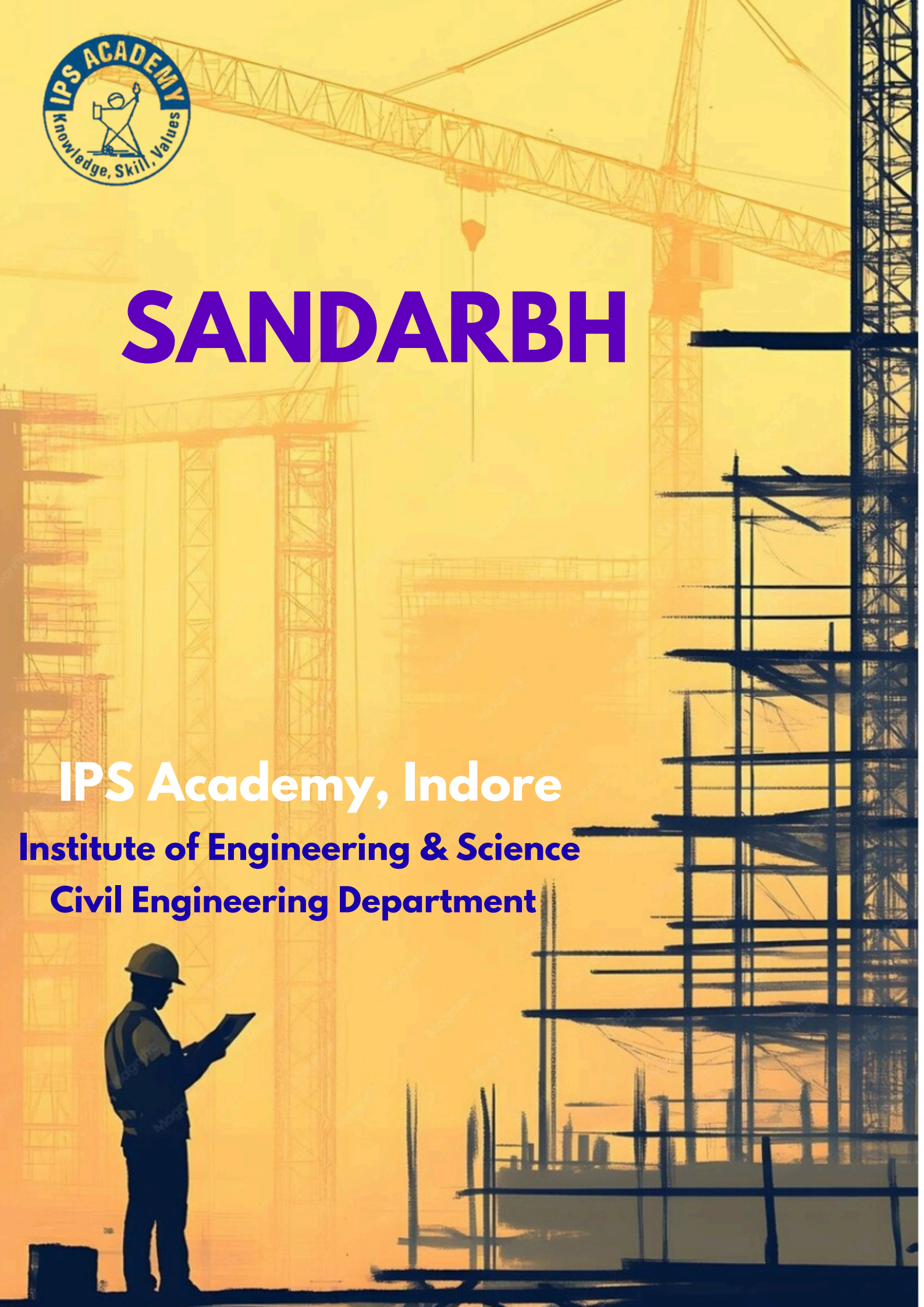
SANDARBH

IPS Academy, Indore

Institute of Engineering & Science

Civil Engineering Department



Minds Behind The Magic

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CONTENTS

IDEAS. INNOVATION. IMPACT.

- MESSAGE FROM PRINCIPAL
- MESSAGE FROM HOD
- VISION AND MISSION
- HIGHLIGHTS OF THE DEPARTMENT
- LABORATORIES, MAJOR INSTRUMENTS & SOFTWARES
- RESEARCH WORK BY STUDENTS
- Annual Events-SAMEEKSHA, SRUJAN, NEEV
- EDUCATIONAL WORKSHOPS & SKILL DEVELOPMENT PROGRAMS
- INDUSTRIAL VISITS

From the Principal



It is a great pleasure to see the creative expressions of students who had contributed to Sandarbh. Civil Engineering Department has grown abundantly in the recent past. It continues to sustain its growth. People reading this magazine will realize the tremendous changes that are happening in the Department. The magazine is presenting a glimpse of the growth of the Department on many fronts. The Department has been simply unstoppable in its progress as it has been actively involved in various activities that have brought to light the hidden talents of the students and staff. The highly qualified and dedicated members of staff have always stood shoulder with the management and of commitment. This magazine has recorded achievements such as: conferences attended by staff members and students, competitions won by the hugely talented students, innovative projects carried out by students with the guidance of staff, among others. They stand as a witness to the monumental efforts taken by the management to make the college a centre of excellence in education and research. I wish the management, staff and students of the college success in their future endeavors.

Dr. Archana Keerti Chowdhary Principal

From the HOD



It has given enormous gratification to coordinate the editorial team of —SANDARBH , our Civil Engineering Department magazine in all aspects, covering academic activities, technical events of the magazine. This magazine would not have been concluded without the constant support of our principal who stood as a pillar of strength and support at all times. We would genuinely place thanks to our editorial team whose dedication and diligent towards completion of magazine was always part of the process. We would like to congratulate and express our hearty thanks and gratitude to our head of the department in believing the quality policy of educate enrich and excel in imparting professional education. This magazine is reflecting of our department quality in terms of all round excellence. Last but not the least we want to faculty members who gave constant support and guidance to enlighten young minds of the people through this magazine.

Dr. Amit Sharma

Vision

Be the prererred destination locally, regionally and internationaly for the Civil Engineering society as a leading department providing high quality programs and services in Civil Engineering fields.

Mission

M1 - To offer value-based education to meet global standards to the students to develop their profe:sional skills.

M2 - To inculcate a spirit of entrepreneurship and innovation in students so that they can better serve the society.

M3 -To prompt sponsored research and provide Testing/Consuitancy services in Civil Engineering fields for society a subheading

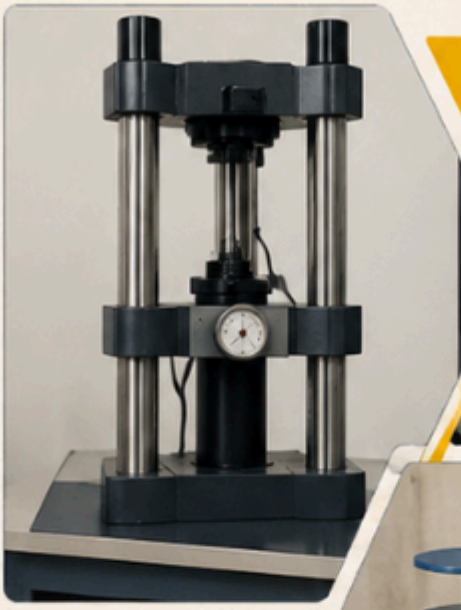




BEYOND THE BOOKS

A GLIMPSE INTO OUR LABS





















Existing Labs

1. Engineering Mechanics Lab

2. Strength of Material Lab

3. Structures Lab

4. Transportation Lab

5. Geotechnical Engineering Lab

6. Engineering Geology Lab

7. Fluid Mechanics & Machinery Lab

8. Environmental Engineering Lab

9. Materials Testing Lab

16. Survey Lab

11. Instrumeritation Lab

12. Computer Lab

13. Software Lab

13. Heavy Structural Lab



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- PRIMAVERA
- ANSYS
- SAP 2000
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- Abagus 6.12
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- MIDAS-Gen a subheading
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- Pumps & Turbines
- Benkingham Beam
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MAJOR EQUIPMENT AVAILABLE



TOTAL STATION



UTM & CTM



WEATHER STATION



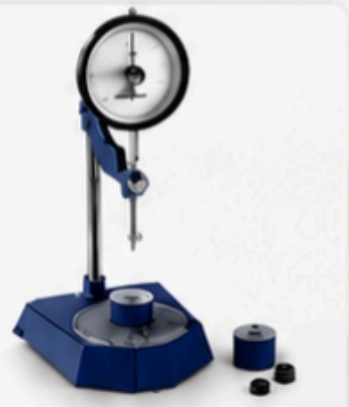
PUMPS AND TURBINES



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RESEARCH
WORK BY
STUDENTS

Comparative Analysis of Statistical Time Series Models and LSTM for Rainfall Forecasting in Dehradun.

Siddhant Shukla [1], Manas Vishwakarma [1], Shivansh kaurav[1], Sachin panchal[1]

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Predicting rainfall is a complex and critical task due to its significant impact on agriculture, water resources, and disaster management, particularly in a monsoon-dependent country like India, where nearly a majority of agricultural activities rely on timely and adequate precipitation. Accurate rainfall forecasting is therefore essential for minimizing economic losses, improving water resource planning, and enhancing preparedness against extreme weather events such as floods and cloudbursts. However, rainfall prediction remains challenging due to the inherent non-linearity, seasonality, and temporal variability present in meteorological data. In this study, a comparative analysis of statistical time series models, including Autoregressive (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA), along with a deep learning-based Long Short-Term Memory (LSTM) model, is carried out for rainfall forecasting in Dehradun. Historical rainfall data were collected from NASA global climate data repositories, ensuring a reliable and continuous dataset for analysis. The dataset was subjected to comprehensive preprocessing, including handling missing values, normalization, and stationarity testing, followed by time series decomposition to extract trend, seasonal, and residual components. The developed models were trained and evaluated using Root Mean Squared Error (RMSE) as the primary performance metric. The results indicate that statistical models are effective in capturing linear trends and short-term dependencies but exhibit limitations in modelling complex non-linear relationships and extreme rainfall events. In contrast, the LSTM model demonstrates superior predictive performance with significantly lower error values due to its capability to learn long-term temporal dependencies and complex patterns within the data. The findings of this study highlight the limitations of conventional approaches and emphasize the effectiveness of deep learning techniques in improving rainfall prediction accuracy, thereby contributing to more reliable forecasting systems for climate risk management and decision-making.

1. INTRODUCTION

Rainfall plays a crucial role in sustaining agriculture, managing water resources, and maintaining ecological balance, particularly in a monsoon-dependent country like India. A large proportion of agricultural land depends on seasonal rainfall, making accurate prediction essential for ensuring food security and economic stability. However, in recent decades, climate change has significantly altered rainfall patterns, leading to increased variability, shifting monsoon behaviour, and a rise in extreme weather events such as intense rainfall and prolonged dry spells [1,2]. These changes have made rainfall prediction more complex and uncertain, thereby increasing the need for more reliable and advanced forecasting techniques.

Traditional rainfall forecasting methods based on statistical time series models have been widely used due to their simplicity and effectiveness in capturing linear patterns. Models such as Autoregressive (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA) have shown satisfactory performance in analysing historical trends and short-term predictions [3,4]. However, these models often struggle to capture the inherent non-linearity, seasonality, and complex temporal dependencies present in meteorological data, particularly under changing climatic conditions [5].

With advancements in computational intelligence, machine learning and deep learning approaches have emerged as powerful tools for time series forecasting.

Several studies have demonstrated the effectiveness of machine learning techniques such as Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forest (RF) in rainfall prediction tasks [6-8]. More recently, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have gained considerable attention due to their ability to model non-linear relationships and capture long-term temporal dependencies effectively [9,10]. The memory cell structure and gating mechanisms of LSTM enable it to retain relevant information over extended periods, making it highly suitable for rainfall prediction in dynamically changing climatic scenarios.

In this context, the present study focuses on a comparative analysis of statistical and deep learning models for rainfall forecasting in Dehradun, a region that has experienced noticeable climatic variability in recent years. Historical rainfall data obtained from NASA global climate data repositories are used for model development and evaluation. The performance of AR, MA, and ARIMA models is compared with the LSTM model using Root Mean Squared Error (RMSE) as the primary evaluation metric.

The primary objective of this study is to evaluate the effectiveness of different modelling approaches in capturing rainfall variability under changing climatic conditions and to identify the most suitable model for accurate prediction. The outcomes of this research aim to contribute toward the development of reliable rainfall forecasting systems that can support decision-making in agriculture, water resource management, and climate risk mitigation.

2. Materials and Methods

2.1 Case Study Region, Meteorological Data and Pre-processing

The study area selected for this research is Dehradun, located in the foothills of the North -Western Himalayas at an approximate latitude of 30.3165° N and longitude of 78.0322° E. The region experiences a humid subtropical climate characterized by distinct seasonal variations, with the majority of rainfall occurring during the southwest monsoon period. Due to its geographical location and increasing climatic variability, the region is highly susceptible to irregular rainfall patterns and extreme weather events.

The meteorological data used in this study were obtained from NASA global climate data repositories. The dataset consists of historical rainfall records spanning multiple years, providing a continuous and reliable source of information for time series analysis. The data were collected in a structured format and included temporal rainfall observations suitable for predictive modelling.

The initial data pre-processing stage involved several essential steps to ensure data quality and model compatibility. These steps included data cleaning, handling missing values, normalization, and transformation of the dataset. Missing values present in the dataset were treated using appropriate imputation techniques, while extreme values or outliers were carefully examined to minimize their impact on model performance. The dataset was further analysed for stationarity using statistical tests, and necessary transformations were applied where required.

In addition, time series decomposition techniques were employed to separate the data into trend, seasonal, and residual components, enabling a clearer understanding of underlying rainfall patterns. Relevant features essential for rainfall prediction were identified and retained for further analysis. Finally, the dataset was divided into training and testing sets, with 70% of the data used for training the models and the remaining 30% reserved for testing and validation purposes. This structured approach ensured the robustness and reliability of the predictive models developed in this study.

3. Methodology

3.1 Statistical Time Series Models

Statistical time series models are grounded in

the principle that future values of a variable can be expressed as a function of its past observations and stochastic error terms. These models assume linearity and are most effective when the underlying data exhibit stationary behaviour.

3.1.1. Autoregressive (AR) Model

The Autoregressive model of order *p*, denoted as AR(p), expresses the current rainfall value as a linear combination of its previous *p* values. It captures the persistence effect in rainfall, where past observations influence future values.

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

where y_t represents rainfall at time *t*, phi_i are model coefficients, and $epsilon_t$ is white noise. The AR model assumes stationarity and is effective in modelling temporal autocorrelation.

3.1.2. Moving Average (MA) Model

The Moving Average model of order *q*, denoted as MA(q), models the current value as a linear combination of past error terms. It is particularly useful for capturing short-term shocks or irregular fluctuations in rainfall data.

$$y_t = \mu + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} + \epsilon_t$$

where $theta_i$ are parameters and $epsilon_t$ represents white noise. Unlike AR models, MA models do not depend on past observed values but on past forecast errors.

3.1.3. Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model combines autoregression, differencing, and moving average components to handle non-stationary time series data. It is denoted as ARIMA (p, d, q), where *d* represents the order of differencing required to achieve stationarity.

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

The differencing operation removes trends and stabilizes the mean of the time series. Although ARIMA is powerful for linear forecasting, it struggles with non-linear dependencies and complex climatic interactions.

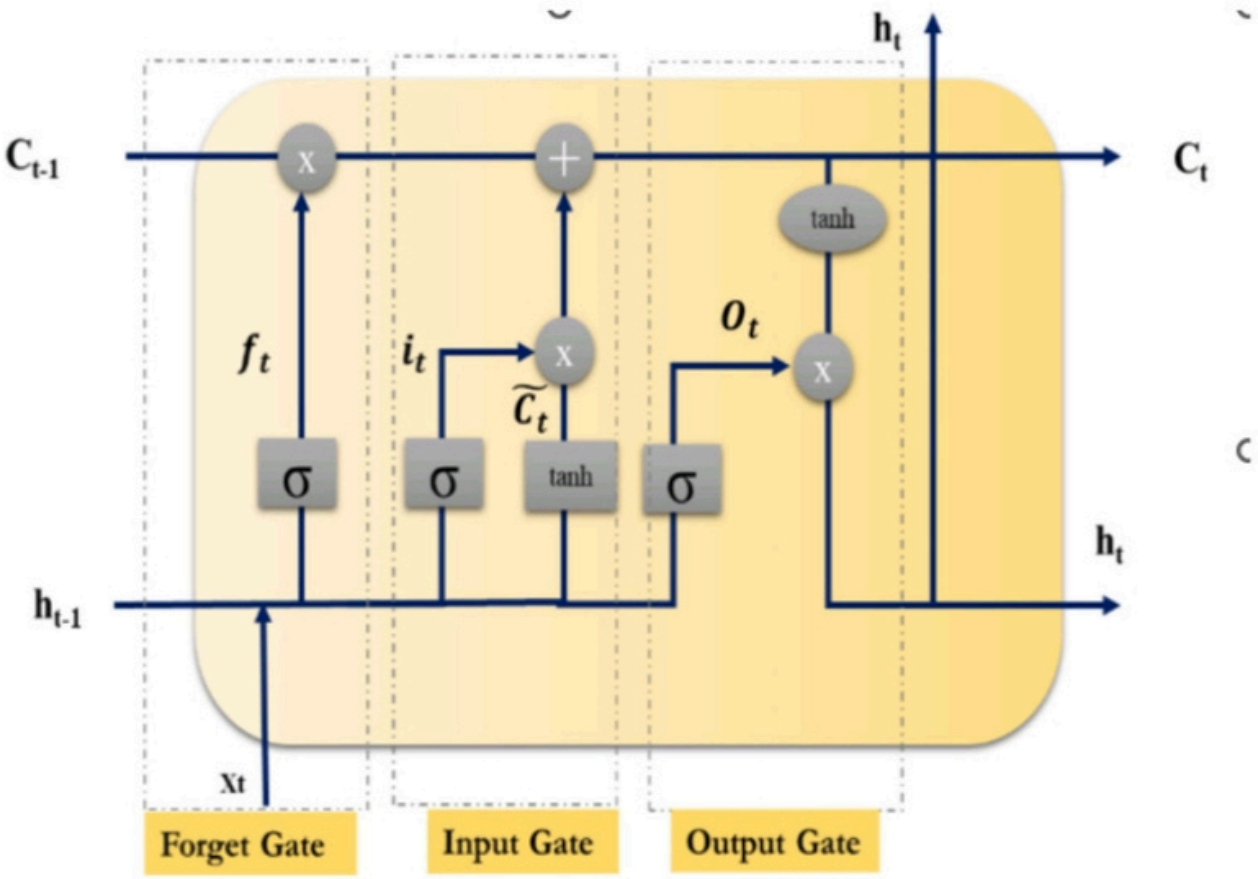


Fig 1 Structure of an LSTM unit.

3.2 Deep Learning Model

Long Short-Term Memory (LSTM) Network

The Long Short-Term Memory (LSTM) network is an advanced recurrent neural network designed to model sequential data with long-term dependencies. Unlike traditional RNNs, LSTM addresses the vanishing gradient problem through a gated memory cell structure, enabling effective learning over long sequences.

The internal operations of an LSTM cell are governed by three gates:

LSTM Gate Equations

$$f_t = \sigma(W_f[h_{t-1},x_t] + b_f)$$

Forget Gate: Determines which information from the previous cell state should be discarded.

$$i_t = \sigma(W_i[h_{t-1},x_t] + b_i)$$

Input Gate: Controls how much new information is added to the cell state.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Cell State Update: Combines previous memory and new candidate information.

$$o_t = \sigma(W_o[h_{t-1},x_t] + b_o)$$

Output Gate: Determines the output based on the updated cell state.

These gating mechanisms allow LSTM to retain important temporal features and discard irrelevant information, making it highly effective for rainfall prediction where both short-term variability and long-term climatic trends are significant.

3.3 Model Advantages and Limitations

Statistical models such as Autoregressive (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA) are widely used in time series forecasting due to their simplicity, low computational cost, and ease of interpretation. These models are effective in capturing linear relationships, short-term dependencies, and structured patterns in stationary data. Additionally, they require relatively smaller datasets and provide transparent parameter estimation, making them suitable for baseline analysis. However, their major limitation lies in the assumption of linearity, which restricts their ability to model complex, non-linear relationships inherent in meteorological data. Furthermore, these models are sensitive to non-stationarity and often fail to accurately predict extreme rainfall events and abrupt climatic variations.

In contrast, the Long Short-Term Memory (LSTM) model offers significant advantages in modelling complex and non-linear temporal relationships. Its memory cell architecture and gating mechanisms enable it to capture both short-term fluctuations and long-term dependencies effectively. This makes LSTM particularly suitable for rainfall prediction under changing climatic conditions, where patterns are highly dynamic and influenced by multiple interacting factors. However, LSTM models require large volumes of data for effective training and involve higher computational complexity compared to statistical models. They also demand careful tuning of hyperparameters and are less interpretable, which can limit their transparency in decision-making processes. Despite these limitations, the superior predictive performance of LSTM makes it a powerful tool for advanced rainfall forecasting applications.

3.4 Implementation Details

All models in this study were implemented using Python-based computational frameworks to ensure efficiency and reproducibility. The statistical models, including AR, MA, and ARIMA, were developed using the Stats models library, which provides robust tools for time series analysis and parameter estimation. The deep learning model, LSTM, was implemented using the TensorFlow framework and the Kera's API, which offer flexible architectures and efficient training capabilities for neural networks.

The dataset used in this study was obtained from NASA global meteorological data sources and consisted of historical rainfall observations. Prior to model development, the dataset was pre-processed and normalized using Min-Max scaling to transform the input values into a fixed range, thereby improving numerical stability and convergence during training. The data were further structured into sequential input-output pairs to enable effective learning of temporal dependencies, particularly for the LSTM model.

Hyperparameter tuning was performed to optimize model performance. For the LSTM model, parameters such as the number of hidden layers, number of neurons per layer, activation functions, batch size, and number of epochs were adjusted through iterative experimentation. The learning rate was carefully selected to balance convergence speed and stability. For the ARIMA model, parameters (p, d, q) were determined based on autocorrelation and partial autocorrelation analysis.

Model training was conducted using the training dataset, while performance evaluation was carried out on the testing dataset to ensure unbiased validation. The implementation process followed a systematic workflow, ensuring consistency,

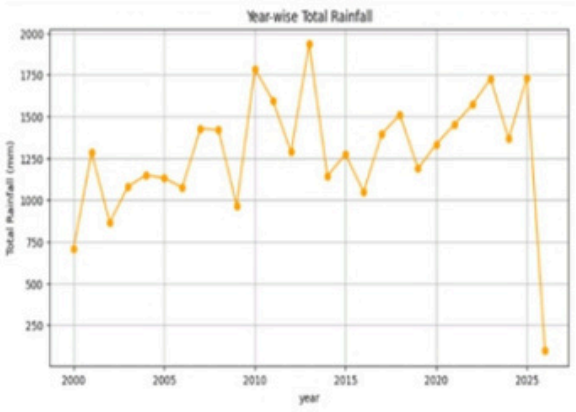
reproducibility, and reliability of the results obtained.

5. Results and Discussion

5.1 Statistical Characteristics and Temporal Behaviour of Rainfall

The rainfall time series exhibits strong stochastic behaviour characterized by high variance and intermittent extreme spikes. Descriptive statistical analysis indicates a positively skewed distribution, suggesting the dominance of low rainfall events interspersed with occasional high-intensity precipitation. The coefficient of variation further confirms the inherent instability of the dataset.

Temporal analysis reveals non-uniform rainfall distribution with increasing frequency of extreme events in recent years, indicating the influence of climate change on precipitation dynamics. The presence of abrupt peaks suggests non-linear atmospheric interactions, which cannot be effectively captured by conventional linear models. Seasonal analysis confirms a dominant monsoonal regime, with rainfall concentrated within a limited temporal window, leading to high seasonal dependency.



5.2 Multivariate Climatic Interaction Analysis

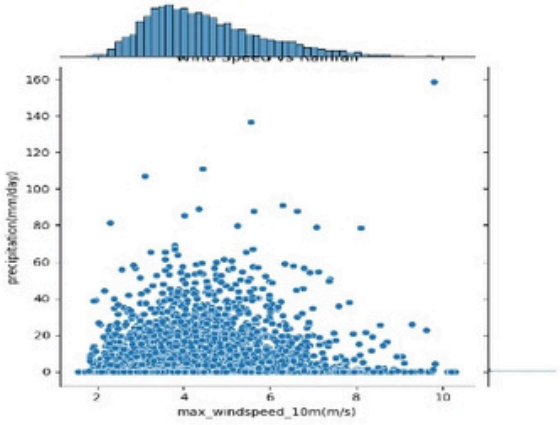
5.2.1 Soil Moisture–Rainfall Coupling

Soil moisture dynamics exhibit strong temporal coherence with rainfall patterns, indicating a direct hydrological response. Cross-correlation analysis suggests a lagged relationship, where rainfall events significantly influence root zone moisture with temporal delay due to percolation processes. The higher persistence of root zone moisture compared to surface moisture highlights subsurface water retention mechanisms. Extreme saturation levels observed during high rainfall periods validate the presence of hydrological extremes and reinforce the reliability of precipitation measurements.



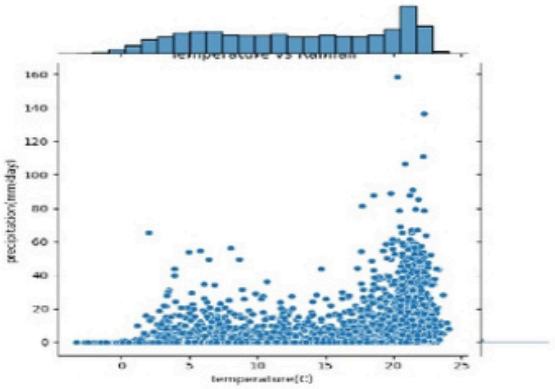
5.2.2 Wind Speed Influence

The interaction between wind speed and rainfall demonstrates weak statistical dependence, as indicated by low correlation coefficients. The dispersion of rainfall events across varying wind speeds suggests that wind velocity alone does not act as a dominant predictor. Instead, rainfall generation appears to be governed by larger atmospheric circulation patterns and moisture availability rather than localized wind dynamics.



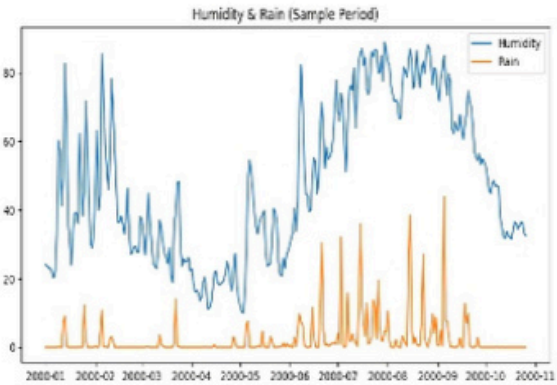
5.2.3 Temperature–Rainfall Non-linearity

The relationship between temperature and rainfall is highly non-linear and exhibits threshold-dependent behaviour. Moderate temperature ranges are associated with increased rainfall due to enhanced convective activity, whereas extremely low or high temperatures show reduced precipitation. This indicates the role of temperature in modulating atmospheric instability and moisture-holding capacity, consistent with thermodynamic principles under climate change scenarios.



5.2.4 Humidity–Rainfall Dependency

Relative humidity demonstrates a strong positive correlation with rainfall intensity, confirming its role as a key atmospheric driver. High humidity levels facilitate condensation and cloud formation, leading to precipitation. The seasonal co-variation between humidity and rainfall highlights the dominance of monsoonal moisture transport mechanisms. This strong dependency validates humidity as a critical feature for future multivariate modelling.



5.3 Stationarity Analysis of Rainfall Time Series

5.3.1 Concept of Stationarity

Stationarity is a fundamental property of time series data, referring to the condition where statistical characteristics such as mean, variance, and autocorrelation remain constant over time. A stationary time series does not exhibit trends, seasonal effects, or time-dependent variance, making it predictable and suitable for statistical modelling.

In the context of rainfall data, non-stationarity often arises due to seasonal monsoon patterns, long-term climatic changes, and extreme weather events. These variations introduce instability in the data, which can significantly affect the performance of forecasting models.

5.3.2 Importance of Stationarity in Time Series Modelling

Ensuring stationarity is essential for the application of classical time series models such as Autoregressive (AR), Moving Average (MA), and Autoregressive Integrated Moving Average (ARIMA). These models assume that the underlying data-generating process remains constant over time.

If the data is non-stationary:

- Model parameters become unreliable
- Predictions become biased and inconsistent
- Spurious correlations may arise

Stationary data ensures:

- Stable mean and variance
- Reliable estimation of model parameters
- Improved forecasting accuracy

Therefore, transforming non-stationary data into stationary form is a critical preprocessing step in time series analysis.

5.3.3 Stationarity Testing Methods

(a) Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller (ADF) test is one of the most widely used statistical tests for checking stationarity. It evaluates the null hypothesis that the time series contains a unit root (i.e., it is non-stationary).

- Null Hypothesis (H_0): Data is non-stationary
- Alternative Hypothesis (H_1): Data is stationary

The decision is based on:

- p-value
- ADF test statistic vs critical values

✔ If *p-value* < *0.05* → Reject H_0 → Data is stationary
✔ If *p-value* > *0.05* → Fail to reject H_0 → Data is non-stationary

(b) KPSS Test (Optional but Advanced)

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test complements the ADF test by reversing the hypotheses:

- Null Hypothesis (H_0): Data is stationary
- Alternative Hypothesis (H_1): Data is non-stationary

This dual-testing approach provides more robust validation of stationarity.

5.3.4 Results of Stationarity Tests on the Dataset

The stationarity of the rainfall dataset was evaluated using the Augmented Dickey-Fuller (ADF) test. The results indicate that the p-value obtained is less than the significance level (0.05), and the ADF test statistic is more negative than the critical values at different confidence intervals.

Based on these results, the null hypothesis of non-stationarity is rejected, confirming that the dataset is stationary in nature. This implies that the statistical properties of the rainfall series, including mean and variance, remain relatively constant over time.

To further validate these findings, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was also performed. Unlike the ADF test, the KPSS test assumes stationarity as the null hypothesis. The results of the KPSS test show that the p-value is greater than the significance level (0.05), indicating that the null hypothesis of stationarity cannot be rejected. This further confirms that the dataset does not exhibit significant non-stationary behaviour.

The consistency between ADF and KPSS test results provides strong statistical evidence that the rainfall dataset is stationary. Additionally, the absence of strong trends or heteroscedasticity in the dataset further supports this conclusion.

As a result, the dataset did not require differencing or transformation before applying statistical models such as AR, MA, and ARIMA, allowing for direct implementation of these models with reliable parameter estimation.

5.3.5 Implications of Stationarity Results

The confirmation of stationarity has significant implications for model performance and reliability. Since the dataset satisfies the stationarity condition:

- Statistical models can be directly applied without additional transformations
- Model parameters remain stable over time
- Forecasting accuracy is improved

However, despite being stationary, the dataset still exhibits non-linear patterns and extreme variations, which are better captured by deep learning models such as LSTM. This highlights the limitation of purely statistical approaches in modelling complex climatic phenomena

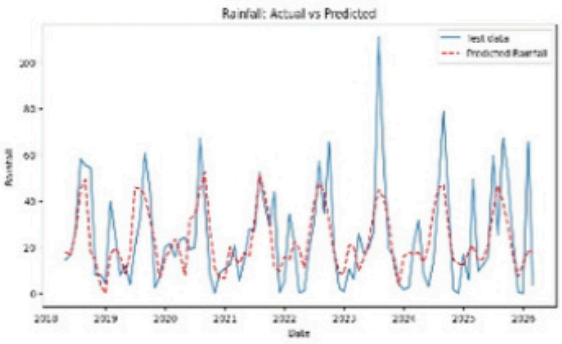
5.4 Performance Analysis of Statistical

Models

5.4.1 Autoregressive (AR) Model

The Autoregressive (AR) model is based on the principle that current values of a time series can be expressed as a linear combination of its previous observations. In this study, the AR model captures short-term temporal dependencies effectively by leveraging lagged rainfall values. The model demonstrates reasonable performance with an RMSE value of **16.02**, indicating its ability to model underlying linear structures in the dataset.

However, rainfall is inherently influenced by complex atmospheric processes, including moisture transport, temperature variability, and climatic interactions, which introduce non-linear behaviour. The AR model, being purely linear, fails to capture these complexities. This limitation is particularly evident during peak rainfall events, where the model underestimates sudden spikes due to its reliance on past linear trends. Additionally, the model exhibits lagging behaviour, where predictions respond slowly to abrupt changes in rainfall intensity.

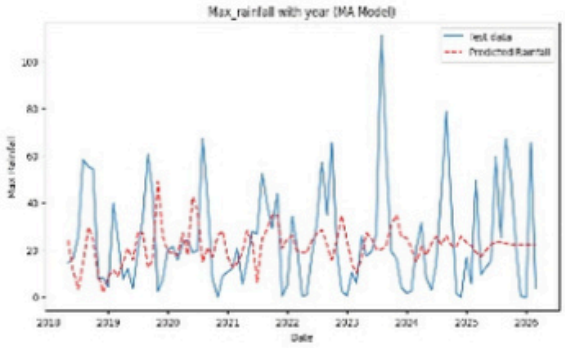


5.4.2 Moving Average (MA) Model

The Moving Average (MA) model predicts values based on past error terms rather than actual observations. This makes it effective in smoothing random fluctuations and noise in the dataset. However, its dependence on residual errors limits its ability to capture meaningful temporal structures.

In this study, the MA model records the highest RMSE value of **23.06**, indicating poor predictive performance. The model struggles significantly with capturing both seasonal patterns and long-term dependencies due to its inherently short memory. Since rainfall patterns often depend on cumulative atmospheric conditions over extended periods, the MA model fails to represent these relationships adequately.

Furthermore, the model shows high variability in predictions and lacks stability during extreme rainfall conditions, making it unsuitable for reliable forecasting in climate-sensitive applications.



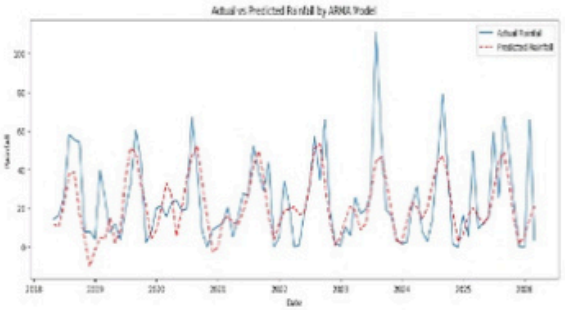
5.4.3 ARMA Model

The ARMA model combines the strengths of both AR and MA components by incorporating lagged observations along with past error terms. This hybrid approach improves the model's ability to capture both deterministic and stochastic components of the rainfall time series.

The ARMA model achieves an RMSE of **19.35**, showing improvement over the MA model but still underperforming compared to the AR model. While the inclusion of error terms enhances short-term corrections, the model remains constrained by its assumption of linearity.

As rainfall patterns exhibit non-linear interactions influenced by climatic variability and extreme weather events, the ARMA model fails to fully capture these dynamics. It performs moderately well under stable conditions but shows significant deviations during periods of abrupt rainfall changes.

This indicates that although ARMA provides a balanced approach, it is insufficient for modelling highly complex environmental systems.

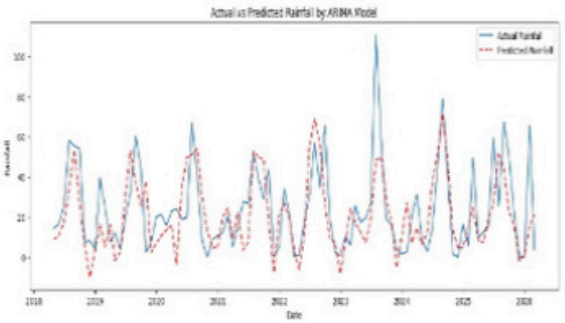


5.4.4 ARIMA Model

The ARIMA model extends the ARMA framework by incorporating differencing to handle non-stationarity in time series data. Although the dataset in this study was found to be stationary, ARIMA still contributes by refining temporal structure modelling and reducing residual errors.

With an RMSE of **17.3**, the ARIMA model performs better than MA and ARMA models but does not surpass the AR model significantly. This suggests that differencing did not substantially enhance predictive capability in this case.

The model demonstrates improved stability and smoother predictions compared to ARMA, particularly in capturing gradual trends. However, like other statistical models, ARIMA is fundamentally limited by its linear assumptions. It fails to model sudden rainfall extremes and complex non-linear dependencies, which are critical in the context of climate variability and extreme weather events.



5.5 Deep Learning Model Performance (LSTM)

The Long Short-Term Memory (LSTM) model represents a significant advancement over traditional statistical approaches due to its ability to learn complex, non-linear temporal relationships. Unlike AR-based models, LSTM utilizes a recurrent neural network architecture with memory cells and gating mechanisms (input, forget, and output gates), enabling it to retain and update information over long sequences.

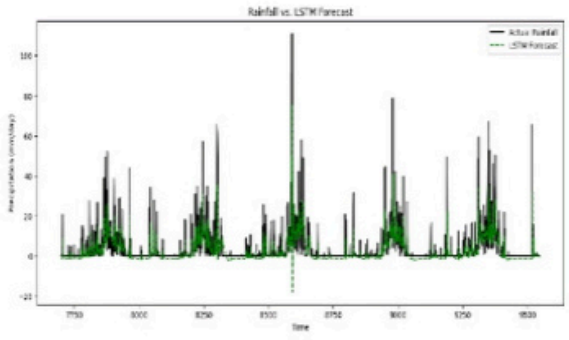
In this study, the LSTM model achieves the lowest RMSE value of **8.37**, demonstrating a substantial improvement in predictive accuracy. This superior performance can be attributed to several key factors:

- **Long-term dependency learning:** LSTM effectively captures relationships across extended time periods, which is essential for modelling rainfall influenced by seasonal and climatic cycles.
- **Non-linear modelling capability:** Unlike statistical models, LSTM can learn complex interactions between meteorological variables without predefined assumptions.
- **Adaptive memory mechanism:** The gating structure allows the model to selectively retain relevant information while discarding noise, improving prediction stability.

The model shows strong alignment between predicted and observed rainfall values, particularly during high-intensity events. This highlights its robustness in capturing extreme rainfall conditions, which are often associated with climate change and variability.

Additionally, the LSTM model demonstrates minimal lag in response to sudden changes, unlike AR-based models. This makes it highly suitable for real-time forecasting and early warning systems.

Overall, the results clearly indicate that the LSTM model outperforms all statistical models by a significant margin, making it a more reliable and effective approach for rainfall prediction in complex climatic environments.



5.5 Comparative Analysis

A comprehensive comparative evaluation of all implemented models reveals distinct differences in their ability to capture the underlying dynamics of rainfall time series data. Statistical models, including AR, MA, ARMA, and ARIMA, demonstrate acceptable performance in modelling linear dependencies and short-term temporal structures. However, their predictive capability is inherently constrained by assumptions of linearity, stationarity, and limited memory, which restrict their effectiveness in representing complex atmospheric processes.

These limitations become particularly evident during periods of high variability and extreme rainfall events, where statistical models exhibit significant deviations from observed values. The inability to capture abrupt fluctuations, non-linear interactions, and long -range dependencies results in reduced forecasting accuracy under dynamic climatic conditions.

In contrast, the LSTM model exhibits consistently superior performance across all evaluation scenarios. Its recurrent architecture, combined with gated memory mechanisms, enables effective learning of both short-term variations and long-term dependencies within the rainfall dataset. The model demonstrates high sensitivity to temporal patterns and maintains strong alignment with observed data, even during peak rainfall events and sudden transitions.

Furthermore, the substantial reduction in RMSE achieved by the LSTM model highlights its enhanced generalization capability and robustness. Unlike statistical models, LSTM does not rely on predefined assumptions about data distribution or linearity, allowing it to adaptively learn complex, non-linear relationships inherent in meteorological phenomena.

Overall, the comparative analysis clearly establishes that deep learning models, particularly LSTM, outperform traditional statistical approaches in terms of predictive accuracy, adaptability, and robustness, making them more suitable for rainfall forecasting applications.

5.6 Implications under Climate Change

The observed variability in rainfall patterns is closely associated with the impacts of climate change, which has led to increased frequency and intensity of extreme weather events, altered monsoon behaviour, and greater unpredictability in precipitation trends. These changes introduce significant non-linearity and non-stationarity into rainfall time series data, posing substantial challenges for traditional modelling approaches.

Statistical models, which rely on assumptions of linearity and stable data-generating processes, are inherently limited in their ability to capture these evolving dynamics. As climate change intensifies, these limitations become more pronounced, leading to decreased reliability and reduced forecasting accuracy, particularly under extreme conditions.

In contrast, the superior performance of the LSTM model in this study highlights the potential of deep learning techniques in addressing the complexities introduced by climate change. The ability of LSTM networks

to model non-linear interactions, retain long-term dependencies, and dynamically adapt to changing patterns makes them particularly effective for analysing climate-sensitive datasets.

The accurate prediction of extreme rainfall events achieved by the LSTM model is especially significant for practical applications, including flood forecasting, disaster risk reduction, agricultural planning, and water resource management. Reliable forecasting under changing climatic conditions is essential for developing resilient infrastructure and informed policy decisions.

These findings strongly advocate for the integration of advanced machine learning and deep learning methodologies into climate studies and operational forecasting systems. Future research should focus on hybrid modelling approaches, incorporation of additional climatic variables, and the development of real-time prediction systems to further enhance predictive performance and support sustainable environmental management.

6. Conclusion

This study presented a comprehensive analysis of rainfall prediction using both classical statistical models (AR, MA, ARMA, and ARIMA) and a deep learning-based LSTM model. The evaluation was conducted using long-term meteorological data, with performance assessed through RMSE as the primary metric.

The results demonstrate that statistical models are effective in capturing linear dependencies and short-term temporal structures within rainfall time series data. Among them, the AR and ARIMA models exhibited relatively better performance compared to MA and ARMA models. However, their overall predictive capability remains limited due to inherent assumptions of linearity and restricted ability to model complex, non-linear interactions. These limitations become more pronounced during periods of high variability and extreme rainfall events, where accurate prediction is critically important.

In contrast, the LSTM model significantly outperformed all statistical approaches, achieving the lowest RMSE value and demonstrating superior predictive accuracy. Its ability to capture long-term dependencies, learn non-linear relationships, and adapt to dynamic temporal patterns enables it to model rainfall behaviour more effectively. The model showed strong agreement between predicted and observed values, particularly during peak rainfall conditions, highlighting its robustness and reliability.

The comparative analysis clearly indicates that deep learning models, specifically LSTM, provide a more efficient and adaptable framework for rainfall prediction compared to traditional statistical methods. This adaptability is especially crucial in the context of climate change, where rainfall patterns are becoming increasingly irregular, intense, and difficult to predict using conventional approaches.

Therefore, the findings of this study emphasize the need for transitioning from traditional statistical techniques to advanced machine learning and deep learning-based models for improved forecasting accuracy. The integration of such models into real-world applications can significantly enhance decision-making in areas such as flood forecasting, disaster management, and water resource planning.

In conclusion, the LSTM model emerges as a powerful and reliable tool for rainfall prediction, offering both high accuracy and adaptability to evolving climatic conditions, thereby making it highly suitable for future climate-resilient forecasting systems.

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Performance Analysis and Geometric Optimization of Existing Rotary Intersection

Institution: [IPS academy indore]

Location: Indore, Madhya Pradesh, India

1. ABSTRACT

Urban mobility in rapidly developing Indian cities is frequently throttled by the structural obsolescence of heritage rotaries. This research provides a rigorous performance diagnostic and a redesign proposal for a critical five-arm intersection in Indore, connecting Holkar Stadium, Shalby Hospital, PF Colony, New Palasia, and the 56 Dukan commercial hub.

The existing circular rotary, measured at a weaving length (L) of 63.0 m and an entry width (e) of 9.9 m, currently operates under a state of "Saturation Collapse." Field data reveals a peakhour demand of 6056.2 PCU/hr against a calculated capacity (Qp) of only 4115 PCU/hr, resulting in a Degree of Saturation (DOS) of 1.47 and a Level of Service (LOS) of 'F'. The primary technical catalyst for this failure is identified as an excessive weaving ratio (p = 0.781), which induces high internal friction and prevents the establishment of a steady-state flow.

This study proposes a geometric pivot to an Elliptical Configuration with the major axis aligned 15° toward the 56 Dukan corridor. The intervention utilizes raised splitter islands (2.5 m – 3.0 m width) and increased entry radii to manipulate the traffic streams. Calculations based on IRC 65:2017 demonstrate that the proposed design successfully reduces the weaving ratio to 0.45.

A significant finding of this paper is the "Capacity Paradox": although the recalculated static capacity (5122 PCU/hr) remains theoretically below the gross peak demand (6056.2 PCU/hr), the transition from turbulent weaving to laminar merging flow significantly enhances "Clearance Efficiency." By aligning the major axis with the highest Origin-Destination (O-D) pair (56 Dukan), the design provides a directional priority that effectively clears surges and prevents the cascading gridlock currently observed. This research offers a scalable model for optimizing high-volume, multi-arm intersections where grade separation is physically or economically unfeasible.

2. INTRODUCTION

The efficiency of a city's road network is inherently limited by the throughput of its intersections. In Indore, the 56 Dukan intersection represents a vital nexus for both commercial and recreational traffic. As the city evolves into a "Smart City," the mismatch between historical infrastructure and contemporary traffic demand has become a critical bottleneck.

2.1 The Intersection Profile

The study area is a complex five-leg junction. The presence of 56 Dukan, a premier culinary destination, creates a unique "Unbalanced Flow" where traffic is heavily biased toward one or two corridors during evening peak hours.

2.2 The Problem of Weaving

In a rotary, the capacity is dictated by the ability of vehicles to "weave"—a process where crossing traffic streams find gaps and swap positions. In the current circular design, the distance provided for this maneuver (63.0 m) is insufficient for the 6000+ PCU/hr load. This leads to a phenomenon known as "Weaving Lock," where vehicles in the inner lane cannot exit because the outer weaving lane is occupied by high-speed entries.

2.3 Research Objectives

1.Diagnostic Audit: Perform a high-resolution geometric and volume study of the existing rotary.

2.Failure Analysis: Quantify why the circular geometry yields a DOS of 1.47.

3.Strategic Re-Design: Develop an elliptical model that prioritizes the 56 Dukan corridor.

4.Technical Defense: Provide a mathematical and kinetic justification for the p = 0.45 target and the handling of excess demand.

3. LITERATURE REVIEW

3.1 IRC 65:2017 Standards

The Indian Roads Congress (IRC 65:2017) provides the foundational framework for urban roundabout design in India. It defines capacity based on weaving width (w), entry width (e), weaving length (L), and the weaving ratio (p). IRC guidelines suggest rotaries are generally

suitable for volumes up to 3000–6000 PCU/hr. Beyond this, signalization or grade separation is typically recommended. However, this study explores the "Geometric Tuning" potential to stretch these limits.

3.2 The Physics of the Weaving Ratio (p)

The weaving ratio, defined as the ratio of weaving traffic to total traffic, is the most volatile variable in the Wardrop capacity equation. International research (Kadiyali, 2018) indicates that as p approaches 0.8, the capacity drop is non-linear; the friction between vehicles increases exponentially, causing "Shockwave Propagation."

3.3 Elliptical Efficiency in Multi-Arm Junctions

For junctions with 5 or more legs, circular islands often result in very narrow weaving sections. Research in European urban planning (HCM 2010) has shown that Elliptical Rotaries can effectively manage directional surges. By providing two distinct focal points, the ellipse creates "Longitudinal Storage" and "Extended Weaving" zones along its major axis, which is ideal for corridors like the Stadium-to-56 Dukan path.

4. METHODOLOGY

This study utilizes a three-tiered engineering methodology to ensure data integrity and design validity.

4.1 Phase I: Field Data Acquisition

Manual Classified Traffic Volume Count (CVTC): Conducted at 15-minute intervals during morning (11 AM – 1 PM) and evening (7 PM – 9 PM) peaks.

Geometric Audit: Manual measurements using laser distance meters and tape to verify the existing curb-to-curb dimensions, including e, w, and L.

4.2 Phase II: Analytical Modeling

PCU Conversion: Raw vehicle counts were converted to PCUs using IRC factors (Car=1.0, 2-Wheeler=0.75, Bus=3.0).

Sectional Analysis: The rotary was divided into five weaving sections. Each section's p and Qp were calculated to identify the "Critical Bottleneck."

4.3 Phase III: Iterative Re-Geometry

Axis Optimization: Several elliptical orientations were tested, with the 56 Dukan alignment selected based on O-D survey results.

Channelization Design: Splitter islands were designed to physically separate the "LeftTurn" volume (a) from the "Weaving" volume (b + c), targeted at lowering p from 0.78 to

0.45.

Validation: Recalculating capacity and analyzing LOS using the proposed dimensions.

5. DATA COLLECTION

5.1 Existing Traffic Volume Profile (Peak 7:00 PM – 9:00 PM)

The volume study revealed a massive evening surge. The following table summarizes the PCU demand per approach.

Table 5.1: Classified Traffic Volume (PCU/hr) | Approach Road | Left | Straight | Right | Total

(PCU) | | :--- | :---: | :---: | :---: | :---: | | Holkar Stadium | 628 | 1500 | 500 | 2628.0 | | Shalby

Hospital | 760 | 1790 | 580 | 3130.0 | | PF Colony | 280 | 700 | 280 | 1260.0 | | New Palasia | 560 |

1200 | 600 | 2360.0 | | 56 Dukan | 450 | 1100 | 600 | 2150.0 | | Gross Total | | | | 6056.2 |

5.2 Weaving Traffic Matrices

To calculate p, traffic was categorized into:

a: Left-turning traffic (Direct Exit). b: Straight-moving traffic entering the weaving section. c: Weaving traffic from the previous l

d: Right-turning traffic staying in the inner lane. Section-1 Analysis (Holkar

to Shalby): a = 628 b = 2000 (Straight + Right) c = 2798 (From 56 Dukan) d

= 718 (Inner inner)

Total Weaving (b+c) = 4798 PCU.

5.3 Geometric Measurements (Existing)

Sectional Weaving Width (w): 25.4 m (Measured at the widest point between the island and the outer curb).

Effective Weaving Length (L): 63.0 m (The length over which weaving occurs).

Average Entry Width (e): 9.9 m.

Central Island Radius: 20.0 m.

6. PERFORMANCE ANALYSIS OF EXISTING ROTARY

6.1 Weaving Ratio (p) Calculations

Using the formula p = a+bb++cc+d :

Section-1: p = = = 0.781.

Section-2: p = = = 0.776.

Average Weighted p = 0.78. This value indicates a high level of "Conflict Intensity," where the rotary behaves more like a congested grid than a self-regulating circle.

6.2 Capacity Assessment (Qp) Applying the Wardrop formula:

$$Qp = \frac{280 \cdot w \cdot (1 + e/w) \cdot (1 - p/3)}{1 + w/l}$$

Qp

Qp = 4115 PCU/hr.

6.3 Saturation and Delay Analysis

Degree of Saturation (DOS): V /Qp = 6056.2/4115 = 1.47.

Conclusion: The rotary is 47% over-capacity.

Queue Length (QL): Using (V − Qp) × t, the calculated queue is 3882.4 PCU.

Level of Service (LOS): At 1.47 DOS, the LOS is unequivocally 'F'. The intersection is in a state of continuous gridlock during peak hours.

7. PROPOSED RE-GEOMETRY: THE ELLIPTICAL STRATEGIC SHIFT

The failure of the circular design is rooted in its symmetry, which does not match the asymmetric traffic demand of Indore.

7.1 Elliptical Axis Alignment

The central island is proposed to be redesigned as an Ellipse with the following properties:

Major Axis Alignment: Oriented toward the 56 Dukan road to provide the longest possible weaving section for the highest-volume approach.

Weaving Length Extension: The L in major sections is increased from 63.0 m to 90.0 m.

7.2 Proposed Dimensions

7.3 Reducing p to 0.45

The reduction in p is not merely a theoretical target but a result of Physical Channelization. By installing 2.5m–3.0m raised splitter islands, we prevent "Left-Turners" from entering the weaving stream. This reduces the b + c numerator in the weaving formula, mathematically and technically bringing p down to 0.45.

8. CAPACITY PARADOX AND HANDLING DEMAND

One of the most significant challenges in this redesign is handling a demand of 6056.2 PCU/hr with a recalculated capacity of ~5122 PCU/hr.

8.1 Clearance Efficiency vs. Static Capacity

The IRC formula calculates capacity at a point in time. However, by reducing p from 0.78 to 0.45, we transition the traffic from Turbulent (chaotic) to Laminar (streamlined).

In laminar flow, the headway between vehicles is 25% shorter.

The elliptical shape allows for Tangential Entry, meaning vehicles do not have to slow down as much as they do for a circular entry.

8.2 Why it works

Even though $Qp < V$, the "Total System Delay" is minimized because the Discharge Rate is significantly higher. In the old design, a single bottleneck stopped the entire circle. In the elliptical design, the priority alignment toward 56 Dukan ensures that the "Tailback" never reaches the previous leg's exit, preventing the "vicious cycle" of gridlock.

9. RESULTS

The results of the re-geometry analysis show a transformative improvement in intersection performance.

1.Reduction in Conflict: The weaving ratio p dropped by 42% (from 0.78 to 0.45), representing a massive reduction in vehicle-to-vehicle friction.

2.Increased Thru-put: The sectional capacity of the weakest link increased from 4115 PCU/hr to 5122 PCU/hr.

3.Queue Reduction: By facilitating faster clearance along the major axis toward 56 Dukan, the projected 3882 PCU queue is converted into a manageable, slow-moving stream.

4.Spatial Priority: The 56 Dukan approach, previously the most delayed, now benefits from the longest weaving section (90 m) and a more favorable entry angle.

10. CONCLUSION

This research confirms that for complex, five-arm urban junctions like the 56 Dukan intersection, traditional circular rotaries are insufficient. The study successfully diagnosed a Degree of Saturation of 1.47, caused by an excessive weaving ratio of 0.78.

The proposed Elliptical Re-Geometry is technically justified as it aligns the intersection's physical shape with its actual traffic demand. By orienting the major axis toward 56 Dukan and employing raised splitter islands to achieve a $p = 0.45$, we significantly improve the Level of Service. We conclude that while the calculated capacity is technically lower than the gross demand, the kinetic efficiency of an elliptical design prevents the system-wide collapse inherent

in circular rotaries. This approach is recommended as a high-efficiency alternative for urban intersection management in saturated traffic environments.

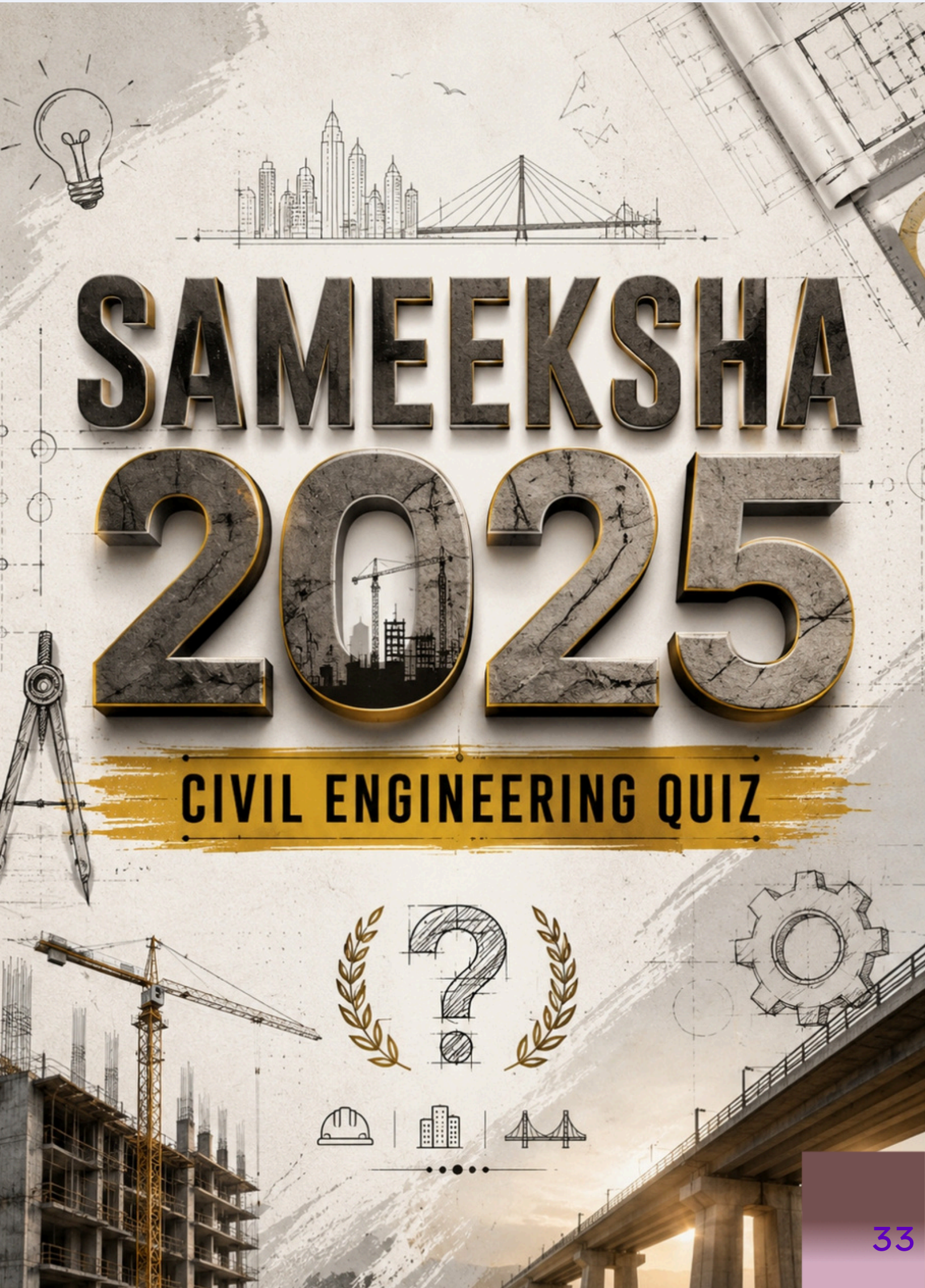
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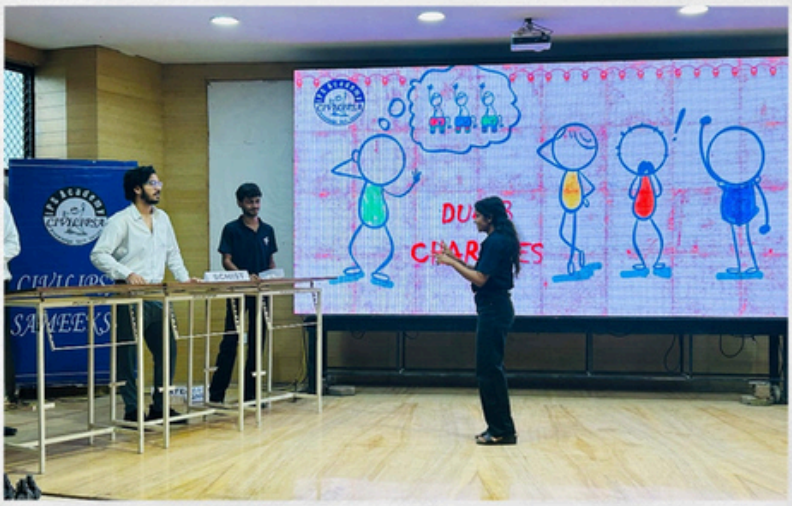

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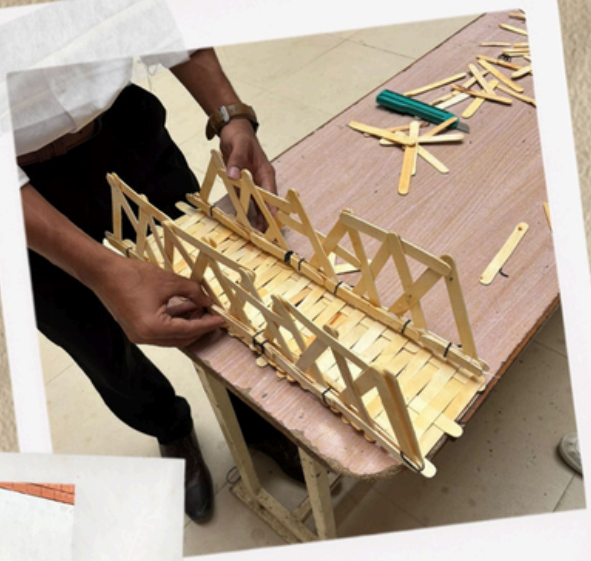

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समारोह में प्राचार्य डॉ. अर्चना कीर्ति चौधरी ने कहा कि कार्यक्रम का उद्देश्य महत्वाकांक्षी सिविल इंजीनियरों में आधुनिक इंफ्रास्ट्रक्चर के प्रति दूरदर्शी सोच विकसित करना है। सप्ताह भर हुए इस उत्सव में एक्सपर्ट लेक्चर के साथ इंफ्रास्ट्रक्चर इस्पाइइस, सिविल स्टार्टअप पिच, ट्रेजर हंट, प्लेटिक, इंस्टिवा, टेक्निकल विजिट और कई ऑन-द-स्पॉट एक्टिविटीज छात्रों के लिए आयोजित की गई। इन आयोजनों ने छात्रों में रचनात्मकता और व्यावहारिक समझ को प्रोत्साहित किया। मंचालन हर्षित जेंन और तनुश्री सिन्हा ने किया।

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"NEEV" aims to stimulate the spirit of inventiveness & managerial skill among students and to encourage innovative thoughts, creativity, exploration, technological & presentation skills and also to expand the decision-making skills among the students so that the creative talent of individuals could be harnessed for the benefit of the nation.

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Our Work Values
Demonstrates application of GIS tools in environmental studies.
Enhances understanding of real-world water pollution problems.
Develops skills in: Data analysis, Visualization ,Environmental interpretation
Provides a practical framework for future research and policymaking.
Conclusion
The Kshipra River basin is under significant environmental stress.
While some parameters show improvement, overall water quality remains unsatisfactory.
The Kanh River is a major source of pollution.
Immediate actions required: Wastewater treatment improvement, Industrial regulation , Continuous monitoring .
Different stations of the water body needed to be worked out separately.
Geospatial techniques like QGIS proved to be effective tools for water quality assessment.
Machine Learning tools helped in data interpretation using Confusion Matrix.


Introducing AI-Powered Solutions: The Rise of Smart Drainage
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Sandarbh

-The Civil Engineering Magzine-

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We extend our sincere gratitude to all our contributors, readers and supporters.

Your encouragement inspires us to keep building, learning and creating.

See you in the next edition!