KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY (KIIT)

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Weather Forecasting

using Explainable AI (XAI)

OUR TEAM

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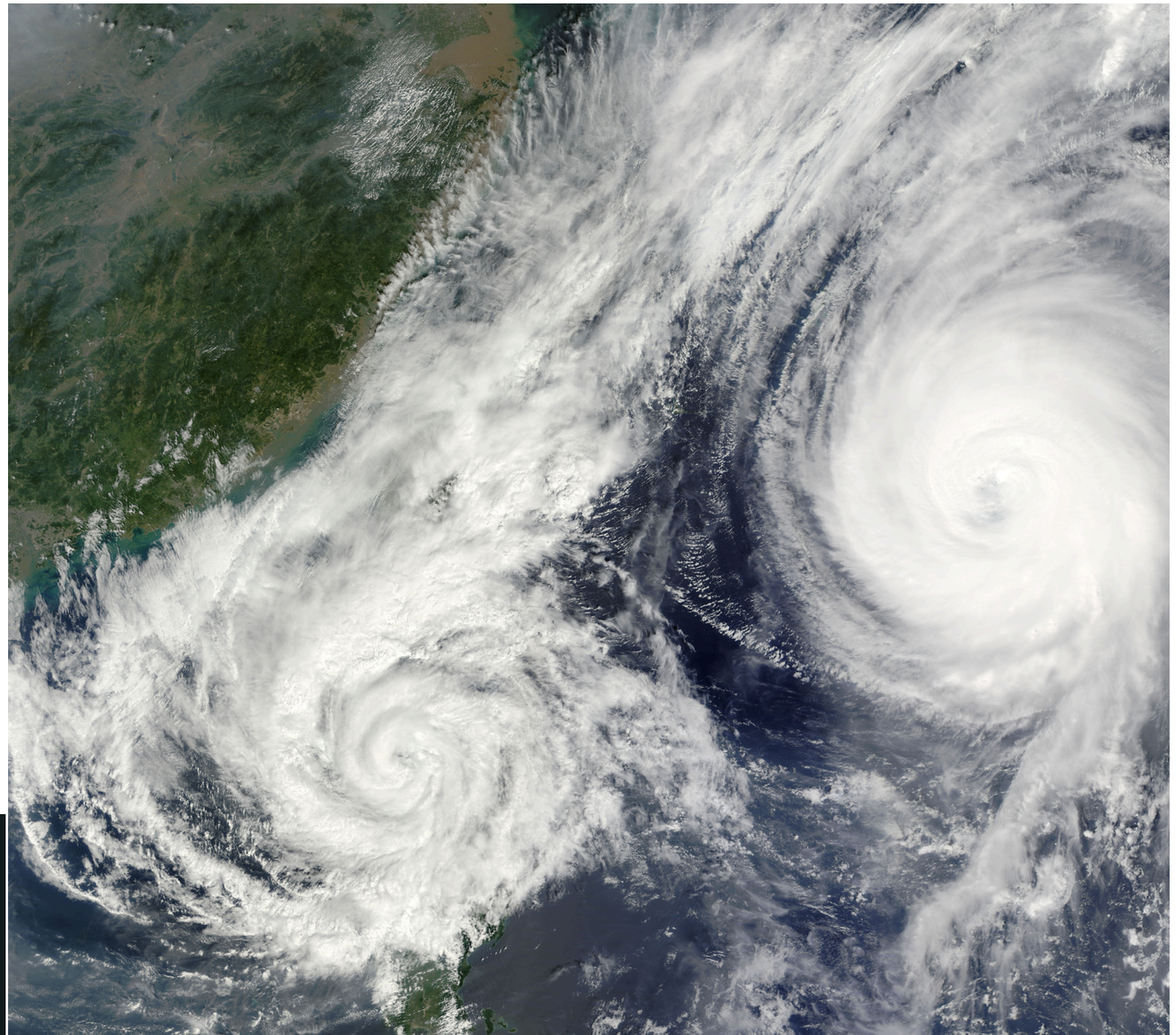
DISCUSSION OUTLINE



Report Coverage

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Introduction

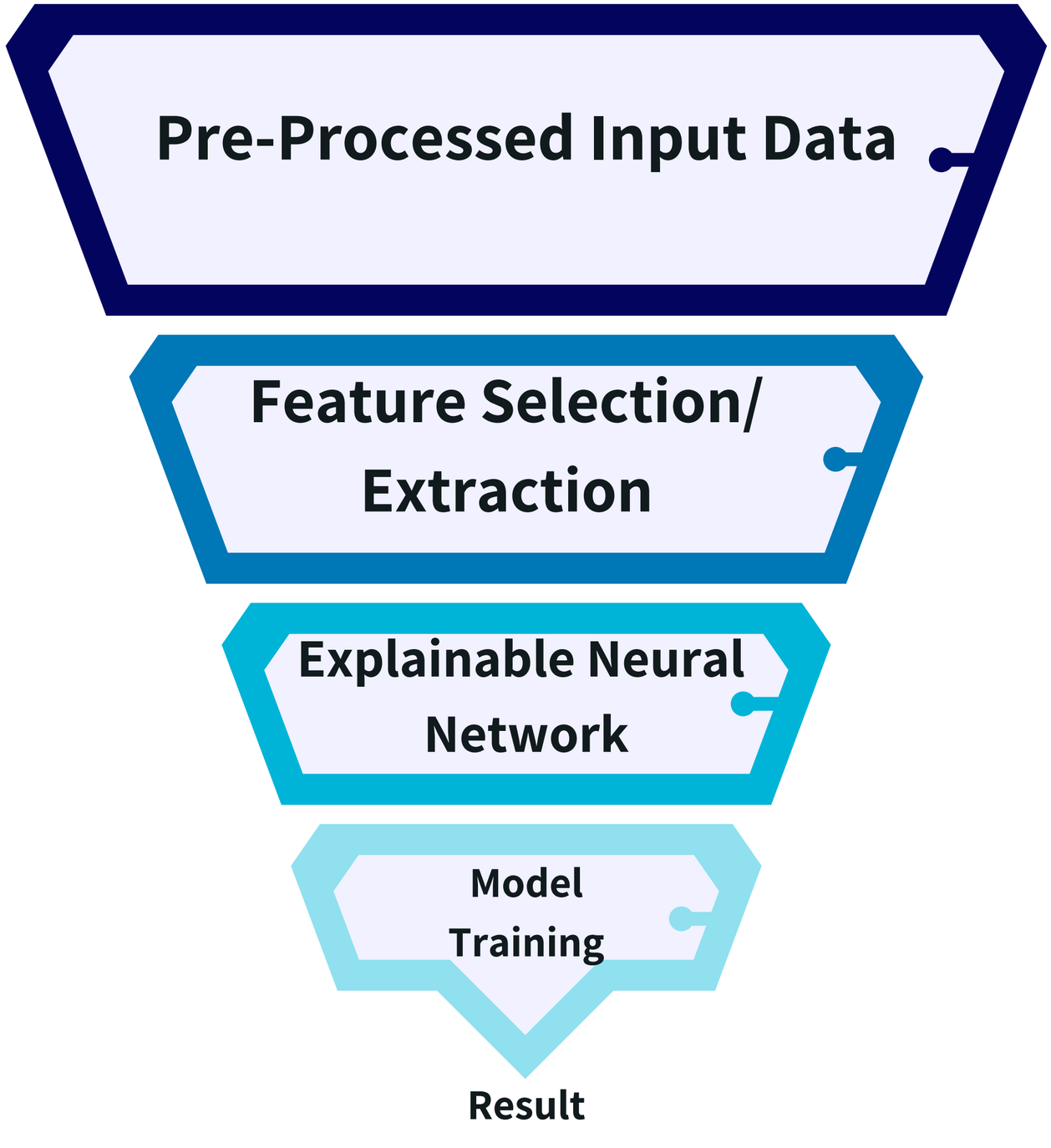
- **Explainable AI (XAI)** is an emerging field with applications in improving the transparency and trustworthiness of AI systems across domains like healthcare, finance, and weather forecasting.
- In this project, we leverage XAI techniques to develop a robust and interpretable weather forecasting model. The goal is to enhance the accuracy of predictions while ensuring that the decision-making process is transparent and understandable to both experts and non-experts.

EXPLAINABLE AI (XAI) FOR WEATHER FORECASTING

Objective

- Our objective is to build an explainable AI (XAI) system that can accurately forecast weather patterns and provide interpretable insights into the factors influencing predictions.

- We aim to achieve high accuracy and real- time performance.



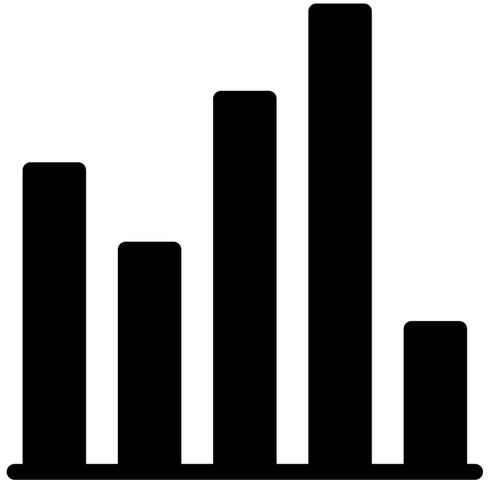
Steps

- Pre-Processed Input Data
- Feature Selection/Extraction
- Explainable Neural Network
- Model Training/ Code
- Explainable Output Generation

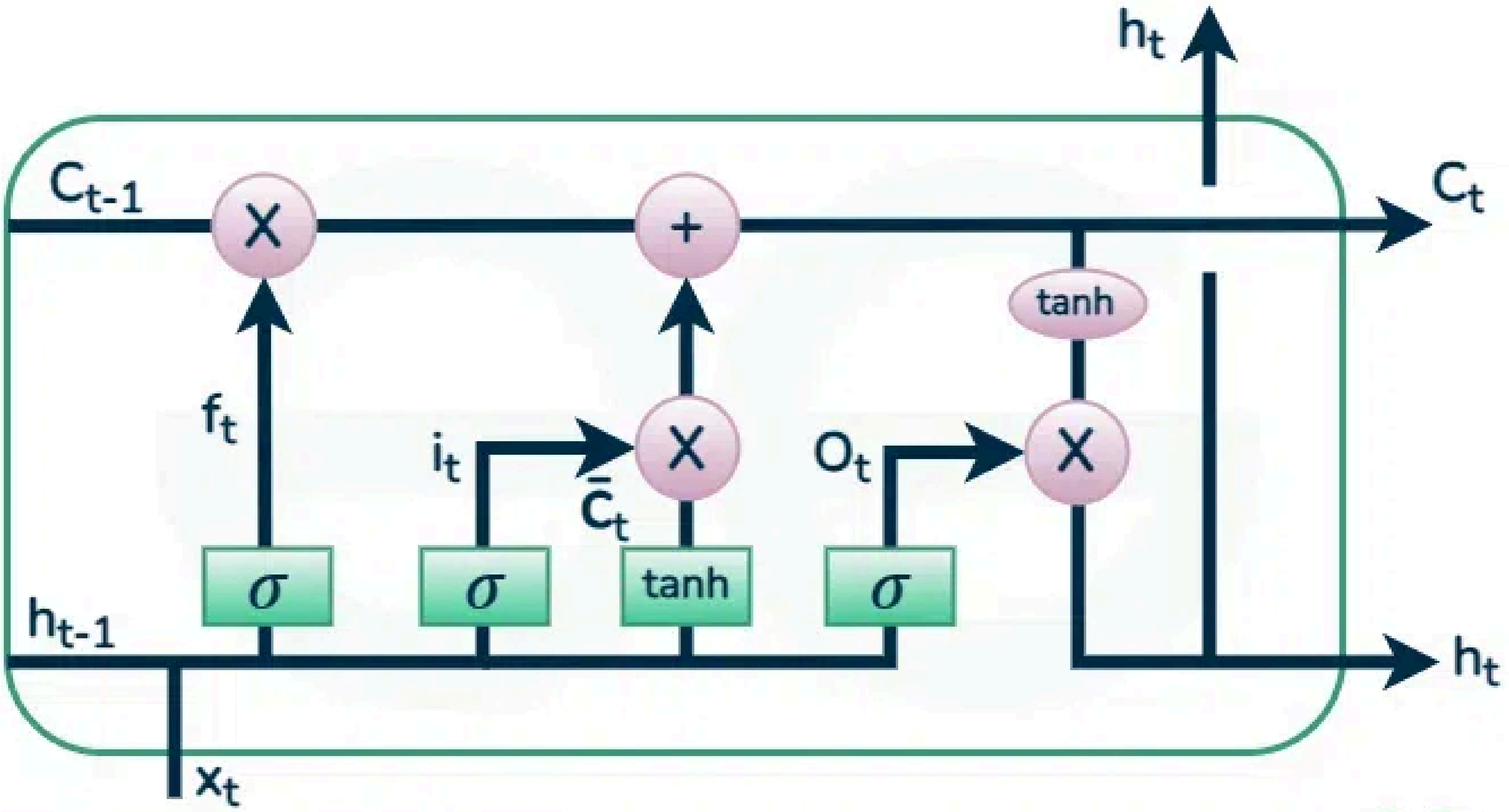
Steps involved in our approach:

1. **Data Aquisition**: Acquiring a diverse dataset of historical and real-time weather data, including temperature, humidity, wind speed, and precipitation.
2. **Preprocessing**: Cleaning and standardizing the data, handling missing values, and transforming variables to ensure consistency and usability.
3. **Model Training**: Training the AI model using advanced architectures like LSTM for sequential data, augmented with Explainable AI techniques for interpretability.
4. **Testing and Evaluation**: Evaluating the model's performance on unseen data to assess accuracy and the clarity of explanations provided by XAI methods.

Model Architecture



- We employed a neural network architecture integrated with Explainable AI techniques for weather forecasting.
- The model leverages a combination of recurrent layers, such as Long Short-Term Memory (LSTM), to capture temporal patterns in weather data and explainability modules to interpret its predictions.
- Our architecture includes attention mechanisms to highlight influential features, ensuring the model provides insights into the factors driving the forecast. Techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can be used to improve interpretability and foster trust in predictions.



LSTM (Long Short Term Memory)

APPROACH AND EXECUTION STRATEGY

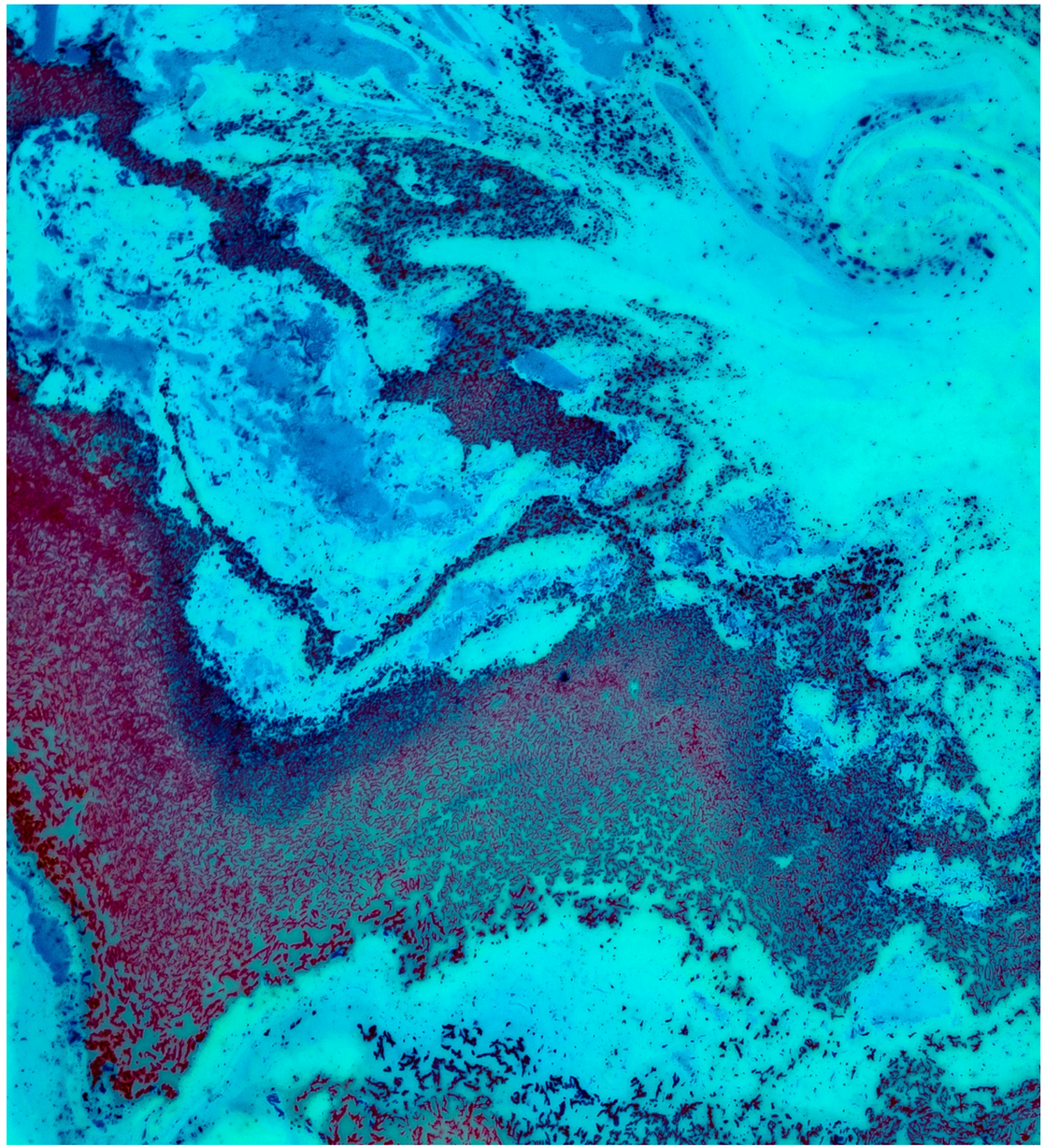
Methodology Overview:

Pre-Processed Input Data

- Cleaning and normalizing weather data, including removing outliers, filling missing values, and scaling features for consistency.

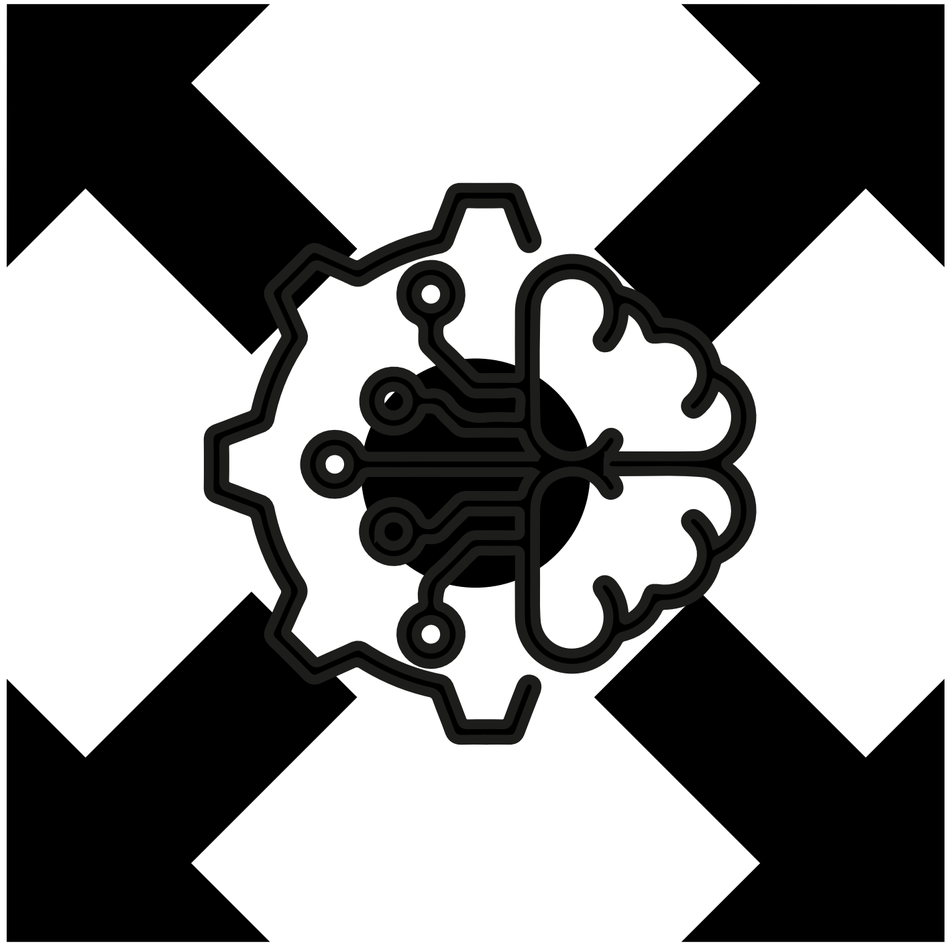
Feature Selection/Extraction

1. Identifying and creating meaningful features from raw weather data, such as calculating moving averages or derived indicators like humidity index.



Explainable Neural network

1. Implementing a backpropagation-based neural network architecture LSTM, to model sequential and complex relationships in weather patterns.



Practical Application

Code Structure

1. Data Collection & Preprocessing

2. Feature Engineering

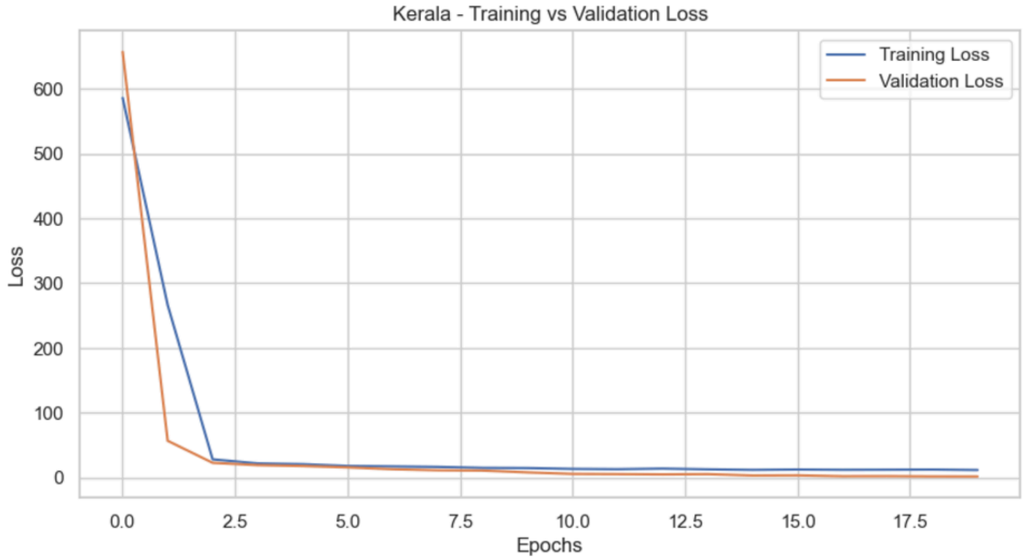
3. Model Training (Region-wise)

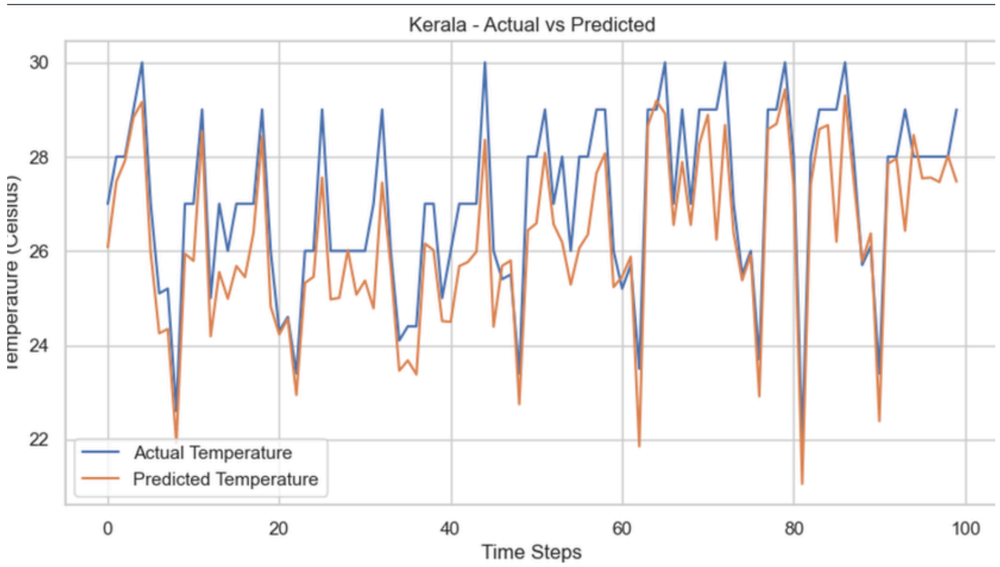
4. Region-wise Prediction

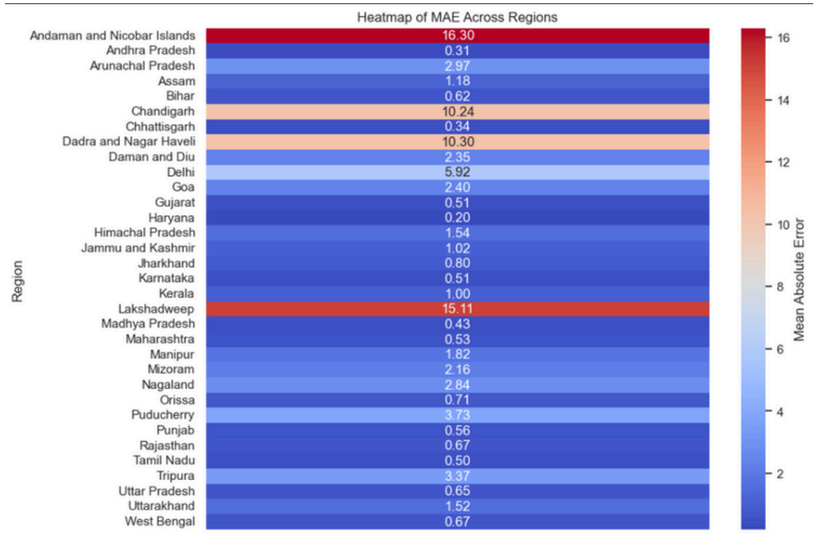
5. Evaluation & Metrics

6. Visualization

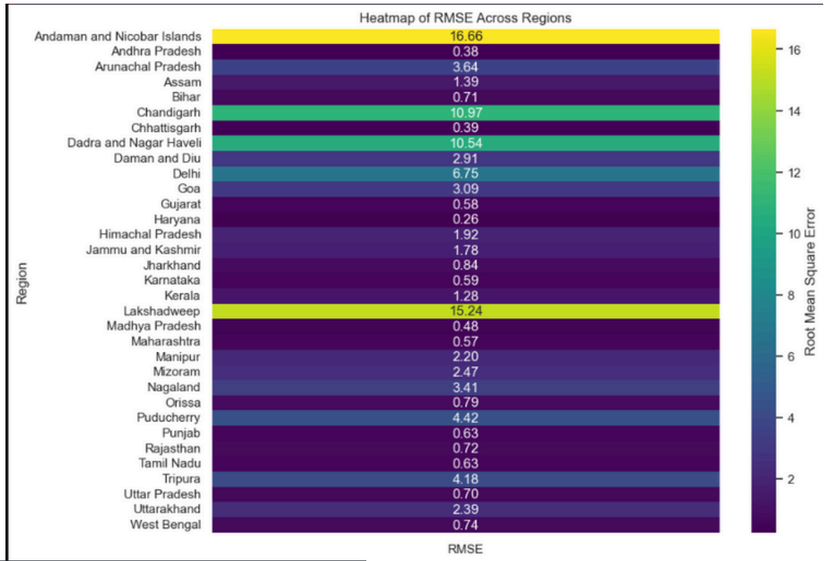
7. Explainable AI (XAI) Integration

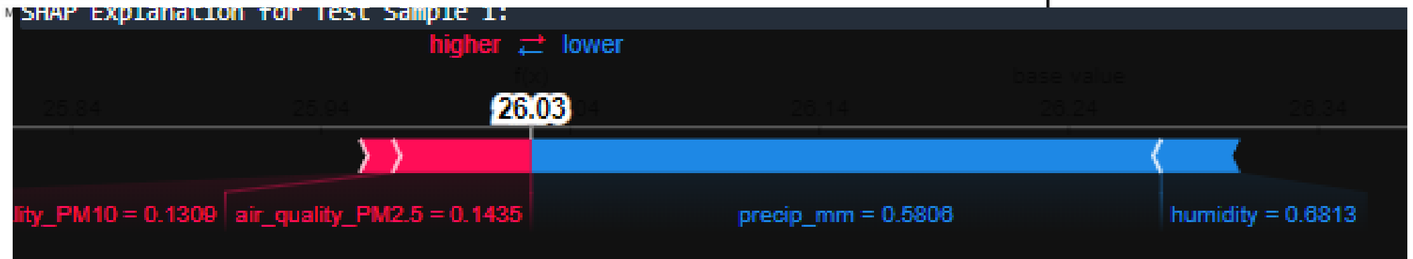

Kerala - Training vs Validation Loss
Training Loss
Validation Loss
Loss
Epochs
0
100
200
300
400
500
600
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5


Kerala - Actual vs Predicted
Actual Temperature
Predicted Temperature
Time Steps
22
24
26
28
30
0
20
40
60
80
100


Heatmap of MAE Across Regions
Region
Mean Absolute Error
Andaman and Nicobar Islands 16.30
Andhra Pradesh 0.31
Arunachal Pradesh 2.97
Assam 1.18
Bihar 0.62
Chandigarh 10.24
Chhattisgarh 0.34
Dadra and Nagar Haveli 10.30
Daman and Diu 2.35
Delhi 5.92
Goa 2.40
Gujarat 0.51
Haryana 0.20
Himachal Pradesh 1.54
Jammu and Kashmir 1.02
Jharkhand 0.80
Karnataka 0.51
Kerala 1.00
Lakshadweep 15.11
Madhya Pradesh 0.43
Maharashtra 0.53
Manipur 1.82
Mizoram 2.16
Nagaland 2.84
Orissa 0.71
Puducherry 3.73
Punjab 0.56
Rajasthan 0.67
Tamil Nadu 0.50
Tripura 3.37
Uttar Pradesh 0.65
Uttarakhand 1.52
West Bengal 0.67
2
4
6
8
10
12
14
16

Output


Heatmap of RMSE Across Regions
Region
RMSE
Root Mean Square Error
Andaman and Nicobar Islands 16.66
Andhra Pradesh 0.38
Arunachal Pradesh 3.64
Assam 1.39
Bihar 0.71
Chandigarh 10.97
Chhattisgarh 0.39
Dadra and Nagar Haveli 10.54
Daman and Diu 2.91
Delhi 6.75
Goa 3.09
Gujarat 0.58
Haryana 0.26
Himachal Pradesh 1.92
Jammu and Kashmir 1.78
Jharkhand 0.84
Karnataka 0.59
Kerala 1.28
Lakshadweep 15.24
Madhya Pradesh 0.48
Maharashtra 0.57
Manipur 2.20
Mizoram 2.47
Nagaland 3.41
Orissa 0.79
Puducherry 4.42
Punjab 0.63
Rajasthan 0.72
Tamil Nadu 0.63
Tripura 4.18
Uttar Pradesh 0.70
Uttarakhand 2.39
West Bengal 0.74
2
4
6
8
10
12
14
16


SHAP Explanation for Test Sample 1:
higher ⇄ lower
base value
26.03
lity_PM10 = 0.1309
air_quality_PM2.5 = 0.1435
precip_mm = 0.5806
humidity = 0.6813

Ablation Studies

- Ablation studies analyze the impact of individual components or design choices in a model by systematically removing or altering them.

- Our dataset is relatively small, so understanding which factors truly matter helps us build an efficient, reliable model.

Ablation Studies: Data

- Feature Importance
- Lookback Window
- Sampling Frequency
- Removing Recent Data

Ablation Studies: Model Architecture

- Architecture Choices
- Sequence Length
- Layer Depth
- Dropout Regularization

Ablation Studies: Training Process

- Loss Function
- Batch Size
- Optimization Algorithm

Advantage

- Enhanced Transparency of Sequential Forecasting
- Trust and Usability in Decision-Making
- Temporal Feature Importance
- Error Diagnosis and Model Refinement
- Uncertainty Quantification for Risk Assessment
- Understanding Long-Term Dependencies
- Feature Ranking and Model Optimization
- Practical Applications in Extreme Weather Events
- Improving Public Communication

Conclusion

- The integration of Explainable AI (XAI) and LSTM networks improves weather forecasting by enhancing accuracy, transparency, and interpretability.
- This combination supports informed decision-making, real-time updates, and better preparedness for extreme weather scenarios.
- It enables scenario-based planning, localized forecasting, and long-term climate analysis, making it a valuable tool for tackling complex meteorological challenges.

References

- Analysis of input parameters for deep learning-based load prediction for office buildings in different climate zones using XAI
  https://doi.org/10.1016/j.enbuild.2022.112521
- Data-driven multi-step prediction and analysis of monthly rainfall using explainable deep learning
  https://doi.org/10.1016/j.eswa.2023.121160
- Explainable AI-Based Interface System for Weather Forecasting Model.
  https://doi.org/10.1007/978-3-031-48057-7_7
- Dataset
  https://www.kaggle.com/datasets/nelgiriyewithana/indian-weather-repository-daily-snapshot/versions/216

THANK'S FOR WATCHING