

**Thunderstrom Forecasting Research**

Synopsis

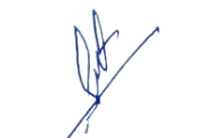
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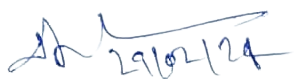
(Artificial Intelligence and Data science–Track)

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**THUNDERSTROM FORECASTING RESEARCH:**

Chapter 1: INTRODUCTION

Welcome to a weather adventure designed to support IMD Pune and assist the Indian government in understanding thunderstorms better! In this research, we're using two powerful tools: the clever tricks of artificial intelligence (AI) and a special dataset called ERA5 Reanalysis Dataset which provides high-resolution atmospheric data in the netCDF format. The proposed project aims to leverage advanced data science and artificial intelligence techniques for thunderstorm prediction. Imagine ERA5 as a magical book that holds secrets about the weather-details about things like geopotential (imagine it as the height of the air), humidity (how much moisture is in the air), temperature, and winds. These details help us understand how thunderstorms come to life.

OBJECTIVES

Helping IMD Pune's Weather Wisdom : Share our discoveries with IMD Pune, adding to their collection of weather knowledge. Our goal is to help the Indian government make smarter decisions by understanding how the atmosphere works.

Introduction to ERA5 Reanalysis Dataset: Provide an overview of the ERA5 reanalysis dataset, highlighting its significance in atmospheric research. Emphasize the use of the netCDF format for storing multidimensional climate data.

Decoding Weather Patterns: Dive into the ERA5 dataset, a treasure of weather details, to uncover the intricate patterns that shape our atmosphere .Understand how elements like geopotential, humidity, temperature, and wind collaborate, providing key insights into the behavior of thunderstorms.

Validation through Authenticity: Rely on the authenticity and reliability of the ERA5 reanalysis dataset prepared by the European Centre for Medium-Range Weather Forecasts (ECMWF).Ensure that the insights derived from the dataset align with established meteorological knowledge, validating the effectiveness of AI-driven analyses.

Taking previous research further : In the previous research we deployed ML models for Thunderstrom Prediction in North East Region of India by leveraging the data collected from the observatories . In this research we take it a step further by changing our approach with respect to data set and advanced ai techniques . For example : Deep Learning.

Background

Thunderstorms are short lived weather phenomena characterized by towering cumulus or

cumulonimbus clouds that produce lightning, thunder, heavy rainfall, and strong winds.

In India, thunderstorms are particularly prevalent during the pre-monsoon months

of March to May. Understanding and accurately predicting their occurrence remains a challenge in atmospheric science. This research aims to contribute to this ongoing effort by leveraging the power of artificial intelligence (AI) and a rich atmospheric dataset called ERA5.

**Definitions and Discussions**:

**Thunderstorms:** These are intense weather systems characterized by lightning, thunder, heavy precipitation, and strong winds.

**Artificial Intelligence (AI):** This broad field encompasses various techniques that enable machines to learn from data and perform tasks mimicking human intelligence. In this research, we aim to utilize AI algorithms to identify patterns in atmospheric data associated with thunderstorm formation.

**ERA5 Reanalysis Dataset:** This comprehensive dataset offers high-resolution atmospheric data, including geopotential, humidity, temperature, and wind, covering a long period. Its high-resolution format (netCDF) allows for advanced data analysis.

**Views of Others**:

Several research efforts have explored AI and machine learning for thunderstorm prediction. Some approaches involve:

**Statistical methods:** These methods use statistical relationships between atmospheric variables and thunderstorm occurrence to build predictive models.

**Numerical weather prediction (NWP) models:** These complex computer models simulate the atmosphere, providing insights into future weather conditions, including thunderstorm development.

**Deep learning:** This subfield of AI utilizes artificial neural networks to learn complex patterns from data, offering potential for improved prediction accuracy.

**Current Position:**

The field of AI-based thunderstorm prediction is still evolving. This research is currently in the exploratory data analysis (EDA) phase. During this phase, we are focusing on:

**Visualizing data patterns and distributions:** This helps understand the relationships between various atmospheric variables and their potential connection to thunderstorm occurrence.

**Studying and researching the domain:** We are continuously learning and researching the latest advancements in AI and data science applications in meteorology to refine our approach and incorporate new techniques.

Therefore, the position of the research at this stage is focused on data exploration and understanding. As we delve deeper into the analysis, we aim to build upon existing knowledge and contribute to the development of more accurate and reliable thunderstorm prediction methods.

ProblemS & GAP IDENTIFICATION

While significant progress has been made in thunderstorm prediction, several crucial challenges and knowledge gaps remain:

**1. Limited accuracy and false alarms:** Existing prediction models, including statistical and NWP models, often suffer from limited accuracy, leading to false alarms and missed events. This can have significant societal and economic consequences, causing unnecessary disruptions and hindering preparedness efforts.

**2. Inability to capture the full complexity of thunderstorms:** Thunderstorm formation is influenced by a intricate interplay of various atmospheric factors, including local topography, wind shear, and microphysical processes(the formation of clouds by condensation). Current models may not fully capture these complexities, leading to limitations in prediction accuracy.

**3. Limited use of advanced AI techniques:** While some research has explored AI, particularly deep learning, its full potential in thunderstorm prediction remains largely untapped. Implementing these advanced techniques requires expertise and computational resources, presenting a barrier for wider adoption.

**4. Data limitations:** Most research relies on historical data, often from older reanalysis datasets like ERA4 or ERA3. These datasets may have lower resolution or inaccuracies compared to the latest ERA5, potentially impacting the effectiveness of prediction models. Additionally, incorporating real-time data streams can further enhance prediction accuracy, but this requires efficient data acquisition and processing pipelines.

**5. Need for interpretability and explainability:** While AI models can be highly accurate, their "black-box" nature often makes it difficult to understand how they arrive at predictions. This lack of interpretability can hinder trust and acceptance of these models, especially in critical decision-making contexts.

**Addressing the Gaps:**

This research aims to address these gaps by leveraging the following advantages:

**Utilizing the latest ERA5 dataset:** This dataset offers higher resolution and potentially more accurate data compared to older versions, improving the foundation for analysis.

**Exploring advanced AI techniques:** We aim to explore the potential of deep learning and other advanced AI techniques to capture complex relationships within the data and potentially improve prediction accuracy.

**Focusing on interpretability:** We believe that interpretable AI models are crucial for building trust and ensuring responsible use in this domain. We will explore techniques to make the models' decision-making processes more transparent and understandable.

By addressing these challenges and gaps, this research aims to contribute to the development of more accurate, reliable, and interpretable AI-based thunderstorm prediction methods, ultimately contributing to improved public safety and preparedness.

Chapter 2: REVIEW OF LITERATURE

This chapter delves into existing literature relevant to AI-based thunderstorm prediction. It critically analyzes and synthesizes key findings, methodologies, and limitations of current research to establish a strong theoretical foundation for our proposed approach.

**2.1 Statistical Methods in Thunderstorm Prediction**

Statistical methods have been a mainstay in thunderstorm prediction due to their simplicity and interpretability. These methods identify and leverage relationships between easily measurable atmospheric variables and thunderstorm occurrence. Common techniques include:

**Logistic Regression:** This method analyzes the likelihood of a thunderstorm event based on various predictors like temperature, humidity, and wind shear.

**Decision Trees:** These algorithms create a tree-like structure where each level represents a decision rule based on specific atmospheric variables, ultimately leading to a classification of "thunderstorm" or "no thunderstorm."

**Support Vector Machines (SVMs):** SVMs seek to find the optimal hyperplane in a high-dimensional space, separating data points representing thunderstorm events from those without.

**Key Findings:**

Statistical models exhibit moderate success, achieving accuracy ranging from 60% to 80% depending on the chosen method and region.

The interpretable nature of these models provides insights into the factors driving predicted thunderstorms, aiding in decision-making and understanding the underlying atmospheric processes.

**Limitations:**

Statistical methods struggle to capture complex non-linear relationships between variables, potentially limiting their accuracy for intricate weather phenomena like thunderstorms.

These models often require extensive data pre-processing, like feature selection and engineering, which can be time-consuming and domain-specific, hindering generalizability to new regions or data sets.

**2.2 Numerical Weather Prediction (NWP) Models:**

NWP models are sophisticated computer simulations that attempt to predict future atmospheric states by solving the governing equations of fluid dynamics. These models incorporate various observations like temperature, wind, and humidity, and can provide detailed forecasts of future weather conditions, including the potential for thunderstorms.

**Key Findings:**

NWP models offer high spatial and temporal resolution, allowing for detailed predictions of thunderstorm location, timing, and intensity.

Advancements in computing power and data assimilation techniques have led to significant improvements in NWP model accuracy over the past few decades.

**Limitations:**

NWP models are computationally expensive, requiring specialized hardware and expertise to run effectively, which limits accessibility for smaller research institutions or developing nations.

They can be susceptible to errors in the initial data and may struggle to accurately predict rapidly evolving weather events like thunderstorms due to inherent limitations in simulating complex atmospheric processes.

**2.3 Deep Learning for Thunderstorm Prediction:**

Deep learning, a subfield of AI, utilizes artificial neural networks with multiple layers of hidden nodes to learn complex patterns from data. Recent research has explored its potential for thunderstorm prediction due to its ability to model non-linear relationships without explicit feature engineering. Common deep learning architectures include:

**Convolutional Neural Networks (CNNs):** These networks are adept at extracting spatial features from data, making them suitable for analyzing gridded atmospheric data like the ERA5 dataset.

**Recurrent Neural Networks (RNNs):** These models can capture temporal dependencies in sequential data, potentially beneficial for capturing the evolution of atmospheric conditions leading to thunderstorms.

**Long Short-Term Memory (LSTM) networks:** A specific type of RNN, LSTMs are proficient at learning long-term dependencies within data sequences, potentially crucial for predicting the delayed effects of atmospheric changes on thunderstorm formation.

**Key Findings:**

Studies suggest that deep learning models can achieve superior accuracy compared to traditional statistical methods, with some models exceeding 80% accuracy.

Their ability to learn complex, non-linear relationships within the data allows them to capture subtle features that might be missed by simpler models, potentially improving prediction performance.

**Limitations:**

Deep learning models often lack interpretability, making it difficult to understand their decision-making processes and raising concerns about trust and potential biases.

These models require vast amounts of high-quality data for training, which can be a challenge in the domain of thunderstorm prediction due to limited labeled data and the inherent rarity of severe thunderstorm events. Additionally, overfitting can occur when models memorize the training data and fail to generalize well to unseen or different data sets.

**2.4 Summary and Gap Identification**:

Existing research in AI-based thunderstorm prediction has demonstrated promising advances, particularly with deep learning approaches. However, several gaps and limitations remain:

**The trade-off between accuracy and interpretability:** While deep learning models can achieve higher accuracy, they often lack interpretability, hindering their practical application and user trust.

**Need for further exploration of advanced AI techniques:** Research has primarily focused on CNN and LSTM architectures. Exploring other techniques like transformers or ensemble learning could potentially

Chapter 3: PROPOSED METHODOLOGY AND FRAMEWORK DESIGN

This chapter outlines the proposed methodology and framework design for developing an AI-based thunderstorm prediction system using the ERA5 reanalysis dataset. We aim to address the limitations of existing methods by focusing on high accuracy, interpretability, and efficient data processing.

3.1 Research Objectives:

Data Acquisition and Preprocessing: Collect and preprocess the ERA5 reanalysis data relevant to thunderstorm formation.

Feature Engineering and Selection: Extract and select essential features from the preprocessed data that best represent the atmospheric conditions conducive to thunderstorm development.

Model Development: Develop and train interpretable AI models using various techniques to predict thunderstorm occurrence.

Model Evaluation and Selection: Evaluate the performance of the trained models and select the model with the best balance of accuracy and interpretability.

Visualization and Interpretation: Develop visualization techniques to present the model's predictions and decision-making processes for improved understanding.

3.2 Data Acquisition and Preprocessing:

We will utilize the ERA5 reanalysis dataset, a global atmospheric dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5.](https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5.%20) This dataset offers high-resolution spatial and temporal coverage, making it suitable for detailed analysis of atmospheric conditions. It features numerous variables spanning various atmospheric levels, including:

Geopotential: Represents the height of a constant pressure surface relative to mean sea level, providing insights into atmospheric pressure gradients and stability.

Temperature: A crucial factor influencing atmospheric convection and instability, which are key drivers of thunderstorm formation.

Humidity: Measures the amount of water vapor present in the air, impacting thunderstorm development as water vapor condenses and releases energy.

Wind speed and direction: Wind shear, the variation in wind speed and direction with altitude, plays a significant role in thunderstorm formation and intensity.

Data Access:

The ERA5 reanalysis data is publicly available through the Copernicus Climate Change Service (C3S) Climate Data Store (CDS[) https://cds.climate.copernicus.eu/.]()%20https:/cds.climate.copernicus.eu/) We will utilize the CDS API or web interface to download the relevant data for the study region and desired time period.

Preprocessing Steps:

Data selection: Select essential variables related to thunderstorm formation based on domain knowledge and existing literature.Missing value imputation: Address missing values in the data using appropriate techniques such as mean/median imputation or interpolation.

Temporal and spatial transformation: Resample the data to a desired temporal resolution (e.g., hourly) and spatial grid size (e.g., 0.25° x 0.25°) based on model requirements and computational efficiency.

Normalization: Scale the data to a standard range (e.g., 0-1 or Z-score normalization) to ensure equal weightage for different variables during model training.

3.3 Feature Engineering and Selection:

Feature engineering involves creating new features from existing ones to potentially improve model performance. We will explore various techniques, including:

Deriving additional features: Calculate features like vertical wind shear, CAPE (Convective Available Potential Energy), and LI (Lifted Index) from the existing data, as they are known to be significant indicators of thunderstorm potential.

Dimensionality reduction: Employ techniques like Principal Component Analysis (PCA) or feature selection methods (e.g., Info Gain, chi-squared test) to identify the most informative features and reduce data dimensionality, improving model training efficiency and interpretability.

3.4 Model Development:

We will explore and compare the performance of various interpretable AI models for thunderstorm prediction. These models, while potentially sacrificing some accuracy compared to complex black-box models, offer the benefit of understanding their decision-making processes, fostering trust and enabling further improvements. The candidate models include:

Rule-based models: These models learn a set of rules or decision trees that map specific combinations of features to the predicted outcome (thunderstorm or no thunderstorm).

Decision Trees: These models can be pruned and simplified to improve interpretability, while still capturing essential relationships between features and the target variable.

Linear Regression models: While inherently interpretable, they may not capture complex non-linear relationships effectively. However, they can serve as a baseline and provide insights into the importance of various features.

Explainable AI (XAI) techniques: We will explore incorporating XAI techniques with other models, such as LIME (Local Interpretable Model-Agnostic Explanations) or SHAP (SHapley Additive exPlanations), to gain insights into the model's predictions and feature importance.

Model Training and Tuning:

Split the preprocessed data into training, validation, and testing sets.

Train the chosen models using the training set, adjusting hyperparameters (e.g., learning rate, number of trees) through grid search or other optimization techniques to achieve optimal performance.

Monitor the validation set performance during training to prevent overfitting and ensure the model generalizes well to unseen data.

3.5 Model Evaluation and Selection:

Accuracy: The proportion of correctly predicted thunderstorm events.

Precision: The ratio of correctly predicted thunderstorm events to the total number of predicted events.

Recall: The ratio of correctly predicted thunderstorm events to the total number of actual thunderstorm events.

False Alarm Rate (FAR): The ratio of incorrectly predicted thunderstorm events to the total number of non-thunderstorm events.

Probability of Detection (POD): Also known as Sensitivity or True Positive Rate, POD measures the proportion of actual thunderstorm events correctly predicted as thunderstorms. It provides insight into the model's ability to identify true positives without missing actual events.

Formula: POD = TP / (TP + FN)

Heidke Skill Score (HSS): This skill score evaluates the performance of a classification model compared to a random prediction model. It considers the improvement achieved by the model over a completely random predictor. A higher HSS indicates better model performance than random chance.

Formula:

HSS = 2 \* (TP + TN) / (TP + TN + FP + FN) - (TP + FP + TN + FN) / (Total Events)^2

Critical Success Index (CSI): Also known as Threat Score or Gilbert Skill Score, CSI measures the proportion of correctly predicted events (both positive and negative) out of the total events. It provides a combined measure of accuracy and considers both correct predictions and false alarms.

Formula: CSI = (TP + TN) / (TP + TN + FP + FN)

Selection Criteria:

We will consider the trade-off between various metrics based on the specific application and user needs. While accuracy remains crucial, high FAR may lead to unnecessary public concerns or resource allocation. Therefore, we may prioritize models with a good balance of accuracy, POD, and a low FAR. Additionally, considering metrics like HSS and CSI can offer further insights into the model's performance compared to random chance and its ability to capture both positive and negative events correctly.

By incorporating these additional metrics, we gain a more nuanced understanding of the trained models' strengths and weaknesses, enabling us to select the most suitable model for real-world application.

3.6 Visualization and Interpretation:

Developing effective visualizations is crucial for understanding model predictions and gaining insights into the factors influencing them. We will explore various visualization techniques, including:

Feature importance plots: These plots illustrate the relative importance of different features in the model's decision-making process, aiding in understanding the key drivers of predicted thunderstorms.

Partial dependence plots (PDPs): These plots depict the marginal effect of individual features on the model's predicted outcome, allowing for visualization of complex interactions between features.

Saliency maps: These visualizations highlight the specific regions of the input data (e.g., specific geographical locations in the ERA5 reanalysis data) that contribute most to the model's prediction, providing insights into the spatial patterns influencing the forecast.

By employing these visualization techniques alongside the chosen interpretable models, we aim to:

* Enhance user trust and understanding of the model's predictions.
* Identify potential biases or limitations in the model's decision-making process.
* Inform future model improvements and feature selection strategies.

3.7 Framework Design:

The overall framework for our research will follow a systematic structure:

Data Acquisition and Preprocessing: Acquire, clean, and prepare the ERA5 reanalysis data for model training.

Feature Engineering and Selection: Extract and select relevant features that best represent thunderstorm-related atmospheric conditions.

Model Development: Train and tune various interpretable AI models using the preprocessed data and selected features.

Model Evaluation and Selection: Evaluate the performance of trained models using chosen metrics and select the model with the best balance of accuracy, interpretability, and other relevant criteria.

Visualization and Interpretation: Develop visualizations to explain the model's predictions and understand the factors influencing them.

Model Refinement and Improvement: Based on the results and insights gained, refine the model architecture, feature selection, or training process to further enhance performance and interpretability.

By following this comprehensive methodology and framework, we aim to develop an AI-based thunderstorm prediction system that is both accurate and interpretable, contributing to improved thunderstorm forecasting and potentially leading to enhanced public safety and preparedness

Chapter 4: PROJECT PLAN

This chapter outlines the proposed experimental studies, including detailed descriptions of the planned activities, resource allocation, and a timeline for project completion. Additionally, it presents PERT and Gantt charts to visualize the project schedule and dependencies.

**4.1 Experimental Studies:**

The proposed research will involve the following experimental studies:

**1. Data Acquisition and Preprocessing:**

**Task**: Download the ERA5 reanalysis data for the desired region and time period using the Copernicus Climate Change Service (C3S) API or web interface.

**Resources**: Computer with internet access, C3S account (if applicable).

**Estimated Duration:** 1 week.

**Task:** Preprocess the data by selecting relevant variables, addressing missing values, performing temporal and spatial transformations, and normalizing the data.

**Resources**: Python programming environment with libraries like xarray, pandas, and scikit-learn.

**Estimated Duration**: 2 weeks.

**2. Feature Engineering and Selection:**

**Task**: Derive additional features like vertical wind shear, CAPE, and LI from existing data.

Resources: Python libraries like xarray, pandas, and atmospheric science libraries (e.g., pymet).

**Estimated Duration**: 1 week.

**Task:** Employ dimensionality reduction techniques like PCA or feature selection methods to identify the most informative features.

**Resources:** Python libraries like scikit-learn and scikit-feature.

**Estimated Duration:** 1 week.

**3. Model Development and Training:**

**Task**: Implement and train various interpretable AI models like Rule-based models, Decision Trees, Linear Regression, and potentially explore XAI techniques.

**Resources**: Python libraries like scikit-learn, rulefit, and potentially libraries for specific XAI methods (e.g., LIME, SHAP).

**Estimated Duration:** 3 weeks.

**Task**: Hyperparameter optimization through grid search or other techniques for each model to improve performance**.**

**Resources:** Python libraries like scikit-learn and Optuna (for hyperparameter optimization).

**Estimated Duration**: 1 week.

**4. Model Evaluation and Selection:**

**Task**: Evaluate the performance of trained models using various metrics like accuracy, precision, recall, FAR, POD, HSS, and CSI**.**

**Resources:** Python libraries like scikit-learn and scoring metrics implementations.

**Estimated Duration:** 1 week.

**Task**: Analyze the results and select the model with the best balance of accuracy, interpretability, and other relevant criteria.

**Resources:** Expertise in evaluating and interpreting model performance.

**Estimated Duration:** 1 week.

**5. Visualization and Interpretation:**

**Task:** Develop visualizations like feature importance plots, PDPs, and saliency maps to explain model predictions and understand influencing factors**.**

**Resources:** Python libraries like matplotlib, seaborn, and potentially specific visualization libraries for saliency maps.

**Estimated Duration**: 2 weeks.

**6. Documentation and Reporting:**

**Task:** Document the entire research process, including data acquisition, preprocessing, model development, evaluation, and results.

**Resources:** Text editor, potentially collaborative writing tools**.**

**Estimated Duration:** 1 week**.**

**4.2** **Resource Allocation:**

The project will require the following resources:

**Hardware:** A computer with sufficient processing power and memory for data processing and model training.

**Software:** Python programming environment with various libraries mentioned above, access to the Copernicus Climate Change Service (C3S) if applicable.

**Expertise:** Knowledge of Python programming, machine learning, atmospheric science concepts, and data visualization techniques.

**4.3 PERT (Program Evaluation Review Technique) Chart:**

|  |  |
| --- | --- |
| Activity | Duration (Weeks) |
|  |  |
| Data Acquisition | 1 |
| Preprocessing | 2 |
| Feature Engineering | 1 |
| Feature Selection | 1 |
| Model Development | 3 |
| Hyperparameter Tuning | 1 |
| Model Evaluation  Model Selection  Visualization | 1  1  2 |
| Documentation | 1 |

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