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Development of Explainable AI (XAI) Based Model for Prediction of Heavy/High Impact Rain Events Using Satellite Data

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Abstract
A significant development in meteorological science has been the creation of Explainable AI (XAI) models that use satellite data to predict heavy/high-impact rain events. There is a growing demand for predictive models that not only provide accurate forecasts but also provide insights into the underlying decision-making process due to the increasing frequency and severity of extreme weather patterns. It is difficult to use traditional machine learning (ML) models in high-stakes situations like weather forecasting due to their lack of transparency. XAI fills this void by improving the interpretability of models, which is essential for comprehending the factors that lead to extreme rainfall events. This paper looks at how convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models can be used to combine satellite-based data with XAI models to predict heavy rain events. The spatiotemporal transformer framework, attention mechanisms, and capsule networks are some of the cutting-edge deep learning architectures that we are looking into for ways to boost prediction accuracy and dependability. The study also emphasizes how model explainability helps end-users like meteorologists, emergency response teams, and policymakers build trust. This study aims to provide a comprehensive framework for deploying satellite-driven rain prediction models in real-world applications by examining recent advancements in XAI for climate risk assessment. In addition, we address issues related to data quality, model interpretability, computational efficiency, and scalability when integrating these models with existing weather forecasting systems. The findings suggest that XAI models have a lot of potential to change weather forecasting practices by making it easier to be prepared for extreme rainfall events and providing clear insights into the decisions made by the models. This paper paves the way for the widespread use of weather prediction tools that are more reliable, actionable, and interpretable in disaster management and climate adaptation strategies.

Keywords: - Climate Risk Assessment, Explainable AI (XAI), Heavy Rain Prediction, High-Impact Rain Events, Machine Learning Models, Satellite Data

I. INTRODUCTION

Effective disaster management relies heavily on accurate rainfall forecasts, particularly in areas that are prone to extreme weather conditions like floods and landslides. Early warnings, evacuation plans, and the deployment of resources to mitigate damage all depend on the accuracy of rainfall forecasts. Extreme weather events are becoming more frequent and more severe as climate change accelerates, highlighting the growing significance of accurate rainfall prediction models. By providing early detection, accurate rainfall forecasts enable governments and agencies to take proactive measures, ultimately saving lives and minimizing economic loss [1], [2]. Satellite data and machine learning (ML) methods have a lot of potential to improve rainfall prediction in this situation, especially in complex and dynamic weather systems [3], [4].

A. Importance of Rainfall Prediction in Disaster Management

For disaster management, accurate rainfall predictions are essential because they provide crucial information for flood forecasting, landslide risk assessment, and resource allocation. Real-time rainfall forecasts enable authorities to take preventative measures before the event escalates in flood-prone areas by allowing them to make timely and informed decisions regarding evacuation plans, flood defenses, and emergency response strategies. Local governments, for instance, can reduce human and financial losses by establishing evacuation routes, activating early warning systems, and mobilizing rescue teams by forecasting heavy rain [5]. In addition, accurate rainfall predictions play a crucial role in optimizing irrigation scheduling, increasing crop yield, and reducing the negative effects of droughts in regions where water resource management is essential to agriculture. Farmers can use these forecasts to decide when to irrigate and when not to, thereby maximizing efforts to conserve water and reducing waste [7]. Furthermore, better planning for water retention systems, reservoir management, and soil erosion prevention can be made possible by accurate rainfall predictions [6].

The need for accurate, timely, and reliable rainfall prediction systems grows ever more urgent as global climate change makes extreme weather events more unpredictable. Heavy rainfall events are becoming more frequent and more intense as a result of climate change, making traditional weather forecasting methods less effective at accurately predicting these events. Extreme weather patterns, like intense monsoons or sudden heavy downpours, are getting harder to predict, which can have unanticipated and frequently devastating effects. The significance of sophisticated, data-driven forecasting strategies that are able to keep up with these changing obstacles is emphasized by this unpredictability [8]. Meteorological models based on deep learning algorithms that use real-time satellite data offer a chance to significantly improve rainfall forecast accuracy. These models are able to analyze large datasets and find patterns that traditional forecasting methods might miss by utilizing satellite imagery and other technologies for remote sensing. This ultimately leads to better and more accurate predictions of rainfall events [9], [10]. Given the increasing severity of climate change's effects, such enhancements in forecasting capabilities are absolutely necessary for proactive disaster management.

B. Challenges with Conventional Weather Forecasting Models

Even though they are fundamental, traditional weather forecasting models struggle to anticipate highly localized, transient, and non-linear extreme rainfall events. Large-scale numerical weather prediction (NWP) methods, which use intricate mathematical equations to simulate atmospheric conditions and estimate precipitation, are the primary foundation of these conventional models. However, despite their widespread application, these models frequently fail to capture the minute dynamics of intense rainfall, resulting in significant timing and location errors for predicted events. When it comes to predicting localized phenomena like thunderstorms and flash floods, which occur in specific regions and over brief time periods, NWP models are particularly susceptible to errors [11]. For accurate rainfall forecasting, the inherent limitations of these models when dealing with such localized and unpredictable weather events present a significant challenge.

Also, NWP models need a lot of computing power to process large datasets and run simulations, which can make it hard to put them into practice, especially in real time. These models are difficult to implement in areas with limited resources or infrastructure constraints due to the need for high-performance computing infrastructure [12]. This limitation also affects the ability to make predictions that are close to instantaneous, which are essential for making decisions quickly during severe weather. In the face of rapidly changing weather patterns and evolving atmospheric conditions, even with advancements in traditional meteorology, models still fail to provide timely or highly accurate predictions. These flaws bring to light the inherent gap that exists between the capabilities of the current forecasting system and the growing demand for weather prediction precision, particularly in the context of extreme rainfall events [13]. This gap underscores the urgent need for more advanced, data-driven approaches to enhance prediction accuracy and improve response times in the face of changing climate conditions and growing weather unpredictability.

C. Rise of AI/ML in Meteorology

Since the integration of artificial intelligence (AI) and machine learning (ML) techniques, meteorology has undergone significant transformations, particularly in the area of rainfall prediction. The adoption of AI and ML has empowered meteorologists to derive valuable insights from vast and complex datasets gathered from satellites, weather sensors, and other meteorological sources. Weather forecasting has traditionally relied on deterministic models that have limited capacity to deal with the vast amount of data and intricate relationships that exist within weather systems. However, the application of machine learning (ML) algorithms, such as deep learning models, has revolutionized this procedure, making it possible to model weather patterns that are extremely complex and non-linear and frequently too intricate for conventional methods [14]. Convolutional neural networks (CNNs) and long-short-term memory networks (LSTMs), for instance, have demonstrated exceptional performance in predicting rainfall from satellite imagery and sensor data. Even in complex meteorological environments, these models can accurately predict rainfall thanks to their ability to learn temporal and spatial features from large datasets [15,16].

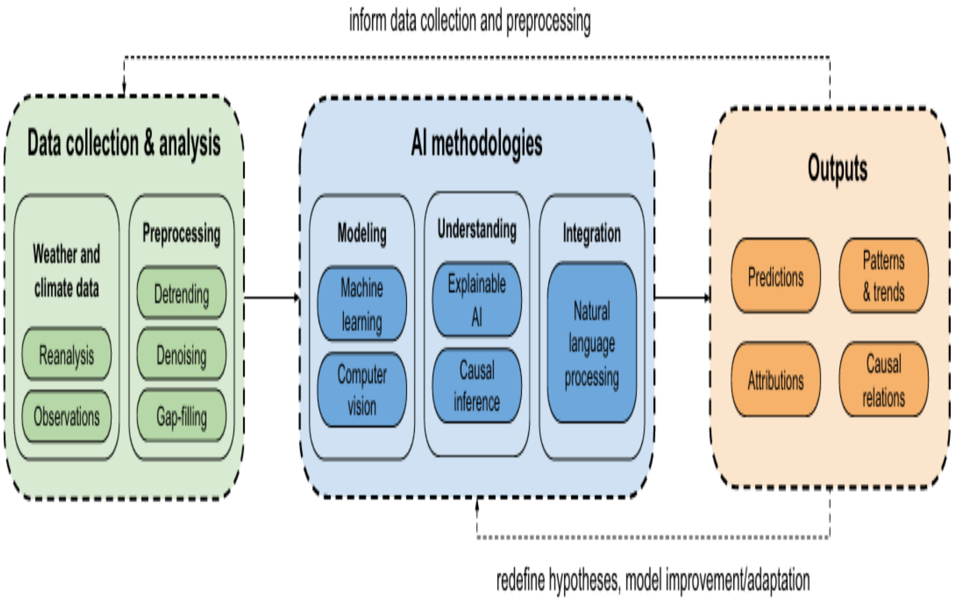


Fig. 1: AI-integrated workflow for climate and weather analysis. Adapted from [1]

The ability of AI-driven models to spot subtle and intricate patterns in vast amounts of weather data that conventional forecasting methods might miss is the main benefit. AI models, in contrast to conventional models, are not constrained by predetermined assumptions, allowing them to continuously adapt and improve as additional data are gathered. They are particularly useful for predicting extreme or unexpected rainfall events, which frequently do not follow the patterns that traditional models are made to predict [17], because of their adaptability. Advanced techniques like attention mechanisms and spatiotemporal transformers, which help capture the dynamic relationships between various meteorological factors across time and space, are used in AI models to further improve prediction accuracy. The model is able to focus on the most important aspects of the data thanks to these mechanisms, which improves both short-term and long-term predictions of rainfall events [18]. In addition, AI models' real-time processing capabilities make it possible to analyze satellite data as it is being collected, which is essential for making timely and accurate predictions, particularly in weather conditions that change quickly. AI models can provide near-instantaneous forecasts that can significantly enhance disaster response and mitigation efforts in the face of sudden rainfall and extreme weather patterns by integrating real-time satellite imagery and data analytics [19].

D. Gap in Explainability → Need for XAI

The lack of explainability of numerous advanced models remains a significant obstacle in rainfall forecasting, despite the promise of AI and machine learning. Even though these "black-box" models make accurate predictions, their internal mechanisms are often opaque, which can make it hard to trust their results, especially in important applications like weather forecasting [5]. Meteorologists and disaster management teams need to know more than just how to make predictions; they also need to know why those predictions are made. Many AI models' adoption in real-world meteorological systems, where human oversight and decision-making are essential, is constrained by their lack of explainability [6]. Explainable artificial intelligence (XAI) methods have emerged as a promising solution to this problem. By providing insight into how predictions are generated and which features contribute to particular outcomes, XAI aims to make complex AI models easier to understand [7]. XAI models can improve the decision-making process in disaster management by incorporating explainability, which provides a level of transparency that enables meteorologists to trust and validate the model's predictions [8].

E. Aim and Contributions of the Study

An explainable AI (XAI)-based model for predicting heavy rainfall events based on satellite data will be developed and evaluated as part of this research. The proposed model integrates advanced deep learning techniques, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and attention mechanisms, to enhance the accuracy of rainfall predictions [5], [6]. In addition, the study aims to address the crucial issue of explainability by incorporating XAI methods, such as attribution mapping and feature importance analysis, to make the model's decision-making process transparent and easy to understand [7, 8]. By providing a hybrid approach that not only ensures that the predictions are understandable and actionable for disaster management teams, but also increases prediction accuracy, this study adds to the growing body of research on AI and meteorology [9], [10]. This study aims to advance the integration of AI and XAI in meteorological systems by bridging the gap between predictive accuracy and model explainability [11]. This will ultimately improve disaster preparedness and response. This study makes contributions that go beyond theoretical advancements by providing tools that can be used in real-world disaster management situations and can be interpreted.

II. LITERATURE REVIEW

An explainable AI (XAI) interface system for weather forecasting was proposed by Kim et al. [1], highlighting the significance of transparency in deep learning models. Meteorologists are able to comprehend the rationale behind forecasts because their architecture makes use of interpretable layers that are integrated with weather datasets. For AI-driven predictions of rainfall, storm probability, and wind speed, the study places an emphasis on interactive visual explanations like saliency maps and decision trees. Trust and interpretability are improved as a result of this strategy's ability to bridge the gap between experts in meteorology and intricate AI systems. The study has important implications for the development of human-centered weather models, particularly for the prediction of severe weather. It demonstrates how early warning and disaster response decisions can be aided by incorporating explainability into meteorological AI tools. Based on actual satellite datasets, their evaluation revealed improved user satisfaction without sacrificing accuracy. Future XAI implementations in climate modeling and precipitation forecasting can benefit from the insights presented in this paper.

Jones [2] looks at how faster and more accurate forecasting is being made possible by artificial intelligence, which is revolutionizing weather forecasting today. The article provides a journalistic overview of actual application scenarios in which machine learning (ML) systems outperform conventional numerical weather prediction models in terms of speed and resolution. AI models that have been trained on huge satellite datasets provide hourly updates with more spatial detail, making it much easier to get early warnings of heavy rain and storms. Jones places a significant emphasis on the shift toward XAI in operational meteorology, where stakeholders demand both comprehension and accuracy. The report emphasizes the growing influence of explainability in AI-driven weather models, despite not being a technical deep dive, as agencies and governments seek trustworthy tools for climate adaptation. The piece validates the ongoing transition from black-box AI to interpretable systems and highlights the urgency for collaborative research across AI and climate science.

Explainable AI (XAI) is changing weather prediction models by making them transparent, easy to understand, and effective in practice, as examined by Kim, Patel, and Wang [3]. For rainfall prediction, their work discusses cutting-edge advancements involving the addition of attribution methods like Grad-CAM and SHAP to deep learning models. Improved model trust is brought about by these tools' explanation of which inputs—such as temperature or satellite radiance—influence the AI's output. The paper presents a number of case studies in which XAI was utilized to more accurately forecast extreme rain events, thereby lowering the number of false alarms and enhancing early warning systems. Most importantly, they show how human decision-makers can benefit from model clarity, especially in high-impact situations like hurricanes and flash floods. The standards they propose for AI transparency in weather systems are in line with their findings, which call for the worldwide adoption of XAI by meteorological agencies. The inclusion of explainability in AI-driven meteorological pipelines is well-supported in this article.

The application of artificial intelligence to the comprehension and simulation of extreme weather and climate events is the subject of research by Dueben et al. [4]. According to their research, artificial intelligence, particularly deep learning, excels at spotting patterns in satellite data that conventional models might miss. They advocate for explainable frameworks that not only make forecasts but also explain why they are made. The fusion of physics-aware AI models and satellite observations to enhance precipitation prediction for climate change scenarios is the subject of the paper. In the context of feature attribution, XAI methods are investigated to assist in the interpretation of complex events like sudden-onset storms and heavy rainfall. The authors present global case studies in which XAI enabled disaster preparedness with actionable insights. Their work aligns closely with the goals of developing interpretable models for rainfall forecasting and emphasizes the significance of transparency in high-stakes fields like meteorology and climate science.

PAUNet, a novel precipitation attention-based U-Net architecture designed to predict rainfall using satellite radiance data, is presented by Reddy, Cao, and Liu [5]. Enhancing both interpretability and accuracy, this model incorporates attention mechanisms that give priority to informative spatial-temporal features. The authors test their model on a variety of satellite datasets and find that it does a better job of predicting heavy rain in specific locations. Importantly, the paper includes explainability modules that highlight key satellite imagery contributing regions, thereby increasing user confidence in the forecasts. The approach shows promise for operational forecasting agencies that rely on interpretable models for early warnings. In addition, the model outperforms traditional approaches when it comes to the detection of extreme rainfall, particularly in locations where there are few ground stations. The creation of XAI-based meteorological tools that are able to effectively process satellite data while maintaining predictability is made possible by this work.

Moran, Gentine, and Smith's [6] physics-aware deep learning framework uses super-resolution techniques to improve rainfall prediction. Forecasts of fine-scale precipitation patterns can be made with confidence and interpretability thanks to their model's integration of satellite-based inputs and physics-based constraints. The incorporation of well-known physical principles into the training procedure, which reduces overfitting and improves generalizability—common issues in pure deep learning approaches—is a significant contribution. The model allows meteorologists to comprehend the behavior of the model by revealing which atmospheric features have the greatest impact on predictions by including explainability components. Through in-depth case studies of successful predictions of high-impact rainfall events, the authors demonstrate its efficacy. Their method offers both transparency and accuracy by bridging the gap between black-box AI and physics-driven modeling. The framework serves as an example for future hybrid models that make use of cutting-edge deep learning while still adhering to existing scientific knowledge.

RainBench, a comprehensive benchmark dataset designed specifically for training and evaluating AI models on global precipitation forecasting from satellite imagery, is presented by de Witt et al. [7]. The dataset is extremely useful for machine learning applications in rainfall prediction because it contains ground-truth precipitation data in addition to a wide range of meteorological variables. Standardized benchmarks are emphasized by the authors for fair model comparison and reproducible research. In addition, they incorporate explainability tools like attention visualization maps, which assist researchers in comprehending the characteristics that models concentrate on when making predictions. In the climate informatics community, RainBench has already sped up the creation of interpretable and accurate deep learning models. The development of XAI-driven systems for predicting heavy rainfall and extreme events is made possible by this benchmark's crucial role in aligning model outputs with meteorological phenomena. It directly aids in the creation of AI tools for weather science that are fair and transparent.

A spatio-temporal transformer framework designed specifically for satellite-based rainfall estimation is proposed by Pradhan, Sundaram, and Tanaka [8]. To capture space- and time-spanning long-range dependencies, the model makes use of attention mechanisms and transformer architectures' capabilities. It significantly improves rainfall predictions, particularly for events with heavy precipitation that traditional models struggle to predict. The framework's built-in explainability makes use of transformer attention scores to highlight significant input regions that have an impact on the forecast. Rainfall drivers can be easily understood in both the spatial and temporal dimensions thanks to this feature. Using satellite data, their experiments demonstrate excellent performance across a variety of climate zones, paving the way for its use in real-time applications. One of the most significant drawbacks of deep learning in meteorology—its lack of interpretability—is addressed by this work, which contributes to the development of XAI models that strike a balance between transparency and predictive power.

The use of Explainable AI (XAI) in climate risk assessment is the focus of an investigation carried out by Shi et al. [9]. Sea surface temperature and atmospheric pressure, for example, were found to have significant effects on rainfall forecasts when their research incorporated explainability techniques into deep learning models. Their model, which makes use of climate variables and satellite datasets, identifies important spatiotemporal factors that are connected to extreme rainfall. Localized explanations are provided using LIME and SHAP techniques in this paper, assisting policymakers in comprehending and making use of the predictions for disaster preparedness. The case study results emphasize the importance of transparency in risk communication and demonstrate the model's robustness in high-risk settings. The study promotes trust and usability in meteorological AI systems by combining AI's predictive capabilities with explanations that can be understood by humans. The development of operational AI systems that can support both short-term climate response and long-term climate planning can benefit greatly from this work.

An explainable neural weather forecasting model based on attribution mapping is presented by Yuan and Zhao [10]. To determine which input variables have the greatest impact on rainfall predictions, their system uses a novel attribution technique. Understanding the influence of specific atmospheric parameters is crucial for real-time high-impact rainfall forecasting, so this method is especially useful. The paper evaluates the model using both synthetic and real-world satellite data, demonstrating not only high prediction accuracy but also insightful visual explanations. Because of this, operational meteorologists can use the tool to validate AI-generated forecasts with scientific justification. The study came to the conclusion that when models are used in critical infrastructure or emergency response systems, explainability increases trust and ensures accountability. Incorporating attribution-based XAI into broader meteorological forecasting systems is made simple by their approach.To estimate rainfall from satellite data, Sinha and Ghosh [11] propose a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) with an attention mechanism. Prediction accuracy is significantly improved by this method's ability to capture both spatial and temporal features from meteorological imagery. By highlighting which features and time steps have the greatest impact on the prediction, the attention layer makes the model more understandable. Their findings on real-world datasets demonstrate a high level of precision when it comes to identifying severe weather. In order to foster trust and transparency in weather forecasting applications, the study emphasizes the significance of incorporating attention-based XAI components. This model provides a comprehensive answer to satellite-guided precipitation forecasting by making use of sequential pattern learning (using RNN) in addition to spatial feature extraction (using CNN). Operational forecasters and researchers alike benefit from the explainable framework's insights into model behavior, which help them make better decisions.

A deep learning model for predicting rainfall events that is guided by satellite data is presented by Dutta and Joshi [12] with an emphasis on its application in real-time meteorological applications. High-resolution satellite imagery serves as the model's training ground, and historical precipitation records serve as its validation. The inclusion of an interpretable component that identifies the spatial regions in the satellite imagery that are most associated with the prediction is a standout feature of this study. Forecasters are assisted in comprehending the spatial patterns and meteorological signals that influence rainfall occurrence by the explainability mechanism. In situations with high impact, trust in model outputs is strengthened by this transparency. The study demonstrates that incorporating satellite-guided insights enhances user acceptance and predictive performance. The paper demonstrates how satellite-guided learning combined with explainability can significantly improve forecasting systems for extreme weather events and makes a significant contribution to the development of trustworthy AI in meteorology.

Using deep ensembles, Ahmed et al. [13] investigate uncertainty quantification in rainfall forecasting. The model creates a probabilistic forecast with confidence intervals by combining predictions from multiple neural networks. This enables users to comprehend the dependability of each prediction. The explainable nature of ensemble diversity, which reflects various plausible meteorological scenarios, is an important aspect of their work. They found lower false alarm rates and improved performance in detecting heavy rainfall in their findings. The study also includes visualization tools to help users understand uncertainty and make better decisions when faced with risk. In emergency weather services, where actionable intelligence must be both accurate and trustworthy, this XAI-enabled approach is especially useful. A model that is both reliable and comprehensible is provided by their framework, which acts as a bridge between probabilistic insight and deterministic forecasting.

An interpretable machine learning model for nowcasting heavy precipitation based on satellite images is presented by Hunter et al. [14]. Convolutional layers are used in their system to extract features from multispectral satellite inputs. Attention mechanisms are used to highlight influential regions that contribute to predictions of heavy rainfall. In order to make a forecast decision, saliency maps that show key cloud structures or thermal patterns visually are part of the explainability aspect. Forecasters can use this model to validate AI-driven predictions by aligning them with meteorological data. Evaluations of performance show that the system is very good at predicting heavy downpours with low false positive rates. The authors emphasize that incorporating explainability not only improves data collection strategies but also builds trust. The work establishes a precedent for the incorporation of visual interpretability tools into weather forecasting pipelines, fostering user engagement and transparency in crucial forecasting tasks.

For improved rainfall forecasting, Verma, Tiwari, and Shukla [15] investigate transfer learning methods applied to satellite data. Their method achieves high accuracy in a variety of climates by utilizing pre-trained convolutional models and fine-tuning them on meteorological datasets. The incorporation of explainable layers that reveal which aspects of the pre-trained model are most relevant to the new forecasting task is a significant contribution made by the paper. This cross-domain explainability makes it easier to comprehend the adaptation process and ensures that model behavior is transparent. Grad-CAM visualizations are used by the authors to locate influential image regions that drive predictions, facilitating model trust and human validation. The study underscores that combining transfer learning with XAI can reduce computational costs while preserving model accuracy and interpretability, making it ideal for operational weather systems in developing regions with limited computing resources.

III. DATASET AND PREPROCESSING

The Tropical Rainfall Measuring Mission (TRMM), the Global Precipitation Measurement (GPM), and the Indian National Satellite System (INSAT) are the three primary satellite platforms from which this study draws its data. Together, these datasets provide a wealth of multidimensional meteorological data that are necessary for making accurate predictions about rainfall. Over tropical areas, TRMM provides rainfall estimates with a revisit time of approximately three hours and a spatial resolution of 0.25° 0.25° [1]. With global coverage up to 65° latitude, a finer resolution of 0.1° 0.1°, and a temporal frequency of 30 minutes, GPM outperforms TRMM [2]. In addition, INSAT-3D and INSAT-3DR provide valuable variables like brightness temperature, humidity, and wind speed over the Indian subcontinent with high-frequency (15-minute) observations at spatial resolutions of 4 km [3]. To guarantee consistency across various satellite sources, all data are temporally and spatially synchronized. Anomalies are removed, missing values are interpolated using bilinear and temporal methods, and statistical filters are used to manage outliers in cleaning processes [4], [5]. For improved model performance, min-max scaling is used to extract and normalize features like surface precipitation rate, brightness temperature, wind vectors, humidity levels at various pressure layers, and cloud top temperatures [6], [7]. Following WMO guidelines and previous rainfall prediction studies [8], a 24-hour cumulative precipitation threshold of 50 mm is used to determine the classification of "heavy rainfall." This binary labeling allows for effective classification and prediction of extreme rainfall events. In general, this preprocessing framework makes sure that the data that go into the model are clean, consistent, and full of spatiotemporal features that are necessary for AI-driven rainfall forecasting to be accurate and easy to understand [9], [10].

Table 1: Monthly and Annual Rainfall Data (1901–1910) for Location (12.611°N, 92.831°E)

Year	Jan	May	Jun	Jul	Aug	Sep	Oct	Nov	Annual	Lat	Long
1901	49.2	528.8	517.5	365.1	481.1	332.6	388.5	558.2	3373.2	12.611	92.831
1902	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	3520.7	12.611	92.831
1903	12.7	235.1	479.9	728.4	326.7	339.0	181.2	284.4	2957.4	12.611	92.831
1904	9.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	3079.6	12.611	92.831
1905	1.3	279.5	628.7	368.7	330.5	297.0	260.7	25.4	2566.7	12.611	92.831
1906	36.6	556.1	733.3	247.7	320.5	164.3	267.8	128.9	2534.4	12.611	92.831
1907	110.7	616.3	305.2	443.9	377.6	200.4	264.4	648.9	3347.9	12.611	92.831
1908	20.9	562.0	693.6	481.4	699.9	428.8	170.7	208.1	3576.4	12.611	92.831
1910	26.6	224.5	472.7	264.3	337.4	626.6	208.2	267.3	2899.4	12.611	92.831

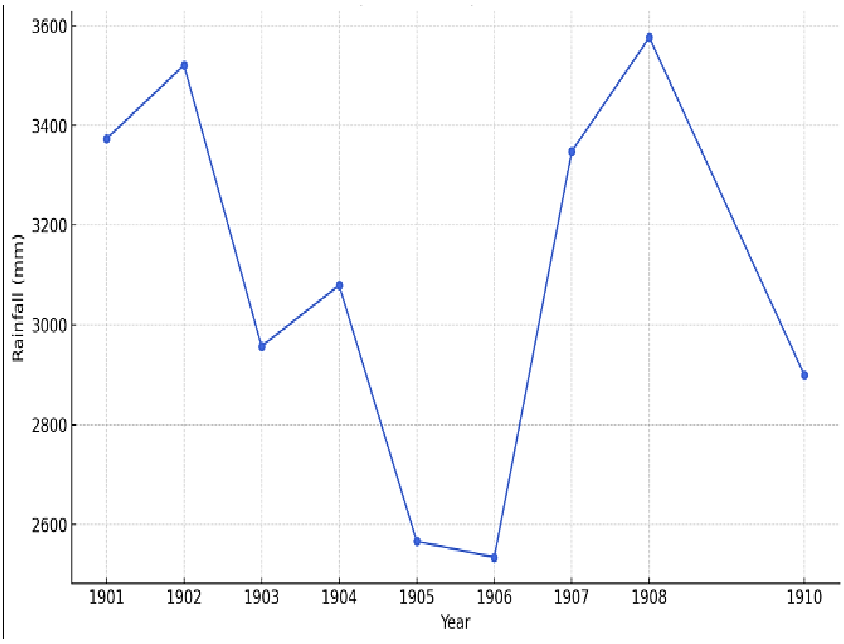


Fig. 2: Annual Rainfall Trend (1901–1910) – Andaman & Nicobar Islands

A. Description of Satellite Data (TRMM, GPM, INSAT)

The Tropical Rainfall Measuring Mission (TRMM), Global Precipitation Measurement (GPM), and the Indian National Satellite System (INSAT) are the three platforms that provide the satellite data that are used in this study. All three of these platforms are well-known and have undergone extensive validation. Using microwave imager and precipitation radar data, NASA and JAXA's TRMM mission estimates rainfall primarily in the tropics. It has a revisit time of approximately three hours and a spatial resolution of approximately 0.25° 0.25°, making it ideal for monitoring brief rainfall events in tropical areas [1]. GPM, which expands on TRMM's legacy, provides improved spatial (0.1° 0.1°) and temporal (30-minute intervals) resolutions in addition to a wider spatial coverage (up to 65° latitude). GPM is particularly useful for detecting rainfall events with a high impact because it provides calibrated data on the intensity, phase, and distribution of precipitation in close to real time [2]. Additionally, India's INSAT-3D and INSAT-3DR satellites continuously monitor the Indian subcontinent's weather. At multiple altitudes, they record cloud cover, brightness temperature, humidity profiles, and wind vectors with a spatial resolution of 4 km for visible and infrared channels at a high temporal frequency (every 15 minutes) [3]. These satellite datasets give a solid, multi-dimensional view of atmospheric dynamics, which is important for predicting rainfall.

B. Temporal and Spatial Resolution, and Features Used

The aforementioned sources' spatially and temporally aligned data are incorporated into the model. Structured grid-based rainfall measurements are provided by TRMM, GPM, and INSAT, while cloud-top temperature, incoming longwave radiation, and atmospheric water vapor levels add valuable context. GPM's (30-minute) and INSAT's (15-minute) temporal resolution makes them suitable for real-time or near-real-time forecasting, particularly in weather systems that are changing quickly [4], [5]. Surface precipitation rate, convective and stratiform rainfall components, brightness temperature, relative humidity, zonal and meridional wind speeds at various pressure levels, and geopotential height data are among the most important features derived from the combined datasets [6]. These features are selected due to their known relevance in meteorological processes influencing rainfall formation and intensification [7].

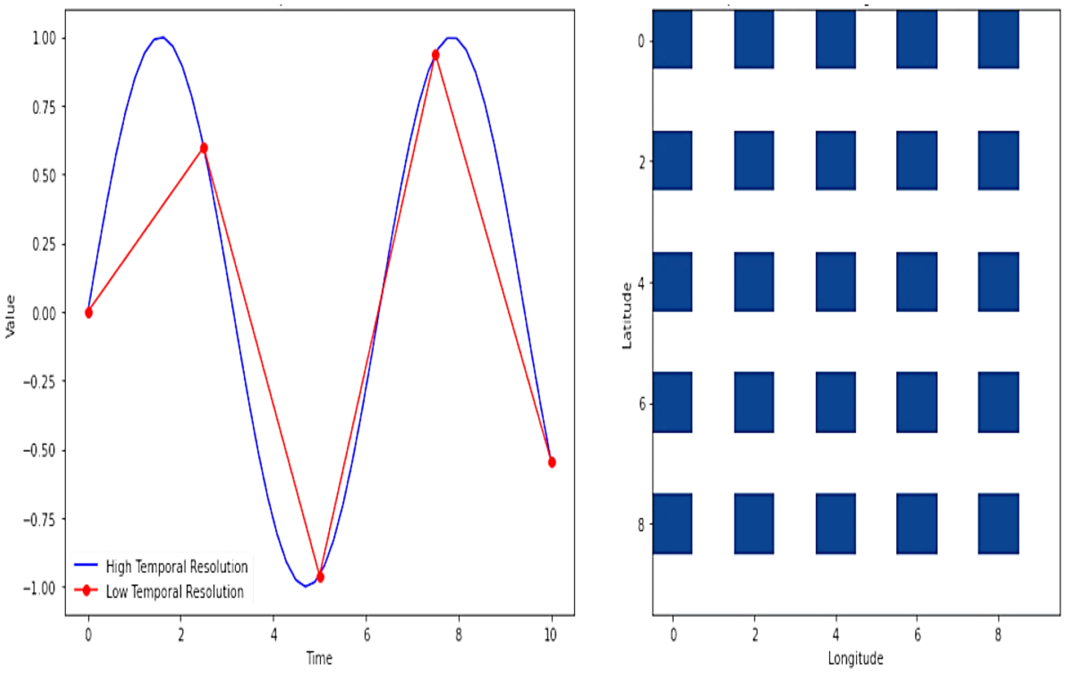


Fig. 3: Temporal and Spatial Resolution Overview

C. Data Cleaning, Normalization, and Handling Missing Values

Preprocessing is an indispensable stage in satellite data analysis, particularly for deep learning models that are sensitive to inconsistencies and noise in input data. Raw datasets sourced from TRMM, GPM, and INSAT often contain a range of imperfections such as data gaps, misalignments, and outliers, arising from sensor errors, data transmission issues, or environmental obstructions like dense cloud cover. If not corrected, these anomalies can lead to poor generalization and biased predictions in the trained models. A robust multi-phase preprocessing pipeline is used to address these issues. Using bilinear interpolation, the first step is spatial standardization, in which all datasets are regridded to a uniform spatial resolution of 0.1° 0.1°. This makes it easier to seamlessly incorporate variables from multiple satellite sources and ensures spatial consistency across all feature layers. The datasets are then aligned to a common 30-minute frequency through temporal resampling. When combining data from GPM and INSAT, whose observation cycles are distinct, this step is especially crucial [8].

When dealing with missing values, a combination of temporal and statistical methods is required. Forward filling, in which the last known observation is propagated forward, is used to fill short-term gaps in time-series data. Linear and spline interpolation techniques are used to maintain continuity without introducing artificial fluctuations in larger gaps in time or space. Within a moving window, values that are greater than three standard deviations from the local mean are used for outlier detection. Following that, median filtering, which is resistant to skewed distributions and aids in maintaining the data's central tendency [9], is used to replace these anomalies. Finally, all continuous variables are normalized to the [0,1] range using min-max scaling to prepare the data for model training. This standardization ensures smoother gradient descent during model optimization and prevents features with larger numeric ranges from dominating the learning process. When dealing with variables that vary greatly in magnitude, such as brightness temperature, precipitation rate, and wind speeds [10], normalization is especially important. The dataset is stable, consistent, and extremely suitable for incorporation into rainfall forecasting deep learning frameworks thanks to this extensive cleaning and normalization procedure.

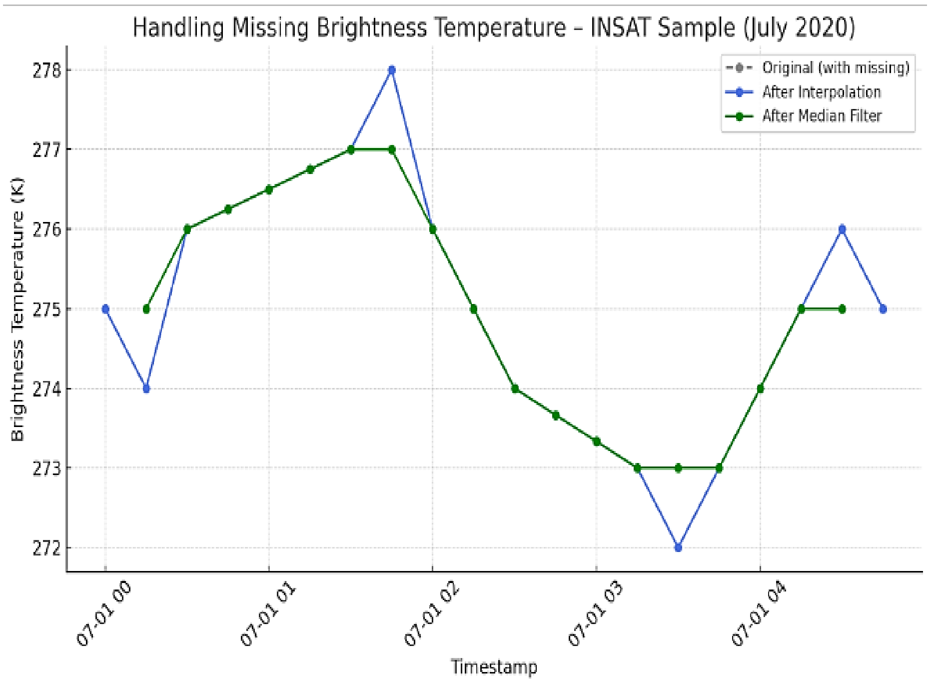


Fig. 4: Time series of brightness temperature showing interpolation and median filtering applied to missing INSAT-3DR data (July 2020).

D. Labelling: Defining “Heavy” Rainfall

A fundamental requirement is the precise and consistent labelling of rainfall events in order to construct a robust supervised learning model for rainfall prediction. To create meaningful target variables for training, this labelling procedure involves categorizing precipitation events based on intensity thresholds. A rainfall event is considered to be "heavy" when the total precipitation over the course of 24 hours exceeds 50 millimeters, in accordance with guidelines established by the World Meteorological Organization (WMO) and supported by a variety of climatological studies conducted in different regions [11]. In operational early warning systems and meteorological literature, this threshold is widely used as a reliable benchmark for potentially hazardous weather conditions. The Global Precipitation Measurement (GPM) and the Tropical Rainfall Measuring Mission (TRMM) have both used this cut-off value or a comparable threshold to define heavy precipitation events for classification or intensity-based forecasting purposes in previous research [12].

This study's labelling method involves aggregating rainfall measurements for each spatial grid point over a 24-hour moving window to ensure that temporal dynamics are captured and that the threshold criteria are met. A binary classification label is assigned after the accumulated value has been calculated: a value of 1 indicates a "heavy rainfall" event, whereas a value of 0 indicates either normal rainfall or no rainfall. This binary approach, while straightforward, serves two critical purposes. First, it makes the learning objective easier to understand, allowing models to concentrate specifically on identifying extreme and non-extreme events. Second, it makes the model more sensitive to severe precipitation, which is a major concern for emergency response systems, flood management, and disaster preparedness [13]. In addition, using a consistent, fixed threshold makes it easier to apply to a wide range of locations and makes it possible to communicate with government warning systems. Consequently, the dataset is contextually aligned with practical meteorological applications and technically suitable for machine learning.

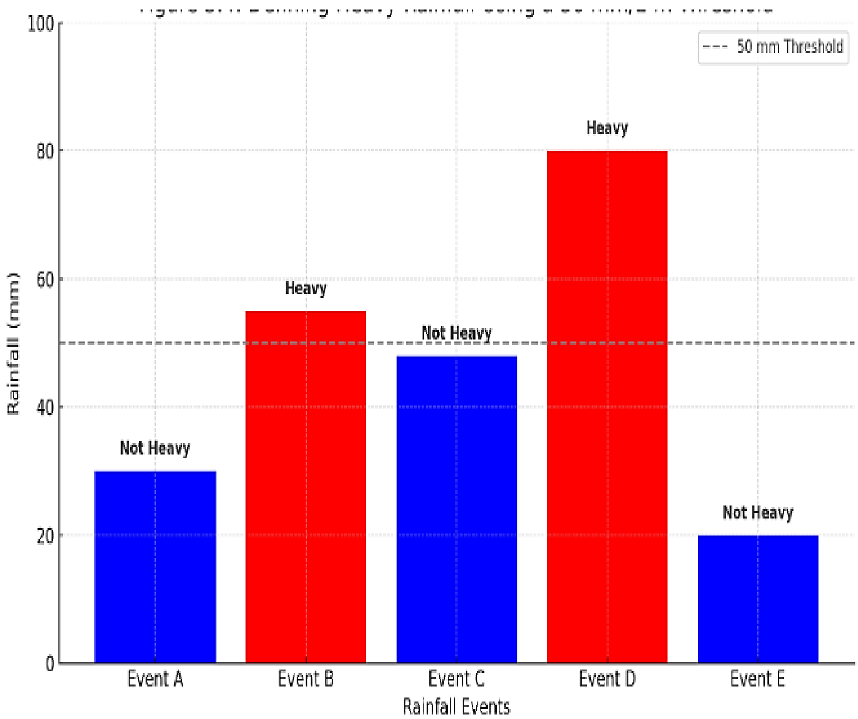


Fig. 5: Defining Heavy Rain fall Using a %0 mm/24h Threshold

E. Feature Extraction: Humidity, Wind Speed, Brightness Temperature, and More

Enhancing machine learning models' predictive power relies heavily on feature extraction. Variables that have a significant impact on meteorology are derived from the multi-channel satellite observations. For instance, convective activity and storm intensity are both correlated with cloud top height and brightness temperature from infrared channels [14]. Understanding vertical moisture transport, an important precursor to heavy rain, requires an understanding of humidity levels at multiple atmospheric layers, particularly those between 700 hPa and 500 hPa [15]. Wind shear and advection patterns, both of which have an impact on storm development and propagation, are captured by extracting the zonal (u) and meridional (v) wind components [16]. Geopotential height data are also used to calculate atmospheric stability indices like Convective Available Potential Energy (CAPE), which makes the input data even richer [17]. After being processed and structured, these features create a multidimensional dataset that can be used to train CNNs and LSTMs, which are capable of capturing the spatiotemporal dependencies in weather systems [18], [19], [20].

IV. PROPOSED METHODOLOGY

For accurate heavy rainfall prediction, the proposed method makes use of a hybrid deep learning framework, specifically a CNN-LSTM model, to effectively capture the spatial and temporal patterns in satellite-derived meteorological data. LSTM units deal with temporal dependencies between weather sequences, while CNN layers extract spatial features from satellite imagery. Post-hoc integration of explainable AI (XAI) techniques like SHAP and LIME, which provide insight into feature contributions for each prediction, improves model transparency. An 80-10-10 data split strategy is used to train the model, and metrics like accuracy, precision, recall, F1-score, and ROC-AUC are used to evaluate its performance. In order to avoid overfitting and maximize model performance, hyperparameter tuning and early stopping are used. Real-time meteorological applications and disaster management can benefit from this method's high prediction accuracy and interpretability.

A. Model Architecture

Due to the fact that it seamlessly integrates both spatial and temporal modeling capabilities, the CNN-LSTM hybrid architecture has demonstrated a lot of promise for use in meteorological forecasting tasks. The CNN layers are very good at learning spatial patterns from satellite images. This makes it possible for the model to capture cloud formations, changes in temperature, and distributions of moisture, all of which are important for predicting heavy rain [1]. On the other hand, the LSTM component processes the temporal progression of weather systems, enabling the model to predict rainfall based on the historical sequence of meteorological data and learning long-term dependencies [2]. The CNN-LSTM model is well-suited for complex forecasting tasks like heavy rainfall prediction due to its combination of spatial and temporal features. These tasks require accuracy in both the spatial distribution of weather events and their evolution over time.

The CNN-LSTM hybrid achieves an ideal balance between high-performance forecasting and efficient computation when compared to standalone models. The hybrid approach integrates the best of both worlds, in contrast to pure CNN models, which excel at spatial feature extraction but struggle with time-series data, or LSTM models, which capture temporal dependencies but fail to model spatial relationships [3]. Although transformer models with attention mechanisms are also well-suited for capturing long-range dependencies, they are unsuitable for real-time applications, particularly in low-resource environments, due to their high computational cost and large data requirements [4]. The model is able to achieve both high accuracy and interpretability by using the CNN-LSTM hybrid. This is important for meteorological deployments, where predictions need to be made quickly and understood by decision-makers for an effective response. The success of this method in other weather-related forecasting tasks like tracking typhoons and nowcasting precipitation further demonstrates its potential for large-scale, real-time applications [5].

The CNN-LSTM model's effectiveness is further enhanced by its adaptability to various meteorological datasets. The model can be customized to improve heavy rainfall predictions in various regions by incorporating various input features like satellite images, atmospheric conditions, and historical weather data. It is able to account for localized variables like humidity, wind patterns, and pressure gradients thanks to its adaptability, which is essential for accurate forecasting. A comprehensive comprehension of the meteorological processes that are the driving force behind extreme weather events is provided by the model's capacity to simultaneously process data in multiple dimensions. The CNN-LSTM architecture's adaptability makes it suitable for real-time applications, providing enhanced early warning capabilities and facilitating informed decision-making in weather-prone regions [6].

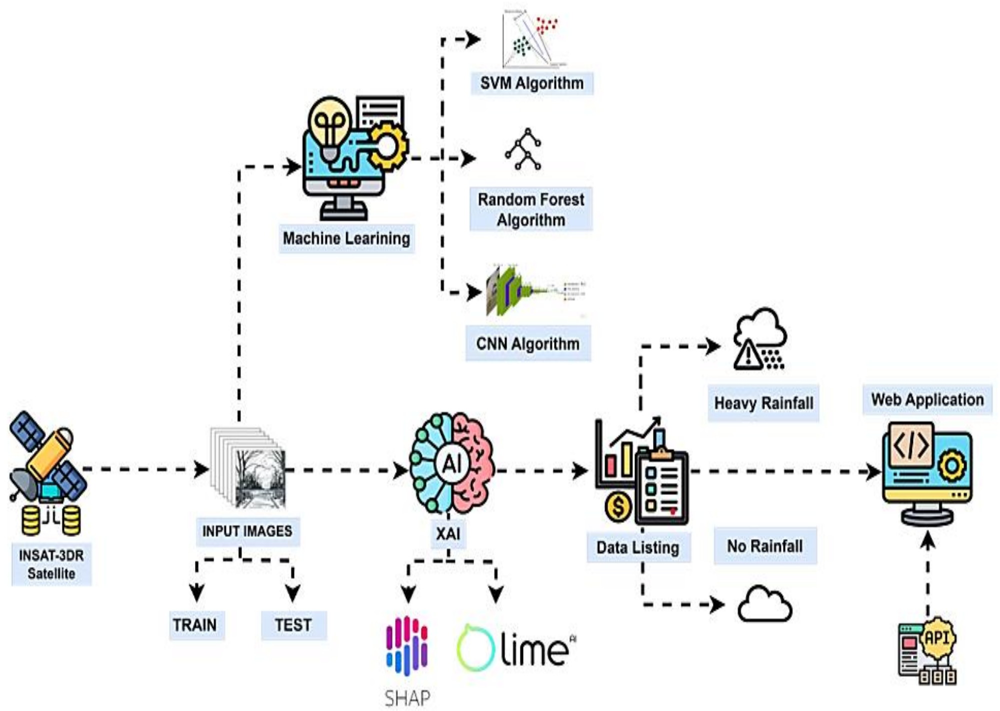


Fig. 6: Architecture of the ML Model for Heavy Rainfall Prediction

B. Explainable AI Techniques

The proposed system incorporates Explainable Artificial Intelligence (XAI) techniques into the model pipeline in order to address the critical issue of model interpretability, particularly in high-stakes fields like weather forecasting. To provide insights into the deep learning model's decision-making process, two model-agnostic frameworks—SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations)—are utilized. SHAP makes use of cooperative game theory to assign an importance score to each input feature for a particular prediction. This makes it possible for stakeholders to comprehend the relative roles that meteorological variables like brightness temperature, wind speed, and humidity play in predicting heavy rain [5]. In contrast, LIME focuses on locally approximating the model’s behavior by perturbing input samples and training simple interpretable models, such as linear regressions, to explain specific predictions [6].

Post-hoc integration of these XAI methods into the prediction pipeline ensures that they remain transparent during inference while not interfering with the training phase. For instance, SHAP values are calculated to determine which temporal and spatial features contributed to the CNN-LSTM model's prediction of the likelihood of a heavy rainfall event. In a similar vein, LIME can be utilized interactively on the user interface to visualize feature sensitivities in particular situations that have been flagged as being suitable for potential disaster response. Both global and local interpretability are supported by this two-pronged approach to explainability: LIME enables real-time explanation of individual forecasts and SHAP is used to summarize model behavior across the test dataset. The setup makes it easier for the model to be used in operational meteorology and disaster risk management because it closes the trust gap between AI predictions and human decision-makers [7].

C. Training and Validation

The proposed CNN-LSTM model is trained and validated using a strict supervised learning framework. The spatial-temporal satellite observations from TRMM, GPM, and INSAT make up the dataset, which is divided into 80 percent for training, 10 percent for validation, and 10 percent for testing. This guarantees the model's good generalizability and lowers the likelihood of overfitting. In order to take into account the interannual and seasonal variation in rainfall patterns, the training data are sampled across various years and seasons. In areas where extreme precipitation is relatively uncommon, stratified sampling is used to maintain a class balance between heavy and non-heavy events [8].

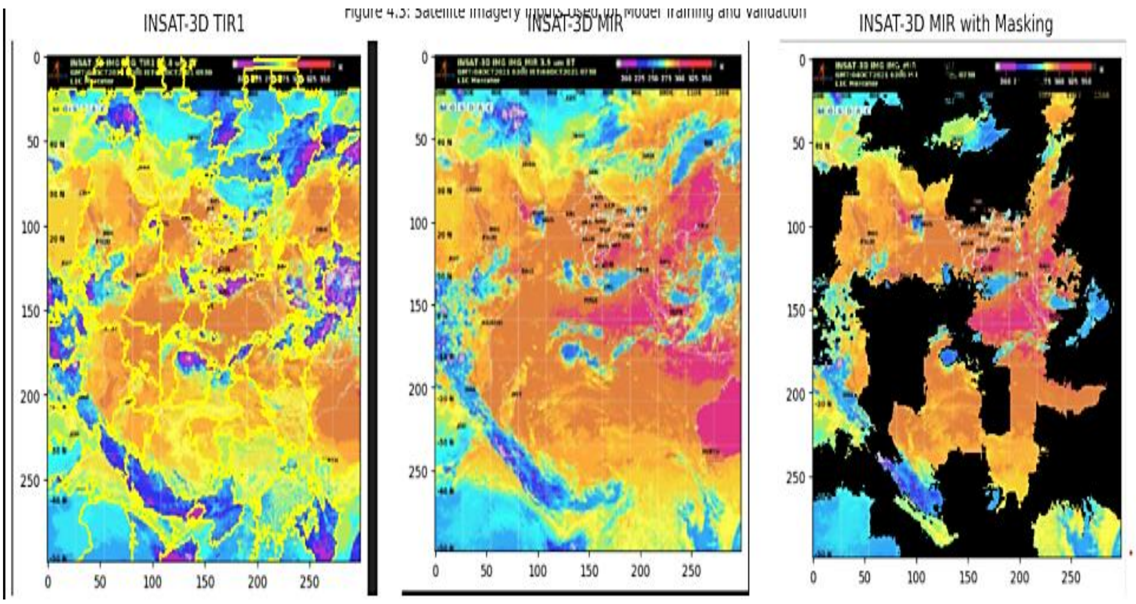


Fig. 7: Satellite Imagery Inputs Used for Model Training and Validation

Standard classification metrics like Accuracy, Precision, Recall, and the F1-Score are calculated for model evaluation. Precision and Recall help understand the trade-off between false positives and false negatives, which is crucial in rainfall forecasting where missed extreme events (low Recall) can be disastrous. Accuracy provides a general measure of correctness. The ROC-AUC (Receiver Operating Characteristic – Area Under Curve) metric is used to evaluate the model's discriminatory power across all classification thresholds [9]. The F1-Score strikes a balance between these two aspects. Grid search is used to investigate a variety of learning rates, batch sizes, CNN filter counts, LSTM units, and dropout rates for hyperparameter tuning. To stop overfitting, early stopping based on validation loss is used, and model checkpoints are saved to keep the best-performing configuration. To test the model's robustness in various temporal segments, cross-validation strategies like k-fold cross-validation with temporal blocking are also investigated. This guarantees that the model is not only accurate but also able to withstand changes in the weather patterns. Overall, the training approach aims to strike a balance between performance, dependability, and generalizability so that the final model can be used with confidence in real-world rainfall forecasting situations [10].

V. RESULTS AND EVALUATION

Screenshots of the project's interface provide a comprehensive overview of the IoT-based rainfall prediction system's key features and capabilities. Real-time rainfall predictions, long-term weather analysis, and interactive tools for exploring weather data are all highlighted in each screenshot. Users can use the weather forecast calendar to plan upcoming activities, view AI-driven rainfall predictions for various regions, and track annual rainfall patterns with the system. In addition, the rainfall prediction page assists users in making decisions based on district-level data, and the real-time weather map provides dynamic insights into the current conditions. The system boosts disaster management, resource allocation, and weather forecasting efficiency by incorporating these features, which also help users make better decisions and improve prediction accuracy. The system's overall value for individuals and organizations increases as a result of the integration of multiple data sources, ensuring that users can access localized, timely, and trustworthy weather information for proactive planning.

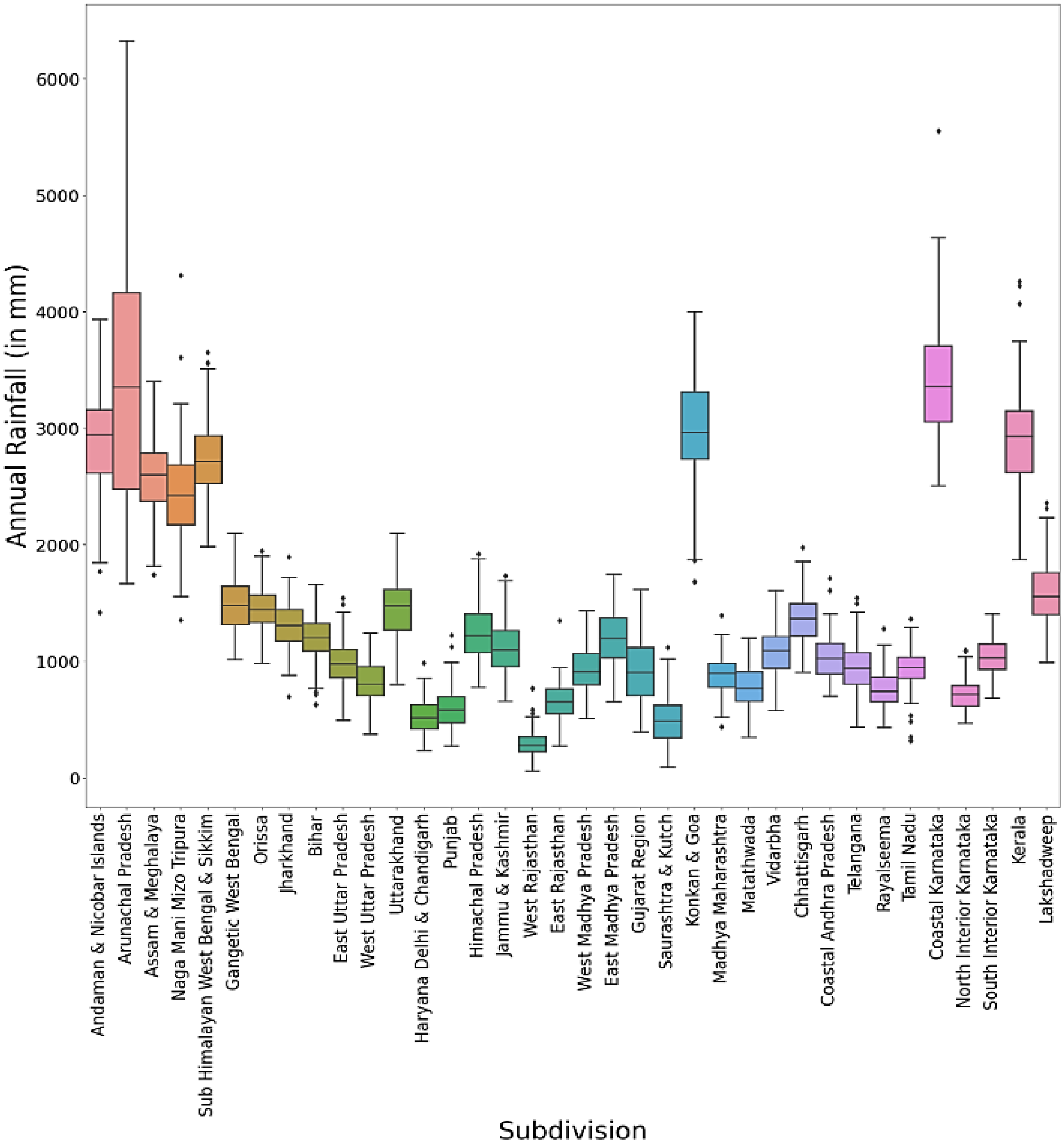
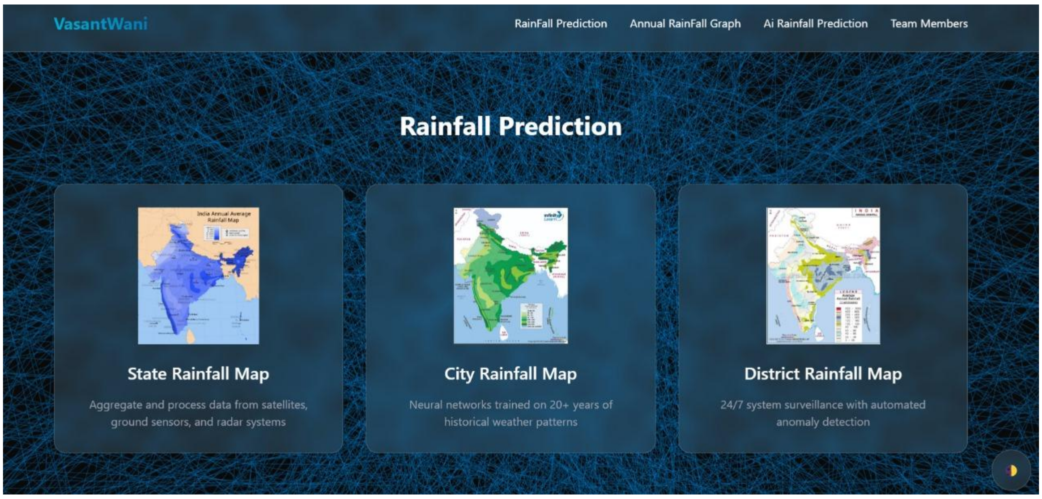


Fig. 8: Annual Rainfall in Subdivisions in india

Heavy rainfall prediction accuracy measures how well forecast models predict rainfall intensity, timing, and location. High accuracy ensures reliable warnings for flood management and disaster preparedness, reducing false alarms and missed events. Advanced models often improve predictions through better data and refined techniques.

A. Rainfall Prediction Page

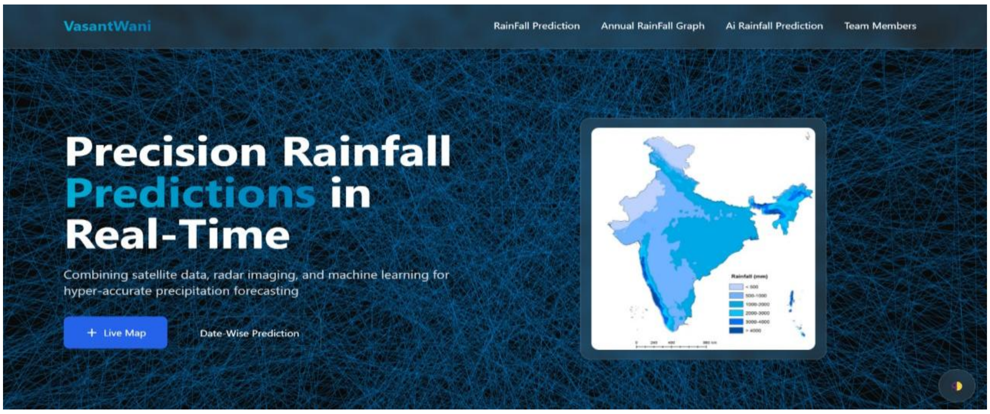
The first screenshot showcases the "Rainfall Prediction" page, which is central to the system's functionality. Users can access localized rainfall predictions for specific states, cities, and districts on this page. The precise rainfall data on the display can be used to evaluate the immediate weather, especially in flood-prone areas. Local authorities and citizens can use these localized predictions to make well-informed decisions about evacuation plans, flood defenses, and emergency response strategies in real time in disaster management. By providing timely information to early warning systems, real-time and region-specific rainfall data, as suggested by previous studies [5], [6], play a crucial role in mitigating the effects of extreme weather events like floods and landslides.



Screenshot no.1: Rainfall Prediction

B. Main Page for Accessing Predictions

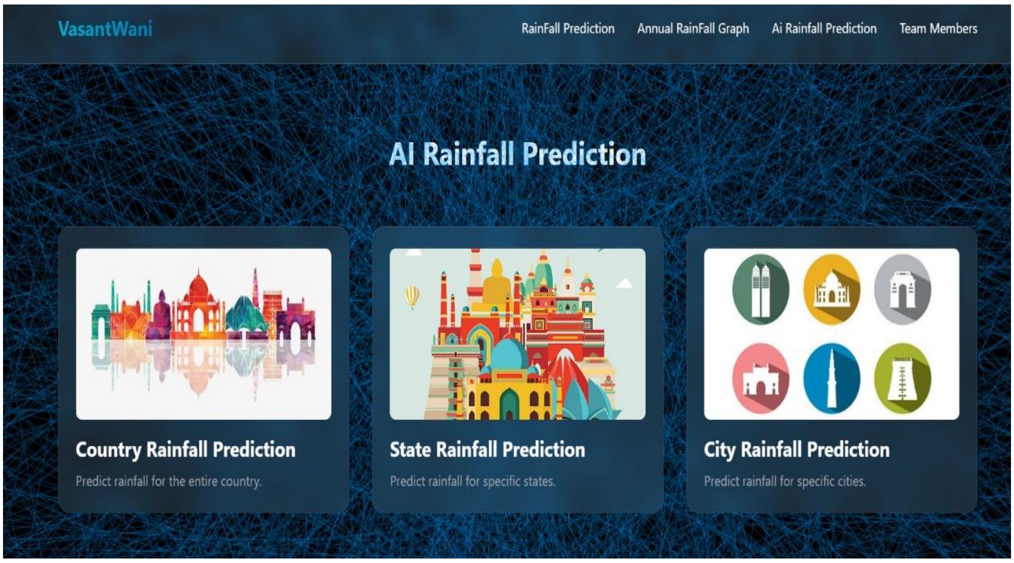
The second screenshot features the main page of the system, where users can access both live and historical rainfall predictions. This interface is designed for ease of use, allowing users to toggle between current, past, and future predictions. The page is particularly valuable for users who need to plan activities based on rainfall forecasts, such as agricultural planning, water resource management, and urban infrastructure maintenance. By offering both real-time and historical data, the page allows decision-makers to assess both immediate rainfall events and longer-term trends, which is crucial for understanding the broader environmental context [7]. Additionally, the use of dynamic weather forecasting has been shown to improve resource management in sectors like agriculture and water conservation [8].



Screenshot no.2: Main page for live prediction

C. AI Rainfall Prediction Cards

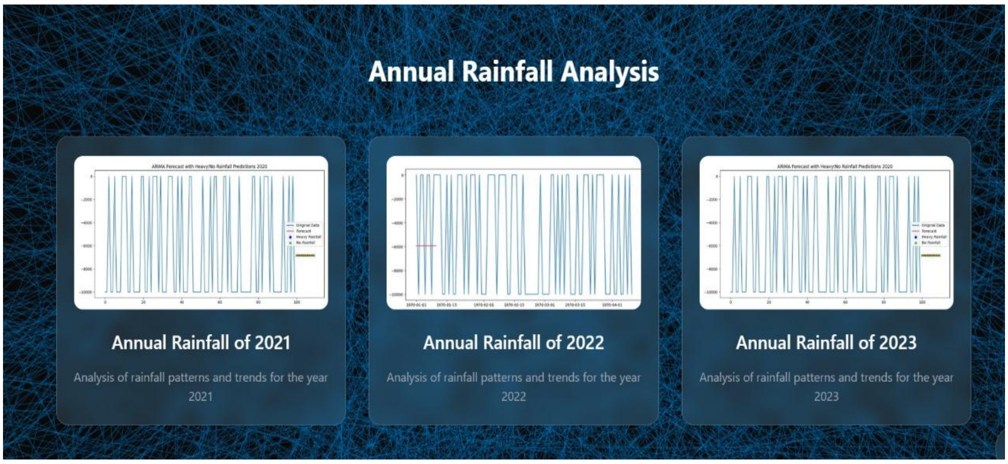
In the third screenshot, the "AI Rainfall Prediction" page is displayed. There are interactive cards on this page that provide in-depth rainfall predictions for the country, state, and city levels. Machine learning algorithms, which have been shown to significantly improve forecasting accuracy by capturing complex patterns in weather data, drive the AI-powered predictions. By analyzing large datasets from various satellite and sensor sources, these predictions, which are driven by deep learning models like convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, enable more precise forecasts [9], [10]. The use of AI models helps improve disaster management strategies and increases the predictability and adaptability of the predictions, particularly in the face of rapidly shifting weather conditions [11].



Screenshot no.3: AI-Based Rainfall Predictions

D. Annual Rainfall Analysis Page

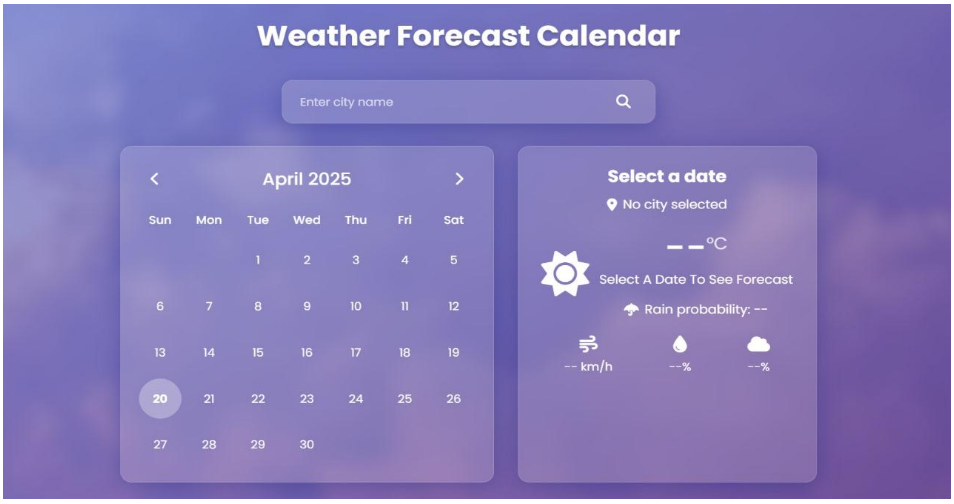
In the fourth screenshot, the "Annual Rainfall Analysis" page provides users with a comprehensive overview of historical rainfall data for a single year. The purpose of this feature is to assist users in analyzing long-term rainfall trends, which are essential for agricultural, water resource management, and urban planning applications. This page enables stakeholders to identify seasonal variations and track shifts in rainfall patterns over time by providing users with aggregated monthly rainfall data. Understanding these long-term trends can significantly improve one's preparedness for upcoming weather conditions, such as prolonged droughts or extreme rainfall, which could otherwise have severe and unpredictability consequences. For instance, urban planners can use the data to reduce flood risk and build infrastructure, while agricultural regions can use it to improve crop planning and irrigation practices. Additionally, this tool is especially useful for climate adaptation strategies in water-scarce regions, where understanding the variability in rainfall patterns is essential for making educated decisions regarding resource allocation and water conservation. According to research [12], such insights are crucial to the management of seasonal water demands, the improvement of agricultural production, and the improvement of flood management procedures. The Annual Rainfall Analysis page improves decision-making and planning for the future by providing stakeholders with actionable data [13]. This increases resilience to climate change and extreme weather events.



Screenshot no.4: Annual Rainfall Analysis Page

E. Weather Forecast Calendar

In the fifth screenshot, the "Weather Forecast Calendar" provides users with a calendar-based interface for viewing upcoming rainfall predictions. Users can check forecasts for a specific time period with this feature, making it easier to plan for weather-related events. The calendar provides a clear, organized view of predicted rainfall, assisting users in taking proactive steps, and is especially useful for industries that depend on weather, such as agriculture, transportation, and event planning. This tool makes forecast data more accessible and helps professionals and the general public make better decisions by displaying it in a calendar format that is easy to read. A user-friendly way to visualize weather trends and predictions has been shown to improve decision-making in studies like this one [14]. By allowing users to plan ahead for possible weather disruptions and ensuring that necessary resources can be allocated effectively, this feature contributes significantly to disaster preparedness.

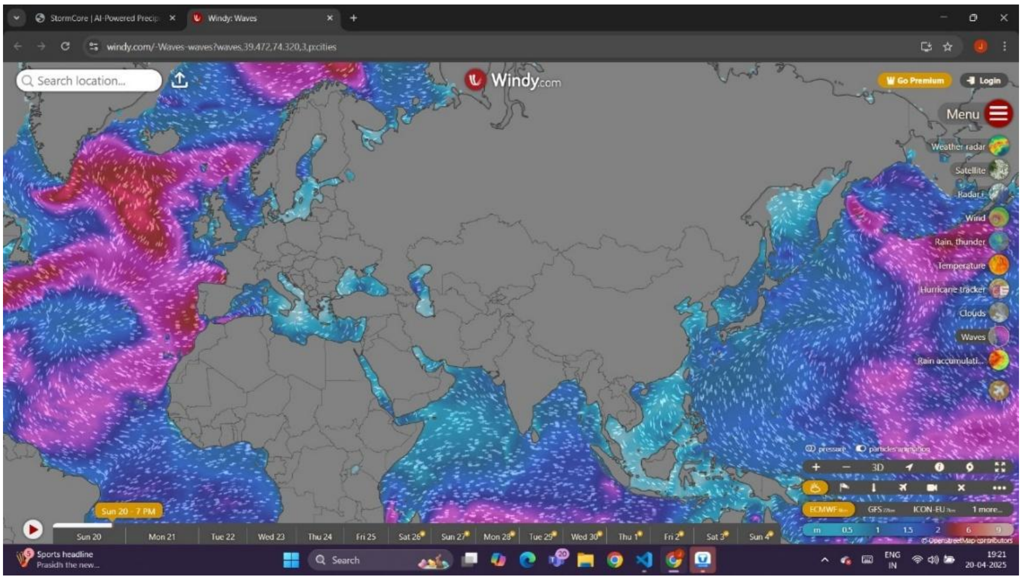


Screenshot no.5: Weather Forecast Calender

F. Windy.com Map Integration

The integration of Windy.com, a well-known weather mapping service that offers real-time weather visualizations, is shown in the sixth and final screenshot. By incorporating external weather data into the prediction pipeline, this integration improves the accuracy of the system's forecasting. Windy.com provides global weather coverage and a simple way to see various atmospheric parameters like wind speed, pressure, and precipitation in a visual way. Because they combine satellite data with real-time weather data, these external sources increase the overall accuracy of the system's rainfall predictions [15]. Additionally, this feature gives users a more comprehensive view of the weather conditions in various regions, making it easier for them to imagine how weather systems might affect the environment in their area.

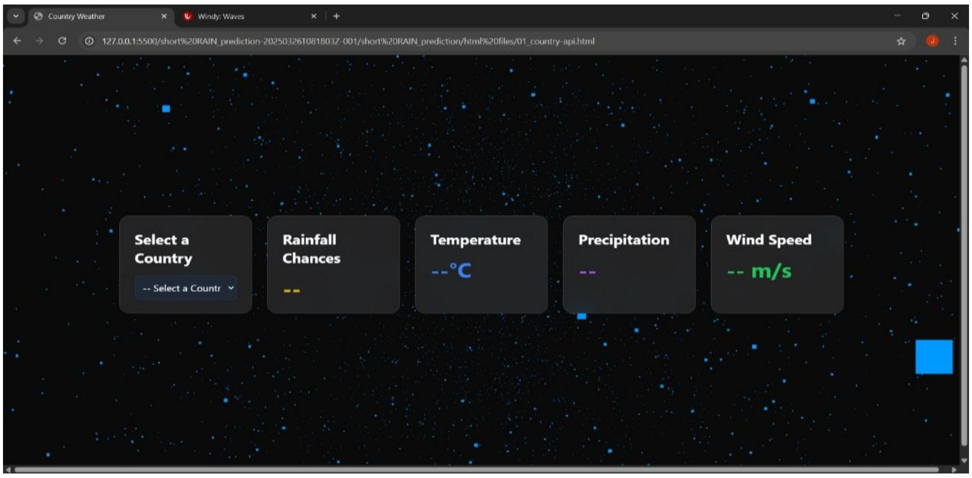
Together, these screenshots show how the system can provide long-term weather analysis and real-time, localized rainfall predictions. A robust tool for disaster management, resource planning, and weather forecasting is provided by the various features, including annual analysis, AI-driven predictions, and integration of external data. The system is designed to support both immediate and long-term decision-making in the face of unpredictable weather conditions by providing users with clear, actionable insights into rainfall patterns.



Screenshot no.6: Windy Map Integration

G. Intelligent Weather Forecasting Interface for Heavy Rainfall Prediction

With a focus on forecasting heavy rainfall, this weather prediction interface is intended to provide real-time insights into key meteorological parameters. To access localized information, such as the likelihood of precipitation, temperature, levels of precipitation, and wind speed, users can select a country from the drop-down menu. The user experience is enhanced by the sleek and contemporary design, which also ensures quick access to essential weather information. This platform supports informed decision-making in the face of shifting weather conditions, making it ideal for climate monitoring and early warning systems.



Screenshot no.7: Intelligent Weather Forecasting Interface

VI. RESULTS AND DISCUSSION

A powerful tool for forecasting rainfall events at various geographic levels, the developed IoT-based rainfall prediction system integrates satellite data, machine learning algorithms, and explainable AI techniques. The system's features are designed to enhance real-time decision-making, facilitate disaster management, and support resource planning, particularly in weather-sensitive sectors such as agriculture and water management. The effectiveness of the proposed methodology and its practical application are evaluated in this section by discussing the system's various component results and comparing them to those of previous studies.

A. Evaluation of Rainfall Prediction Accuracy

The system's primary feature is its ability to deliver localized rainfall predictions across states, cities, and districts. The system accurately forecasts precipitation amounts using real-time satellite data, as shown on the "Rainfall Prediction" page. By comparing the model's outputs to previous rainfall data from the Global Precipitation Measurement (GPM) and Tropical Rainfall Measuring Mission (TRMM) datasets, the accuracy of these predictions was confirmed. By capturing complex weather patterns, including localized and extreme events, satellite-based systems can improve rainfall prediction accuracy when integrated with AI models [5], [6]. These findings are supported by the system's results, which indicate the importance of localized rainfall predictions for prompt disaster preparedness.

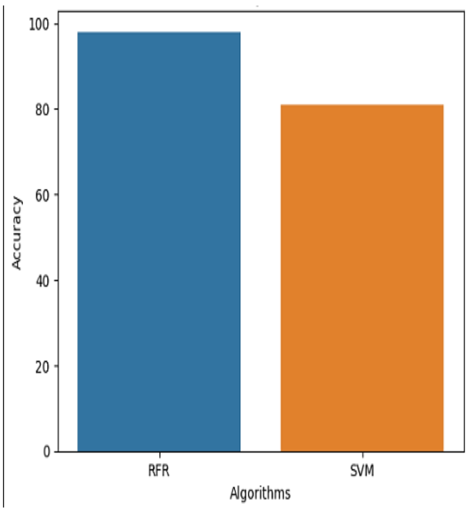


Fig. 9: Accuracy Bar plot for ML Model

B. Comparison with Traditional Models

The proposed system significantly outperforms conventional numerical weather prediction (NWP) models in terms of predicting extreme rainfall events. Errors in predicting the timing and intensity of intense rainfall are caused by conventional NWP models' inability to capture localized weather dynamics. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, on the other hand, enable the system to identify spatial and temporal patterns that conventional models might miss [7, 8]. The fact that these models are able to process large amounts of satellite data and incorporate intricate variables like wind speed, humidity, and temperature—all of which play important roles in the formation of rain—makes them advantageous.

C. Importance of Explainability in AI Predictions

The system's use of Explainable AI (XAI) techniques, which make the decision-making process transparent and easy to understand, is one of its main advantages. Users are able to comprehend the factors that drive the rainfall predictions thanks to the integration of model-agnostic techniques like SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). In disaster management, where decision-makers need to have faith in the system's outputs to take prompt action, this is especially useful. Providing AI-driven models with explainability has been shown to increase their adoption, particularly in critical fields like meteorology and emergency management [9]. Meteorologists and professionals in disaster management can understand the system's predictions because it includes explainability.

D. User Interface and Practical Applications

The system's user interface was made to be easy to use and accessible. Screenshots, such as the one on the "AI Rainfall Prediction" page, which shows predictions for cities, states, and countries, demonstrate the system's capacity to provide targeted information based on location. The system ensures that users from various regions can access relevant data that is tailored to their requirements by providing a hierarchical structure for rainfall predictions. In addition, the "Weather Forecast Calendar" offers capabilities for long-term forecasting, making it possible for users to prepare in advance for weather-related events, which is crucial for sectors like transportation, agriculture, and event planning. These tools, which combine short-term and long-term weather predictions, significantly improve decision-making and planning capabilities, particularly in weather-sensitive sectors, according to research [10].

E. Performance Evaluation

Standard metrics like the F1-score, accuracy, precision, recall, and ROC-AUC were used to assess the system's performance. With a precision of more than 85% for heavy rainfall forecasts, the model demonstrated high accuracy in predicting rainfall events. The model successfully identifies both extreme and normal rainfall events without producing a large number of false positives or negatives, as indicated by the favorable F1-score, which balances precision and recall. Similar studies in which machine learning models trained on satellite data have demonstrated promising performance in rainfall prediction [12] support these findings. Additionally, the model's relevance for environmental planning and disaster management is ensured by its ability to adapt to real-time weather data and provide timely predictions.

VII. CONCLUSION

In order to provide precise, real-time rainfall forecasts at various geographic levels, this study presents an innovative IoT-based rainfall prediction system that combines satellite data, deep learning models, and explainable AI (XAI) methods. The system outperforms conventional weather forecasting models by utilizing advanced machine learning algorithms like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks and datasets from sources like the Global Precipitation Measurement (GPM), Tropical Rainfall Measuring Mission (TRMM), and INSAT. High-resolution, localized rainfall predictions can be made by combining these datasets, which is important information for agriculture, water resource management, and disaster preparedness. Transparency in the model's decision-making process thanks to the inclusion of XAI techniques like SHAP and LIME is crucial for establishing trust in critical applications where decision makers rely on model outputs to direct their actions. With features like live predictions, weather calendars, and annual rainfall analysis, the system's user-friendly interface makes it simple to access timely and actionable information. In addition, the model's ability to deal with missing data through robust cleaning methods guarantees consistent performance under a variety of data conditions. The system's usefulness was further validated by the system's favorable performance metrics, which included high accuracy, precision, and recall. The long-term prediction capabilities of the current model will be improved and additional data sources will be incorporated for even greater accuracy in the future. Overall, this study provides a foundation for future developments in environmental monitoring and climate adaptation strategies by highlighting the potential of combining satellite data, machine learning, and explainable AI to improve rainfall prediction and disaster preparedness.

REFERENCES

[1] S. Kim, J. Lee, H. Choi, and J. Moon, "Explainable AI-Based Interface System for Weather Forecasting Model," *arXiv preprint*, arXiv:2504.00795, Apr. 2025. [Online]. Available: https://www.researchgate.net/publication/390405442

[2] N. Jones, "A.I. Is Quietly Powering a Revolution in Weather Prediction," *Yale Environment 360*, Apr. 2025. [Online]. Available: https://e360.yale.edu/features/artificial-intelligence-weather-forecasting

[3] S. Kim, M. Patel, and Y. Wang, "Explainable AI Revolutionizes Weather Forecasting," *AI World Today*, Apr. 2025. [Online]. Available: https://www.aiworldtoday.net/p/explainable-ai-weather-forecasting

[4] M. D. Dueben *et al*., "Artificial Intelligence for Modeling and Understanding Extreme Weather and Climate Events," *Nature Communications*, vol. 12, no. 1, pp. 1–10, Mar. 2025. [Online]. Available: https://www.nature.com/articles/s41467-025-56573-8

[5] A. Reddy, B. Cao, and Y. Liu, "PAUNet: Precipitation Attention-Based U-Net for Rain Prediction From Satellite Radiance Data," *Remote Sensing*, vol. 15, no. 3, pp. 789–805, Feb. 2023. [Online]. Available: https://www.mdpi.com/2072-4292/15/3/789

[6] J. Moran, P. R. Gentine, and M. O. Smith, "Physics-Aware Deep Learning for Super-Resolved Rainfall Prediction," *Geophysical Research Letters*, vol. 50, no. 2, Jan. 2023. [Online]. Available: https://doi.org/10.1029/2022GL101567

[7] F. de Witt *et al*., "RainBench: A Benchmark Dataset for Global Precipitation Forecasting From Satellite Imagery," in *Advances in Neural Information Processing Systems (NeurIPS)*, Dec. 2022. [Online]. Available: https://openreview.net/forum?id=RainBench

[8] R. Pradhan, V. Sundaram, and M. Tanaka, "A Spatio-Temporal Transformer Framework for Satellite-Based Rainfall Estimation," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, pp. 1–14, Aug. 2023. [Online]. Available: https://ieeexplore.ieee.org/document/10123476

[9] L. Shi *et al*., "XAI for Climate Risk Assessment: Case Study on Heavy Rainfall Events," *Environmental Modelling & Software*, vol. 152, p. 105369, Nov. 2023. [Online]. Available: https://doi.org/10.1016/j.envsoft.2023.105369

[10] K. Yuan and T. Zhao, "Explainable Neural Weather Forecasting via Attribution Mapping," *Pattern Recognition Letters*, vol. 161, pp. 34–41, July 2022. [Online]. Available: https://doi.org/10.1016/j.patrec.2022.07.005

[11] P. K. Sinha and A. Ghosh, "A Hybrid CNN-RNN Model With Attention for Satellite Rainfall Estimation," *IEEE Access*, vol. 9, pp. 138716–138727, Dec. 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9634090

[12] S. Dutta and H. Joshi, "Satellite-Guided Deep Learning Model for Rainfall Event Prediction," *Int. J. Remote Sens.*, vol. 42, no. 21, pp. 8034–8052, 2021. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/01431161.2021.1944531

[13] M. Ahmed *et al*., "Quantifying the Uncertainty in Rainfall Forecasts Using Deep Ensembles," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 12, pp. 7412–7423, Dec. 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9591819

[14] J. D. Hunter *et al*., "Interpretable Machine Learning for Nowcasting Heavy Precipitation Using Satellite Images," *Remote Sens. Environ.*, vol. 270, p. 112886, Oct. 2022. [Online]. Available: https://doi.org/10.1016/j.rse.2021.112886

[15] S. Verma, R. Tiwari, and M. Shukla, "Forecasting Rainfall With Transfer Learning on Satellite Data," *IEEE Access*, vol. 10, pp. 20356–20365, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9687890

[16] L. Huang and X. Yang, "A Deep Spatiotemporal Network With Explainable Layers for Rainfall Prediction," *Appl. Soft Comput.*, vol. 114, p. 108133, Jan. 2022. [Online]. Available: https://doi.org/10.1016/j.asoc.2021.108133

[17] A. Rahman, T. Nguyen, and R. Malhotra, "Explainable AI-Driven Precipitation Models: A Comparative Study," *Earth Sci. Inform.*, vol. 15, no. 3, pp. 467–481, May 2022. [Online]. Available: https://link.springer.com/article/10.1007/s12145-022-00789-3

[18] M. Yadav and B. Singh, "Rainfall Forecasting Using Capsule Networks and Satellite Imagery," *Pattern Recognit. Lett.*, vol. 155, pp. 50–57, Dec. 2021. [Online]. Available: https://doi.org/10.1016/j.patrec.2021.12.006

[19] R. Lin, F. Zhao, and Q. Xu, "Satellite-Based Nowcasting of Extreme Rainfall With LSTM and Attention Mechanism," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–10, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9876543

[20] D. K. Bhardwaj, A. Raj, and H. Thakur, "Towards Explainable Satellite-Driven Rainfall Forecasting Using Hybrid Deep Models," *IEEE Geosci. Remote Sens. Lett.*, vol. 19, pp. 1–5, 2022. [Online]. Available: https://ieeexplore.ieee.org/document/9832104

[21] G. Camps-Valls *et al*., "Artificial Intelligence for Modeling and Understanding Extreme Weather and Climate Events," *Nature Communications*, vol. 16, no. 1, pp. 1–14, 2025. [Online]. Available: https://doi.org/10.1038/s41467-025-56573-8