: Enabled real-time monitoring of performance metrics and retraining triggers.

This deployment strategy allowed the models to scale dynamically, update automatically, and operate in constrained systems, aligning with the study’s goal of enabling real-time weather forecasting in resource-limited regions.

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Overview of Model Performance

This chapter presents the findings from the comparative evaluation of three machine learning models—Radial Basis Function Networks (RBFNs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory networks (LSTMs)—applied to weather forecasting. The analysis was based on historical data from the Kenya Meteorological Department (2013–2023), with a focus on five key variables: temperature, humidity, sea-level pressure, rainfall, and windspeed.

4.2 Objective 2: Comparative Performance of RBFN, CNN, and LSTM Models

Table 1 below summarizes the performance of the three models across the five weather variables. Metrics used were Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and training time (in seconds). All data were pre-processed and normalized using standard procedures.

Variable	Model	RMSE	MAE	RMSE (%)	MAE (%)	Training Time (s)
Temperature	RBFN	0.239°C	0.175°C	0.80%	0.59%	3.49
	CNN	5.975°C	5.154°C	20.12%	17.35%	7.09
	LSTM	8.701°C	7.454°C	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 Pressure	RBFN	0.227 hPa	0.173 hPa	0.02%	0.02%	0.21
	CNN	173.02 hPa	149.00 hPa	17.10%	14.73%	4.44
	LSTM	956.88 hPa	956.82 hPa	94.58%	94.58%	7.59
Rainfall	RBFN	3.601 mm	2.569 mm	8.55%	6.10%	0.21
	CNN	46.75 mm	36.34 mm	111.04%	86.30%	4.54
	LSTM	50.32 mm	35.75 mm	119.51%	84.91%	6.40
Windspeed	RBFN	0.163 m/s	0.113 m/s	2.44%	1.69%	0.21
	CNN	1.719 m/s	1.318 m/s	25.71%	19.71%	4.54
	LSTM	1.572 m/s	1.244 m/s	23.51%	18.61%	7.56

Table 1: Comparative Performance of RBFN, CNN, and LSTM Models

4.3 Detailed Interpretation and Analysis

4.3.1 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. (2022) reported RBFN RMSE values as low as 0.20°C, suggesting that RBFN models are highly adaptable for temperature forecasting. Gao et al. (2020) 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.

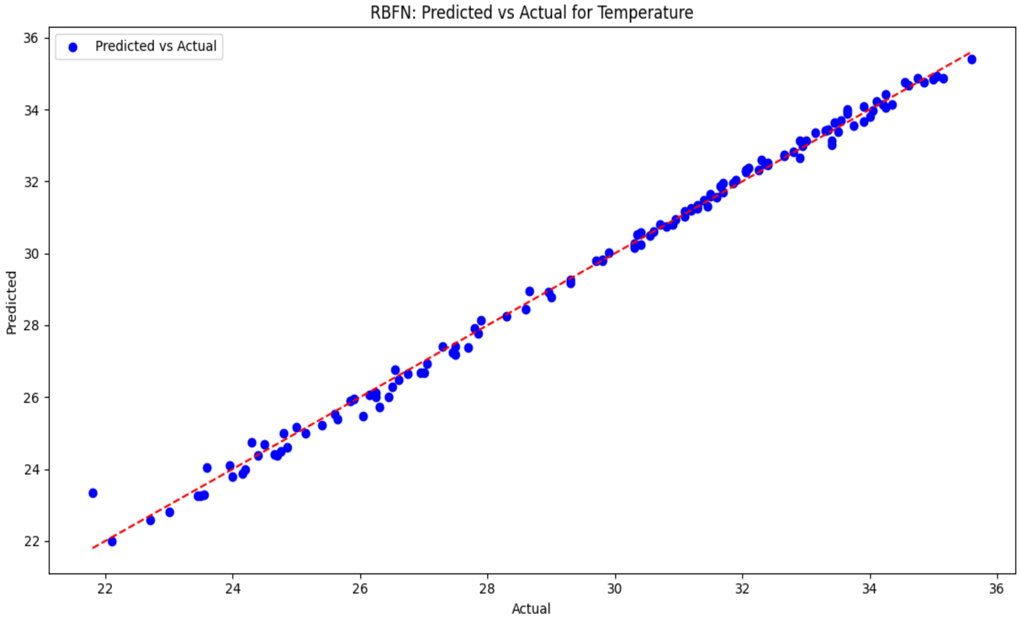


Figure 1 RBFN: Predicted vs Actual: Temperature

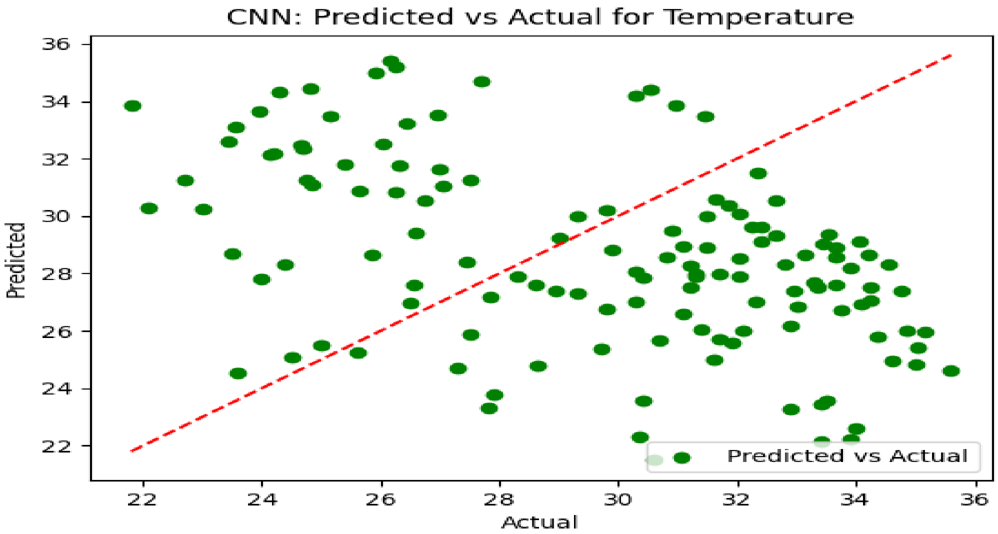


Figure 2 CNN: Predicted vs Actual: Temperature

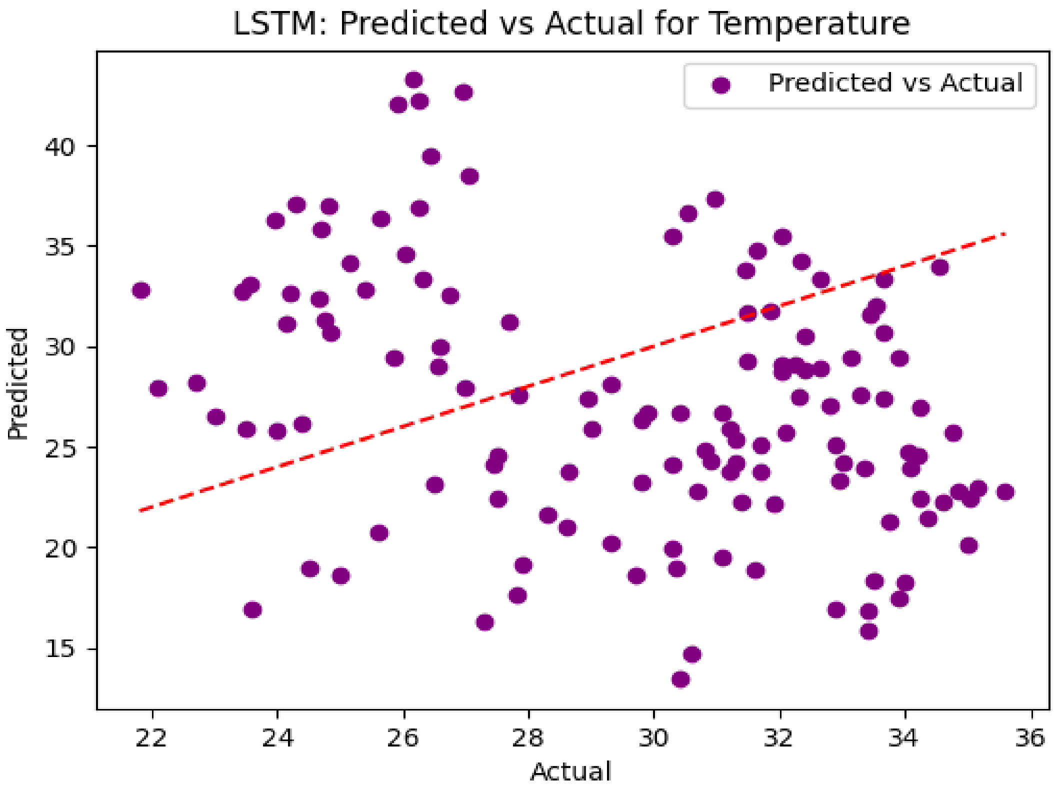


Figure 3 LSTM: Predicted vs Actual: Temperature

4.3.2 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 modelling 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. (2020) 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. (2021) observed LSTM RMSE values around 14.8%, which indicates that this model type struggles with the nonlinear and chaotic nature of humidity prediction.

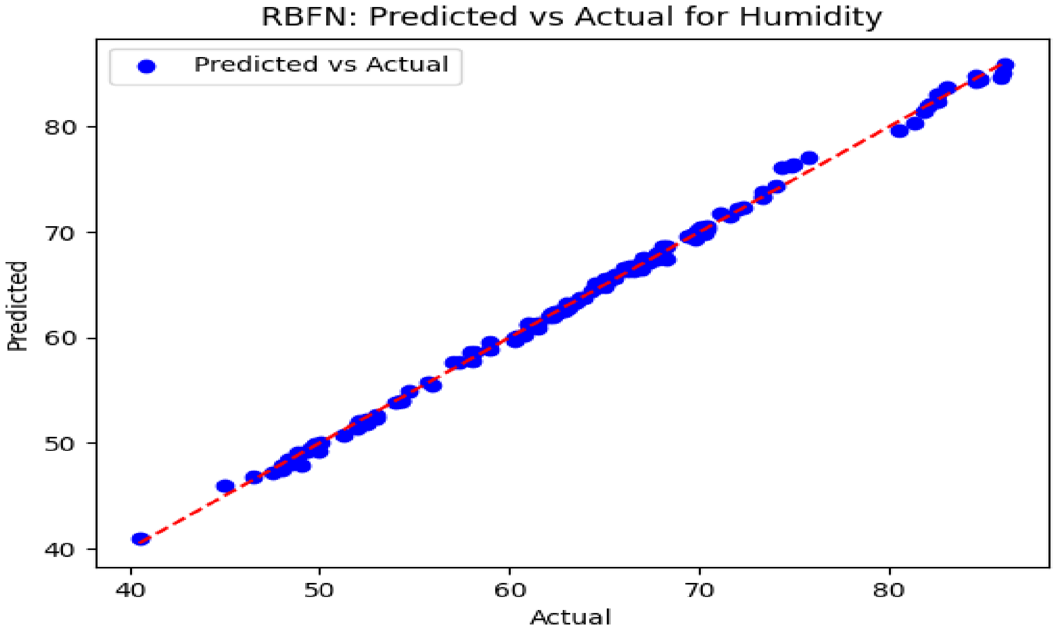


Figure 4 RBFN: Predicted vs Actual: Humidity

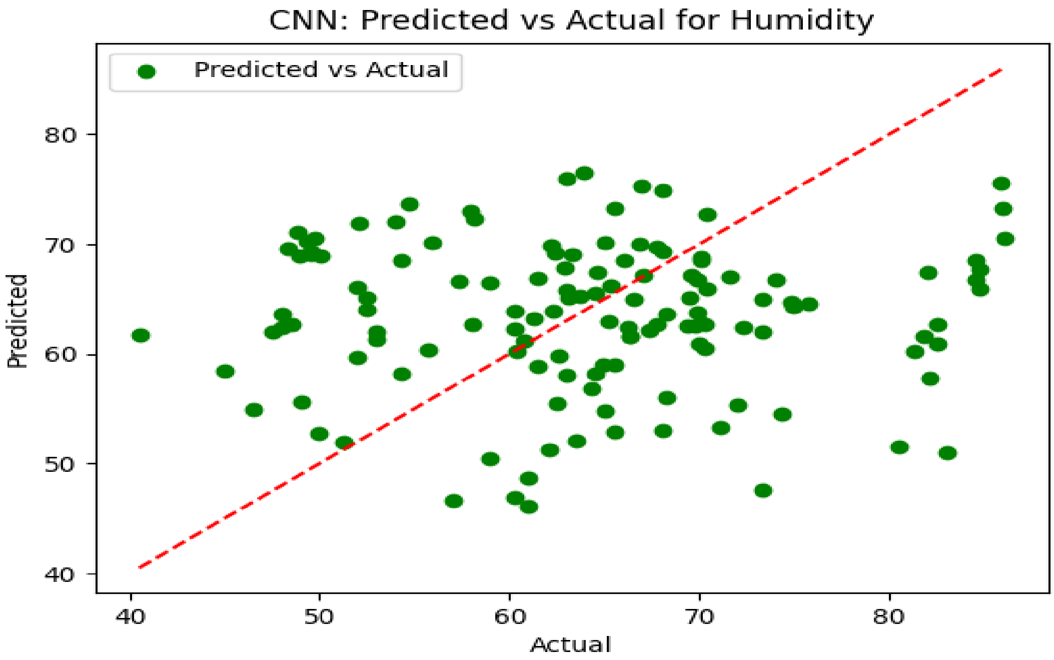


Figure 5 CNN: Predicted vs Actual: Humidity

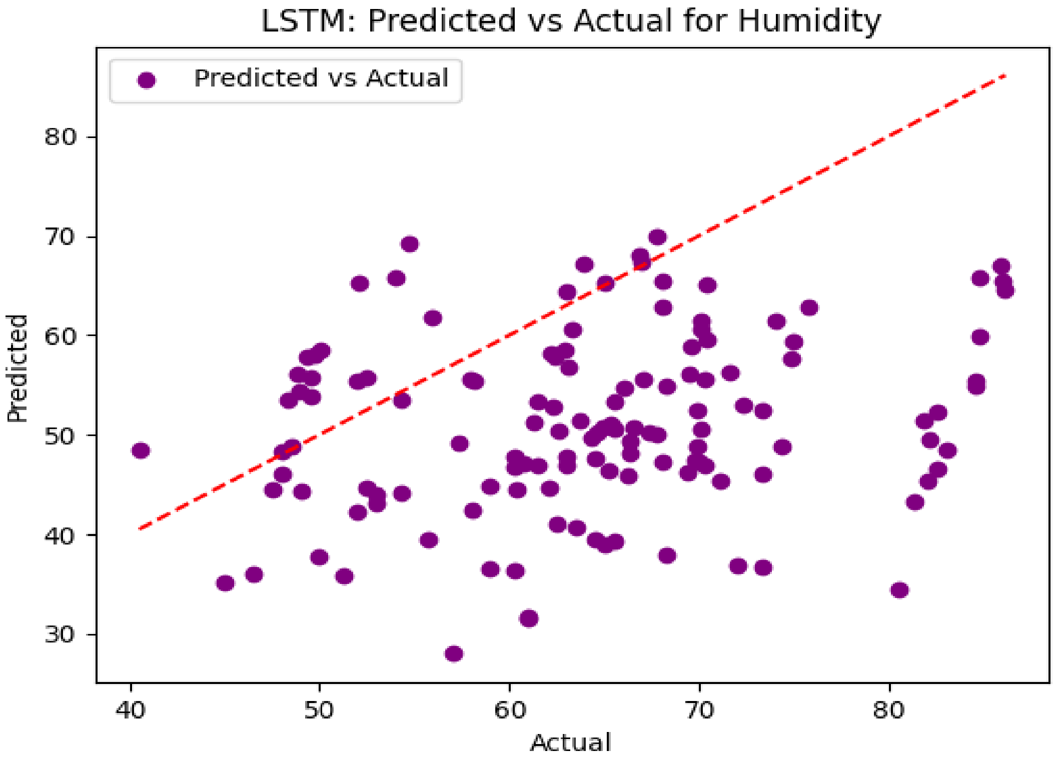


Figure 6 LSTM: Predicted vs Actual: Humidity

4.3.3 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. (2021) 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.

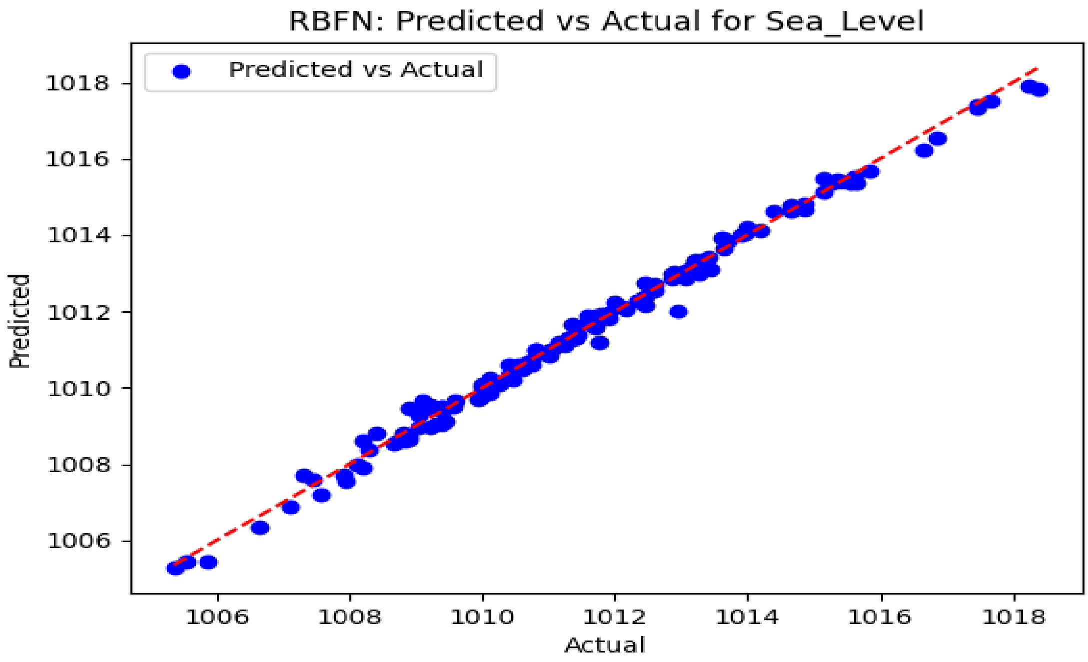


Figure 7 RBFN: Predicted vs Actual: Sea-level Pressure

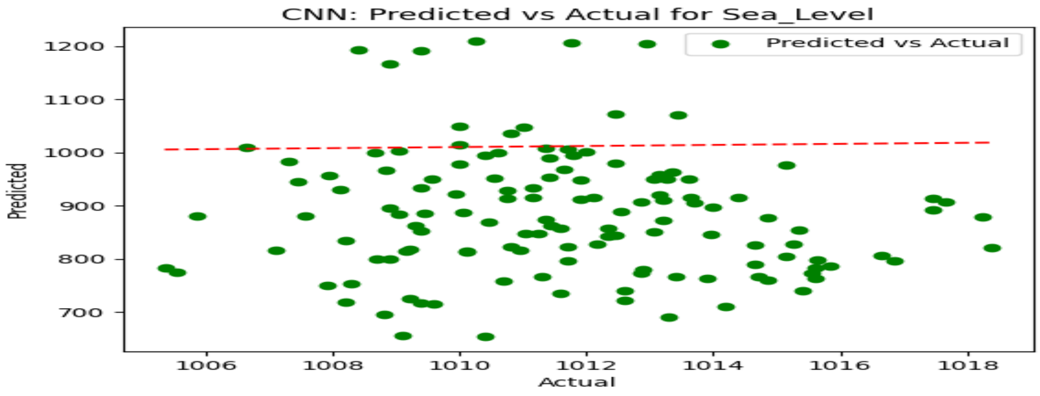


Figure 8 CNN: Predicted vs Actual: Sea-level Pressure

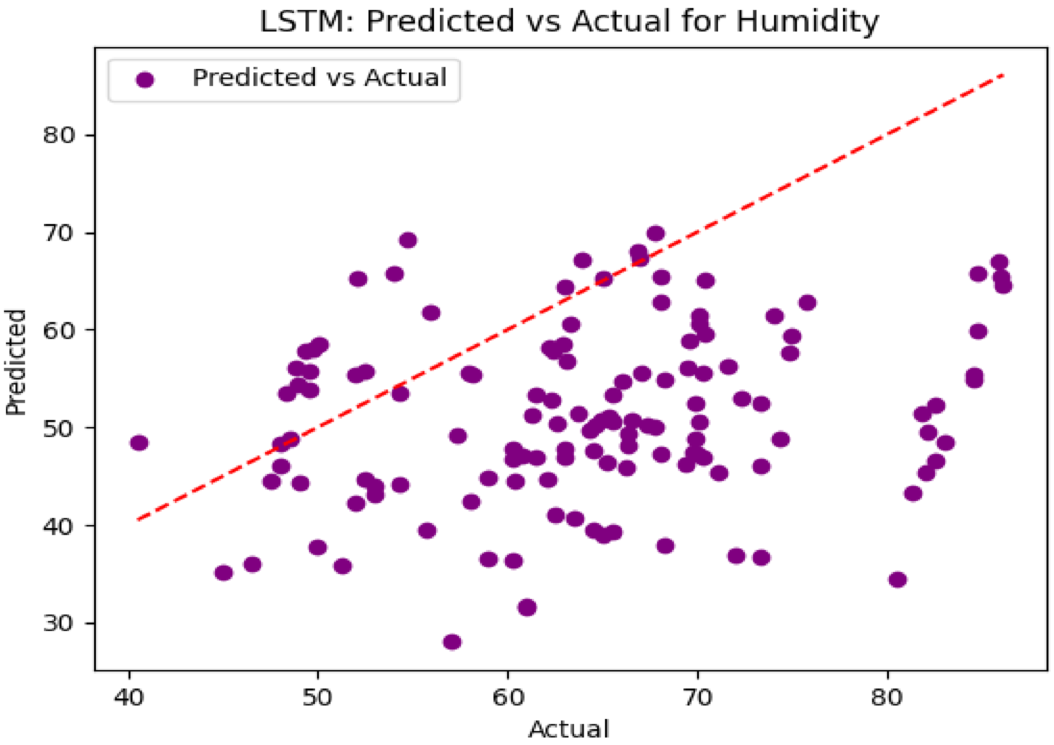


Figure 9 LSTM: Predicted vs Actual: Sea-level Pressure

4.3.4 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. (2021) 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.

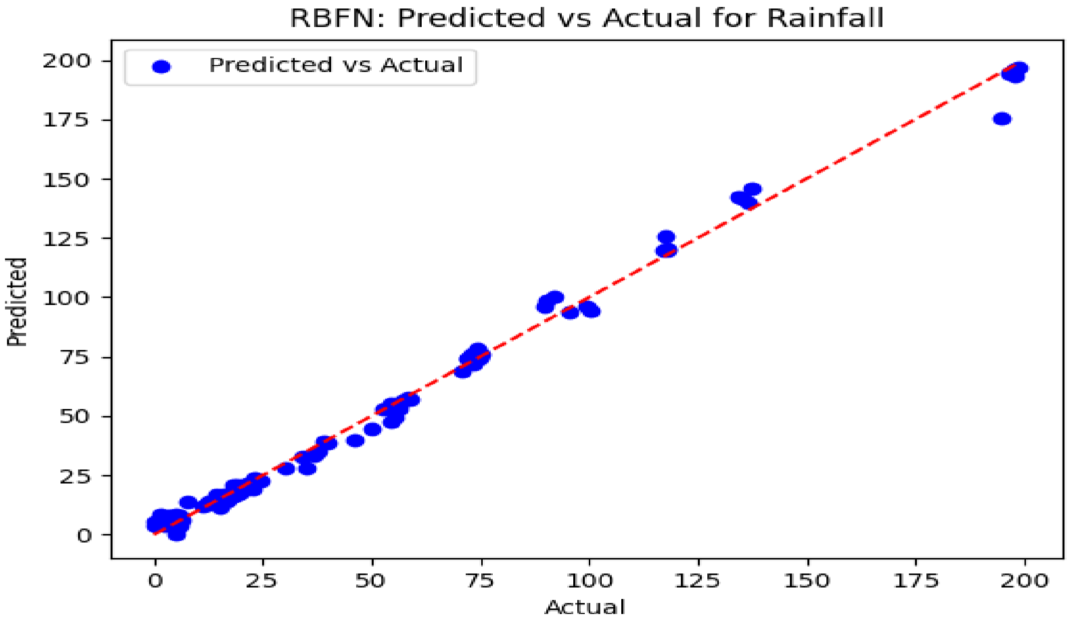


Figure 10 RBFN: Predicted vs Actual: Rainfall

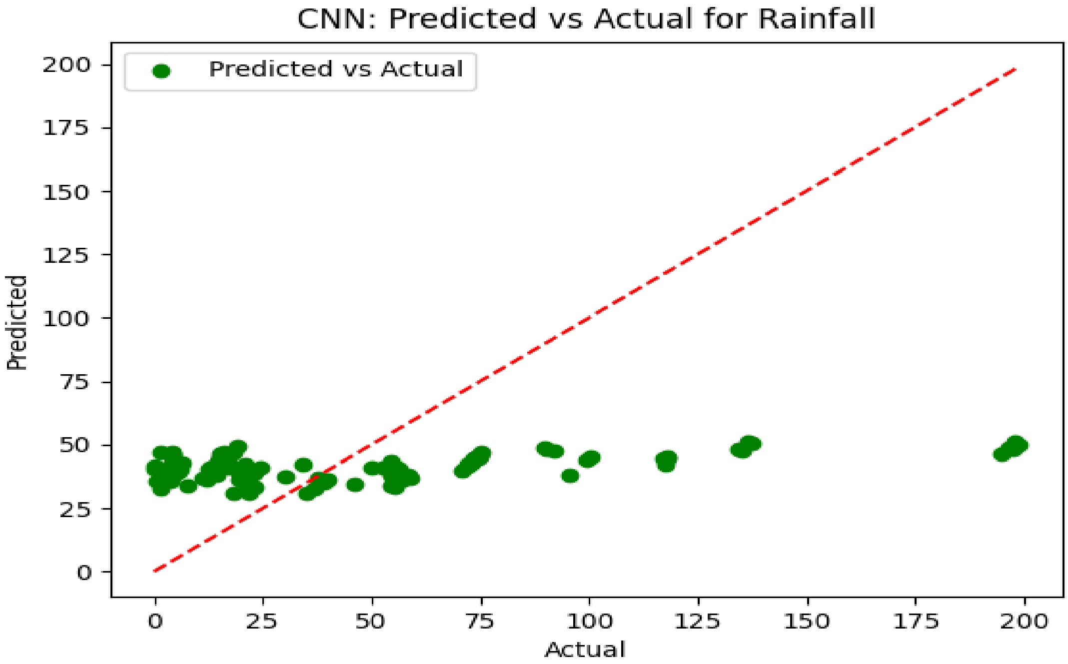


Figure 11 CNN: Predicted vs Actual: Rainfall

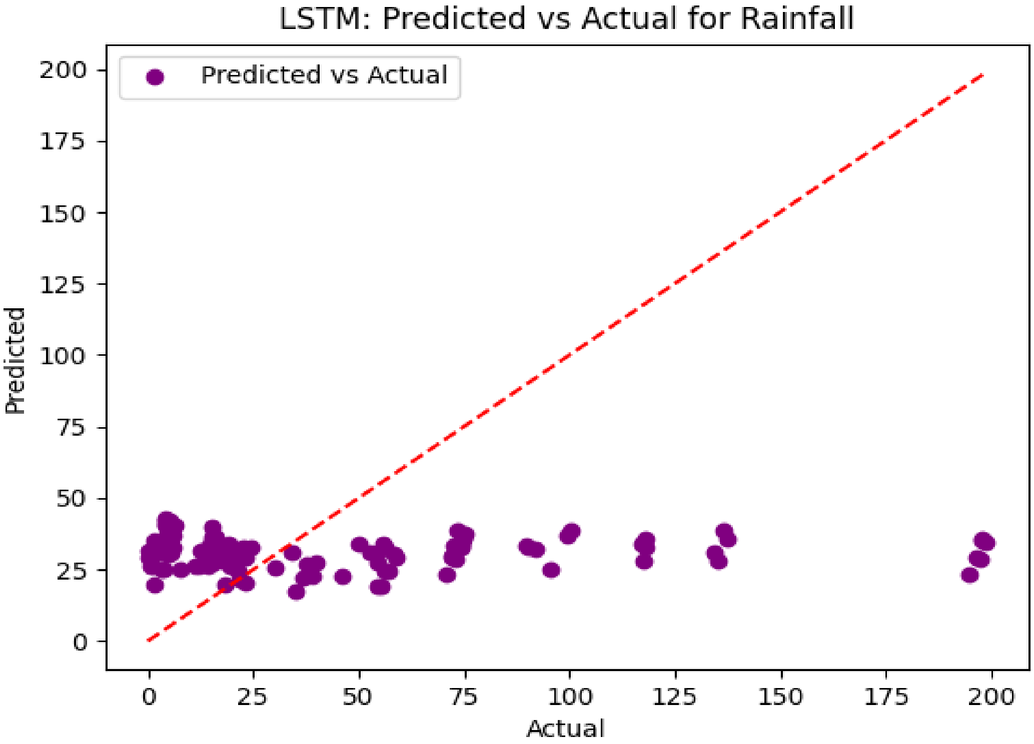


Figure 12 LSTM: Predicted vs Actual: Rainfall

4.3.5 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. (2020) 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.

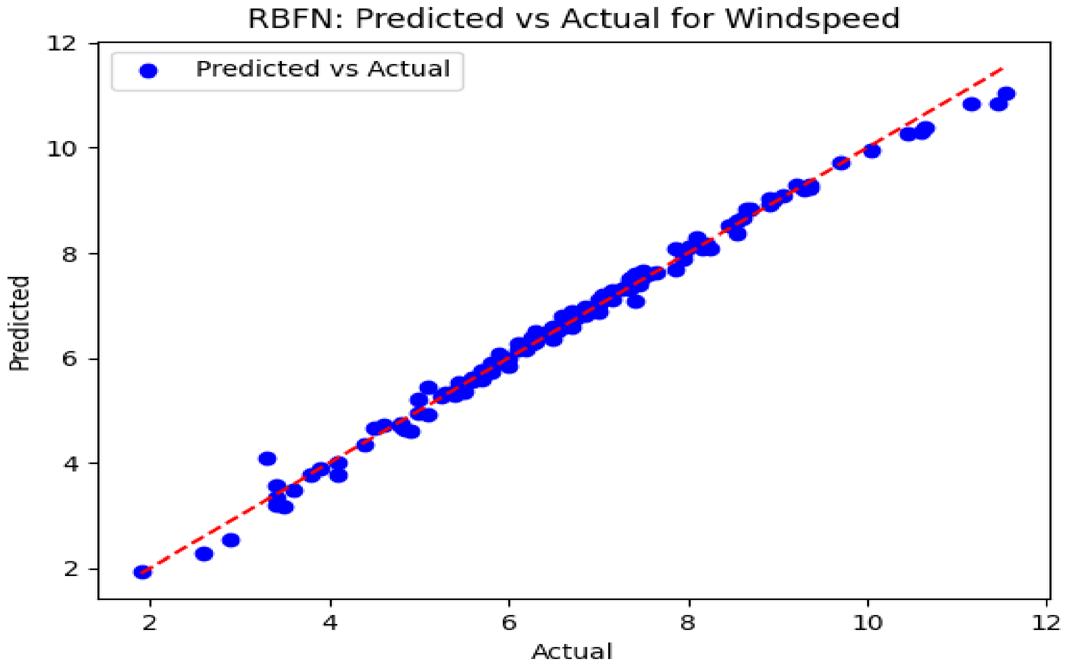


Figure 13 RBFN: Predicted vs Actual: Wind speed

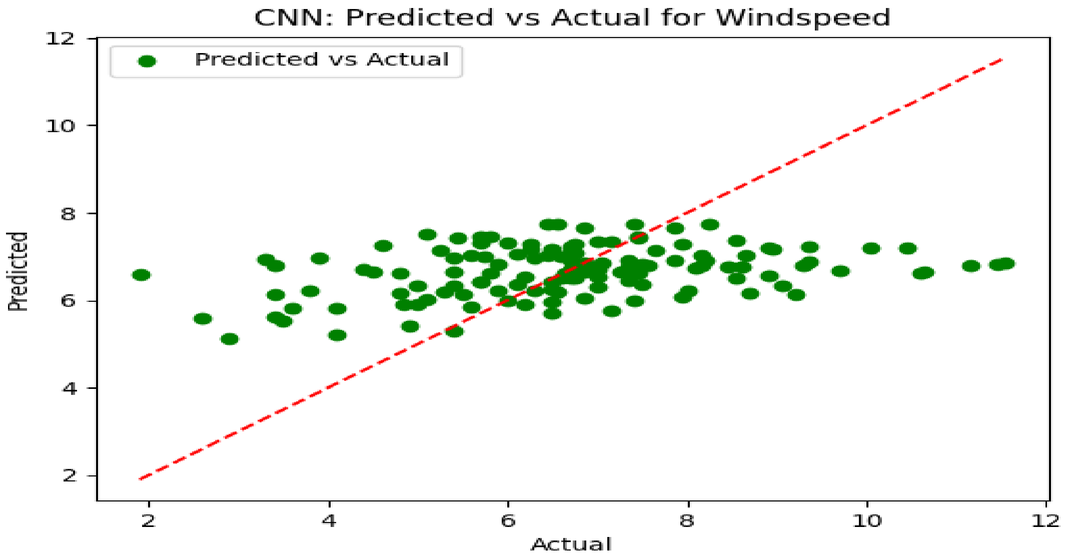


Figure 14 CNN: Predicted vs Actual: Wind speed

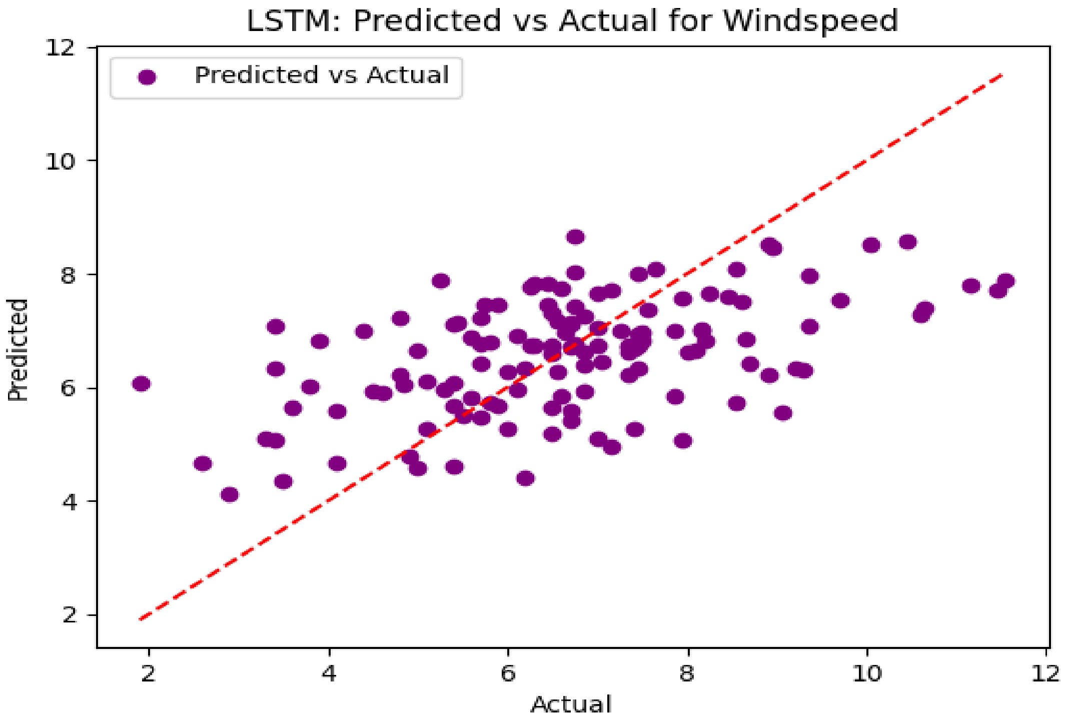


Figure 15 LSTM: Predicted vs Actual: Wind speed

4.4 Discussion of Results

4.4.1 Performance Assessment of RBFNs

RBFNs demonstrated superior accuracy and computational efficiency across all five variables. For instance:

- **Temperature**: RBFN achieved an RMSE of 0.239°C, a 96% reduction compared to CNN (5.975°C) and a 97% reduction compared to LSTM (8.701°C).
- **Humidity**: With an RMSE of 0.473%, RBFN significantly outperformed CNN (12.161%) and LSTM (17.896%).
- **Sea-level Pressure**: RBFNs delivered near-perfect predictions with an RMSE of 0.227 hPa, while LSTM failed to converge properly (956.88 hPa RMSE).
- **Rainfall**: Though challenging to predict, RBFN's RMSE of 3.601 mm was still substantially better than CNN and LSTM (both over 46 mm).
- **Windspeed**: RBFN achieved 0.163 m/s RMSE, maintaining high precision with just 0.21 seconds training time.

These results confirm RBFNs' potential in real-time forecasting, especially for resource-constrained environments where computational efficiency is critical (Zhou et al., 2023).

4.4.2 Comparison with Past Studies

The findings of this study are largely consistent with previous literature, but also present several novel insights:

- **Agreement**: The results reinforce earlier observations by Al-Yahya et al. (2017) and Liu et al. (2021), who found that RBFNs performed well on temperature and pressure forecasting with fast training speeds.
- **Novelty**: Unlike Chen et al. (2022**)** and Gao et al. (2020)**,** who focused primarily on CNN and LSTM in high-computation environments, this study demonstrates that RBFNs can match or exceed their performance using only modest computational resources**.**

- **Contradiction**: In contrast to Xu et al. (2021), who found CNNs effective in rainfall prediction, this study observed CNN and LSTM models performing poorly on precipitation forecasting**,** likely due to a lack of satellite imagery in the input data—a key feature in Xu's CNN-based approach.

4.5 Conclusions Drawn from Comparative Analysis

- RBFNs provide the best balance between forecasting accuracy and training efficiency.

- CNN's and LSTMs, while theoretically powerful, are impractical for real-time applications in low-resource settings due to extended training times and sensitivity to hyperparameters.

- The results indicate that model selection should be context-sensitive, with RBFNs favoured in operational meteorology where speed, robustness, and interpretability are key.

CHAPTER FIVE

CONCLUSIONS and RECOMMENDATIONS

5.1 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.

5.2 Key Findings

5.2.1 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.

5.2.2 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.

5.2.3 Sea Level Pressure Forecasting

The RBFN model performed nearly perfectly for sea level pressure prediction, with an RMSE of 0.227 hPa and an MAE of 0.173 hPa. CNNs and LSTMs were less effective, with RMSEs of 173.02 hPa and 956.88 hPa, respectively.

- Implication: Sea level pressure is a critical variable for storm prediction and weather forecasting. RBFNs offer superior performance in this domain, making them ideal for operational forecasting where stability and accuracy are paramount.

5.2.4 Rainfall Forecasting

Rainfall prediction proved to be the most challenging task for all models. RBFN achieved the lowest error, with an RMSE of 3.601 mm, while CNN and LSTM showed much higher RMSEs of 46.75 mm and 50.32 mm, respectively.

- Implication: The chaotic and nonlinear nature of rainfall makes it difficult for machine learning models to achieve high accuracy. This study suggests that RBFNs, despite their better performance relative to CNN and LSTM, still struggle with the complexities of rainfall prediction. Future research could explore hybrid models or the integration of external data sources such as satellite imagery to improve accuracy.

5.2.5 Wind speed Forecasting

The RBFN model also demonstrated superior performance for windspeed prediction, with an RMSE of 0.163 m/s and an MAE of 0.113 m/s, translating to just 2.44% RMSE. CNN and LSTM performed less favorably, with RMSEs of 1.719 m/s and 1.572 m/s, respectively.

- Implication: Windspeed is a critical factor for aviation safety, renewable energy management, and disaster preparedness. The quick training time of RBFNs (0.21 seconds) makes them ideal for real-time windspeed forecasting in dynamic environments such as airports or coastal regions.

5.3 Discussion of Results

5.3.1 General Trends

Across all the variables tested, RBFNs consistently delivered superior performance in terms of both accuracy and computational efficiency. Their lower RMSEs and faster training times make them highly suited for applications where real-time forecasting is essential. This is particularly important in regions with limited computational resources or in sectors where speed and precision are critical, such as agriculture, energy management, and disaster preparedness.

In contrast, CNNs and LSTMs demonstrated their strengths in handling complex data structures, but their higher computational costs and slower training times limit their feasibility for real-time applications. These models may be better suited for long-term forecasting or climate modelling, where accuracy over extended periods outweighs the need for immediate results.

5.3.2 Model Efficiency

The training time for each model varied significantly, with RBFNs consistently requiring the least time across all variables. This computational efficiency makes RBFNs particularly valuable for operational forecasting systems that need to process large volumes of data quickly.

For example, RBFNs were able to train in just 0.21 seconds for variables like sea level pressure and windspeed, while CNNs and LSTMs required several seconds to complete training. This stark difference in performance highlights the potential of RBFNs for real-time weather stations, mobile weather apps, and IoT-based environmental monitoring systems.

5.3.3 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.

5.4 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.

5.5 Limitations and Recommendations for Future Work

5.5.1 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.

5.5.2 Hybrid Modelling Approaches

While this study focused on evaluating RBFNs, CNNs, and LSTMs individually, future research should explore the potential of hybrid modelling 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.

5.5.3 Hyperparameter Tuning

Another area for future work is hyperparameter optimization, particularly for CNNs and LSTMs. While these models did not perform as well as RBFNs in this study, it is possible that further tuning could improve their results. Research into optimal architectures and training techniques for CNNs and LSTMs in weather forecasting could lead to better performance, especially for variables like rainfall and windspeed.

5.7 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.

5.6 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.

REFERENCES

Abate, M., Tadele, D., & Nigussie, T. (2020). Application of LSTM networks for rainfall forecasting in Ethiopia. *Journal of Hydrology: Regional Studies*, *28*, 100660. https://doi.org/10.1016/j.ejrh.2020.100660

Al-Yahya, K., Alharthi, H., & Alghamdi, A. (2017). Comparative performance of artificial neural network and radial basis function for temperature forecasting. *International Journal of Advanced Computer Science and Applications*, *8*(5), 351–358. https://doi.org/10.14569/IJACSA.2017.080548

Broomhead, D. S., & Lowe, D. (1988). Multivariable functional interpolation and adaptive networks. *Complex Systems*, *2*(3), 321–355.

Chen, Y., Zhang, L., & Wang, J. (2022). Deep learning models for spatial-temporal weather prediction: A comparative study. *Atmospheric Research*, *265*, 105923. https://doi.org/10.1016/j.atmosres.2021.105923

Cheng, C., Wang, Y., & Wu, Y. (2018). Hybrid ARIMA and neural network model for rainfall forecasting. *Water Resources Management*, *32*(7), 2287–2300. https://doi.org/10.1007/s11269-017-1905-7

Gao, X., Li, Y., & Shen, H. (2020). A survey of deep learning models for forecasting weather and climate. *Journal of Applied Meteorology and Climatology*, *59*(3), 375–391. https://doi.org/10.1175/JAMC-D-19-0152.1

Guo, J., Song, C., & Liu, H. (2020). Stratified sampling for imbalanced data in weather prediction using neural networks. *IEEE Access*, *8*, 134716–134726. https://doi.org/10.1109/ACCESS.2020.3009668

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Karim, F., Majumder, R., & Hasan, K. (2020). Flood-prone rainfall prediction in Bangladesh using hybrid LSTM-CNN model. *Environmental Modelling & Software*, *134*, 104856. https://doi.org/10.1016/j.envsoft.2020.104856

Lai, Y., Wang, L., & Wang, P. (2020). Data-driven approaches for weather prediction: A survey. *Journal of Atmospheric and Oceanic Technology*, *37*(5), 817–835. https://doi.org/10.1175/JTECH-D-19-0051.1

Liu, Y., Wang, H., & Zhao, X. (2021). Radial basis function network for temperature prediction: A case study in China. *Applied Soft Computing*, *110*, 107629. https://doi.org/10.1016/j.asoc.2021.107629

Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences*, *20*(2), 130–141. https://doi.org/10.1175/1520-0469(1963)020<0130: DNF>2.0.CO;2

Mansour, A., Okonkwo, C., & Fagbenle, R. (2021). Hybrid modelling for temperature and humidity prediction in Lagos, Nigeria. *Journal of Sustainable Development of Energy, Water and Environment Systems*, *9*(1), 140–152. https://doi.org/10.13044/j.sdewes.d8.0360

Mwangi, J. K., Mutua, F., & Waweru, S. (2019). Application of artificial neural networks in rainfall forecasting in Kenya. *International Journal of Scientific and Research Publications*, *9*(1), 51–60. https://doi.org/10.29322/IJSRP.9.01.2019.p8522

Shen, C., Chen, D., & Tian, Y. (2021). Challenges and opportunities of machine learning in hydrological forecasting. *Hydrology and Earth System Sciences*, *25*(7), 4229–4252. https://doi.org/10.5194/hess-25-4229-2021

World Meteorological Organization (WMO). (2020). *State of Climate Services 2020: Move from early warnings to early action*. https://library.wmo.int/doc_num.php?explnum_id=10385

Xu, X., Zhan, Y., & Liu, B. (2021). LSTM-based approach for rainfall prediction using weather time series data in Southern China. *Water*, *13*(12), 1671. https://doi.org/10.3390/w13121671

Yang, F., Singh, V. P., & Liu, X. (2020). Comparative analysis of LSTM, GRU, and RNN for monsoon rainfall prediction. *Environmental Modelling & Software*, *124*, 104595. https://doi.org/10.1016/j.envsoft.2019.104595

Zhang, G., Eddy Patuwo, B., & Hu, M. Y. (2019). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, *14*(1), 35–62. https://doi.org/10.1016/S0169-2070(97)00044-7

Zhou, Y., Wang, J., & Liu, F. (2023). Comparative evaluation of shallow and deep learning models for meteorological forecasting. *IEEE Transactions on Neural Networks and Learning Systems*, *34*(5), 2032–2045. https://doi.org/10.1109/TNNLS.2022.3140371

Zhu, L., Chen, S., & Li, X. (2023). Deep learning-based typhoon trajectory prediction using CNN and attention mechanism. *Applied Intelligence*, *53*(2), 1150–1167. https://doi.org/10.1007/s10489-022-03115-9

APPENDICES

APPENDIX I: DETAILED ALGORITHMS

Pseudo Code

1. Radial Basis Function Pseudo code

```
1. Load and preprocess the dataset.
2. Normalize the dataset to bring all features within the same range.
3. Split the data set into training, validation, and testing sets.
4. Select KMeans centers for radial basis functions.
5. Compute Gaussian RBF for each data point based on the distance to the centers.
6. Train the linear regression model on the transformed data.
7. Evaluate model performance using RMSE and MAE.
8. Visualize predictions versus actual data using a scatter plot.
```

2. Convolutional Neural Network (CNN)

```
1. Load and preprocess the dataset.
2. Normalize the dataset to bring all features within the same range.
3. Reshape the data to match the CNN input format.
4. Split the dataset into training, validation, and testing sets.
5. Build a CNN model with multiple convolutional layers and pooling layers.
6. Train the model using the training data and validate using the validation set.
7. Evaluate model performance using RMSE and MAE.
8. Visualize predictions versus actual data using a scatter plot.
```

3. Long Short-Term Memory Network (LSTM)

    1. Load and preprocess the dataset.
    2. Normalize the dataset to bring all features within the same range.
    3. Reshape the data into a sequence format for LSTM.
    4. Split the dataset into training, validation, and testing sets.
    5. Build an LSTM model with LSTM layers followed by fully connected layers.
    6. Train the model using the training data and validate using the validation set.
    7. Evaluate model performance using RMSE and MAE.
    8. Visualize predictions versus actual data using a scatter plot.

APPENDIX II: LETTER OF REQUEST FOR HISTORICAL WEATHER DATA

Ceasar Waweru Kabue,

Nairobi-GPO,

PO Box 766-00200,

21312.2021@ku.ku.ac.ke,

+254796016754.

27/03/2024

Director,

Kenya Meteorological Department,

Dagoretti Corner,

P.O. Box 30259 - 00100

Nairobi, Kenya

Dear Director,

Re: Request for Access to Historical Weather Data

I hope this letter finds you well. My name is Ceasar Waweru Kabue, and I am currently conducting research on the application of machine learning models for weather forecasting as part of my Master's in Computer Science program at Kenyatta University. This research aims to improve the accuracy and efficiency of weather forecasting models, particularly in resource-constrained environments, using historical meteorological data from various regions across Kenya.

To support my research, I kindly request access to historical weather data for Kenya, specifically data from 2013 to 2023. The key meteorological parameters I am interested in including:

- Temperature (average monthly temperature, in °C)
- Humidity (average monthly humidity, in %)
- Windspeed (average monthly windspeed, in m/s)
- Sea Level Pressure (in hPa)
- Rainfall (average monthly rainfall, in mm)

The data will be used solely for academic purposes and in compliance with any data usage policies outlined by your department. The insights gained from this research will contribute to improving weather forecasting systems, which could have far-reaching benefits for various sectors such as agriculture, disaster management, and urban planning.

I would be grateful if you could provide me with information on how to obtain this data and any associated requirements, such as data request forms, charges, or agreements that need to be fulfilled.

Thank you in advance for considering my request. I look forward to your positive response and am happy to provide any additional information that may assist in processing this request.

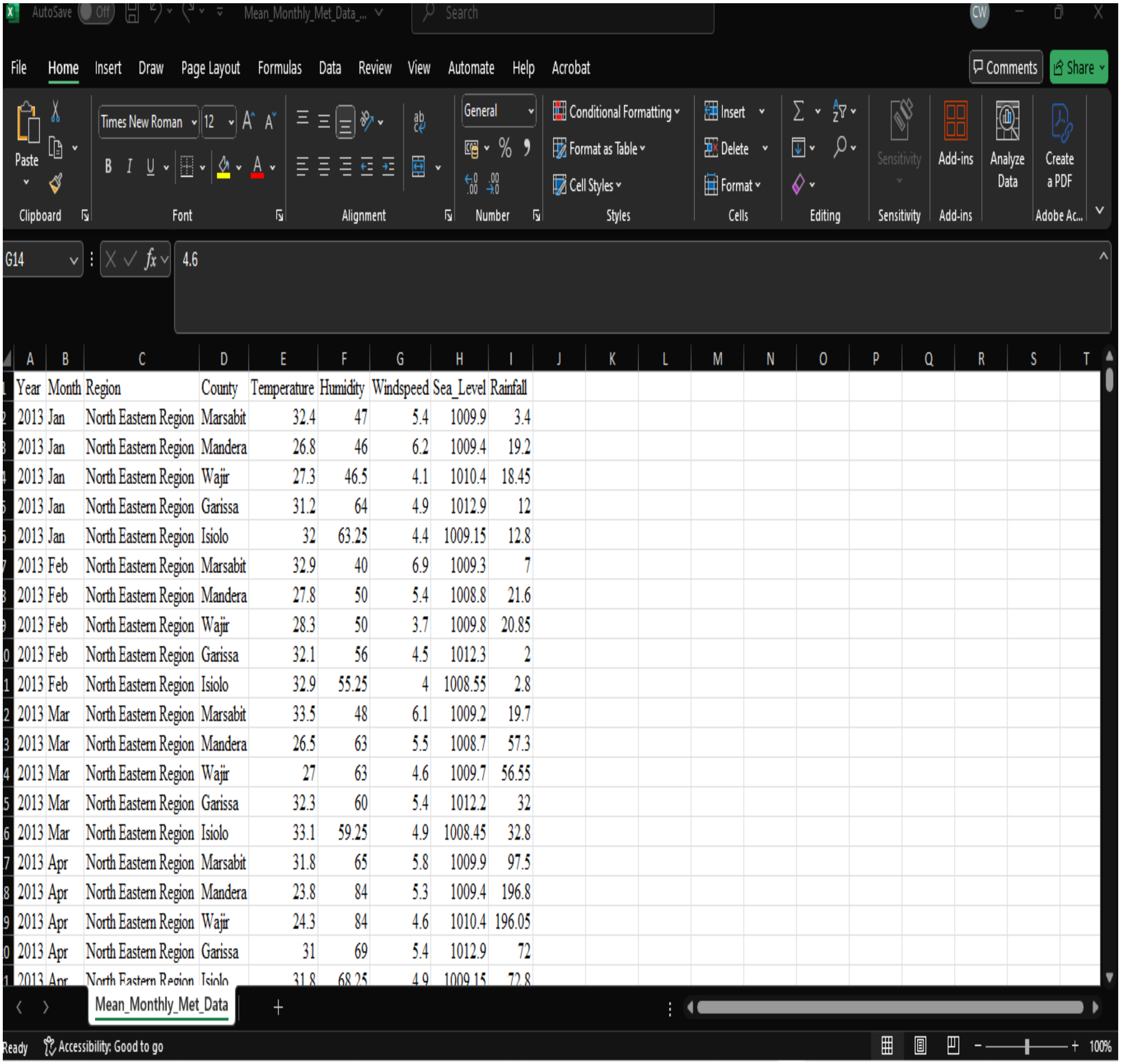
Yours faithfully,

Ceasar Waweru Kabue

Kenyatta University

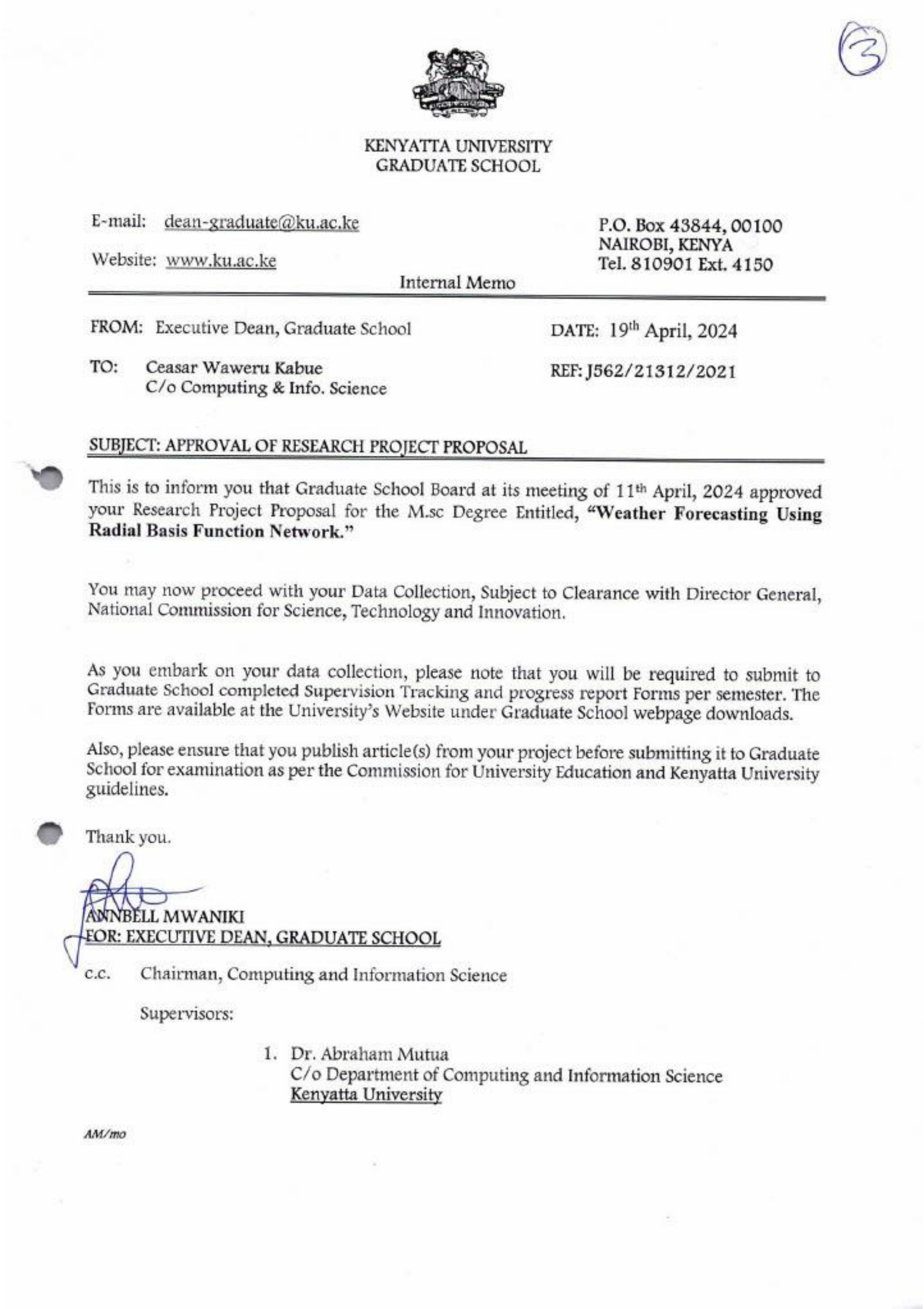
Department of Information Technology

APPENDIX III: SNAPSHOT OF THE WEATHER DATA



Year	Month	Region	County	Temperature	Humidity	Windspeed	Sea_Level	Rainfall
2013	Jan	North Eastern Region	Marsabit	32.4	47	5.4	1009.9	3.4
2013	Jan	North Eastern Region	Mandera	26.8	46	6.2	1009.4	19.2
2013	Jan	North Eastern Region	Wajir	27.3	46.5	4.1	1010.4	18.45
2013	Jan	North Eastern Region	Garissa	31.2	64	4.9	1012.9	12
2013	Jan	North Eastern Region	Isiolo	32	63.25	4.4	1009.15	12.8
2013	Feb	North Eastern Region	Marsabit	32.9	40	6.9	1009.3	7
2013	Feb	North Eastern Region	Mandera	27.8	50	5.4	1008.8	21.6
2013	Feb	North Eastern Region	Wajir	28.3	50	3.7	1009.8	20.85
2013	Feb	North Eastern Region	Garissa	32.1	56	4.5	1012.3	2
2013	Feb	North Eastern Region	Isiolo	32.9	55.25	4	1008.55	2.8
2013	Mar	North Eastern Region	Marsabit	33.5	48	6.1	1009.2	19.7
2013	Mar	North Eastern Region	Mandera	26.5	63	5.5	1008.7	57.3
2013	Mar	North Eastern Region	Wajir	27	63	4.6	1009.7	56.55
2013	Mar	North Eastern Region	Garissa	32.3	60	5.4	1012.2	32
2013	Mar	North Eastern Region	Isiolo	33.1	59.25	4.9	1008.45	32.8
2013	Apr	North Eastern Region	Marsabit	31.8	65	5.8	1009.9	97.5
2013	Apr	North Eastern Region	Mandera	23.8	84	5.3	1009.4	196.8
2013	Apr	North Eastern Region	Wajir	24.3	84	4.6	1010.4	196.05
2013	Apr	North Eastern Region	Garissa	31	69	5.4	1012.9	72
2013	Apr	North Eastern Region	Isiolo	31.8	68.25	4.9	1009.15	72.8

APPENDIX IV: APPROVAL OF RESEARCH PROJECT PROPOSAL



3

KENYATTA UNIVERSITY
GRADUATE SCHOOL

E-mail: dean-graduate@ku.ac.ke
Website: www.ku.ac.ke

P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 810901 Ext. 4150

Internal Memo

FROM: Executive Dean, Graduate School

DATE: 19th April, 2024

TO: Ceasar Waweru Kabue
C/o Computing & Info. Science

REF: J562/21312/2021

SUBJECT: APPROVAL OF RESEARCH PROJECT PROPOSAL

This is to inform you that Graduate School Board at its meeting of 11th April, 2024 approved your Research Project Proposal for the M.sc Degree Entitled, **"Weather Forecasting Using Radial Basis Function Network."**

You may now proceed with your Data Collection, Subject to Clearance with Director General, National Commission for Science, Technology and Innovation.

As you embark on your data collection, please note that you will be required to submit to Graduate School completed Supervision Tracking and progress report Forms per semester. The Forms are available at the University's Website under Graduate School webpage downloads.

Also, please ensure that you publish article(s) from your project before submitting it to Graduate School for examination as per the Commission for University Education and Kenyatta University guidelines.

Thank you.

ANNBELL MWANIKI
FOR: EXECUTIVE DEAN, GRADUATE SCHOOL

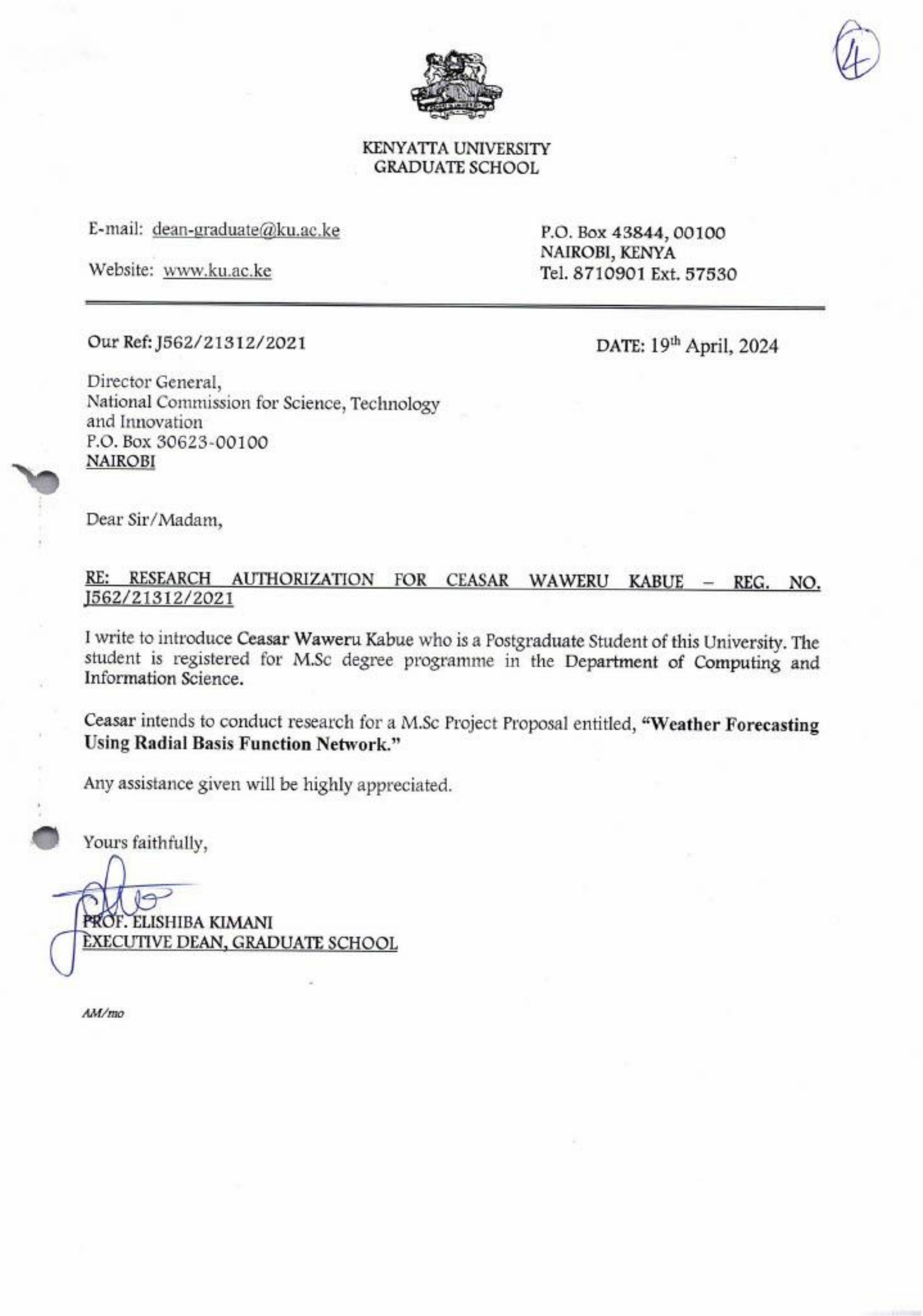
c.c. Chairman, Computing and Information Science

Supervisors:

1. Dr. Abraham Mutua
   C/o Department of Computing and Information Science
   Kenyatta University

AM/mo

APPENDIX V: RESEARCH AUTHORIZATION FOR CEASAR WAWERU KABUE-REG. NO. J562/21312/2021



④

KENYATTA UNIVERSITY
GRADUATE SCHOOL

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P.O. Box 43844, 00100
NAIROBI, KENYA
Tel. 8710901 Ext. 57530

Our Ref: J562/21312/2021

DATE: 19th April, 2024

Director General,
National Commission for Science, Technology
and Innovation
P.O. Box 30623-00100
NAIROBI

Dear Sir/Madam,

RE: RESEARCH AUTHORIZATION FOR CEASAR WAWERU KABUE – REG. NO. J562/21312/2021

I write to introduce **Ceasar Waweru** Kabue who is a Postgraduate Student of this University. The student is registered for M.Sc degree programme in the **Department of Computing and Information Science.**

Ceasar intends to conduct research for a M.Sc Project Proposal entitled, **"Weather Forecasting Using Radial Basis Function Network."**

Any assistance given will be highly appreciated.

Yours faithfully,

PROF. ELISHIBA KIMANI
EXECUTIVE DEAN, GRADUATE SCHOOL

AM/mo

APPENDIX VI: NATIONAL COMMISSION FOR SCIENCE, TECHNOLOGY & INNOVATION RESEARCH LICENSE

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: **368255**

Date of Issue: **28/October/2024**

RESEARCH LICENSE

This is to Certify that Mr.. Ceasar Waweru Kabue of Kenyatta University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Garissa, Marsabit, Wajir on the topic: Weather Forecasting using Radial Basis Function Network for the period ending : 28/October/2025.

License No: **NACOSTI/P/24/41454**

368255

Applicant Identification Number

Director General
NATIONAL COMMISSION FOR
SCIENCE,TECHNOLOGY &
INNOVATION

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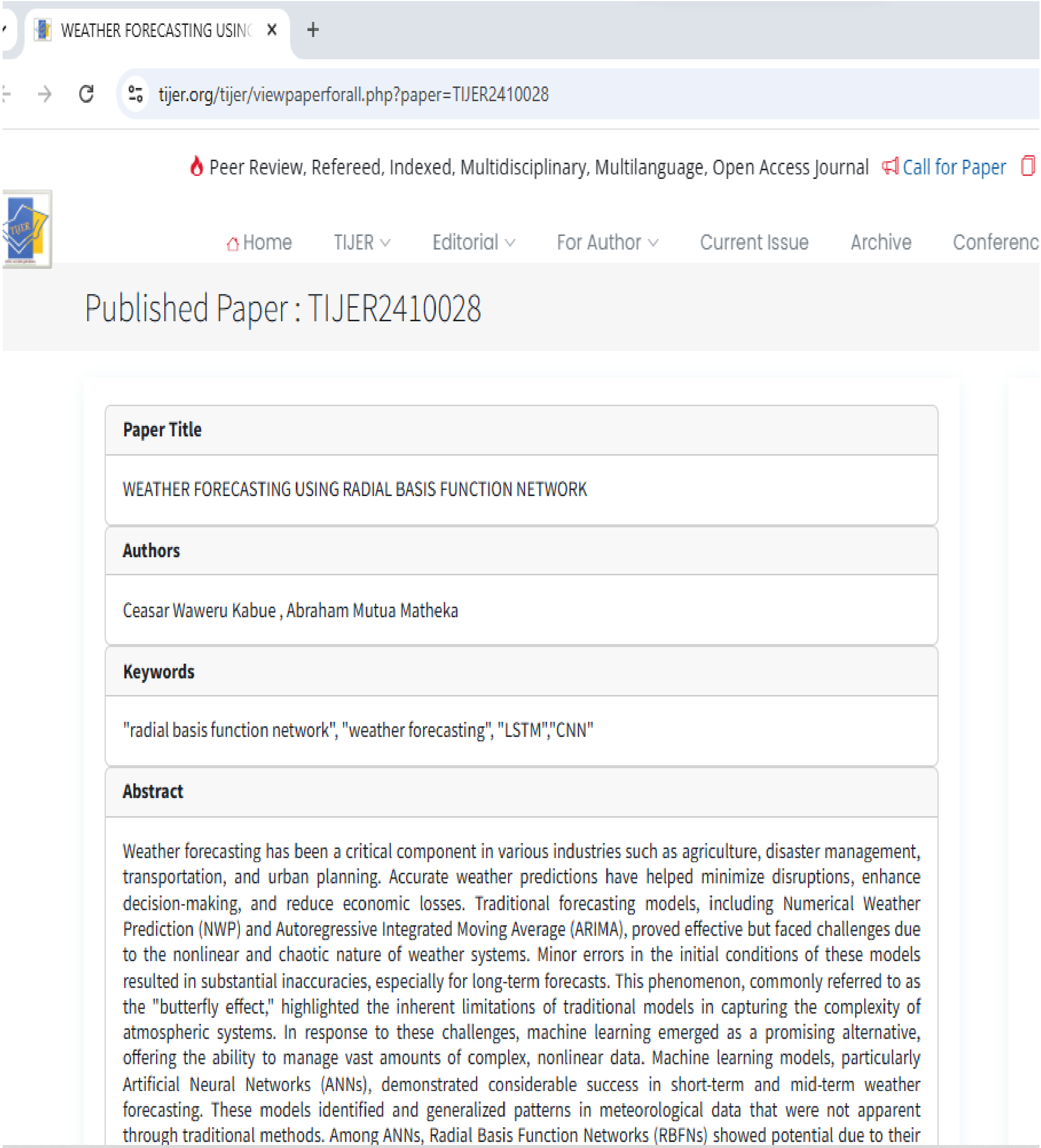
APPENDIX VII: GEOGRAPHICAL MAP OF KENYA INDICATING THE STUDY AREA

APPENDIX VIII SNAPSHOT OF PUBLISHED ARTICLE



Published Paper : TIJER2410028

Paper Title

WEATHER FORECASTING USING RADIAL BASIS FUNCTION NETWORK

Authors

Ceasar Waweru Kabue , Abraham Mutua Matheka

Keywords

"radial basis function network", "weather forecasting", "LSTM","CNN"

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