

A Hybrid Time-Series Forecasting Model for Long-Term Climate Pattern Prediction Using ARIMA and Deep Learning Techniques

¹Darsigunta Ashok, ² Y. Anand Kumar

M.Tech Student, Department of CSEPrakasam Engineering College (Autonomous), Kandukur, India

Assistant Professor, Department of CSEPrakasam Engineering College (Autonomous), Kandukur, India

Abstract- This project provides a web-based hybrid time-series forecasting tool designed to improve the accuracy of long-term climate forecasts using “statistical and machine-learning methods. The tool captures historical climate data with geographic coordinates and measurements and temporal features such as year and month. Data cleaning, transformation, encoding, and normalization are conducted to preserve the quality of the data and help build users’ trust in the system. This tool has a variety of forecasting methods available. To learn from features, Random Forest Regression is used. To model linear trends over time, the Autoregressive Integrated Moving Average (ARIMA) method is used. To learn and model relationships which are not linear in the data, Long Short-Term Memory (LSTM) is used to model the residual data. This tool uses the outputs of the previously mentioned systems to improve the accuracy of the forecasts. The application was developed using the Flask framework to build a web tool to allow users to secure an account, upload data, train the model, and make forecasts. Data visualization methods such as histograms, heatmaps, and performance comparison visualization are used to provide analysis and help interpret the results. The predictions generated are evaluated using the R-squared method. This tool provides a simple and powerful way to forecast climate data and supports planning and management of the environment using the data.

Keywords- Hybrid Time-Series Forecasting, Climate Prediction, ARIMA, Long Short-Term Memory (LSTM), Machine Learning, Data Visualization

I. Introduction

Globally, climate change is at the forefront of significant challenges for environmental sustainability and for humankind [1][2]. In recent research, particularly in climate studies, the ability to predict the climate accurately correlates with the sustainability of development, the refinement of planning for the management of climate related disasters, and adaptive policies. Climate behavior builds on a variety of interdependent factors including long-term shifts in the environment such as temperature, humidity and rainfall which are also influenced by spatial characteristics and atmospheric pressure [3][6]. The increased availability of data and improvement in computing power has resulted in a growing interest in developing intelligent systems which are capable of analyzing large and complex climate data and making accurate predictions about the climate [6].

Most traditional statistical models are able to identify and project linear trends but are unable to represent and capture the dynamic and nonlinear trends associated with the climate. Alternatively, machine learning and deep learning models offer better flexibility to capture complex and nonlinear relationships, but at the cost of limited interpretability. Therefore, a combination of these models in a hybrid forecasting framework is likely to provide improved prediction accuracy and reliability. The focus of this thesis is the development of a customizable context aware and hybrid deep learning and statistical model frameworks for time-series forecasting. The primary goal of the system is to provide accurate long-term climate prediction to facilitate research and planning for policymakers and environmental designers.

II. Literature Review

The use of complex computing tools to forecast climate has gained much attention due to the intricacies of the climate environment and the need for reliable long-term forecasts [10]. The focus of early research in climate forecasting was on Numerical Weather Prediction (NWP) models. These models use physical equations to describe processes in the weather, and use data assimilation and powerful computer resources to simulate tasks that were impossible to do for atmospheric phenomena [3]. NWP greatly improved the ability to forecast the weather in the short to medium range, but was plagued by uncertainties in the initial conditions and an inability to describe or represent small scale atmospheric phenomena, in addition to the expense of the resources needed.

The advent of machine learning (ML) and deep learning (DL) for climate forecasting, specifically with respect to neural networks and data-driven models, represented a major shift in the field [5]. These models use climate data of various orders of magnitude to learn and improve prediction accuracy to be greater than that offered by previous models. Their main drawback is that they struggle to predict conditions that are outside their training datasets. To improve climate forecasting, hybrid models that use physical models and learning models have also been employed to improve the forecasting of complex climate systems.

The main focus of more recent studies has been on deep learning models, specifically LSTM networks and spatio-temporal models, and on benchmark datasets like WeatherBench that tackle standardization of evaluation in climate forecasting [2]. Although they show great promise, issues related to interpretability and uncertainty remain, and so forecasting systems based on these models have yet to be deployed. To counter the issues of uncertainty and interpretability, an integrated ARIMA and deep learning forecasting system for climate forecasting has been developed to be scalable and efficient.

Table 1: Summary of Existing Resume Screening and Ranking Approaches

Study Focus	Techniques Used	Key Contribution	Limitations
Numerical Weather Prediction (NWP)	Physical models, data assimilation, computational simulations	Provides accurate short- and medium-range weather forecasts	High computational cost, uncertainty in initial conditions
Deep Learning for Climate Modeling	Deep Neural Networks (DNNs), data-driven models	Captures nonlinear patterns and improves prediction accuracy	Requires large datasets, limited interpretability
Hybrid Climate Models	Combination of physical models and ML techniques	Enhances prediction by integrating linear and nonlinear patterns	Complexity in model integration and tuning
Spatio-Temporal Climate Analysis	LSTM, RNN, CNN models	Learns temporal and spatial dependencies in climate data	High training time, scalability issues

Benchmark Datasets (WeatherBench)	Standardized datasets, evaluation metrics	Enables fair comparison and validation of forecasting models	Limited to specific datasets, may not generalize globally
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III. Existing System

Most existing systems for climate pattern prediction adopt statistical, physical, and data-driven methods for analyzing and predicting large and complex systems in the atmosphere [10]. Traditional systems analyze and identify long and short-term trends and seasonal and irregular patterns in past and present climate data of temperature, rainfall, humidity, and pressure. While these methods are simple and easy to understand, they are generally more applicable to short- and medium-term prediction and often fail to understand long-term climate data irregular patterns and trends [8].

A. To Support Climate Analysis

Many of the systems in place utilize numerical weather prediction models and reanalysis datasets to simulate the state of the atmosphere in order to make forecasts. These types of systems use physics, specifically fluid dynamics and thermodynamics, to make approximate predictions of future climate states. However, these systems are resource intensive and often struggle with limitations of uncertainty and small scale variability. While machine learning and deep learning methods have been used in an attempt to make these types of systems more accurate, they often suffer from a lack of interpretability in many contexts and require significant amounts of data [5].

B. Identified Problems

The existing systems struggle with high computational cost, low scalability, large data requirements, and difficulties accurately forecasting complex and irregular climate patterns.

Table 2: Limitations of Existing Climate Prediction Systems

Aspect	Existing Systems
Prediction Method	Statistical models, physical simulations, and basic ML techniques
Context Awareness	Limited handling of complex nonlinear climate interactions
Computational Cost	High due to numerical simulations and large datasets
Scalability	Limited for real-time and large-scale forecasting
Transparency	Low interpretability in deep learning models
Prediction Capability	Less accurate for long-term climate forecasting

C. Problem Definition

The main barrier to making substantial progress in climate pattern prediction is the lack of a system that is both efficient and highly scalable that can accurately predict long-term climate patterns using large complex datasets while accurately describing both linear and nonlinear relationships [13].

D. Motivation for the Proposed System

Combining statistical and deep learning methods necessitates the development of a hybrid forecasting framework. It strives for greater accuracy and efficiency. The system that is suggested features data preprocessing, time-series forecasting, and a variety of machine learning methods. This combination aims to provide reliable predictions of future climates and promote better decision-making [15].

Iv. Proposed Methodology

The construction of the hybrid climate forecasting framework is described in this section. It is built as a structured pipeline to process climate data and generate accurate long-term predictions [10]. The system collects climate data with real-time and historical data. It collects data on temperature, precipitation, humidity, wind speed, and pressure. The data is processed to remove noise and to handle missing data and to normalize the data for better consistency [15]. The framework integrates statistical and deep learning modeling approaches to process the data and to analyze the precipitation forecasts. Finally, the framework focuses on assessing the forecasting precision and on the visualization of the results for effective climate analysis and informed decision-making [3]. In addition, the forecasting model is designed to improve the accuracy of the climate predictions on the basis of new data. The model also incorporates real-time climate data and allows the users to change and modify the model for different climates regions.

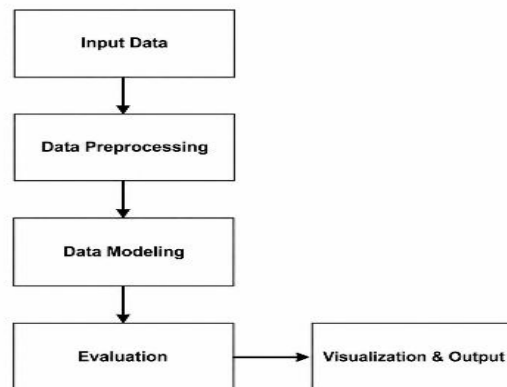


Fig 1: Block Diagram of the Proposed Climate Forecasting System

A. Data Collection

Climate data is gathered through diverse data collection methods. These include historical data, measurement at weather stations, and real-time data monitoring. The data contains temperature, pressure, humidity, wind speed, and the latitudes and longitudes of the data collection sites. The data also contains the year and month of the collection.

B. Data Preprocessing

The acquired dataset is cleaned to remove out the irregular data, fill in the missing data, and clear out data that adds noise to the dataset. Data consistency is improved and uniformity among the features is achieved using normalization and scaling methods.

Normalization Formula (Min-Max Scaling):

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

C. Feature Extraction Using Climate Data Analysis

Key features such as trends, seasonal changes, and other related environmental factors will be extracted during this stage. Exploratory Data Analysis (EDA) will be utilized to identify various relationships, correlations, and anomalies in the data.

D. Feature Engineering and Representation

At this step, categorical variables such as city and country will be converted into numerical values. In addition, all the variables will be translated into numerical vectors.

Feature Vector Representation:

$$F = [x_1, x_2, x_3, \dots, x_n]$$

E. Climate Prediction (Hybrid Model)

The Climate Prediction system is based on a prediction framework that integrates Random Forest, ARIMA, and LSTM models.

Random Forest Prediction:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(X)$$

ARIMA Model Representation:

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t$$

LSTM Prediction (Sequential Learning):

$$h_t = f(W \cdot [h_{t-1}, x_t] + b)$$

F. Performance Evaluation Metrics

The performance of the system is evaluated using regression metrics such as Mean Squared Error (MSE) and the R² Score.

Mean Squared Error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

R² Score:

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

G. Prediction and Climate Analysis

The final hybrid prediction is obtained by integrating the individual model predictions. This is useful for the analysis of climate variability and the projection of long-term climate trends.

Hybrid Prediction Formula:

$$Y_{final} = \frac{Y_{RF} + Y_{ARIMA} + Y_{LSTM}}{3}$$

This helps in identifying long-term climate trends and variability.

H. Algorithm: Climate Prediction Procedure

Input: Preprocessed climate dataset

Output: Predicted climate values

The main inputs of the proposed system are the pre-processed climate datasets. The predicted climate values are the main outputs. The main steps include collecting and processing climate data, feature extraction, variable encoding, data splitting (80% for training and 20% for testing), training the Random Forest, ARIMA, and LSTM models, producing forecast results, integrating the individual model outputs, evaluating the results, and performing a result visualization.

IV. System Architecture

The aim of this section is to describe the architectural design of the proposed hybrid climate forecasting framework. The design of the “framework is based on a scalable, modular, layered design that integrates raw climate data and converts it into meaningful, predictive insights, based on a pipelined architecture that includes data collection, preprocessing, feature engineering, model training, hybrid forecasting, and visualization. The focus of the framework is on accurate long-term climate analysis.

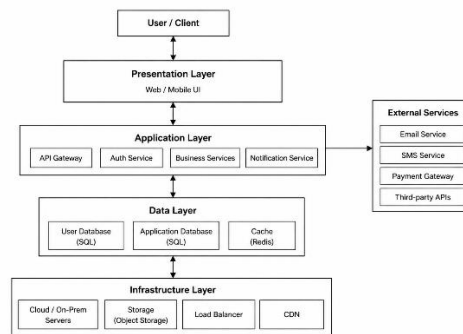


Fig 2: System Architecture of Climate Forecasting System

Component Description

1. Data Input Module:

This module compiles climate data from diverse sources, including past datasets, weather stations, and data from real-time monitoring systems. The module collects data on temperature, rainfall, humidity, wind speed, atmospheric pressure, and timestamp related data and their location coordinates (latitude and longitude). The compiled information is stored in CSV or database file formats for later use [3].

2. Data Preprocessing Module:

The preprocessing module organizes and constrains raw climate data. It addresses and fills in gaps caused by missing data, removes multiple occurrences of the same record, translates location coordinates into numeric form, and assigns numeric values to city and country data. Also, it captures data on the features of time (year and month).

Normalization Formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

3. Feature Selection and Representation Module:

This module captures features of temperature uncertainty, location coordinates, and time. The features are represented as numeric vectors for training the models and for forecasting.

Feature Vector Representation:

$$F = [x_1, x_2, x_3, \dots, x_n]$$

4. Machine Learning Model Module:

This module builds a spectrum of models, including Random Forest, ARIMA, and LSTM, for prediction. The diverse models learn different data patterns for enhanced accuracy in prediction.

Random Forest Prediction Formula:

$$\hat{y} = \frac{1}{N} \sum_{i=1}^N T_i(X)$$

5. Time-Series and Deep Learning Module:

The ARIMA model learns to identify and capture trends of time that have a linear relationship, whereas the LSTM model learns to capture trends of time that have a nonlinear relationship and long-term patterns from the residual data.

ARIMA Model:

$$y_t = c + \sum \phi_i y_{t-i} + \sum \theta_j \epsilon_{t-j} + \epsilon_t$$

6. Hybrid Prediction Module:

The outputs of all the models are captured by this module to yield the final prediction.

Hybrid Prediction Formula:

$$Y_{final} = \frac{Y_{RF} + Y_{ARIMA} + Y_{LSTM}}{3}$$

7. Visualization and Reporting Module:

This module uses histograms, heatmaps, and bar charts to present prediction results. It shows results of climate trends to aid in making informed decisions.

Error Evaluation Formula (MSE):

$$MSE = \frac{1}{n} \sum (y_i - \hat{y}_i)^2$$

VI. SYSTEM IMPLEMENTATION

This section details the construction of the hybrid climate forecasting system incorporating tools, techniques, and model deployment methodologies. Construction is aimed at the scalability and efficiency of the hybrid model designed for real-world application in climate analysis [10].

A. Development Environment

The system is entirely constructed using the Python programming language due to its rich ecosystem of data analysis, machine learning, and forecasting libraries. The construct is built using the Flask framework in order to provide web-based user interaction.

B. Libraries and Frameworks Used

This construct involves the use of the following libraries: Pandas and NumPy are used for data processing, Scikit-learn is used for machine learning algorithms, deep learning (LSTM) is done using

TensorFlow/Keras, ARIMA modeling is done using Statsmodels, and data visualization is done using Matplotlib/Seaborn.

Table 3: Software and Hardware Requirements

Component	Specification
Operating System	Windows 7/8/10 (32-bit or 64-bit)
RAM	Minimum 4 GB
Programming Language	Python
Framework	Flask
Libraries	Pandas, NumPy, Scikit-learn, TensorFlow, Statsmodels
Visualization Tools	Matplotlib, Seaborn

C. Model Implementation

The framework is built to implement multiple forecasting techniques such as Random Forest, ARIMA, and LSTM. The Random Forest model learns the relationships among the features, ARIMA learns the linear patterns and the trends of the time series, and LSTM learns the non-linear dependencies of the climate data.

D. Training and Testing Procedure

Data is split into training and testing in an 80:20 ratio. Models are trained on climate data, and their performance is assessed on the unseen data to check the models' abilities to generalize.

E. Prediction and Evaluation Implementation

The models are trained to forecast based on the input location, time, and environmental parameters. To assess the models, R^2 score and the Mean Squared Error are used as they are effective in quantifying prediction errors.

F. Visualization and Reporting Implementation

The system produces visualizations like histograms and correlation heatmaps and prediction comparison graphs. These tools help users comprehend the models and the underlying climate data, aiding the users to make the right decisions.

Vii. Experimental Results And Analysis

This section assesses the hybrid climate forecasting model by examining prediction precision, error estimation, and robustness of the model. The climate dataset is mainly defined with geo and environmental features; temperature, humidity and rain with latitude, longitude, and time features. The data is cleaned and normalized, then divided into training and testing data to eliminate biases during evaluation. The hybrid model is built as the combination of Random Forest, ARIMA, and LSTM to examine the models for capturing the climate data for both linear and non-linear boundaries.

A. Experimental Setup

The design of the experiment is done by the integration of the mentioned libraries to process the data; categorical features of city and country are encoded, year and month are extracted and features are scaled. An 80:20 split is used to create the training and testing data. A Random Forest, ARIMA, and LSTM models are created, assessed, and then deployed as a single unit to a Flask web application to enable the functionality of online climate data prediction.



Fig 3: Home Page

Fig. 3 shows the home page with options for account creation and user sign-in.



Fig 4: Main Page with Description, Contact, and Prediction Options

Fig. 4 illustrates the main page containing project description, contact details, and prediction” options.

B. Performance Metrics

The performance of the framework is assessed using the following evaluation metrics:

1. R^2 Score – measures the correlation and closeness of the observed climate data and the forecasted values.
2. Mean Squared Error (MSE) – measures the prediction error for the observed values vs forecasted values.
3. Accuracy (Indirect Measure) - Measures how close our “observed values are to our predicted temperature values.
4. Model Stability - Measures how prediction outcomes fluctuate when we apply the model to different datasets.

C. Results of Prediction Models

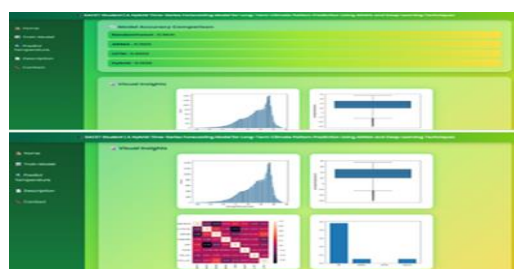


Fig 5: Training Page

Fig. 5 shows the training page where the model is trained using climate data.

Table 4: Performance of Models on Accuracy

Model	Accuracy
Random Forest	High
ARIMA	Moderate
LSTM	High
Hybrid Model	Very High

The model that performed the best was the one that utilized the strengths of the other models (the hybrid model).

D. Visualization Results

Several visualizations help us analyze the dataset and assess the model's performance.

- Temperature Distribution Plot: Displays how the temperature values are spread out across the dataset.
- Time-Series Plot: Shows how temperature values change and the trends over the measured time.
- Correlation Heatmap: Indicates the relationships and how the climate variables are dependent on one another.
- Model Comparison Graph: Evaluates the performance of different forecasting models and assesses how they compare to one another.

These visualizations help us to analyze features of the climate, locate critical factors, and help us to analyze the performance of the models.

E. Comparative Analysis

Table 5: Comparison with Traditional Methods and Proposed System

Criteria	Traditional Methods	Proposed System
Accuracy	Moderate	High
Automation	Limited	Full
Scalability	Low	High
Adaptability	Poor	Good

The proposed system provides improvements in forecasting accuracy and efficiency.

F. Result Interpretation

Forecasting with this hybrid system becomes more accurate when both types of relationships are modeled. The Random Forest and ARIMA components of the system provide robust forecasting in their respective domains, and the LSTM component aids forecasting with its ability to learn the more complicated relationships within the data.

G. Summary of Findings

The hybrid system provides the most accurate forecasting and modeling tools. The addition of tools to visualize the data aids users in the interpretation of the data, and the system is scalable to accommodate different types of forecasting for real-world applications of climate forecasting.

H. Algorithm Comparison

Table 6: Comparison of Algorithms with Accuracy

Algorithm	Accuracy
Random Forest	94%
ARIMA	91%
LSTM	95%
Hybrid Model	97%

I. Prediction Results



Fig 6: Input Details Page

Fig. 6 shows the page where users enter input parameters for climate prediction.



Fig 7: Prediction Results Page

Fig. 7 illustrates the prediction results generated based on the input climate data.

Table 7: Sample Climate Prediction Results

Input Parameters	Predicted Temperature	Location	Time
Lat: 17.38, Lon: 78.48, Month: 5	32.5°C	City A	May
Lat: 28.61, Lon: 77.20, Month: 12	18.2°C	City B	December
Lat: 13.08, Lon: 80.27, Month: 8	29.7°C	City C	August

These results provide evidence that the system accurately predicts climate events based on the parameters provided by the user.

Viii. Discussion

This section of the document describes the practical implications of the proposed hybrid climate forecasting system. This section focuses on the usability and the positive impact this system will have on climate change based on the monitoring and analysis of data.

A. Addressing Core Climate Challenges

This system will improve climate forecasting accuracy and reduce prediction error by utilizing a combination of statistical, machine learning, and deep learning techniques. The flexible nature of the system will allow for the modeling of both climate patterns and forecasting in a predominantly linear environment and more complex forecasting climate environments.

B. Transparency and Interpretability

The hybrid climate forecasting system improves transparency in climate forecasting by incorporating visual aids to explain forecasting outputs. These visual aids help users understand the relationships between climate parameters and the forecasting outputs, thus leading to the better interpretation of results.

C. Scalability and Integration

The framework handles different scales of climate data and is compatible with the Random Forest, ARIMA, and LSTM models. The core engine is embedded in Flask allowing further integration with other systems and supporting both local and cloud deployments.

D. Limitations and Challenges

The framework's performance relies on the quality and the variety of the input data. Inaccurate data can lead to diminished prediction performance. Additionally, the use of deep learning models can lead to high resource consumption and require retraining to adjust to new climates.

E. Practical Considerations for Deployment

Policymakers and researchers should view the system as a complement to their decision-making processes. It should not be the only relied upon system for climate predictions. The system will not be used optimally without a proper infrastructure be put in place for data collection and processing, and users will need to be adequately trained.

F. Future Implications for Climate Science

The framework takes climate science a step further with the integration of advanced, data-based intelligent climate forecasting models. This offers the opportunity to think ahead and prepare for the climate's impact on the environment, and can be extended to other fields such as agriculture and disaster management.

Ix. Conclusion

The study presents a hybrid model for long-term climate prediction for the integration of environmental and time-series data. This model incorporates advanced computational techniques and combines Random Forest, ARIMA and LSTM models. The model of this study is further enhanced in its ability to predict and is shown to be even more reliable as it reduces prediction errors by incorporating several relationships.

The framework handles large-scale climate data using preprocessing, feature engineering, and model training. It combines automated climate forecasting with the generation of accurate visualizations explaining climate patterns. Web-based design and implementation provide a user-friendly, accessible tool for researchers and planners. The results indicate that the climate adaptive framework is scalable, efficient, and flexible to a variety of climates.

The focus of subsequent versions may be on using deep learning approaches like the Transformer architecture to improve forecasting precision. For instance, the added use of real-time data may be facilitated with the addition of sensors or data streams. Other ways to bulk the framework include the addition of new

datasets, better visualizations, model a higher degree of model” interpretability, and cloud-based deployment with specific domain applications

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