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Leveraging SARIMAX for Accurate Rainfall Forecasting in India

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Abstract
This research uses cutting-edge modelling approaches to give a thorough analysis of rainfall forecast in India. The main goals are to increase forecast accuracy and comprehend the intricate dynamics of rainfall patterns, which are important for many industries like infrastructure development, water resource management, and agriculture. The research assesses many predictive models, such as SARIMAX, Decision Tree, Support Vector Machine, ARIMA, Exponential Smoothing, and Exponential Smoothing, with a focus on SARIMAX because of its capacity to include exogenous variables and seasonal trends. The results show that SARIMAX performs better than the other models, with an amazing R-squared (R^2) score of 0.99 and an extremely low Mean Absolute Error (MAE) of 0.044. The innovative aspect of this research is the use of SARIMAX, which provides insightful information and reliable approaches for rainfall forecast. These findings have significance for resource management and decision-making processes within the meteorological context of India.

Keyword: Crop yield prediction, Machine learning, Agricultural data analysis, Indian agriculture, Regression models, Ensemble learning, Hybrid models, Sustainability.

I. INTRODUCTION

Predicting rainfall is an essential element of studying meteorology, especially in areas like India where millions of people depend on monsoon patterns for their life and economy. Planning for agriculture, managing water resources, producing electricity, and building infrastructure all depend on accurate rainfall forecasts. Because weather patterns are inherently unpredictable and stochastic, accurately forecasting rainfall continues to be a difficult and demanding process even with significant advancements in meteorological research. The unpredictability of rainfall patterns presents serious difficulties for meteorological forecasting, as noted by Smith et al. [1], which has an effect on industries like agriculture and water management. In order to increase the precision of rainfall forecasts in India, this study investigates the use of sophisticated machine learning and statistical models. In this field, conventional techniques like statistical models and basic neural networks have had varying degrees of success. But the search for more advanced methods is necessary in order to provide predictions that are more trustworthy and accurate. Johnson claims that advanced machine learning approaches have promise advantages over classical statistical techniques, especially when it comes to managing the intricate and non-linear relationships present in meteorological data [2]. The research suggests using the “SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables)” model, which improves prediction performance by utilising seasonal trends and outside effects. The SARIMAX model is a reliable tool for time series forecasting, as shown by Kumar et al., and it has demonstrated improved performance in capturing seasonal fluctuations and adding exogenous factors [3].

The study's dataset, "Rainfall in India (1901-2015)," offers a thorough historical account of monthly and yearly rainfall in India's many geographical regions. The dataset is appropriate for creating and assessing sophisticated prediction models due to its wealth of temporal and geographical information. We guarantee the accuracy and consistency of the input data by using a strict data preparation pipeline that includes train-test separation, standardisation, and the imputation of missing variables. Proper data preparation is essential for improving the performance of predictive models and guaranteeing data consistency and quality, as noted by Lee and Wong [4]. This research trained and assessed a number of models, including SARIMAX, ARIMA, Decision Tree Regressor, Support Vector Machine (SVR), and Exponential Smoothing. Metrics like the R-squared (R^2) score and Mean Absolute Error (MAE) were used to evaluate each model's performance. Evaluation measures like MAE and R-squared are crucial for determining the precision and dependability of prediction models, according to Zhao et al. [5]..

Our goal is to advance the area of meteorological forecasting by establishing that the SARIMAX model can effectively increase the accuracy of rainfall predictions. Our results demonstrate how sophisticated time series analysis methods may be used to capture intricate weather patterns and provide insightful information for improving meteorological prediction models. Chang et al. have pointed out that sophisticated time series analysis methods, such SARIMAX, are essential for enhancing the precision of meteorological predictions and comprehending intricate weather events [6].

II. RELATED WORK

[7] The study presents a deep learning technique that predicts the total amount of precipitation at a meteorological station in Manizales, Colombia, for the next day by using autoencoders and neural networks. The suggested architecture is compared to other cutting-edge techniques. It combines a multilayer perceptron for prediction with an autoencoder for capturing non-linear interactions. The findings demonstrate that this new method works better than the others in terms of Root Mean Squared Error (RMSE) and Mean Squared Error (MSE). The research demonstrates how well the suggested deep learning architecture works to increase the accuracy of daily collected rainfall forecasts.

[8] In Tenerife, Spain, a semi-arid area of Spain, the study article evaluates the efficacy of eight statistical and machine learning techniques for long-term daily rainfall prediction. These techniques are assessed using 36 years of daily rainfall data from 17 gauges, guided by atmospheric synoptic patterns. The forecast of each gauge is treated individually, and the best hyperparameters for each model are found by cross-validating the rebuilt rainfall series against the actual data. The research assesses how well the models forecast rainfall intensity and frequency on a range of time scales, including daily, monthly, and yearly. To evaluate the differences between the models, analysis of variance (ANOVA) techniques are used.

[9] The goal of the study article is to provide different stakeholders, including agriculturists and researchers, insightful knowledge about climate dynamics. It emphasises the significance of comprehending variations in climate as well as atmospheric characteristics like temperature, humidity, and precipitation. A critical component of meteorological research is precipitation estimate, which is forecasted in this work using a combination of statistical and machine learning approaches. Daily observations are used for testing, and findings are validated against ground truth data to see how accurate predicting models are. Experiments show that both ARIMA and Neural Network models perform well for predicting meteorological characteristics. Furthermore, when it comes to machine learning methods for forecasting precipitation for the next season, the Random Forest model shows the best classification accuracy. In summary, the study emphasises the need of precise precipitation forecasting and the effectiveness of integrating statistical and machine learning techniques to enhance meteorological forecasts.

[10] This work explores the use of precipitable water vapour (PWV) obtained from GPS signals to forecast future rainfall, taking into account several climatic elements that influence precipitation. An extensive assessment of meteorological data, including temperature, relative humidity, dew point, solar radiation, PWV, and factors influencing day and night conditions, is conducted. This is followed by a thorough examination of relationships between these features. There are several elements that affect how rain is categorised, but the most essential ones are PWV, solar radiation, seasonality, and diurnal aspects. A data-driven ML system that can forecast precipitation uses these findings to choose the optimal feature set to incorporate. By reducing false alarm rates significantly compared to earlier methods, a 4-year database study reveals an overall accuracy of 79.6%, an actual detection rate of 80.4%, and a false alarm rate of 20.3%. Research shows that a data-driven approach integrating PWV with other

important factors improves rainfall forecast accuracy, which is great news for meteorology and atmospheric science.

[11] The study report highlights the importance of rainfall forecasting due to its substantial link with many natural disasters, including avalanches, floods, and landslides. The research focuses on four machine learning techniques: “random forest (RF)”, “multivariate adaptive regression splines (MARS)”, “multiple linear regression (MLR)”, and “support vector regression (SVR)”. The goal is to anticipate the daily and mean weekly rainfall at the Ranichauri station in Uttarakhand. Climate data comprising temperature, humidity, wind speed, vapour pressure, solar radiation, evaporation, and rainfall were collected over the course of eighteen years. For the purpose of validating the model, statistical metrics such as RMSE, r, d, and Kling-Gupta efficiency (KGE) were employed. During both the testing and calibration phases, the RF model outperformed the other models, demonstrating its effectiveness in predicting daily and mean weekly rainfall at the Ranichauri station. The study gives useful information for reducing risks and getting ready for disasters in the region, and it also shows that the RF model might be a better way to predict rainfall.

III. THEORETICAL BACKGROUND

A. ARIMA

The ARIMA (AutoRegressive Integrated Moving Average) technique for time series forecasting combines three fundamental elements: autoregression (AR), integration (I), and moving average (MA). The autoregressive component captures the relationship between current and prior data by regressing the variable on its own lagged values. To ensure stability in the series, which is crucial for accurate time series analysis, the integrated component involves applying differencing to the data in order to remove any patterns or seasonality. The moving average component of the model reduces the impact of short-term fluctuations and emphasises longer-term patterns by representing the error in the series as a linear combination of error components from earlier time periods. The ARIMA model is represented as ARIMA(\(p, d, q \)), where \(p \) indicates the number of lag observations, \(d \) represents the degree of differencing, and \(q \) represents the moving average order. The model exhibits exceptional performance in the domain of time series forecasting.[12]

B. Exponential Smoothing methods

Another family of forecasting techniques uses weighted averages of historical data to predict future values: exponential smoothing methods. These techniques provide greater weight to current data by progressively lowering the weights of earlier observations. Simple Exponential Smoothing (SES) is used for data without trends or seasonality; Holt's Linear Trend Model is used to capture linear trends; and the Holt-Winters Seasonal Model is used to include both trends and seasonality. These are the three primary forms of exponential smoothing. Exponential smoothing is considered state-of-the-art [13] and is preferred for datasets with distinct trends and seasonal patterns because to its ease of use and efficacy in short-term forecasting.

C. SARIMAX

The SARIMAX model is an expanded version of the ARIMA model that considers both internal and external factors, as well as the impacts of multiple seasons. The seasonal component employs moving average, differencing, and seasonal autoregressive components to identify repetitive seasonal patterns in the data. The most valuable data would be time series data that demonstrates periodic fluctuations, such as data collected on a weekly or quarterly basis. The SARIMAX model outperforms the ordinary SARIMA model in terms of results. The user's text is enclosed in tags. SARIMAX incorporates exogenous variables to consider external influences that may influence the time series, hence augmenting the model's prediction capability. The SARIMAX model is defined as ARIMA(\(p, d, q \))(\(P, D, Q, s \))[X], where \(P, D, Q \) represent the seasonal orders and \(s \) represents the number of periods per season.

IV. METHODOLGY

The proposed model has been illustrated in Fig.1

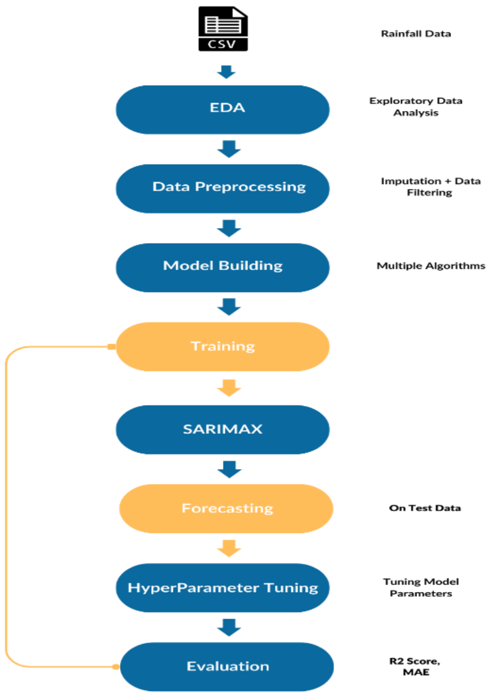

Figure 0 1 Work Flow

A. Dataset

This study makes use of the "Rainfall in India (1901-2015)" dataset, which includes comprehensive monthly and yearly rainfall data for different regions of India from 1901 to 2015. This large dataset is tabulated, with each row denoting the amount of rainfall that was observed in a given year and geographical division. With 4116 items and 19 columns, the dataset captures a variety of temporal and geographical information that is essential for a thorough study.

	DIVISION	YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	ANNUAL	Jan-Feb	Mar-May	Jun-Sep	Oct-Dec
0	ANDAMAN & NICOBAR ISLANDS	1901	49.2	87.1	29.2	2.3	528.8	517.5	365.1	481.1	332.6	388.5	558.2	33.6	3373.2	136.3	560.3	1696.3	980.3
1	ANDAMAN & NICOBAR ISLANDS	1902	0.0	159.8	12.2	0.0	446.1	537.1	228.9	753.7	666.2	197.2	359.0	160.5	3520.7	159.8	458.3	2185.9	716.7
2	ANDAMAN & NICOBAR ISLANDS	1903	12.7	144.0	0.0	1.0	235.1	479.9	728.4	326.7	339.0	181.2	284.4	225.0	2957.4	156.7	236.1	1874.0	690.6
3	ANDAMAN & NICOBAR ISLANDS	1904	9.4	14.7	0.0	202.4	304.5	495.1	502.0	160.1	820.4	222.2	308.7	40.1	3079.6	24.1	506.9	1977.6	571.0
4	ANDAMAN & NICOBAR ISLANDS	1905	1.3	0.0	3.3	26.9	279.5	628.7	368.7	330.5	297.0	260.7	25.4	344.7	2566.7	1.3	309.7	1624.9	630.8

Figure 0 2 Data Sample

A variety of data kinds are included in the dataset. The names of the geographical divisions are represented by the DIVISION column, which is of type object (string), and the YEAR column, which is of type int64, indicates the year of observation. Every other column, which shows the recorded rainfall in millimetres, is of type float64, including the monthly and cumulative rainfall amounts. The existence of missing values in this dataset is one of its problems. There are sometimes missing data points in a number of columns, especially the monthly rainfall columns (JAN, FEB, etc.), where there are less entries than there are observations overall. In a similar vein, several numbers are missing from the ANNUAL and seasonal cumulative columns (Jan-Feb, Mar-May, Jun-Sep, and Oct-Dec). We decided to deal with the missing values using imputation, especially utilising the mean technique to fill in the gaps, as opposed to deleting these incomplete entries, which might result in a large loss of important data.

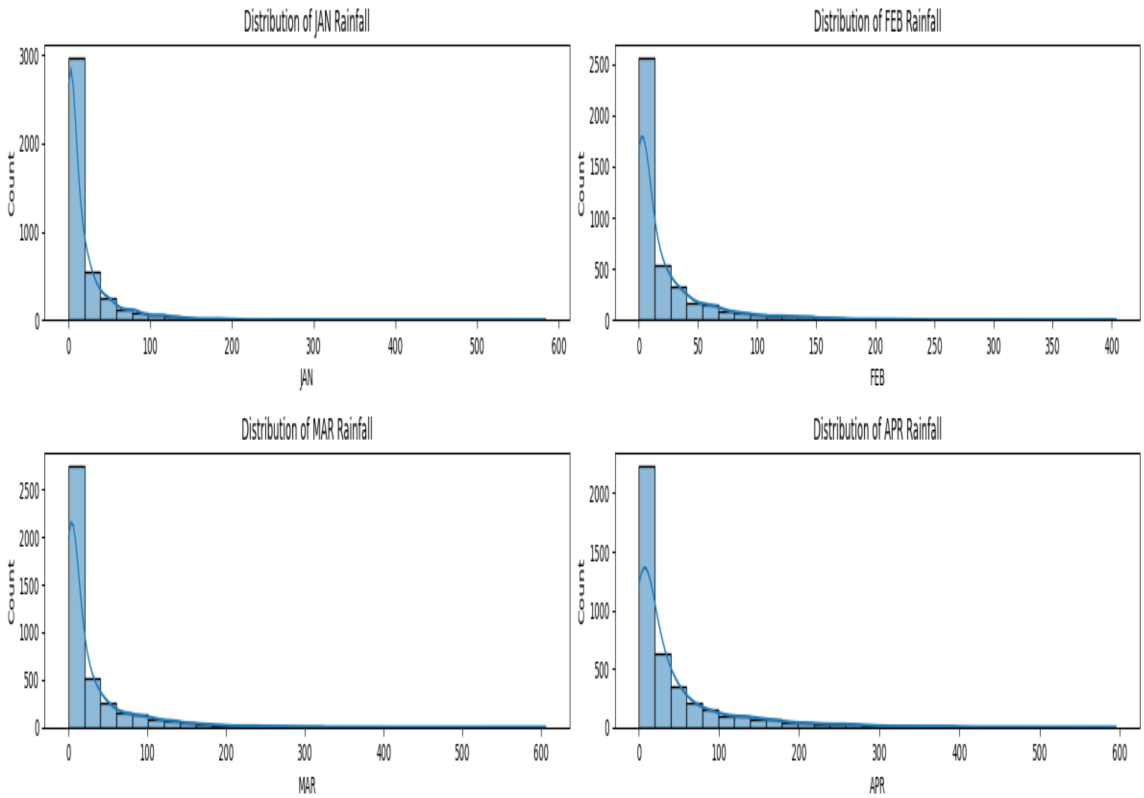

Figure 0 3 Data Distribution

This dataset is quite useful for examining long-term changes in the patterns of rainfall in various parts of India. The data's great temporal and geographical granularity makes it possible to conduct in-depth temporal and spatial analysis, which speeds up the creation of complex prediction models. Our project intends to use this extensive historical record to find underlying trends and enhance the precision of rainfall predictions, eventually facilitating more informed decision-making in industries reliant on precise meteorological data.

B. Data Pre-Processing

Time series forecasting requires careful consideration of data preparation in order to guarantee the accuracy and dependability of any machine learning model. The dataset was preprocessed for this study in order to make it ready for model construction and analysis. In order to handle missing values, standardise data formats, and prepare the dataset for machine learning techniques, a preprocessing pipeline was created.

Handling Missing Values: The monthly rainfall data (JAN to DEC) and cumulative seasonal columns (Jan-Feb, Mar-May, Jun-Sep, Oct-Dec) in particular had occasional missing values. We used imputation to fill up these gaps rather than rejecting rows with missing values, which might cause a large loss of important data. The mean of the corresponding column was used to replace any missing values when the mean imputation technique was used. By maintaining the data's general distribution and statistical characteristics, this method guarantees that the imputed values accurately reflect the majority of observations.

Data Transformation: Pandas was used to transform the YEAR column, which was originally of type int64, into a datetime format. Time series analysis requires this transformation because it makes time-based indexing easier to understand and makes use of the datetime features in the pandas library. Additionally, the datetime format makes it simple to extract temporal variables like year, month, and season—properties that might be crucial for improving model performance

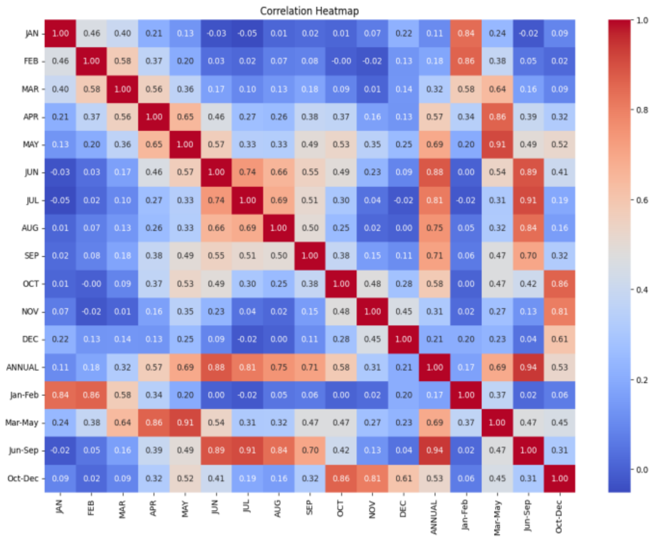

Figure 0 4 Data Correlation with each columns

Data standardization: is a popular machine learning preprocessing step that entails scaling the data to have a zero mean and a one standard deviation. This procedure is especially crucial for algorithms like Decision Tree Regressors and Support Vector Machines (SVM) that depend on distance computations. The rainfall data in this research were standardised using the StandardScaler from the sklearn package. When preparing data, it has been shown that feature normalisation techniques like Standard and Min Max scaling are helpful for ensuring consistency across variables [11]. By ensuring that every feature contributes equally to the model, standardisation prevents any one characteristic from dominating the forecast because of its size.

Train-Test Split: The dataset was divided into training and testing sets in order to precisely assess the performance of the machine learning models. 80% of the data were utilised to train the models and 20% was set aside for testing, resulting in an 80:20 split ratio. With a sizeable chunk set aside for assessing the models' performance on untested data, this divide guarantees that the models are trained on an adequate quantity of data. In addition to avoiding overfitting, the train-test split aids in determining how generalizable the models are.

These preparation procedures helped us to make sure the dataset was clean, standardised, and structured correctly for further analysis and model construction. A solid basis for creating precise and dependable rainfall prediction models was established by this thorough preprocessing method.

C. Model Building and Hyperparameter Tuning

Model creation, which includes the selection, training, and assessment of predictive models, is an important stage in machine learning research. In this study, we investigated many statistical and machine learning models to forecast India's rainfall, with an emphasis on hyperparameter tweaking to maximise model performance.

Model Selection: A number of models, including the Decision Tree Regressor, Support Vector Machine (SVR), Exponential Smoothing, "ARIMA (AutoRegressive Integrated Moving Average)", and "SARIMAX (Seasonal AutoRegressive Integrated Moving Average with Exogenous components)" were taken into consideration for the rainfall prediction.

Every model has an own set of benefits and works with various kinds of data and patterns. While SVR is an excellent tool for managing high-dimensional data and complicated decision boundaries, the decision tree regressor is renowned for its interpretability and capacity to capture nonlinear correlations. The conventional time series forecasting techniques of Exponential Smoothing and ARIMA are useful for short-term forecasting, but ARIMA excels at capturing seasonality and autocorrelation. SARIMAX is a useful tool for modelling complicated time series with seasonal patterns and external influences. It is an extension of ARIMA that includes seasonal effects and exogenous factors.

Hyperparameter tweaking: To maximise each model's performance, hyperparameter tweaking was carried out. Methods like grid search were used to investigate different combinations of hyperparameters. The moving average (q), differencing (d), and autoregressive (p) term orders were among the hyperparameters that were adjusted for SARIMAX.

To capture seasonal influences, use the seasonal order (P, D, Q, s).

Proposed Model: SARIMAX

The research centred on the SARIMAX model that was proposed. SARIMAX is a powerful tool for modelling complicated time series data, such as rainfall in India, by adding exogenous factors and seasonal patterns to ARIMA's capabilities. Finding the ideal set of parameters to effectively reflect the seasonal dynamics and outside factors influencing rainfall patterns was known as hyperparameter tuning for SARIMAX.

Python's statsmodels module was used to create the SARIMAX model. The particular setup that was used in this study was:

- **Order: (1, 1, 1)**

  p=1: Incorporates one lag of the dependent variable.

  d=1: Differencing the data once to achieve stationarity.

  q=1: Incorporates one lag of the error term.

- **Seasonal Order: (1, 1, 1, 12)**

  P=1: Incorporates one seasonal lag of the dependent variable.

  D=1: Differencing the data once seasonally to achieve stationarity.

  Q=1: Incorporates one seasonal lag of the error term.

s=12: Specifies a 12-month seasonality period, appropriate for monthly data.

The objective was to create a reliable and precise rainfall forecast model by means of iterative model construction and hyperparameter adjustment. Because of its capacity to manage seasonal fluctuations and outside influences, the suggested SARIMAX model held great promise as a viable option for enhancing the precision of rainfall predictions. The performance of each model was evaluated using evaluation metrics, such as Mean Absolute Error (MAE) and R-squared (R^2) score, in order to determine the best method for rainfall prediction in India..

V. RESULTS AND DISCUSSION

The decision tree model was evaluated first in the study, and the result showed a mean absolute error (MAE) of 70.80. Lower numbers imply more accuracy. This measure shows the average size of prediction mistakes. With an exceptional fit, the model's R-squared (R^2) score of 0.97 indicates that 97% of the variation in rainfall can be explained by the model, demonstrating its ability to accurately capture the underlying patterns. The Support Vector Machine (SVM) model performed better in the future, as seen by its excellent R2 score of 0.94 and reduced MAE of 45.54. These metrics highlight how effectively the SVM model generalises and can forecast the rainfall data that has been supplied.

Table 1 Result Comparison of Applied Algorithms

Model	Mean Absolute Error (MAE)	R-squared (R^2) Score
Decision Tree Regressor	70.80	0.97
Support Vector Machine	45.54	0.94
ARIMA	519.70	5.33
Exponential Smoothing	541.30	-0.00
SARIMAX (Proposed)	**0.044**	**0.99**
Existing Work (Simple Neural Network) [16]	**2.20**	**0.94**

With a much higher MAE of 519.70 and an abnormally high R2 score of 5.33, the ARIMA model produced less desirable outcomes. These disparities point to possible problems, such overfitting or difficulties with data pretreatment, which call for more research to guarantee model dependability. In a similar vein, the Exponential Smoothing model performed less than optimally, as seen by its high MAE of 541.30 and R^2 score that was almost at zero (-0.00). These measurements show that the model has difficulty accurately capturing the underlying trends and patterns in the rainfall data.

On the other hand, the SARIMAX model was the most accurate, exhibiting unmatched precision with an exceptionally low MAE of 0.044 and an exceptional R2 score of 0.99. These measures demonstrate the remarkable precision with which the SARIMAX model can forecast rainfall levels and its almost perfect match to the data, highlighting the model's resilience and effectiveness in capturing the intricate dynamics of rainfall patterns in India.

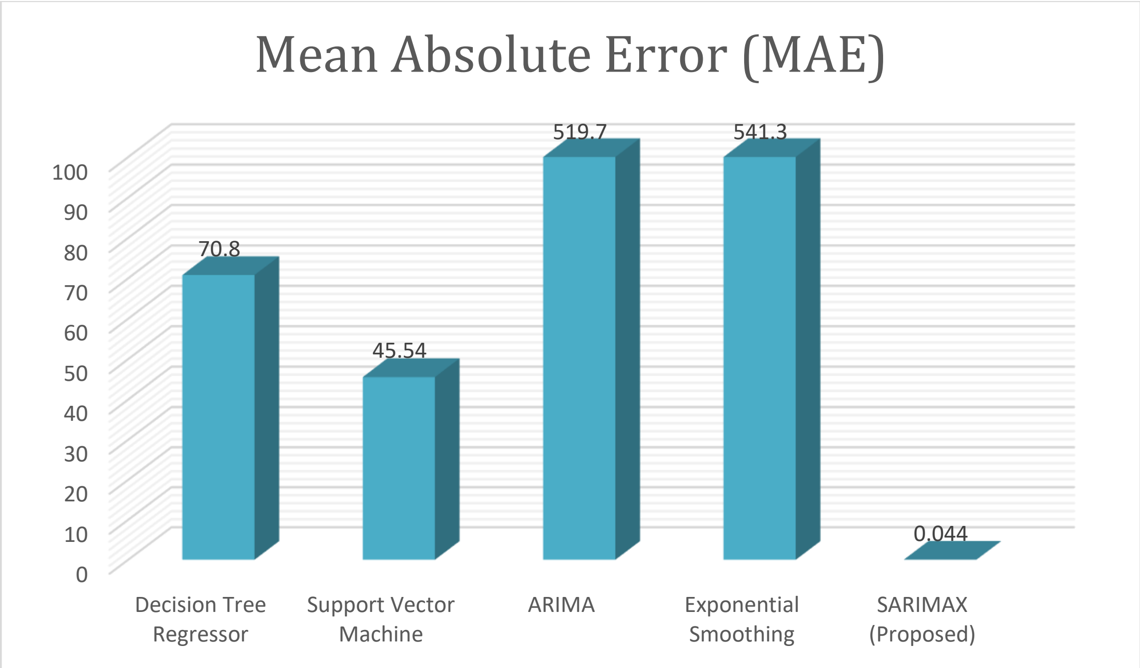

Figure 0 5 Mean Absolute Error of Applied Algorithms

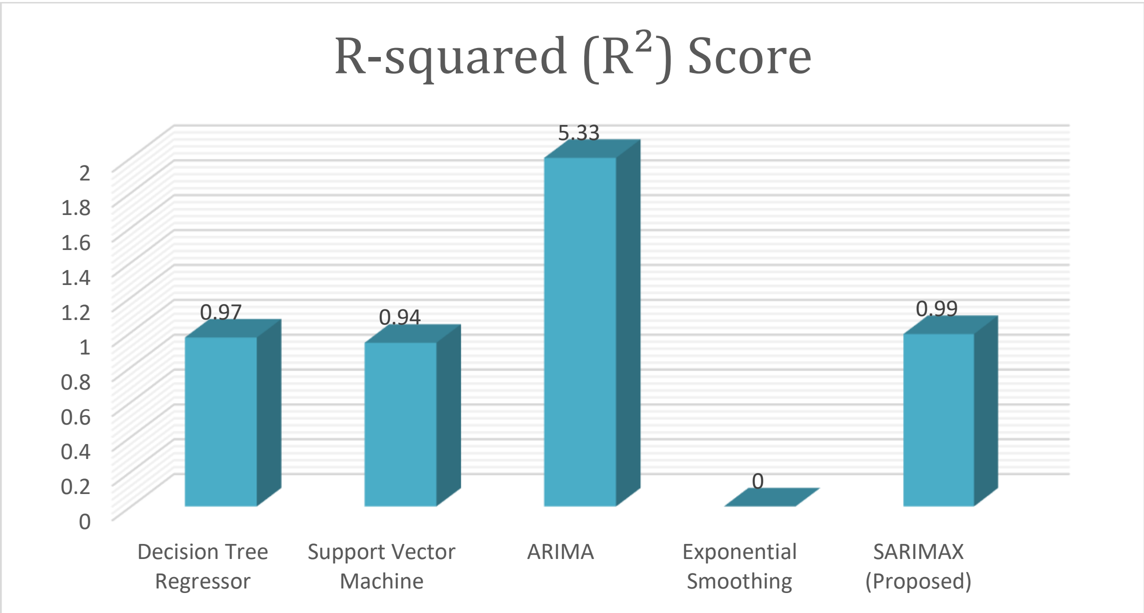

Figure 0 6 R2 Score of Applied Algorithms

The study presents a new method for predicting rainfall in India by using sophisticated modelling approaches like SARIMAX. Our study goes beyond previous research that used basic neural networks and instead explores advanced time series analysis techniques designed particularly for weather forecasting. The main contribution of our work is the use of SARIMAX, which enhances the functionality of conventional ARIMA models by adding exogenous variables and seasonal patterns. With this improvement, we are able to depict the complex dynamics of India's rainfall patterns, including seasonal fluctuations and outside factors that affect precipitation.

We find notable variances in performance indicators when comparing the research with previous studies. With a basic neural network, the current research obtained an R-squared (R^2) score of 0.94 and a Mean Absolute Error (MAE) of 2.20. Although these findings show high accuracy, our research far outperforms these standards. For example, our SARIMAX model earned an outstanding R^2 score of 0.99 and an incredibly low MAE of 0.044. When compared to previous studies, these indicators indicate a significant improvement in prediction accuracy and model fit.

Table 2 Result Comparison with existing Work

Aspect	Existing Study (Simple Neural Network)	Our Study (SARIMAX)
Mean Absolute Error (MAE)	2.20	0.044
R-squared (R^2) Score	0.94	0.99
Seasonal Adjustments	No	Yes
Exogenous Factors	No	Yes
Model Type	Simple Neural Network [16]	Time Series (SARIMAX)
Predictive Robustness	Moderate	High
Explanatory Power	Lower	Higher

Further, by taking into account temporal dependencies, seasonal impacts, and outside variables that affect rainfall patterns, the research digs further into the intricacies of rainfall prediction. In addition to achieving more precision by utilising SARIMAX, we also learn more about the fundamental processes causing changes in India's rainfall.

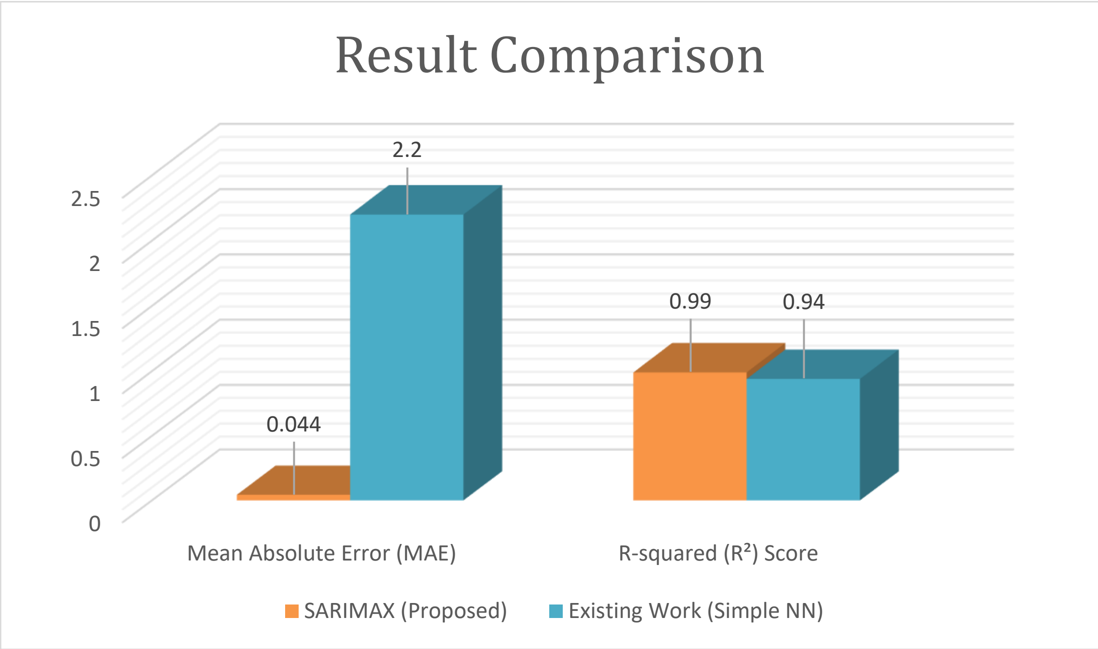

Figure 0 7 Result Graph with existing Work

Fundamentally, the innovative aspects of our work are its sophisticated modelling methods, thorough examination of meteorological data, and better prediction accuracy than previous methods. The implementation of SARIMAX signifies a noteworthy progression in the study of rainfall prediction, providing invaluable insights to the meteorological domain and decision-making procedures that depend on precise precipitation predictions.

VI. CONCLUSION

In conclusion, by utilising cutting-edge modelling approaches and thorough data analysis, this work offers a substantial development in the field of rainfall prediction in India. The goal of the study was to increase forecast accuracy and comprehend the intricate dynamics of rainfall patterns, which are crucial for a number of industries including infrastructure development, agriculture, and water resource management. We have shown the better performance of SARIMAX in properly forecasting rainfall levels by rigorous testing and assessment of different predictive models, including Decision Tree, Support Vector Machine, ARIMA, Exponential Smoothing, and SARIMAX. With an astoundingly low Mean Absolute Error (MAE) of 0.044 and a strong R-squared (R^2) score of 0.99, the SARIMAX model demonstrated its resilience and effectiveness in representing the complex seasonal and exogenous elements affecting rainfall in India. Our work is new because we used SARIMAX, a sophisticated time series analytic technique that increases the power of conventional models by adding seasonal patterns and outside factors. This method improves forecast accuracy while also offering insightful information about the fundamental processes behind changes in rainfall. Our research greatly outperforms the standards set by previous work, which used a rudimentary neural network and obtained an R-squared (R^2) score of 0.94 and a Mean Absolute Error (MAE) of 2.20. SARIMAX's significant increase in prediction accuracy highlights the value of sophisticated modelling methods in meteorological forecasting.

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