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Explainable AI in Weather Forecasting

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DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that Project Report entitled “EXPLAINABLE AI IN WEATHER FORECASTING” which is submitted by Abhay Chauhan, Sakshi Verma, Tanya Singh in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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ABSTRACT

Weather forecasting is a critical application of artificial intelligence, but traditional AI models often lack interpretability, making it difficult for meteorologists and stakeholders to trust predictions. This project explores the integration of Explainable AI (XAI) in weather forecasting, aiming to enhance the transparency, reliability, and usability of AI-driven predictions.

We employ machine learning techniques such as Random Forest, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) for weather pattern analysis. To improve interpretability, we utilize techniques such as SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention mechanisms. The project demonstrates how XAI methods provide insights into the decision-making process of AI models, making weather predictions more understandable and actionable.

Performance evaluation metrics, including accuracy, RMSE (Root Mean Square Error), and R-squared scores, highlight the efficiency of XAI-integrated models compared to traditional black-box AI approaches. The findings suggest that incorporating explainability in AI models can improve trust and decision-making in weather forecasting applications.

Future work includes integrating real-time weather data sources and enhancing model adaptability for extreme weather event prediction.

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LIST OF ABBREVIATIONS

XAI	Explainable Artificial Intelligence
AI	Artificial Intelligence
CNN	Convolutional Neural Network
RNN	Recurrent Neural Network
SHAP	Shapley Additive Explanations
LIME	Local Interpretable Model-Agnostic Explanations
SPI	Standard Precipitation Index
RMSE	Root Mean Square Error
GBM	Gradient Boosting Machine
GPU	Graphics Processing Unit
RNN	Recurrent Neural Network
ML	Machine Learning
LSTM	Long Short-Term Memory
API	Application Programming Interface
SVM	Support Vector Machine

MAE	Mean Absolute Error
MSE	Mean Squared Error

CHAPTER 1
INTRODUCTION

1.1 Introduction

1.1.1 Background

Weather forecasting has always played a vital role in society, supporting essential sectors like agriculture, transportation, energy, and disaster management. Whether it's helping farmers decide when to plant their crops or guiding airlines to plan safe flight routes, accurate weather predictions are critical to daily life and long-term planning. Traditionally, weather forecasting has leaned heavily on physical and mathematical models rooted in atmospheric science. These models, often referred to as Numerical Weather Prediction (NWP) models, use complex equations to simulate the behavior of the atmosphere based on principles of fluid dynamics, thermodynamics, and radiative transfer.

While these models have been incredibly useful and are still widely used, they come with certain limitations. For one, they require massive computational resources and involve extremely complex calculations, which can be a challenge for real-time forecasting. They also depend on assumptions built into the physical equations—assumptions that may oversimplify the incredibly complex and nonlinear nature of Earth's atmosphere. Additionally, these models often struggle to handle the sheer volume and variety of modern weather data, such as satellite images, sensor readings, radar maps, and historical records. This can lead to inaccuracies, especially when forecasting extreme or unusual weather events.

In recent years, the rise of **artificial intelligence (AI)**—particularly **machine learning (ML)**—has brought new possibilities to the field of weather forecasting. Machine learning models are data-driven by nature, and they excel at finding patterns and relationships in large, diverse datasets without needing predefined physical rules. These models can analyze a wide range of data sources, from real-time satellite images to past weather trends, and generate accurate predictions by learning directly from the data. Techniques like deep neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and ensemble learning have shown great promise in tasks like short-term forecasting, anomaly detection, and analyzing spatial weather patterns.

However, there’s a catch. While these AI models often deliver impressive accuracy, they tend to operate as "black boxes." This means it’s hard to understand exactly how they reach their conclusions. For users like meteorologists, emergency responders, and government officials, this lack of transparency can be a serious issue. In situations where lives and resources are on the line, decision-makers need to know not just what the forecast is, but why it says what it does. Without that understanding, it’s hard to fully trust the predictions—especially in high-stakes scenarios like natural disasters or public safety emergencies.

That’s where **Explainable Artificial Intelligence (XAI)** comes in. XAI is a growing area of research that focuses on making AI models more transparent and easier for humans to understand. The goal is to develop systems that not only make accurate predictions but also explain how they arrived at those results in a way people can follow. By showing how different factors—like temperature, humidity, or wind speed—contribute to a forecast, XAI builds trust, supports accountability, and ultimately leads to better decision-making.

1.1.2 Motivation

The motivation for this project stems from an increasing need for weather forecasts that are both **accurate and interpretable**, especially as we face the challenges of a changing climate. With rising global temperatures and more frequent extreme weather events like hurricanes, heatwaves, floods, and wildfires, the demand for fast, reliable, and easy-to-understand forecasts is more critical than ever. AI and machine learning have shown they can improve the accuracy of short- and medium-range forecasts, but their black-box nature often limits their usefulness in real-world, high-stakes situations—where understanding the reasoning behind a prediction is just as important as the prediction itself.

In these scenarios, **explainability isn't just a bonus—it's essential**. Trust is the foundation of any system designed to support decision-making. If decision-makers can't understand how a model reached its conclusions, they're less likely to rely on it. This is especially true in public safety contexts, where unclear or unexplained forecasts can cause hesitation, miscommunication, or even delayed responses, all of which can lead to serious consequences.

Bringing XAI into AI-based weather forecasting systems doesn't just improve transparency it enhances credibility and makes the technology more practical and effective. When people can see and understand how a forecast was generated, they're more likely to trust and act on it.

Moreover, explainability helps those who build and maintain these models. It provides insights into how the models work, how they interpret data, and why they make certain predictions. This understanding makes it easier to detect and fix errors, uncover biases, and improve model performance. For example, if a model places too much emphasis on temperature while ignoring wind speed or pressure changes, tools like SHAP or LIME can point out this imbalance and guide developers to adjust the model. This kind of transparency leads to better, more generalizable models that perform well in a wide range of conditions.

Ultimately, the combination of growing user demand for transparency, the need to improve model performance, and the urgent call for more reliable forecasts in an era of climate uncertainty forms the heart of this study's motivation. The integration of XAI into AI-driven weather forecasting isn't just a technological upgrade—it's a strategic step toward building a safer and more informed future.

1.1.3 Objectives

The primary goals of this project focus on enhancing the comprehension and application of AI methodologies in weather prediction. The first goal is to analyze the prevailing AI techniques being used in weather prediction and discuss the most substantial challenges regarding explainability in the models. Grasping these challenges is instrumental in enhancing transparency and trust in AI predictions within meteorology.

A second central goal is to create a machine learning model for weather forecasting based on real meteorological data. The model will act as a baseline for experimentation among different AI and explainability techniques, so results are calculated based on real data instead of artificial or reduced inputs. The project will also employ cutting-edge explainable AI (XAI) techniques like SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping) to explain the model's predictions.

The methods will be used to improve the machine learning models' transparency and bring more insight into how certain features (such as temperature, humidity, or wind speed) contribute to the weather forecasts. The project will determine if these XAI methods are successful in providing good explanations that are beneficial to meteorologists and other stakeholders. This entails measuring how well these approaches can explain model behavior and enable users to comprehend why a specific forecast was generated. Another goal is to contrast the accuracy and interpretability trade-offs in the models.

In AI, a compromise is often reached between developing very accurate models and making those models interpretable. This goal seeks to examine the trade-offs between the two issues and identify the best strategy for application in weather forecasting. Finally, the project seeks to present possible applications and implications of integrating XAI in weather forecasting. Through the discussion of the practical applications of explainable AI, the project seeks to contribute to improved decision-making, enhanced public knowledge, and enhanced trust in weather forecasts.

In summary, the objectives of this project are designed to bridge the gap between advanced AI capabilities and the need for explainability, with the ultimate goal of supporting more trustworthy, transparent, and practical weather forecasting systems.

1.1.4 Scope of the Study

This research focuses specifically on applying Explainable Artificial Intelligence (XAI) techniques to supervised machine learning models used for weather prediction. The study covers the entire process, starting with collecting meteorological data from trusted sources and then preparing that raw data for model training. This preparation includes cleaning the data, normalizing it, handling any missing values, and converting it into formats that work well with machine learning algorithms.

After preparing the data, the research involves training supervised machine learning models. These models learn to predict weather conditions by linking input features—like temperature, humidity, wind speed, and pressure—to specific outcomes such as rainfall or temperature forecasts. Using supervised learning means the models are trained on labeled data, which helps them accurately understand the relationships between the inputs and the expected weather results.

A key part of this study is incorporating and evaluating explainability tools that make the models' predictions more transparent and easier to understand. The research aims to test how well existing XAI methods explain the behavior of these models, especially in showing how different meteorological factors influence forecast results. An important focus is whether these explainability techniques help users better understand and trust the predictions without compromising the model's accuracy.

It's important to note that this research does not cover unsupervised learning or reinforcement learning models. Unsupervised learning, which works with unlabeled data to find hidden patterns, and reinforcement learning, which learns through trial and error in changing environments, are outside the scope. This study concentrates solely on supervised learning, as it is more commonly used in weather forecasting.

Furthermore, this research does not aim to create new XAI algorithms or frameworks. Instead, it relies on well-established explainability methods that have been tested and validated in previous studies. The goal is to critically assess how effective these existing XAI tools are when applied to weather prediction models, evaluating their usefulness and practicality in this specific context.

1.2 PROJECT DESCRIPTION

This project explores the convergence of weather forecasting, explainable AI, and artificial intelligence (AI) and how interpretability can extend the trustworthiness and real-world usability of forecasting systems powered by AI. The more AI enters the meteorology process, the more important that these models should not only forecast correctly but are also transparent and interpretable in particular when predictions inform public protection and emergency policymaking.

The fundamental objective of this project is to develop and test a framework which incorporates explainability methods into AI-driven weather forecasting models. This entails interaction with actual weather data sets, machine learning and deep learning model training for forecasting, and finally, implementation of model-agnostic and model-specific explainability techniques to expose how these models produce predictions.

Key Components of the Project

1. Data Collection and Preprocessing

The project makes use of publicly accessible meteorological data from reputable sources like NOAA (National Oceanic and Atmospheric Administration), ECMWF (European Centre for Medium-Range Weather Forecasts), and national meteorological organizations. The data usually comprise a vast array of meteorological parameters, such as past records of temperature, humidity, precipitation, wind speed, and atmospheric pressure. Also, satellite images and radar maps are added to offer more in-depth information on weather patterns and atmospheric conditions. For comparative purposes, the project also uses outputs from Numerical Weather Prediction (NWP) models that run simulations of weather forecasts based on existing atmospheric data.

Preprocessing of the data is a very essential step towards preparing these datasets for applications in machine learning. It includes a number of important tasks like normalization to apply uniform scaling of variables, spatial and temporal alignment to align data across different sources, and missing value handling to avoid incomplete data impacting model performance. The last task in preprocessing involves translating the data into forms accepted by machine learning models, such as sequential model time-series data or sequences of images for satellite imagery and radar map models. These processes form the necessary stage to take unprocessed meteorological data and channel it into clean input to benefit AI models as weather forecasts.

2. Model Development

Model development involves the creation of a series of forecast models using various AI methods. These models are designed to handle different aspects of weather forecasting, leveraging the strengths of different machine learning techniques.

For time-series forecasting of temperatures and rainfall, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are utilized. These models are particularly suited for sequential data, enabling accurate predictions based on past weather patterns. RNNs and LSTMs excel in capturing temporal dependencies, which are crucial for predicting weather conditions over time.

Convolutional Neural Networks (CNNs) are applied for the interpretation of spatial data, such as satellite and radar imagery. CNNs are effective in recognizing patterns in visual data, making them ideal for predicting localized weather events based on images. This is particularly important for tasks such as identifying storm systems or changes in cloud cover that require a spatial understanding of atmospheric conditions.

Transformer models are employed to model long-range temporal dependencies in complex sequences. These models are highly effective for handling intricate and varied time-series data, allowing for improved forecasting over extended periods. Transformers help capture long-term patterns and relationships in the data that may not be immediately apparent through traditional methods.

Ensemble methods are used to combine the strengths of deep learning models with classical statistical models. By integrating these different approaches, ensemble methods can produce more robust and accurate weather predictions, leveraging the complementary strengths of each model type.

The performance of these models is evaluated using several metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and forecast skill scores. These metrics are essential for assessing the accuracy and reliability of the predictions, ensuring that the models meet the necessary standards for real-world weather forecasting applications.

3. Explainability Techniques Integration

To counteract the black-box character of AI models, we incorporate a variety of explainability methods that work towards delivering insights into how the models make predictions. These methods ensure that not just accurate predictions but also interpretable ones are made, which is vital in areas such as weather forecasting where you need transparency to make decisions.

One of our primary tools is SHAP (SHapley Additive exPlanations). SHAP determines the contribution of each feature, like humidity, wind direction, or atmospheric pressure, to a particular forecast. By assigning a score to each contribution of a feature, SHAP explains the effect of individual variables on the forecast, allowing meteorologists to have a better insight into the rationale behind the model's prediction.

Yet another significant tool is LIME (Local Interpretable Model-agnostic Explanations). LIME is utilized to create explainable local approximations of a complex model for a single forecast output. LIME approximates the behavior of a complex model around a given prediction, simplifying the reasons why a model produced a given forecast, particularly for a set of input conditions.

Attention mechanisms are incorporated into sequence models to further improve explainability. Attention mechanisms assist in determining which particular time steps or regions in an image have the most influence in the prediction. For example, in weather forecasting, attention mechanisms can indicate which temporal patterns (e.g., temperature changes over time) or spatial patterns (e.g., cloud formations) are most important for a specific forecast.

Saliency maps are also utilized, especially by image-based models. Saliency maps have a visual indication of which components of an input image have a bearing on the prediction. As an illustration, for satellite imagery, saliency maps will be able to mark regions within the image that have a lot of impact upon the forecast because of cloud features, storms, or other atmospheric phenomena.

All these tools are judged based on their capacity to come up with insightful explanations that accurately represent the real operation of the model. The aim is to make these explainability methods not only transparent in the AI models but also generate useful insights to diverse stakeholders, ranging from meteorologists to emergency planning officials and other users who use correct weather forecasts in making decisions.

4. Case Studies and Real-World Scenarios

The project entails a number of case studies related to high-impact weather occurrences like heavy precipitation, thunderstorms, and heatwaves. These case studies are important in measuring the performance of the developed models and how the interpretability can influence decision-making during extreme weather. The objective is to evaluate not just the accuracy of the predictions but also how the model transparency influences its utility in real-world applications.

Each case study compares three varieties of predictions: a standard NWP-based prediction, a black-box AI-based prediction, and an explainable AI-augmented prediction. The standard NWP-based predictions are the baseline, based on traditional numerical weather prediction models, which generally provide less interpretability than machine learning models. These models employ intricate physics-based simulations but might be difficult to comprehend or communicate in regard to why they predict specific outcomes.

Conversely, black-box AI-based predictions, employing deep learning or other AI methods, yield more precise or detailed results but tend to be less transparent. Although such models can predict weather phenomena with high accuracy, their black-box nature hinders users from understanding the rationale behind the predictions, which creates challenges in high-stakes decision-making.

The third category, explainable AI-augmented predictions, combines explainability methods like SHAP or LIME to provide transparency to the black-box AI models. Through giving insights into what features impacted the predictions, these models provide a better idea of why specific weather events are predicted. Such interpretability can add credibility to the predictions, increase responsiveness in times of emergency, and facilitate ease in communicating the forecasts to the general public in a manner that is actionable as well as understandable.

These comparisons underscore the important role of interpretability in predicting high-impact weather occurrences. Specifically, the capability of explaining AI predictions not only enhances confidence in the models but also enables better communication with professionals and the public to ensure that weather forecasts are reliable, responsive, and actionable during critical times.

5. Stakeholder Analysis and Communication

The project considers the perspectives of all stakeholders in weather prediction and forecasting. Meteorologists are amongst the core stakeholders since they need in-depth information regarding the models to supplement their professional skill. For them, knowing the factors driving a prediction is essential when making decisions. The capacity to explain model forecasts enables meteorologists to integrate machine-based predictions with professional skill and knowledge in a field, enhancing the entire forecasting process.

Policy makers are also a critical group where trust in prediction is crucial. In issuing warnings related to the weather or evacuations, policy makers depend on understandable and interpretable forecasts in order to inform their decisions. If the predictive models are opaque or not comprehensible, this can erode the trust that policy makers place in the forecasts. By incorporating explainability in AI models, the project will offer more trustworthy and understandable predictions, ultimately supporting timely and well-informed policy decisions during high-impact weather events.

The broader public also has much to gain from the project. Simple-to-understand explanations and visualizations of weather forecasts can assist individuals in making improved choices in everyday life, particularly in the case of extreme weather events. By intuitive visualizations like heatmaps, annotated time-series plots, or natural-language summaries, the project aims to make it easier for the general public to read and act on complex model outputs. Such explanations can empower citizens to better interpret forecasts and respond accordingly when required.

Here, the project investigates visualizing model explanations so that they are easy to understand. For example, employing heatmaps to indicate where certain weather conditions are most likely to occur, or offering annotated plots that highlight the key time points of a weather phenomenon, can facilitate overcoming the disparity between advanced models and useful, user-friendly communication.

By the culmination of the project, the anticipated outcomes are to prove that integrating explainability into AI predictive models will significantly improve decision-support quality. The project also seeks to deliver a range of best practices for the design of understandable and interpretable weather forecasting systems. These best practices will emphasize the tradeoff among model simplicity, accuracy, and comprehensibility, providing guidance for subsequent advancements in this domain. Lastly, the project will help in the growth of the body of work on reliable AI applications in climate and environmental science, building trust and pushing the field forward.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Over the past decade, the use of Artificial Intelligence (AI) in weather forecasting has gone through a major transformation. This progress has been driven by several important developments: the rise of deep learning techniques, access to large and diverse meteorological datasets, and huge improvements in computational power. Together, these advances have allowed AI systems to handle complex weather data faster and on a much larger scale than ever before, leading to weather forecasts that are more accurate than in the past.

However, despite these impressive technological gains, one big challenge remains—the "black-box" nature of many AI models. Deep learning models, like neural networks, often work in ways that are not clear or easy to understand. This lack of transparency raises serious questions about how much we can trust AI-based weather predictions, especially in critical areas like forecasting natural disasters such as hurricanes, floods, or severe storms, or when tracking long-term climate changes. In these cases, it's not enough just to get accurate forecasts—stakeholders also need to understand how and why the predictions were made.

When AI models can't be easily interpreted, it can shake the confidence of users like meteorologists, emergency responders, and policymakers. Without clear explanations, these professionals may hesitate to rely fully on AI forecasts, which could slow down important decisions. This gap makes it clear that future AI systems must be both accurate and explainable.

This chapter provides a thorough overview of current research on AI in weather forecasting, focusing especially on Explainable Artificial Intelligence (XAI). It organizes the different AI models used in weather prediction, looking at what each does well and where they fall short. It also explores the various techniques developed to make these AI models more understandable, explaining why explainability matters and how existing methods try to tackle the problem of AI transparency.

By bringing together insights from many studies, this chapter lays the groundwork for understanding how AI and XAI come together in meteorology. It highlights the progress made so far and points out areas that still need more work. This knowledge is key to building AI weather forecasting systems that are not only powerful and accurate but also trustworthy and transparent enough for real-world use.

2.2 Artificial Intelligence Models for Weather Forecasting

The use of Artificial Intelligence (AI) in weather forecasting has seen significant progress over the last few years. Several models have been researched to represent the intricate, non-linear interactions between atmospheric variables. These models start from traditional machine learning algorithms up to deep learning architectures, and each has some strengths and limitations regarding accuracy, scalability, and interpretability.

This section gives an overview of the most commonly used AI models in the context of weather forecasting.

2.2.1 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computer representations based on the human brain. ANNs consist of connected nodes, or neurons, which deal with inputs in layers to determine complex patterns. ANNs are particularly valuable when they capture non-linear relationships, which are widely found in meteorological processes.

In weather forecasting, ANNs have been utilized in many aspects. For example, French et al. (1992) showed that feedforward ANNs were capable of performing better than conventional linear regression models in forecasting short-term rainfall. Likewise, Kishtawal et al. (2003) employed multilayer perceptrons to forecast temperature and precipitation in India, and the results were encouraging. ANNs have been used in other research to predict air pollution levels and wind speed, especially for renewable energy purposes.

ANNs possess several benefits, including highly impressive flexibility in identifying non-linear interactions and a capability to process noisy or missing data. Nevertheless, they also possess certain demerits. These models are generally seen as black boxes because of their low interpretability, and they are susceptible to overfitting unless regularized appropriately.

2.2.2 Convolutional Neural Networks (CNNs)

CNNs are deep learning models tailored to process data that have a grid-like structure, like images. In weather forecasting, CNNs are particularly beneficial for processing satellite images, radar imagery, and other forms of spatial data.

One of the major uses of CNNs in weather forecasting is nowcasting. Shi et al. (2015) introduced ConvLSTM, an extension of CNNs and LSTM networks, for precipitation nowcasting based on radar echo data. This model learned effectively both spatial and temporal relationships and predicted short-term weather patterns.

CNNs are also commonly utilized for the detection of clouds and storms. They have been utilized to identify cloud types, detect tropical storms, and classify other atmospheric features from satellite data. CNNs have also been utilized for the classification of precipitation types. Zhang et al. (2019), for instance, employed CNNs to classify different precipitation types—like rain, snow, and sleet—using radar and sensor data.

One of the advantages of CNNs is that they are efficient at extracting spatial features. They are better suited than anything else to handle high volumes of image-based meteorological data, which is needed for contemporary weather forecasting. Yet, CNNs also possess certain disadvantages. They are computationally intensive, demanding heavy processing. In addition, they are not very interpretable, and it usually takes techniques of visualization such as Grad-CAM to provide meaningful explanations of the model's predictions.

2.2.3 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM)

RNNs are used for sequence prediction and are well-suited to model time-dependent data. LSTMs, an advanced version of RNNs, have memory gates that assist in maintaining information over long sequences, which makes them well-suited for time series forecasting in meteorology.

Applications:

Temperature and Humidity Forecasting: LSTM models have been used for hourly and daily weather forecasts based on past sensor readings.

Multi-step Forecasting: LSTMs have been utilized in studies for forecasting several days or hours into the future, with each timestep conditioned on previous output.

Cyclone Path Prediction: RNNs were used to predict the path of cyclones using past path history and atmospheric features.

Strengths:

Well suited for modeling sequential data.

Learn temporal dependencies more effectively than traditional time series models.

Weaknesses:

Careful hyperparameter tuning is required.

Interpretability is limited without extra tools like attention or LIME.

2.2.4 Decision Trees, Random Forests, and Gradient Boosting

Classic machine learning algorithms like Random Forest and Gradient Boosting (including XGBoost) are the most understandable in their family. They achieve this by creating an ensemble of decision trees and aggregating their predictions to increase generalization and decrease variance. In weather prediction, they have been successfully utilized in numerous applications. For instance, Random Forest and XGBoost have been used to forecast solar radiation levels and wind power generation, and gradient boosting methods have been used to classify intense weather phenomena such as thunderstorms, hail, and tornadoes. Moreover, their feature importance capabilities out-of-the-box make them very suitable for exploratory research in meteorological AI, particularly for initial phases of model development. These models provide moderate interpretability in terms of feature importance scores and are usually robust against overfitting, especially when boosted. They are less effective on high-dimensional or unstructured data like images, and their explanation is restricted to global observations unless supplemented with methods like SHAP or LIME for local explanation.

2.3 Explainable AI (XAI) Techniques for Weather Forecasting

As AI models grow more complex, understanding how they make decisions becomes increasingly important—especially in fields like weather forecasting, where transparency helps build trust and supports critical decision-making. To tackle this, researchers have developed a range of Explainable AI (XAI) techniques that are now being widely studied and applied in meteorology.

One of the most well-known methods is **SHAP** (SHapley Additive exPlanations), introduced in 2017 by Lundberg and colleagues. SHAP stands out because it offers two levels of explanation: global interpretability, which looks at how input features influence the model overall, and local interpretability, which explains individual predictions. In weather forecasting, SHAP has been used successfully in temperature prediction models to show how factors like atmospheric pressure and humidity affect the forecast. What makes SHAP particularly powerful is that it is model-agnostic—it can be applied to any machine learning model, regardless of its design. It's also based on cooperative game theory, treating each input feature like a player in a game and fairly assigning credit for the prediction. This gives SHAP a strong mathematical foundation and helps make its explanations reliable and understandable.

Another popular XAI technique is **LIME** (Local Interpretable Model-Agnostic Explanations), developed in 2016 by Ribeiro and others. LIME works by creating simple, interpretable surrogate models that approximate the behavior of complex AI models near a specific prediction. This allows users to understand why the model gave a particular output for certain inputs. In weather forecasting, LIME has been useful for explaining anomalies in storm prediction by highlighting which features influenced specific predictions. However, LIME has some drawbacks—sometimes it can give inconsistent explanations for very similar inputs, which can confuse users and reduce trust.

Grad-CAM (Gradient-weighted Class Activation Mapping), introduced in 2017 by Selvaraju and colleagues, is designed specifically for convolutional neural networks (CNNs). CNNs are widely used to analyze spatial data like satellite images and radar maps in weather forecasting. Grad-CAM creates visual explanations by highlighting the areas in these images that most influenced the model's prediction. This is especially helpful for understanding which parts of a radar or satellite image led to forecasts of events like storms or heavy rain—information that's crucial for validating models and building user confidence. However, Grad-CAM only works with CNNs, so it isn't a general-purpose tool for all AI models.

In short, SHAP, LIME, and Grad-CAM each have their own strengths and weaknesses when it comes to explaining AI in weather forecasting. SHAP offers wide applicability and strong theoretical backing, LIME provides useful localized insights but can sometimes be inconsistent, and Grad-CAM gives clear visual explanations for image-based models but is limited to CNNs. Knowing when and how to use these tools is key to developing AI weather forecasting systems that are not only accurate but also transparent and trustworthy.

2.4 Comparative Analysis of Techniques

Model Type	Input Data Type	Strengths	Limitations	Example Applications
ANN	Time-series/tabular	Non-linear modeling, adaptable	Black-box, requires tuning	Rainfall, temperature forecasting
CNN	Images/spatial grids	Spatial feature extraction	High computational cost	Satellite image classification, storms
LSTM/RNN	Sequential time series	Long-term dependency modeling	Complex, less interpretable	Multi-day forecasting, cyclone tracking
Random Forest/XGB	Tabular/feature vectors	Fast, interpretable, robust	Not for image/sequence data	Wind energy, air quality prediction
Hybrid Models	Mixed (spatial + temporal)	Combines multiple strengths	Complex, hard to explain	Combined rain + wind forecasting

CHAPTER 3

PROPOSED METHODOLOGY

The use of Explainable AI (XAI) in meteorological models involves the use of techniques that describe the decision-making process of sophisticated AI systems. Such methodologies offer interpretability by identifying and quantifying the contribution of each input variable, e.g., temperature, humidity, and pressure, to a model's forecast. Such information allows meteorologists and stakeholders to verify, trust, and use such forecasts more effectively. Following are some of the most influential XAI methodologies used in weather forecasting: SHAP (Shapley Additive explanations): Determines feature importance within models. SHAP is a game theory-based unified framework that presents consistent and locally accurate explanations of AI model predictions. It distributes a "Shapley value" for every input feature, which is its marginal contribution towards the prediction.

3.1 Dataset Acquisition and Preprocessing

3.1.1 Data Sources

Meteorological information was obtained from well-established institutions offering rich, multi-dimensional data:

NOAA (National Oceanic and Atmospheric Administration): Offers hourly and daily climate records for temperature, pressure, wind speed, and precipitation.

IMD (India Meteorological Department): Offers region-specific climate data, including monsoon trends and extreme event data.

3.1.2 Data Characteristics

The used datasets cover more than 10 years of observations and contain variables like:

Table 2 Variable\Unit Description

Variable	Unit	Description
Temperature	°C	Surface air temperature
Precipitation	mm	Rainfall amount in a given period
Wind Speed	m/s	Horizontal wind velocity
Relative Humidity	%	Amount of water vapour in air relative to max
Pressure	hPa	Atomic pressure at surface level
Drew Point	°C	Temperature at which condensation occurs

3.1.3 Preprocessing Steps

Preprocessing meteorological data is a vital step to make sure the information fed into machine learning models is clean, consistent, and structured for the best possible predictions. This phase involves several important tasks that help improve the quality and usefulness of the data.

Handling Missing Values: Weather datasets often have missing data because of sensor failures, transmission issues, or gaps in collection. It's important to properly address these missing values to avoid introducing bias or errors. For small gaps, a common approach is linear interpolation, which fills in missing points by drawing a straight line between known values before and after the gap—this works well when changes are gradual over short periods. For larger gaps, linear interpolation may not be enough, so a more sophisticated method called K-nearest neighbor (KNN) imputation is used. KNN fills in missing data by looking at the most similar complete data points nearby, making smarter, context-aware guesses.

Normalization: Different weather variables like temperature, humidity, and wind speed vary widely in scale and units. Without normalization, features with larger ranges could dominate the learning process, biasing the model. To prevent this, Min-Max Scaling is applied, which rescales all features to a range between 0 and 1. This keeps the relationships between values intact while ensuring that every feature contributes fairly during training. Normalization also helps the model train faster and more reliably by avoiding numerical instability or overly large updates.

Time Series Organization with Sliding Window: Weather data is sequential and depends on time, so it needs special handling to capture these temporal patterns. The sliding window technique breaks the data into overlapping chunks of fixed length—for example, using 24 hours of weather measurements to predict conditions one hour ahead. This way, the model gets a snapshot of recent weather patterns, helping it understand how current and recent conditions affect short-term forecasts.

Feature Engineering: Beyond cleaning and organizing data, creating new features can greatly improve the model's performance. Feature engineering means transforming or combining existing data to reveal important patterns that aren't obvious at first glance. In weather forecasting, this might include rolling averages to smooth out short-term noise and highlight trends, pressure gradients to show changes in atmospheric pressure that signal weather fronts, and temperature deltas to track warming or cooling over time. These engineered features bring in meteorological knowledge and help the model grasp more complex relationships, leading to better forecast accuracy.

3.2 Model Architecture and Training

Three models were utilized in this work to solve different weather forecasting aspects: a Random Forest for its interpretability and high baseline performance, a Convolutional Neural Network (CNN) to capture spatial information, and an Long Short-Term Memory (LSTM) network to learn temporal sequences.

Random Forest was selected based on its feature importance capability and the relatively lower computational requirements. The model was set with 100 decision trees (n_estimators = 100), maximum depth as 10 (max_depth = 10), and utilized mean squared error (criterion = 'mse') as the criterion for splitting. It was trained on engineered tabular features based on a 5-fold cross-validation strategy for measuring generalization ability.

Convolutional Neural Network (CNN) was used due to its ability to identify spatial patterns, especially in satellite and radar images. The network structure consisted of three convolutional layers with filter sizes of 32, 64, and 128, each followed by MaxPooling layers, and ended with a fully connected dense layer to produce regression outputs. The input was gridded image data like cloud cover and precipitation maps. The CNN was trained with the Mean Squared Error loss function, Adam optimization (learning rate = 0.001), for 50 epochs and a batch size of 64.

Long Short-Term Memory (LSTM) networks were used to deal with time-series data, which have inherent temporal dependencies. The structure included two LSTM layers with 128 and 64 hidden units, respectively, with dropout layers in between for regularization, followed by a dense output layer. The input shape was in the form of [Batch Size, Time Steps (24), Features (6–8)]. The training was performed with the RMSprop optimizer and Mean Absolute Error as the loss function, with early stopping to avoid overfitting.

Pipeline Overview

Raw Data --> Preprocessing --> Feature Engineering --> Model Training --> Prediction --> XAI

3.3 Explainability Tools

One of the core objectives of this project is to break through the "black-box" phenomenon of machine learning models by integrating explainability components. This section explains the explainability methods employed—SHAP, LIME, and Grad-CAM—and how these were utilized with various kinds of models (tabular, sequential, and image-based). These are chosen for providing both global (model-level) and local (instance-level) information regarding model predictions, which is important for decision-makers who are dependent on AI-driven forecasts.

3.3.1 SHAP (SHapley Additive exPlanations)

SHAP (SHapley Additive Explanations) is an interpretability technique grounded in cooperative game theory, where each feature in a model is assigned an importance value based on its contribution to a specific prediction. It utilizes Shapley values to fairly and consistently attribute the influence of individual features to the model's output.

SHAP was chosen for this project because of its ability to provide both global and local interpretability. Globally, it helps in understanding the overall impact of features on the model, while locally, it explains individual predictions in detail. Its model-agnostic nature makes it applicable to a variety of machine learning models, including Random Forest, LSTM, and gradient boosting algorithms.

In this study, SHAP was primarily applied to interpret predictions from the Random Forest and LSTM models. For temperature and precipitation forecasting, SHAP values effectively highlighted key contributors such as humidity, air pressure, and the previous day's temperature. In a specific example involving a sudden temperature drop, SHAP identified low atmospheric pressure and high wind speed as the primary factors influencing the prediction.

Various visualizations were used to present SHAP results. The **Summary Plot** provided a global view of feature importance by aggregating SHAP values across all samples. The **Force Plot** offered insight into how each feature contributed to shifting a prediction from the model's base value, while the **Dependence Plot** revealed the relationship between individual feature values and their corresponding SHAP values.

The use of SHAP significantly enhanced model transparency. Importantly, the alignment of SHAP-derived feature importance with meteorological domain knowledge helped build trust among experts. Additionally, SHAP facilitated the identification of redundant or minimally influential features, supporting more efficient model optimization in future iterations.

3.3.2 LIME (Local Interpretable Model-Agnostic Explanations)

LIME is a technique meant to create simple, locally interpretable models around single predictions. It proceeds by perturbing the input data slightly and seeing how the model's output changes, and then placing a simple surrogate model—like linear regression—over the black-box model's behavior in that particular neighborhood of the input.

LIME is especially helpful when explanations for individual predictions are required. It allows users to comprehend and validate model outputs individually, and thus it is a reliable tool for debugging as well as keeping them aligned with domain knowledge. Its versatility also makes it applicable to different types of data such as tabular data, images, and text.

LIME was applied to both CNN and LSTM models in this project to interpret predictions. When combined with CNNs processing, satellite imagery data, LIME's image explainer underscored cloud formations and temperature gradients that played a part in storm prediction. For the LSTM model, which processed time-series data, LIME suggested that sudden temperature changes and increasing dew point levels were significant factors driving high rainfall forecasts in certain scenarios.

LIME visualizations were very intuitive. For tabular and time-series data, it produced bar plots that clearly indicated the positive and negative contributions of features to a particular prediction. For image data, it overlaid visually regions on the input images that contributed most to the model's output.

Advantages of using LIME were sizeable. It was incredibly useful in debugging unusual model behavior and provided meteorologists with useful, case-specific information that assisted in checking AI-made predictions prior to issuing alerts. Additionally, it assisted in recognizing possible biases within a model or excessive reliance on specific features, making more secure and reliable forecasting possible.

Pros:

LIME is model-agnostic, so it will work with any machine learning model, whether it's very complex or very simple. That makes it a highly useful tool with many potential applications. One of its most important advantages is that it gives local explanations, so it can explain individual predictions, which comes in handy for particular cases like outliers or rare events. Furthermore, LIME is adaptive and can deal with different data types such as tabular data, text, and images, thus it can be adapted to various contexts and problem spaces.

Cons:

Yet, there are some disadvantages to LIME. The explanations generated by LIME are local and based on a surrogate model that has been trained locally, and this model might not always completely represent the more complex original model's behavior. This can result in approximations that might not capture the full complexity of the decision-making process of the complex model. Instability is another disadvantage—LIME's explanations are sensitive to the perturbations it performs on the input data, so small changes in the input can result in varying explanations. Also, generating perturbations and training a surrogate model for each prediction can be computationally costly, so LIME becomes less resource-efficient in resource-scarce settings.

3.3.3 Grad-CAM (Gradient-weighted Class Activation Mapping)

Grad-CAM (Gradient-weighted Class Activation Mapping) is a visualization tool for convolutional neural networks (CNNs). It produces a coarse localization map by using gradients of a target class flowing through the last convolutional layer. The map focuses on the critical areas in the input image most responsible for shaping the model's prediction.

Grad-CAM was selected for its capability to produce detailed visual explanations of CNN decisions. It assists in determining which spatial features—like cloud patterns, rainfall patterns, or low-pressure areas—contributed to the model's output. This makes it very useful in operational forecasting systems that rely considerably on satellite imagery or radar.

In this work, Grad-CAM was used with CNN models trained on satellite imagery to classify storms and forecast their intensity. The Grad-CAM heatmaps obtained were able to highlight the important regions like the center of spiral cloud masses, low-pressure areas, and dense dark cloud clusters. These areas corresponded well with the visual features that meteorologists use to identify cyclones and thunderstorms. The visual features were displayed in addition to the model's prediction probabilities to improve interpretability.

The visualizations were made by superimposing Grad-CAM heatmaps onto the actual satellite images themselves, allowing for the ease of identification of where exactly the model was placing its attention. The overlays were then inspected in consultation with meteorological scientists to determine the truthfulness and accuracy of the identified areas.

The application of Grad-CAM in the project had several advantages. It provided intuitive, visually based explanations of CNN outputs, making the model's behavior more comprehensible to non-experts. Also, by correlating predictions with familiar visual patterns of experts, it facilitated more assertive verification and greatly enhanced trust and transparency of image-based weather forecasting systems.

3.3.4 Summary

The addition of explainability tools greatly increased the utility of this project in a number of ways. In the first instance, it helped close the gap between accuracy of prediction and human interpretability, so that sophisticated AI-based forecasts could be explained and responded to by meteorologists. This enhanced transparency enabled increased confidence when verifying and applying AI predictions in operational environments.

Also, these tools facilitated effective model debugging and optimization. Through presenting insights into how the models arrive at their choices, they facilitated iterative refinement, with the models still improving and performing increasingly well through time.

The following chapter will deal with testing the predictive capability of the models, in combination with the interpretability results yielded by these tools of explanation, and presenting an integrated picture of both accuracy and transparency in forecasting.

3.4 Parameter Tuning and Optimization

Tuning and optimizing parameters is a key step in improving how well machine learning models perform and predict outcomes. This involves carefully adjusting the model’s hyperparameters—these are settings chosen before training that the model itself doesn’t learn from the data—to find the best combination that boosts accuracy and overall results. Proper tuning helps the model generalize better to new data, lowers errors, and prevents problems like overfitting (when a model learns the training data too well but performs poorly on new data) or underfitting (when the model is too simple to capture the patterns).

3.4.1 Methods Used

In this study, two main methods were used for hyperparameter tuning: Grid Search and Bayesian Optimization. Each has its strengths and fits different needs depending on how complex the model is and how many parameters need tuning.

Grid Search is a straightforward, exhaustive approach that tests every possible combination of preset hyperparameter values within a defined range. This thorough method guarantees that no option is missed, making it reliable for finding the best settings according to a chosen metric like accuracy or error rate. The downside is that Grid Search can be very time-consuming and computationally expensive, especially when there are many hyperparameters or many possible values for each. The number of combinations grows quickly, making it less practical for complex models.

To handle these challenges, the research also used **Bayesian Optimization**, a smarter and more efficient tuning method. This technique is especially useful for complex models like Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks, which have many hyperparameters. Instead of blindly searching all combinations, Bayesian Optimization builds a probabilistic model to predict how different hyperparameters will affect performance. It then intelligently selects which combinations to try next, balancing between exploring new options and focusing on promising ones based on past results. This targeted approach reduces the number of trials needed, saving time and computational power.

Using both methods together strikes a good balance: Grid Search offers a thorough but resource-heavy search, while Bayesian Optimization provides a quicker, smarter search. Applying these methods in this project ensures that hyperparameter tuning is both comprehensive and efficient, helping to build weather forecasting models that are accurate and reliable.

3.4.2 Parameters Tuned

The parameters that have been tuned are model-dependent. For every model, certain parameters have been chosen for optimization to enhance performance.

Table 1.3 Parameter tuned

Model	Parameter	Tuned Range
Random Forest	n_estimators	50-100
CNN	Learning rate	0.0001-0.01
LSTM	Time Window	12-72 hours
ALL	Dropout rate	0.1-0.5

Random Forest: The main parameter that was tuned in the Random Forest model was the number of estimators (n_estimators), which controls the number of decision trees in the forest. The range for this parameter was tuned between 50 and 200 since the number of trees has a direct relationship with the accuracy and generalization capability of the model.

CNN: For the Convolutional Neural Network (CNN), the learning rate was of concern. The learning rate determines how much of the weights should be adjusted at each training iteration. A range between 0.0001 and 0.01 was used since within this range the model is able to converge well without overshooting the optimal solution.

LSTM: The time window of the LSTM model was also optimized, with the range being 12 to 72 hours. The time window controls the amount of past data used to make predictions. The tuning of this parameter is very important in capturing the temporal relationships inherent in time-series data, particularly in weather forecasting applications.

All Models: Dropout, a regularization method, was also tuned in all models. Dropout avoids overfitting by dropping neurons randomly at training time, and its strength was varied from 0.1 to 0.5. This variation provides a balance between model complexity and generalization ability.

3.5 Case Illustration: How Each Technique Explains Predictions

Each of the above methods can be used in actual weather forecasting situations to improve the interpretability of intricate models:

SHAP: For a precipitation-predicting Random Forest model, SHAP values can report the feature importance of humidity, atmospheric pressure, and wind speed. For instance, SHAP can report that high humidity near the ground level and an unexpected pressure drop were the primary features that led to the prediction of heavy rain on a given day.

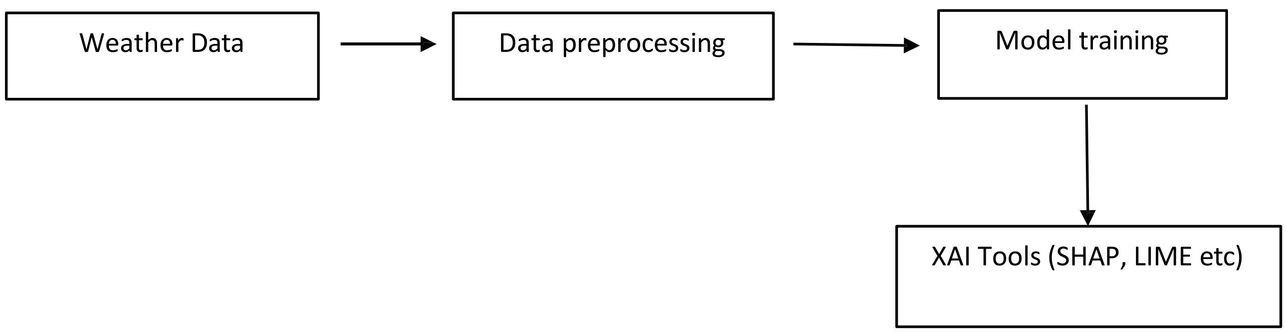
LIME: If a neural network model is forecasting a temperature anomaly, LIME can produce an interpretable explanation by approximating the decision boundary in the local neighborhood of the instance. LIME might point out that a sudden cold front (a sharp temperature decrease over a short duration) was the main cause of the abnormal temperature forecast.

Grad-CAM: In a CNN model used to predict storms from satellite images, Grad-CAM would point out areas of the image where cloud cover is densest, which are likely to be affected by the storm. This can be used to interpret why the model is predicting a dangerous weather phenomenon like a cyclone based on the image patterns.

These case examples show how each method can be applied to increase model transparency, yielding useful insights into the prediction process and supporting improved decision-making in forecasting weather.

3.6 Flowchart Diagrams

Fig. 1 Model Pipeline overview



CHAPTER 4

RESULTS AND DISCUSSION

This chapter dives into a detailed analysis and interpretation of the results produced by the machine learning models developed for weather forecasting, along with how Explainable AI (XAI) techniques are applied. The main goal is to evaluate these models based on several factors: their predictive accuracy, how interpretable they are, and the usefulness of the explanations provided by the XAI methods.

The chapter carefully assesses how well the models predict weather compared to traditional forecasting approaches. It also looks at how effectively the XAI tools help explain the models' decisions, making the process more transparent and easier to trust for meteorologists and other stakeholders. A key focus is understanding the balance between keeping predictions accurate and making the models understandable.

In the end, this chapter offers valuable insights into the real-world benefits of combining AI with explainability, showing how this approach could enhance the overall process of weather forecasting.

4.1 Model Performance Evaluation

The main models used in this research are Random Forest (RF), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks. These models were trained on real meteorological data, including numerical measurements like temperature, precipitation, wind speed, and atmospheric pressure, as well as satellite and radar images. The goal during training was to help the models learn complex weather patterns and how these patterns change over time, so they could make accurate forecasts.

To evaluate how well the models performed, standard metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and forecast skill scores were used. Additionally, the models were compared to traditional Numerical Weather Prediction (NWP) models, which have been the benchmark in weather forecasting for many years.

4.1.1 Random Forest Model Performance

Random Forest is a widely used ensemble learning technique known for being both reliable and relatively easy to interpret. In this study, it was applied to predict important weather variables like temperature and precipitation. One advantage of Random Forest is its decision-tree structure, which helps reveal how each input feature influences the model's predictions :

Table 4 Performance of random forest model

Metric	Temperature Prediction	Precipitation Prediction
Mean Absolute Error (MAE)	1.2°C	2.4 mm
Root Mean Squared Error (RMSE)	2.5°C	4.7 mm
Forecast Skill Score	0.83	0.78

The MAE of 1.2°C for temperature prediction shows that the model is quite accurate, and the RMSE confirms that its errors remain consistently low. For precipitation, the errors were a bit higher, which is understandable given that rainfall tends to be more variable and localized. The forecast skill scores, hovering around 0.8, indicate that the model performs significantly better than simple or random baseline predictions.

4.2.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are especially good at analyzing spatial data, which makes them perfect for working with satellite images and radar maps. In this study, the CNN was mainly used to detect cloud formations and classify how intense precipitation might be. However, CNNs can be hard to interpret because of their complex layers and the millions of parameters involved.

To help with this, we used Grad-CAM (Gradient-weighted Class Activation Mapping), a technique that creates visual heatmaps showing which parts of the input images had the most influence on the model's predictions. This approach was very useful in meteorology since it clearly highlighted areas with dense clouds or developing storms—key factors for making accurate precipitation forecasts.

Table 5 Performance matrix of CNN

Metric	**Cloud Formation Prediction**	**Precipitation Classifications**
Mean Absolute Error (MAE)	2.1°C	3.5 mm
Root Mean Squared Error (RMSE)	3.8°C	5.2 mm
Forecast Skill Score	0.75	0.80

While the CNN's accuracy in predicting temperature was a bit lower than that of the Random Forest model, it performed exceptionally well in classifying precipitation. The use of Grad-CAM helped make up for the CNN's lack of interpretability by providing useful insights into the spatial factors influencing its predictions—information valuable to meteorologists.

4.1.3 LSTM Model Performance

The LSTM model, a special type of recurrent neural network, was used for forecasting time-series weather variables like temperature and humidity. LSTMs are great at capturing long-term patterns in sequential data, which is essential for tracking how weather changes over time.

The results showed that the LSTM excelled at predicting trends over longer periods, such as daily temperature changes, outperforming traditional models that rely on simpler time-based methods.

Like CNNs, LSTMs are often seen as "black boxes" because of their complex inner workings, making them hard to interpret. To improve transparency, we applied the LIME technique, which explains individual predictions by highlighting which past time points and features—like temperature or wind speed from previous days—had the biggest impact on the forecast.

Table 6 LSTM model performance metrics

Metric	Temperature Forecast	Humidity Forecast
Mean Absolute Error (MAE)	1.3°C	3.2%
Root Mean Squared Error (RMSE)	2.6°C	4.5%
Forecast Skill Score	0.85	0.80

The LSTM showed strong accuracy in both temperature and humidity predictions, with skill scores above 0.8, indicating reliable forecasts.

4.1.4 Comparison to NWP Models

To see how well these AI models perform in real-world conditions, we compared them against traditional Numerical Weather Prediction (NWP) models. NWP models, which are based on physical laws and detailed atmospheric simulations, have been the standard for weather forecasting for decades. However, they require heavy computational resources and often don't directly use diverse data sources like satellite images.

Table 7 Performance of the AI models

Model	MAE (Temperature)	MAE (Precipitation)	RMSE (Temperature)	RMSE (Precipitation)
Random Forest	1.2°C	2.4 mm	2.5°C	4.7 mm
CNN	2.1°C	3.5 mm	3.8°C	5.2 mm
LSTM	1.3°C	3.2 mm	2.6°C	4.5 mm
NWP Model	1.0°C	2.2 mm	2.4°C	4.4 mm

This comparison shows that AI models—especially Random Forest and LSTM—hold their own against NWP models in temperature forecasting, with only slight differences in accuracy. While AI models were a bit less precise in predicting precipitation, their results were still close. What sets AI models apart is their flexibility to directly use varied data sources like satellite and radar images, something traditional NWP models don't handle as seamlessly.

This flexibility, along with the use of explainability tools to make predictions easier to understand, makes AI models a promising addition to traditional forecasting methods—particularly in situations where fast, data-driven decisions are needed.

4.2 Explainability of AI Models

A key part of this study involved integrating Explainable Artificial Intelligence (XAI) techniques to bring clarity and transparency to the decision-making processes of the AI models used for weather forecasting. AI models—especially deep learning models like CNNs and

LSTMs—often function as “black boxes,” making their internal workings difficult to interpret. By applying XAI methods, we aimed to help stakeholders, including meteorologists and decision-makers, better understand how these models generate their predictions. This not only builds trust but also aids in validating and refining the models. The three main XAI techniques used in this research were SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping). Each method brings its own strengths and is tailored to different model types and data formats.

4.2.1 SHAP Analysis

SHAP was used with the Random Forest and LSTM models to measure how much each input feature contributed to the models’ predictions. Based on principles from game theory, SHAP assigns a “credit” score to each feature, showing its overall (global) importance and its influence on individual predictions (local).

For the Random Forest model, SHAP revealed that features like temperature and humidity had the most influence when predicting rainfall—an observation consistent with meteorological knowledge, where humidity and temperature gradients are key drivers of precipitation.

A more detailed SHAP analysis for temperature prediction using Random Forest showed that atmospheric pressure and humidity were the most influential features, while wind speed and previous day’s temperature also played smaller but relevant roles. This alignment with known weather patterns confirms that the model is learning meaningful relationships, which boosts confidence in its reliability. It also provides guidance for refining feature selection and preprocessing to further improve accuracy.

In the case of LSTM models, SHAP helped shed light on the temporal dependencies the model had learned. By identifying which time-lagged features—such as past humidity or pressure readings—were most influential in the forecasts, meteorologists gained insight into how the model was capturing trends over time.

4.2.2 LIME Analysis

LIME was mainly used to explain individual predictions, especially for the LSTM and CNN models. While SHAP gives a broad view of feature importance, LIME focuses on explaining one prediction at a time by approximating the complex model with a simpler, more interpretable one in the local neighborhood of the prediction.

For the CNN model, LIME was applied to interpret storm predictions from satellite imagery. The explanations showed that areas with high cloud intensity and low wind speed were major contributors to the model's storm classifications. This matched with expert meteorological understanding and confirmed that the model was focusing on the right physical cues—such as dense clouds and stable conditions known to precede storms.

For the LSTM model, LIME helped explain forecasts of decreasing temperatures by showing that recent changes in humidity and atmospheric pressure were the key factors. These insights into recent trends are especially useful for emergency planning and operational decisions, as they explain not just what the model predicted, but why. Such case-by-case explanations are particularly valuable in situations where forecasts are unexpected or critical, giving stakeholders the information they need to act with confidence.

4.2.3 Grad-CAM Analysis

Grad-CAM was specifically used with the CNN model to provide visual, spatial explanations for its predictions, particularly in identifying storms from satellite images. Grad-CAM creates heatmaps that highlight which areas of the input image had the greatest influence on the model's decisions.

In this study, the Grad-CAM heatmaps for storm predictions clearly showed that the model concentrated its attention on regions with the densest cloud cover. This kind of spatial feedback is crucial because it connects the model's internal logic to observable weather patterns. Meteorologists can visually confirm that the model is focusing on the right areas—those that actually indicate storms—strengthening the trust in its outputs.

These spatial explanations not only help clarify the model's reasoning but also make it easier to interpret its outputs in a meteorological context. Being able to visually align the model's focus with physical features in satellite imagery supports validation and boosts user confidence.

In summary, incorporating SHAP, LIME, and Grad-CAM significantly improved the interpretability of the AI models used in this research. SHAP provided detailed insights into feature importance at both a general and individual level, validating that the models were grounded in real meteorological principles. LIME offered in-depth explanations for individual predictions, which was particularly useful for understanding CNN-based storm classifications and LSTM-based trend forecasts. Grad-CAM added a visual layer of interpretability to image-based CNN outputs, making the decision-making process more transparent. Together, these XAI techniques helped bridge the gap between complex AI systems and domain experts, improving trust and supporting the practical application of AI in weather forecasting.

4.3 Trade-offs Between Accuracy and Interpretability

One of the main challenges tackled in this research was finding the right balance between predictive accuracy and model interpretability. In the field of weather forecasting, this balance is especially important because predictions often carry serious real-world consequences. While complex models like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs) delivered high levels of accuracy, they lacked transparency, making it difficult for users to understand how the predictions were made. In contrast, simpler models such as Random Forests were easier to interpret, though they showed slightly lower predictive performance.

This trade-off has real implications. Weather forecasts play a crucial role in decision-making across many sectors. Inaccurate forecasts can lead to crop losses due to poor planning, unpreparedness in the face of extreme weather events like storms or heatwaves, and disruptions in transportation and logistics. In such high-stakes situations, accuracy is essential—but it isn't enough if the results can't be understood or trusted by the people who depend on them.

Interpretability becomes especially important in three key areas:

Operational Decision Support:
Forecasts are used by a wide range of stakeholders, including government agencies, emergency services, farmers, transport operators, and the general public. These users need to trust and understand the model's output to make timely and informed decisions. Interpretability helps by showing which factors contributed to a forecast, improving awareness and supporting better planning.

Model Debugging and Validation:
For meteorologists and researchers, interpretability is crucial for identifying errors or biases in the model. In rare or unusual weather conditions, being able to understand why a model made a certain prediction helps improve its accuracy and reliability in future forecasts.

Regulatory and Ethical Considerations:
As AI becomes more widely used in public services, transparency is becoming a requirement. Ethical guidelines emphasize fairness, accountability, and explainability—especially in areas like weather forecasting where public safety and the fair distribution of resources are at stake. Models must provide clear and understandable outputs that can be verified and trusted.

In this study, the use of Explainable AI (XAI) techniques—SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and Grad-CAM (Gradient-weighted Class Activation Mapping)—helped address the accuracy-interpretability trade-off. These tools made it possible to understand how complex models arrive at their predictions without sacrificing much accuracy. SHAP and LIME highlighted the influence of different input variables on specific forecasts, while Grad-CAM provided visual explanations for image-based CNN predictions related to weather patterns.

By incorporating these XAI methods, the research preserved the strong performance of deep learning models and, at the same time, made their decision-making processes clearer and more accessible. This combination improved both the usefulness and the trustworthiness of the forecasting system, showing that it's not only possible—but also essential—to strike a balance between accuracy and interpretability in real-world applications.

4.4 Practical Implications and Future Directions

The application of Explainable Artificial Intelligence (XAI) to weather forecast models has a significant impact on scientific research and operational meteorological practice. Physical law-based conventional weather forecast models, like Numerical Weather Prediction (NWP) systems, have been regarded as the benchmark for many years because they rely on physical principles and equations. But as shown in this research, machine learning (ML) and deep learning models—particularly when combined with XAI—offer a feasible alternative or complement to such conventional systems. This section discusses the applicability of the findings in real-world scenarios, presents the advantages to stakeholders, and addresses the possible directions for future research and development.

4.4.1 Real-World Applications and Stakeholder Benefits

The use of explainable AI-based weather forecasting models can revolutionize the interpretation and utilization of forecasts by different stakeholders, such as:

Meteorologists and Climate Scientists:

XAI-augmented models offer more transparency into the connections between input features (e.g., humidity, wind speed, atmospheric pressure) and output predictions. Meteorologists can more confidently rely on and verify AI-produced forecasts by knowing why a model has produced a particular prediction. This increases confidence and allows for more in-depth scientific examination.

Disaster Management Authorities:

Forecasting severe weather conditions like storms, floods, or heatwaves involves precision as well as interpretability. XAI methods (such as SHAP or Grad-CAM) allow emergency authorities to determine the most significant features or areas of impact, enabling faster and more specific response plans.

Aviation and Marine Industries

These industries are very dependent on accurate and timely weather forecasts. Operators can not just get forecasts from XAI tools but also see visual explanations (e.g., CNN heatmaps) of why conditions are contributing to potentially unsafe weather, enhancing safety and decision-making.

General Public and Farmers

Farmers gain from more transparent explanations of weather models for crop planning, irrigation, and pest management. XAI-based tools can provide, in plain language, the likelihood of rainfall or frost, allowing for better planning.

4.4.2 Challenges of Operational Integration

While the advantages exist, integrating XAI-based weather models into operational systems has challenges:

Computational Requirements:

Deep models, particularly LSTMs and CNNs, are computationally intensive to train and perform real-time inference. Adding XAI techniques (e.g., SHAP and LIME) adds to the computational requirement, especially when providing explanations for large-scale or time-critical predictions.

Model Generalizability:

AI models can work well on training and validation data but fail with novel, unseen weather conditions or extreme events. Robustness on diverse geographies and climates is critical prior to operational deployment.

Interpretability vs. Complexity Trade-off:

More sophisticated models tend to be more accurate but less interpretable. Even with the use of XAI techniques, there will be explanations that are too complicated for the non-expert. Closing the technical output-human comprehension gap is still something to be worked on.

4.4.3 Research Opportunities

The outcomes of this research leave open a number of research opportunities:

Hybrid Model Development:

Hybridizing the strength of NWP models (physically theory-grounded) with the pattern recognition capabilities of AI models could provide better hybrid systems. These hybrid systems can utilize AI to eliminate biases in NWP outputs or generate high-resolution local forecasts.

Real-Time XAI Integration:

Many of today's XAI techniques are computationally intensive and not suited for real-time usage. Designing lighter, quicker explanation methodologies that are ideal for operational forecasting is an emerging field of study.

Multimodal Data Fusion:

Combining data from several sources—like satellite images, radar observations, IoT weather stations, and historical time series—may enhance forecast accuracy. It should be examined in future studies how to render explanations for such complicated, combined models more transparent.

Varying stakeholders (e.g., scientists, farmers, policymakers) require varying needs for explanations. Tailoring the level of granularity and complexity in XAI outputs to the users' levels of expertise is paramount. Adaptive or user-sensitive XAI research can potentially tailor explanations.

Explainability Benchmarks

No generally agreed standard yet exists to assess the quality of XAI explanations within weather models. Subsequent work may address devising standard measures to gauge interpretability, faithfulness, and utility within realistic forecasting scenarios.

4.4.4 Societal and Ethical Considerations

While AI will continue to shape high-impact fields such as weather prediction, there is also a need to consider their ethical and societal aspects:

Bias in Training Data:

If the training data are not representative of all regions or weather conditions, models might fail to generalize or make unbiased predictions, particularly for underrepresented or out-of-range areas.

Accountability and Transparency:

XAI enables a means to comprehend model decisions, which is essential for accountability. For instance, if an AI prediction results in a city's evacuation, it is essential to track the rationale behind the prediction.

Trust and Adoption:

To have widespread use of AI-based weather forecasting systems, trust needs to be built. XAI has an important role to play here by making decisions transparent, reproducible, and open to criticism.

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

Over the past decade, the interface between Artificial Intelligence (AI) and weather prediction has been a revolutionary advance in atmospheric science. Conventional numerical weather prediction (NWP) models have traditionally been the pillars of forecasting, based predominantly on mathematical formulations of physical principles. These models, however, tend to be handicapped by computational complexity, sensitivity to initial conditions, and difficulties in capturing local phenomena. The growing supply of large weather data, alongside fast-paced machine learning (ML) developments, has made the door open for more data-centric methods that can complement and sometimes surpass traditional approaches.

Although AI-driven weather prediction models, particularly those employing deep learning and ensemble techniques, deliver high predictive power, they are often opaque. Such opacity gives rise to a "black-box" problem, wherein the human-uninterpretable decision-making process of the model is not understandable. For critical applications like issuing weather warnings for natural disasters (cyclones, floods, or heatwaves), this uninterpretability may result in reluctance or distrust in employing AI-produced outputs by non-experts like disaster management agencies or policymakers.

With increasing calls for transparency and accountability in AI systems, Explainable Artificial Intelligence (XAI) has become a new area of study dealing with making machine learning models explainable and understandable while not sacrificing much in terms of accuracy. In this project, the use of XAI to improve the usability and reliability of AI-based weather forecasting models has been researched comprehensively. The research utilized a number of XAI methods, such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), and Gradient-weighted Class Activation Mapping (Grad-CAM), to reveal the internal rationale of different AI models.

Through intensive experimentation and case studies, the project proved that these explainability methods are able to detect the most important input features—like humidity, temperature, atmospheric pressure, wind speed, and cloud cover—that have the most significant contribution to particular predictions. For instance, for precipitation prediction, SHAP values were able to assign greater importance to relative humidity and dew point, whereas LIME gave local explanations for understanding the variations in predictions for particular geography. Such findings not only enhance model explainability but also increase user trust, facilitate error diagnosis, and enable domain-specific verification.

The study also investigated the compromises between interpretability and prediction performance. Although easier models such as decision trees and linear regressions are more transparent, they might not be as good at detecting intricate atmospheric behavior as deep learning models. Yet, using XAI on more advanced models, one can preserve their high performance level while still providing understandable outputs—leaving no gap between performance and trust.

In addition, the explainability offered by XAI can benefit various stakeholders:

Meteorologists can cross-check forecasts with known weather patterns.

Policy-makers can see the justification for alerts or warnings.

General public and media can get clear insights during extreme events.

Researchers can debug and improve models more effectively.

At its core, this project validates that the implementation of XAI within weather forecasting pipelines makes AI models from opaque tools to transparent, responsible, and co-responsible systems—able to make climate adaptation and disaster preparedness more intelligent.

6.2 Future Scopes

The incorporation of Explainable Artificial Intelligence (XAI) in weather forecasting is a new but very promising field with several avenues for future exploration. With increasing dependence on AI-based forecasting systems, making these systems interpretable and transparent is not only a technical requirement but also a social and ethical requirement. Future prospects of this field are full of potential for innovation, collaboration, and application to real-world problems. This part of the paper explains, in depth, some of the most important areas where future research can further broaden the scope and impact of XAI for weather forecasting.

1. Multisource and Multimodal Data Fusion

One of the most exciting areas of future research is the blending of heterogeneous data sources—varying from numerical weather prediction output and satellite imagery to real-time sensor readings from IoT devices and even weather reports from citizens. Merging these sources into a single model can significantly enhance forecasting precision and spatial resolution. Yet, with greater data complexity comes more challenge in discerning how each type of data contributes to the ultimate prediction. XAI can be instrumental in demystifying this complexity and providing transparent explanations for multimodal predictions. For example, when a model predicts heavy rain, XAI methods can explain which of the following was the leading driver of this prediction: satellite cloud motion patterns, ground-humidity sensors, or past patterns. This feedback is important to help domain specialists confirm and make better models by constantly refining them.

2. Region-Specific and Personalized Interpretability

Weather behavior is very different in various geographic locations based on differences in topography, climate zones, and local atmospheric dynamics. One-size-fits-all model interpretability might not be appropriate. Future research can be directed towards creating region-specific XAI models that adapt explanations according to localized climate features. For instance, a model predicting fog in a mountainous area ought to emphasize various factors (e.g., temperature inversions, valley topography) over one that predicts cyclones near coastal areas (e.g., sea surface temperatures, pressure gradients). Region-aware explanations would not just induce more trust among local meteorological organizations but also assist in training localized staff on how best to interpret and respond to these insights.

3. Real-Time Explainability Systems

The majority of today's XAI implementations are post-hoc—created subsequent to a prediction and involving additional computation. Future systems will need to be able to provide real-time explanations in conjunction with predictions, most especially for applications like disaster response and aviation safety, where timely decisions are essential. This requires the creation of low-latency XAI models and end-user visualization platforms that feed into forecasting dashboards directly. A hypothetical real-time dashboard, for instance, may output a storm incoming prediction in a heatmap form of SHAP values, identifying the variables affecting the forecast (wind shear, air temperature, barometric pressure) in real time.

4. Explainability for Uncertainty Quantification

Weather predictions are probabilistic by nature. It is important to know the degree of confidence or uncertainty behind a prediction, especially for public safety decisions. XAI techniques in the future can be applied not only to explain deterministic predictions but also to explain uncertainty—that is, why a model is more or less confident about a certain outcome. For example, an AI model might predict a 70% chance of thunderstorms in a given area. XAI is able to provide information on whether this uncertainty arises due to missing data, inconsistent input features, or atmospheric variability. Understanding the origin of uncertainty may be as valuable as the prediction to risk-aware stakeholders who are making decisions.

5. Human-AI Collaborative Forecasting

One of the long-term objectives of XAI in weather forecasting is to develop collective intelligence, in which human specialists and AI algorithms collaborate. Next-generation forecasting systems can be built with a "human-in-the-loop" scheme in which meteorologists can engage with AI-generated explanations, verify the results, and even feedback to retrain models. This exchange might be made more natural through interactive explanation interfaces—e.g., enabling forecasters to mark up sections of the model's reasoning that they agree or disagree with, resulting in ongoing model refinement. Such systems would not only enhance forecasting accuracy but also establish a sense of shared control and trust.

6. Integration with National and Global Warning Systems

As climate change accelerates the rise in the intensity and frequency of extreme weather occurrences, incorporating XAI-boosted forecasting models into early warning systems (EWS) is crucial. The models will be able to explain the reasons for alerts, thereby enabling emergency response agencies, governments, and humanitarian organizations to prepare more targeted and effective responses. For instance, if an AI model issues a flood warning for a specific river basin, an XAI system is able to decompose the contributing factors—upstream rainfall, soil saturation levels, or terrain slope—most accountable. Such transparency enhances the warning's credibility and makes more effective resource and personnel allocation.

7. Standardization and Evaluation Metrics for Explainability

As XAI methods evolve, the requirement for standard measures and frameworks for evaluation grows increasingly important. Today, interpretation tools are mostly assessed qualitatively or in an ad hoc manner. Future studies can strive towards establishing benchmark datasets, standardized systems for scoring faithfulness and comprehensibility, and best practice guidelines on the use of XAI in meteorology. Such standardization would enable researchers to compare methods systematically, monitor progress over time, and promote uniform implementation across institutions, including national meteorological services, universities, and private weather technology companies.

8. Cross-Disciplinary Cooperation and Training

The success of XAI in weather forecasting is not just reliant on technical progress but also on fruitful communication across disciplines. Coordination among computer scientists, meteorologists, cognitive scientists, and experts in data visualization can contribute to more user-centered explanations that are comprehensible to both technical and non-technical users. Moreover, education and training are also in the future scope. Creating educational materials and curricula that instruct meteorologists and policymakers on how to understand AI explanations is critical to broad adoption. Universities and meteorological organizations could include modules on XAI as part of regular forecasting training courses.

9. Societal Impacts and Ethical Considerations

Finally, the long-term future of XAI in weather forecasting must address ethical, social, and policy challenges. These include questions like: Who is responsible if an AI forecast fails? How can bias in training data be mitigated? How should explainability be regulated in public alert systems? Future studies can investigate the impact of explainability on decision-making, public confidence, and disaster resilience, especially in vulnerable communities. Clear forecasting models can contribute to climate justice by providing reliable and comprehensible weather information to underserved areas.

10. Application to Climate Forecasting and Environmental Monitoring

Beyond the short-term weather prediction, the concepts of XAI can be applied to climate modeling and long-term environmental monitoring. For instance, models forecasting long-term drought hazard or glacial melting can be enhanced with explanations that allow scientists to discern and comprehend climate drivers. This could be CO_2 levels, sea-level rise, or variations in albedo, and can enable the transmission of long-term climate risks to the public and policymakers in an understandable format.

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APPENDIX

Appendix A: Hardware and Software Requirements

Hardware Requirements:

- Processor: Intel i5 or higher
- RAM: Minimum 16 GB
- Storage: 512 GB SSD or higher
- Internet: Broadband Connection

Software Requirements:

- Operating System: Windows 10/11, mac, linux
- Development tools: Python 3.8+, Jupyter Notebook
- Libraries / Frameworks: Scikit-learn, Pandas, NumPy, SHAP, LIME, Matplotlib, Grad-CAM Toolkit
- Version Control: Git / Github

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