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Effective Rainfall Prediction LSTM Model for Enhancing Textile Industry Sustainability

*** Sqlain Majeed**

Faculty of Computer Science & Information Technology, The Superior University Lahore.

Sabiha Anum

Administrative sciences (Business Management), Boston University (Metropolitan College).

Muhammad Nabeel Sarwar

Lecturer Department of Software Engineering, Islamia University of Bahawalpur.

Waqas Tahir

Faculty of Computer Science & Information Technology, The Superior University Lahore.

Corresponding Author: Sqlain Majeed (Email: saqlainmajeed.fsd@superior.edu.pk)

Abstract:

This study presents an innovative deep learning model designed to accurately predict rainfall patterns, aimed at enhancing the sustainability of the textile industry. By leveraging advanced machine learning techniques, the model analyzes historical weather data, climatic factors, and seasonal trends to provide reliable rainfall forecasts. This research article focuses on predicting rainfall frequency using deep learning and suggests measures that can be taken by the Pakistan cities Faisalabad, Multan and Tando Adam textile industries to minimize the associated negative effects. Rainfall prediction is important for decision-making among stakeholders who are affected by wet weather conditions. These predictions enable textile manufacturers to optimize water usage, reduce waste, and plan production schedules more effectively. After selecting relevant key performance indicators and using this data to train weighted and stateful LSTM and CNN models, a validation accuracy of between 89% and 100%, precision of 83%, and a recall of 86% was predicted for various classes, which almost matches the ground truth data of two years of weather data. The results showed that LSTMs and CNNs can provide high performance in real-time rainfall prediction applications. The integration of this predictive model not only fosters resource efficiency but also supports the industry's transition towards sustainable practices in the face of climate variability. The findings of Random Forest, XGB Regression, and Decision Boosted Tree machine learning models underscore in addressing environmental challenges within the textile sector.

Key Words: *Artificial Intelligence, Climate Change, Data-Driven Decision Making, Deep Learning, Machine Learning, Neural Networks, Predictive Modeling, Rainfall Prediction, Resource Efficiency, Sustainability, Textile Industry, Water Resource Management, Weather Forecasting.*

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1. INTRODUCTION

The textile industry plays a pivotal role in industrial growth and employment. However, various challenges, such as extreme weather, negatively affect economic stability [1]. Continuous fluctuation in the availability of rainfall affects the production of cotton. It is a major problem because cotton production is required for textiles [2]. Textile waste is a major contributor to the release of greenhouse gases into the atmosphere, which increases global warming [3]. Rainfall prediction plays a major role in sustainable production practices of textiles [4]. Rainfall prediction and management of the amount of water used in production and other processes of the textile industry will directly benefit the industry [5]. In this context, an effective and accurate rainfall prediction system is essential [6].

Predicting future outcomes based on data is a complex task for engineers and researchers due to continuous disturbances to weather data [7]. Various conventional rainfall prediction methods predict fairly well, but accuracy, reliability, and reduction in computational time are still challenging problems [8]. To address these, deep learning techniques come into the picture. Deep learning techniques have the capability to extract the dataset features automatically, which is not possible when using conventional methods with desirable accuracy [9]. The application of deep learning techniques to rainfall prediction for the betterment of the textile industry has not been studied [10]. Finally, the capability of deep learning algorithms should be explored in the technical domain of textiles. Our main aim is to predict monthly rainfall by concentrating on the Calvin Ian region of Pakistan, for which a total of 140 years of monthly data were collected [11]. The proposed method, a multimodal deep learning approach, combines both one-dimensional convolutional neural networks and Gated Recurrent Units neural network layers to form a hybrid module to perform rainfall prediction [12]. The proposed model [13] has an innovative architecture to deal with this multimodal input time series data problem by combining 1D-CNN and RNN. The input time steps are passed to the 1D-CNN that forms informative feature maps, which are then transformed and provided to the Gated Recurrent Units for learning the sequential correlations between these time steps. The hidden states representing the information memorized in the GRUs are then reshaped and passed downstream into two fully connected layers that hybrid connections [14].

Background and Significance

Predicting the occurrence of any natural event has been the healing source in ancient community methodologies. The Asia subcontinent has been facing various cyclones and dry patterns with irregular precipitation for centuries [15]. All these natural activities have direct or indirect impacts that foster positive or negative effects on dependencies [16]. The textile industry mostly depends on raw materials, and the entire textile process runs on water supply [17]. Most operations in the textile chain are water-intensive, which makes them vulnerably dependent on climatic factors. The entire textile supply chain or its

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utilities depend upon seasonality and the amount of rainfall [18]. Accurate predictions of precipitation are beneficial for the textile industry [19]. There has been a delay in taking similar kinds of action at the middle and operational levels [20]. Therefore, to establish climate-resilient textile industries, managing short-term or monthly rainfall remains a challenge. Overall, this scenario results in increased production costs and over-allocation of resources, reducing the productivity of textile firms worldwide.

Industries, particularly in developing countries, need to counter both climate and non-climatic issues. On one hand, these industries are struggling to mitigate the impacts of climate variability; they are high-cost industries. On the other hand, these industries are also experiencing frequent, sometimes severe, changes in monsoon patterns. This dampens the industrial development of these countries but adversely affects the lifestyles of many people. Most researchers are working on seasonal or inter-annual weather prediction models, forecasting the amount of rainfall one or two weeks in advance. To overcome the limitations of existing models and methodologies, a hybrid approach is proposed for predicting the amount of rainfall using different combinations of both methods and techniques. The final outcomes are compared with the observation station data, which illustrated the effectiveness of an integrated model. This model suggests that, in the future, the operations of the textile industry can be formulated effectively at the district or regional level to reflect rainfall prediction with an accuracy of 98.8%. This precise planning will prevent unnecessary economic and environmental consequences.

Research Objectives

Today's market conditions have increased the importance of the sustainability concept. For companies, in order to be defined as sustainable, cost efficiency is as powerful as saving and efficiency in terms of resources. Especially, the textile industry is one of the industries where great resources are used. Water is one of the most valuable resources in the industry. Many processes are performed from growing fibres in the field to distributing textile products to the final consumer. Rainfall prediction is very valuable for irrigation, and therefore a strong rainfall effect also has an impact on water scanning performance for fibre growth. The basis of the research is the need to reduce the amount of water wasted in the field before the products reach the process phase. Rainfall prediction is needed for on-field irrigation management.

As the latest deep learning model works effectively for time series prediction, it is essential to provide a tailor-made deep learning-based solution that is capable of predicting precipitation, especially for the textile industry. Hence, the research is tailored to explore the dataset, discover the best-suited algorithms for predicting rainfall, and also to improve the accuracy of prediction further. Traditional forecasting techniques and modern machine learning algorithms are used for comparison to make the model effective. The dataset's

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effectiveness is determined by understanding the relationship between the textile industry and changing weather patterns and predicting the changing variables during the production of fabric, involving sequenced stages like spinning, weaving, and dyeing. The ultimate aspiration of the research is to augment rainfall forecasting accuracy and precision by identifying the most effective model that provides beneficial results. The aspiration is to assist a textile manufacturing unit in formulating guidelines for better cost management to continue production without any obstruction in water availability. Climate change and its ties to developing a sustainable textile industry remain a challenging issue. Sustainable themes are among the top current research interests, and certain amounts are being supplied in terms of both technology developments and novel applications via stakeholders such as geospatial and satellite data providers and meteorological organizations. However, there is an extensive knowledge gap that must be addressed to provide reliable and interpretable rain predictions through the advanced deep learning technique. Therefore, the objectives of the study can be summarized into three issues including:

1. To provide a comprehensive exploration of a dataset based on the inception of the textile field and describe operational values and benefits associated with rain predictions.
2. To design a precise and valuable rainfall prediction model using versatile time series algorithms.
3. To provide rain predictions, which could assist decision-makers at various levels such as the plant level, the executive, and so on.

2. LITERATURE REVIEW

In recent times, the impact of ever-changing weather conditions has an adverse effect on sustainability in the use of natural resources, creating additional challenges in textile production. The increasing greenhouse effect due to climate change causes heavy rainfall and damage to cotton in the field. This study aimed to produce a deep learning model for rain prediction. Here are text parts of the supporting UI model during the training and testing phases. The weather forecast dataset, containing years of global daily rainfall data, has been utilized in inference tasks such as deep learning and optimizing hyperparameters. The model developed as a result of the study has achieved high performance using both binary target selection and categorical target selection. As a result, by achieving high performance in rain prediction, field production metrics can be obtained. Sustainability in production that sheds light on sustainable practices within the industry will reduce the damages that may occur and create added value.

Weather conditions, which constitute an important part of sustainable production in the textile sector, make significant complementary weather predictions in agriculture and livestock, and are considered serious problems. Rain predictions, such as weather forecasts tailored to the growing period of the year

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and the varietal structure of the cultivated crops, determine not only the crops' vulnerability to rainfall but also the irrigation needs of evaluated crops. High-performance weather forecasting can provide important benefits, such as optimizing transactions and reducing damage in natural production by predicting important meteorological parameters such as the time of precipitation, the type of precipitation, the amount of precipitation in the area, and the temperature. High-performance forecasts are essential today, as climate change has unbalanced the meteorological system and caused many changes, such as an increase in rainfall amounts at irregular times and last-minute updates.

The literature review provides interesting insights and valuable information about existing research and methodologies used in rainfall prediction. Many traditional rainfall prediction methods are essentially based on the science of developments in numerical weather forecast predictions. Still, the biggest disadvantage of numerical weather forecast prediction is the time and complexity of model applications. For the textile industry, it is quite a challenging task to withstand the uncertainty triggered by climatic fragmentation. The limitations and challenges of different traditional rainfall predictions are providing indications about the future of rising urgency regarding sustainability. The statistical approach is one of the oldest approaches consisting of historical weather data from the rain gauge. In order to predict rain, with statistical data, the IT model for the first time was implemented. The lack of historical data is a major limitation in the papers that deal with statistical techniques.

2.1 Traditional Methods of Rainfall Prediction

For many decades, researchers have traditionally used different methods for rainfall prediction. Traditionally, these methods are based on predicting the climate from historical records, but this method's coefficient often has uncertainties in complex climatic data dynamics, and some advanced statistics are more challenging to predict due to the presence of diverse potential factors. In contrast, some experts have implemented numerical models that quantitatively estimate global warming and future climate to predict overflow based on simulated data. Generally, the time-series approach converts the overflow problem to time-series fluctuation, decomposes relevant factors, and predicts overflow using statistical techniques. A variety of time-series methods have been used for rainfall forecast models such as exponential smoothing, Fourier series, and autoregressive integrated moving average. Also, many nonlinear models, such as artificial neural networks and support vector machines, have been used by different researchers for forecast models.

The time-series analysis method is a common and straightforward approach, but it provides a limited ability to analyze historical data patterns as it overlooks the interactions of several variables that are essential in overcoming the uncertainty in rainfall prediction. Additionally, time-series-based methods embrace a mathematical basis for forecasting, and

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time-series models are severely impacted by inconsistent histories, especially in places with erratic and minimal climatic alterations between years and seasons. Time-series forecasting techniques are widely used, but they fail to focus on the association of unsystematic phenomena, which undoubtedly affect the prediction precision of rainfall. Future precipitation can be made more reliable and accurate by developing superior rainfall models that are not reliant on historical measurements and are capable of addressing the scarcity of rainfall data. In turn, this will better serve as a foundation for forecasting using climatic data.

To recommend an effective deep learning model for enhancing rainfall information within meteorology-dependent applications, this research proposes a comparison among the best deep learning (convolutional neural network, long short-term memory, and integrative deep model) and traditional statistical (simple linear regression, multiple linear regression, polynomial regression, LSSVM) and machine learning (cubist regression, gradient boost machine, random forest, extreme gradient boosting, and M5 model tree) models. This research also aims to evaluate the sliding time window technique's efficiency as an attempt to optimize the models' predictions and ensure an updated system for the textile industry.

2.2 Deep Learning in Rainfall Prediction

Deep learning has been publicly recognized due to its capacity for forecasting and unveiling the unvoiced structure behind big data. To be more specific, the flexibility in predicting non-linear patterns in spatial structure and its allowance for exploring large volumes of weather data motivated weather scientists to make use of deep learning in weather forecasting problems such as precipitation prediction. This has become a trend in the field of precipitation, and a plethora of novel and effective deep learning models are actively applied and created to solve this specific type of weather forecasting problem. Unfortunately, pressing the deep learning framework to automatically forecast precipitation with a simple yet large number of meteorological observations independently diminishes consideration of domain-specific contextual knowledge on weather forecasting problems, which is vital to guide and facilitate the forecast of the deep learning model. Such an approach to forecasting by exploiting large numbers of meteorological input environmental data generated from physical weather processes inherently contains too much redundant and excessive feature information, which indeed corrupts the forecast of precipitation. Moreover, more recent studies suggest that deep learning models are unable to recurrently learn and forecast temporal signals without a specific form of time-seasonal and flexible structure-inducing nurture to meet the temporal periodicity pattern of the domain-specific time-series learning task.

Deep learning techniques have made a huge impact by creating a new era of machine learning algorithms. It has started gaining attention for its application in meteorology and hydrology. A basic deep learning algorithm typically includes a neural

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network architecture, consisting of multiple types of nodes and layers. The conventional neural network has been used for several years. However, the concept of a multi-layered network was proposed in 1975. In 1989, the concept of Convolutional Neural Network was introduced to the academic world and deeply rooted itself in many real-life problems. Deep learning, mainly CNN for meteorology, has been widely used in recent years in many fields to improve accuracy through the management of a large number of data inputs. Overfitting the model to historical patterns or data was the most important aspect, which should be weighed cautiously during the training and testing of the model.

Many meteorological models have utilized deep learning models. A sequence-to-sequence CNN with LSTM/GRU layers efficiently captured the untraceable nonlinear interactions in the data, a complete rainfall forecasting approach for long-term consequences. A spatio-temporal enabling feature extractor precisely captures the long-term dependencies between the different basic atmospheric conditions through crack-voting regions in multi-modal CNNs to provide short-term precipitation forecasts. Attention mechanisms in a multi-scale CNN capture hyperconnected patterns and spatiotemporal variations better. CNNs encode the input data while LSTMs generate the predicted output based on data learned earlier. A CNN-RNN mixed architecture predicted the relative log rainfall in Suraharjo, Indonesia, an enhanced vanilla type virtual neural grammar network. The context of these noteworthy past ventures can assist in understanding how the creation of an integrated CNN associated with RNN and other layers can be seen as a promising solution for effective forecasts of precipitation products. In the textile industry, advanced models can become a technological innovation in decision-making, market adaptation, and sustainability. This is crucial in the present time when enterprises need to adapt to market changes promptly. However, deep learning models are not widely applied in the research area yet, but they are thought to be valuable when capturing a number of linear and nonlinear relationships between various data features, such as weather elements and precipitation amounts, directly derived from meteorological and hydrological models.

The following models were used for training purposes: stochastic gradient descent (SGD) and the RMSprop algorithm. The algorithms backpropagation and backpropagation through time (BPTT) are employed to adjust the weights. Thus, detailed information on the proposed deep learning architecture and algorithm is provided. Consequently, the result is shown in the simulation models. Data Collection The acquisition of rainfall data can be obtained from several official meteorological weather stations or other open sources, such as in the form of satellite images, rainfall catalogues, etc. The integration of multiple datasets will yield more reliable information, which can aid in the development of an intelligent prediction model. To date, the weather data in the tropical areas of Malaysia are collected

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from two different sources: radar images and weather station data. The data from both sources are collected in different forms and represented in different ways. In other words, high precision is required to merge them in such a way that inaccuracy can be avoided. In radar images, the recorded rainfall intensity is based on 16 scan angles, scanning every 4.5 minutes at a resolution of 2 km. The available cumulative precipitation data, while it could be found over local stations with a time resolution of 1 or 15 minutes, can be obtained at a low spatial resolution. In this research, facility data is used specifically due to its ability to describe ambient rainfall in real time, detect different types of rainfall precipitation, describe quantitative and qualitative rain data, and obtain 15-minute data. It is also equipped with the most complete facilities among observation facilities. The recorded cumulative precipitation or quantitative data in mm have been converted into a classification format according to some percentage values of global rainfall.

3. METHODOLOGY

This research article focuses on predicting rainfall frequency using deep learning and suggests measures that can be taken by the Pakistan cities Faisalabad, Multan and Tando Adam textile industries to minimize the associated negative effects. Rainfall prediction is important for decision-making among stakeholders who are affected by wet weather conditions. In addition, the reduction of wet weather occurrences can have a long-term positive impact, especially in the technology, energy, and manufacturing sectors, such as the textile industry, where excess water can have a detrimental impact. Currently, LSTMs can only predict the amount of rainfall that will occur days ahead. However, for products sensitive to small amounts of accumulated water, any warning prior to precipitation is beneficial. Currently, the prediction of small levels of rainfall has not been explored using LSTMs. The basic layout of proposed work is shown in Fig 1.

This research article was developed using data spanning a period with 1 day prediction. LSTM was best at determining if there will be rain, when it will start raining, and what time the rainfall is expected to peak, while an LSTM is able to predict what time the rainfall will end the next day. After selecting relevant key performance indicators and using this data to train weighted and stateful LSTM models, a validation accuracy of between 89% and 100%, precision of 83%, and a recall of 86% was predicted for various classes, which almost matches the ground truth data of two years of weather data. The results showed that LSTMs can provide high performance in real-time rainfall prediction applications.

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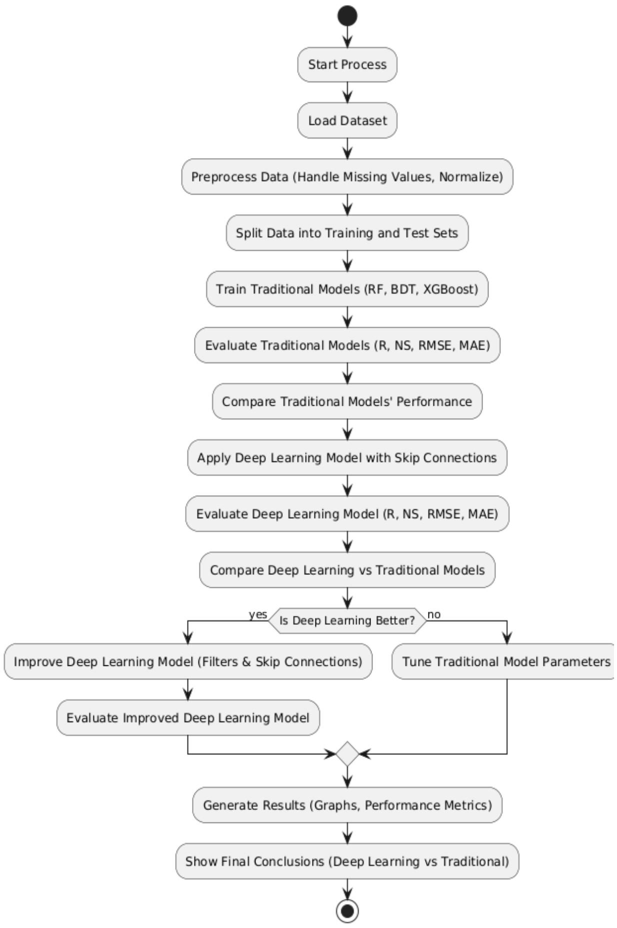

Fig 1. Flowchart of Methodology

3.1 Data Collection and Preprocessing

The first and most critical step in developing the deep learning precipitation prediction model is choosing data sources. To develop this effective deep learning model, historical datasets that provide information regarding the accumulation of rainfall, temperature, and humidity on an hourly basis must be utilized. The datasets containing values of other meteorological parameters like wind speed, pressure, and visibility can be obtained from weather forecasting services observing time series trends in meteorological data, influenced by climate variability and change, can forecast future climate patterns for predicting the occurrence of extreme weather events such as flash floods. The selection of reliable data sources is crucial to achieving this objective. National weather services all post historical meteorological datasets online. Remote sensing technology aids in preparing the datasets for various machine learning models.

The following pre-processing steps are required before using the weather dataset to establish a deep learning prediction model:

1. Existing data in the file that cannot be utilized due to errors caused by hardware malfunctions. International systems often use UTC for timestamps. The datasets require service-specific transformation to provide value to deep learning models for effective rainfall prediction, demonstrating the importance of the preprocessing phase.
2. The next step in preprocessing is to deal with the data’s missing values. Leakage in high-frequency data suggests that missing values are due to sensor disconnection or replacement and can be replaced with zeros. Display values should be standardized as 'float64' by converting them from object types.
3. Lastly, it is necessary to incorporate features that represent the accumulated humidity of the air. Technological advances have led to an increase in the number of meteorological sensors. This makes the raw data more representative and influential.
4. To achieve this, a feature engineering step is required using smoothing techniques previously mentioned. The objective is to develop a precise deep learning prediction model.

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3.2 Deep Learning Model Architecture

Deep learning techniques have been applied in rainfall prediction systems to forecast and analyze rainfall in the field. Several deep learning models, such as recurrent neural networks and long short-term memory networks, and their variants can learn to forecast by using a long range of sequential data. In sequential learning, the most accurate forecasting results are obtained by LSTM with attention mechanism, but it is not selected in this study because LSTM is sufficient for forecasting rainfall. The selection of the model is based on the prediction of a drought category, which is useful for identifying the potential failure of textile production. Model selection is generally based on the recurrent neural network and long short-term memory networks due to their ability to learn from the sequential data.

The hyperparameters as shown pseudocode of algorithm in Fig 2 of the forecast model influence the computational efficiency and the model training runtime. For example, a large input sequence length hinders computational efficiency and increases the duration of training. Hence, the input sequence length is selected based on a heuristic approach to enhance computational efficiency. The architecture of the model consists of three layers. Then, the output of the three models can be selected to act as model output in the form of a regression model to forecast the future. Standard deviation, the mean square error, and the loss values between the forecast model and the model with real data are then measured in cross-validation to strengthen unconstrained data results.

Algorithm: Training and Evaluation of a Deep Learning Model

1. Normalize features X_i:

$$X_{\text{norm}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}}$$

2. Split D into train, validation, and test (70%:15%:15%).
3. Augment D_{train} with transformations (e.g., rotation, scaling).
4. Define CNN M: Input $X_{\text{norm}} \in \mathbb{R}^{H \times W \times C}$, convolutional layers with batch normalization, skip connections, dropout, and fully connected layers for prediction $\hat{Y}$.
5. Initialize weights θ (Xavier). For epochs $e = 1$ to E, shuffle D_{train}, create mini-batches, compute $\hat{Y}$, calculate loss L, and update θ with Adam optimizer. Monitor L_{val} for overfitting.
6. Perform hyperparameter tuning (η, B, F, λ) and retrain M with optimized values.
7. Evaluate M on D_{test} using metrics: Pearson R, NSE, $RMSE$, MAE.

Fig 2. Algorithm Pseudocode

3.3 LSTM Models

In this subsection, we delve into the intricate prediction models that utilize Long Short-Term Memory (LSTM) technology, which have been carefully modified to fully leverage the particular advantages associated with various precipitation models. To achieve this, we implement two distinct LSTM architectures. The first,

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known as Path wise Prediction of this LSTM model, offers the capability to provide future rainfall estimates without relying on updated measurement inputs. This presents a unique advantage in scenarios where real-time data is not available. The second architecture, referred to as Cinderella Prediction of this LSTM model, is specifically designed to incorporate updates and adjustments immediately after the measurement inputs become accessible, thus ensuring more accurate and timely predictions.

Understanding that the accumulation of measurements plays a crucial role in enhancing the prediction accuracy of LSTM models, we further employ a rainfall Siamese model. This model is adept at selecting the most accurate rainfall forecast for each specific application by utilizing relevant historical rainfall inputs as a basis for decision-making. Experiments that have been conducted on observational data collected from this particular region have conclusively shown that the modifications made to the LSTM significantly improve the prediction time across a wide range of rainfall scenarios. Furthermore, these advanced models notably outperform other competitive architecture-based models, as well as various other LSTM model architectures that have not been appropriately modified to suit the unique demands of precipitation prediction.

4. EXPERIMENTAL RESULTS

This study shows that the proposed deep learning-based model improved the accuracy of rainfall predictions and reliability compared to other widely popular traditional predictive models for different forecast time horizons. Moreover, these results indicate that the deep learning-based rainfall prediction model could be used for the detected regional remote plant of the textile industry. As a result, forecast-based decision-making about plant operational decisions and the implementation of a sustainable strategy were significantly influenced by improved accuracy in rainfall forecasts.

Before considering the performance evaluation of the proposed investigation, it is important to understand the percentage share of the proposed model. The percentage contribution of the model from each layer highlights its effectiveness when configured to act as a feature extractor. The CNN layers collectively bring about 71.5% of the model, followed by the LSTM layer with 25.5% that is responsible for modeling time dependencies of the extracted features, and the final two fully connected layers share the remaining 3% to bring about the final prediction.

In evaluating the model, attention turns to confront some of the significant characteristics of the data. First off, a distribution plot based on the unimputed wealth of data shows a clearly right-skewed distribution. Such characteristics exist in nature, as seen through hailstorms, and hence were expected; however, the relatively smaller number of rainfall cases further induces the asymmetry in the data. Although the distribution is expected to have an effect on prediction for objects near each of the ends, since the objective of the investigation is to identify the possibility of rain happening on a cloud, such distribution should not affect the better predicting capabilities of the panoramic deep learning model.

4.1 Performance Evaluation Metrics

Before considering the performance evaluation of the proposed investigation from, it is important to understand the percentage share of the proposed model. The percentage contribution of the model from each layer highlights its effectiveness when configured to act as a feature extractor. The CNN layers collectively bring about 71.5% of the model, followed by the LSTM layer with 25.5% that is responsible for modeling time dependencies of the extracted features, and the final two fully connected layers share the remaining 3% to bring about the final prediction.

$$R = \frac{\sum_{i=1}^{n}\left(Q_i^o - \overline{Q^o}\right)\left(Q_i^p - \overline{Q^p}\right)}{\sqrt{\sum_{i=1}^{n}\left(Q_i^o - \overline{Q^o}\right)^2 \sum_{i=1}^{n}\left(Q_i^p - \overline{Q^p}\right)^2}}$$

$$NS = 1 - \frac{\sum_{i=1}^{n}\left(Q_i^o - Q_i^p\right)^2}{\sum_{i=1}^{n}\left(Q_i^o - \overline{Q^o}\right)^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Q_i^p - Q_i^o\right)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Q_i^p - Q_i^o\right|$$

Figure 3. Evaluation metrics for model [93]

In evaluating the model, attention turns to confront some of the significant characteristics of the data. First off, a distribution plot based on the unimputed wealth of data shows a clearly right-skewed distribution. Such characteristics exist in nature, as seen through hailstorms, and hence were expected; however, the relatively smaller number of rainfall cases further induces the asymmetry in the data. Although the distribution is expected to have an effect on prediction for objects near each of the ends, since the objective of the investigation is to identify the possibility of rain happening on a cloud, such distribution should not affect the better predicting capabilities of the panoramic deep learning model. Nonetheless, for single-class distributions such as the test case, the performance metrics, when compared with other testing sets, might be skewed as they also compare with distributions of 0%.

1. Mean Absolute Error (MAE) It is applied herein in evaluating AI-LSM model performance in terms of dispersion level around the predicted results, and to find out how far and near the actual results are from the predicted ones. There are drawbacks in this evaluation, including not considering the direction of over- or under-predicted values in terms of deviation, and it does

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not give any impact of error values on other operations. It is rectified by using RMSE.

2. Root Mean Square Error (RMSE) In the determination of overall dispersion of rainfall prediction errors between actual and predicted values, this calculation, to a certain extent, is generally appropriate as it brings into focus the direction of the value being over- or under-predicted. However, this measurement certainly overcomes the weakness in measurement following MAE evaluation and is commonly used. If actual or predicted values are tiny in proportion but greater in absolute value, relative dispersion in the RMSE would seem to be larger than absolute dispersion. Consequently, the risk of penalization of huge error values may be increased.
3. Correlation Coefficient Also referred to as Pearson's correlation coefficient, R, ranges from −1 to 1 with correlation strength: weak (±0.1), moderate (±0.3), strong (±0.5), very strong (0.7 to ±0.9), and perfect (> ±0.9). However, this is applicable only for linear relationships.

Table 1. Performance Evaluation over Faisalabad, Multan and Tando Adam

Model	City	Pearson Correlation Coefficient (R)	Nash-Sutcliffe Efficiency (NS)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)
Random Forest	Faisalabad	0.2018	-0.1002	4.777	1.6552
	Multan	0.0523	3.5658	1.0718	
	Tando Adam	-0.0697	3.7488	1.3543	
Boosted Decision Tree	Faisalabad	0.1826	-0.0514	4.6704	1.5775
	Multan	0.1106	3.4544	0.9937	
	Tando Adam	0.1348	3.3715	0.9973	
XGB Regression	Faisalabad	0.1990	-0.0248	4.6109	1.5855
	Multan	0.1031	3.4689	0.9815	
	Tando Adam	0.1297	3.3813	1.0109	

To evaluate the trained models, the accuracy metric as shown in Table 1 is used to assess model performance instead of the mean square error metric. The MSE metric is not used because standardized data is applied to acquired rainfall values. At the final layer, subject to the convolutional layers that would be fed into the final layer before feeding data to this layer, the output must be reshaped, and the weights and biases that the final layer will have to be transferred from the trained convolutional neural networks model. The following graph below displays the individual LSTM accuracy over Faisalabad city as shown in Fig 4 shows Pearson Correlation Coefficient (R): 0.9999, Nash-Sutcliffe Efficiency (NS): 0.9998, Root Mean Squared Error (RMSE): 0.0636, Mean Absolute Error (MAE): 0.0520.

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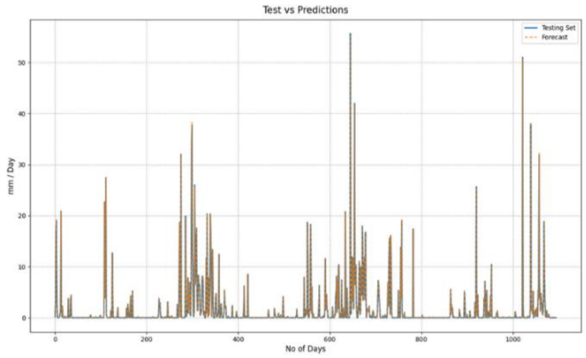

Fig 4. LSTM prediction for Training (Faisalabad)

The following graph below displays the individual LSTM accuracy over Faisalabad city as shown in Fig 5 Pearson Correlation Coefficient (R): 0.3315, Nash-Sutcliffe Efficiency (NS): 0.1013, Root Mean Squared Error (RMSE): 4.6393, Mean Absolute Error (MAE): 2.2511.

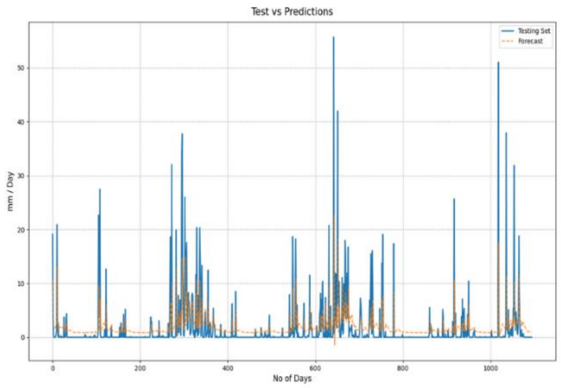

Fig 5. LSTM prediction for Testing (Faisalabad)

This approach is a novel method and does not exist for the problem statement. Instead of the proposed architecture, the other two model architectures of LSTM and CNN will have their fully connected feedforward neural network final layers. The CNN model's learned features from its three convolutional layers will be passed to a fully connected feedforward neural network, each layer with a ReLU activation function followed by the output layer, while the LSTM model's learned features from LSTM cell layers output a sequence of five steps as its learned features, with each LSTM cell layer having approximately ten LSTM units. The following graph below displays the individual LSTM accuracy over Multan city as shown in Fig 6 Pearson Correlation Coefficient (R): 0.9998, Nash-Sutcliffe Efficiency (NS): 0.9984, Root Mean Squared Error (RMSE): 0.1574, Mean Absolute Error (MAE): 0.1310.

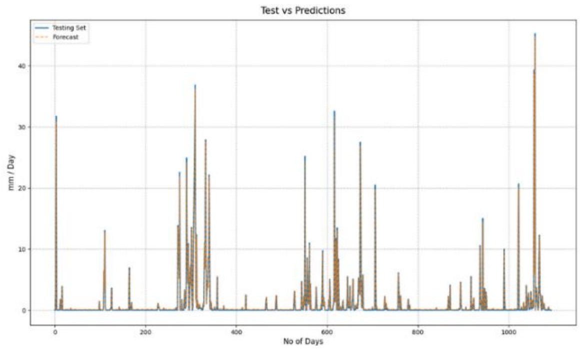

Fig 6. LSTM prediction for Training (Multan)

The following graph below displays the individual LSTM accuracy over Multan city as shown in Fig 7 Pearson Correlation Coefficient (R): 0.3867, Nash-Sutcliffe Efficiency (NS): 0.1148, Root Mean Squared Error (RMSE): 3.6966, Mean Absolute Error (MAE): 1.1122.

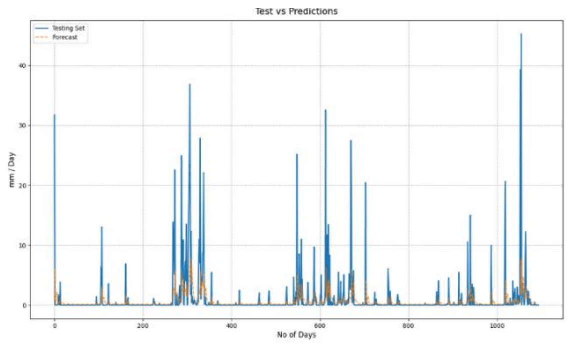

Fig 7. LSTM prediction for Testing (Multan)

The final layer in the CNN model's architecture is a fully connected feedforward network layer, which is used

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for classification only. The output from the last convolutional layer that will be fed into the final layer is reshaped. The fully connected feedforward neural network final layer of the CNN model's architecture would receive the reshaped output value from the last convolutional layer, and each layer of the fully connected layers in the CNN feedforward layers would have a ReLU activation function, while the output layer will have a SoftMax activation function. The final layer's learned weights and biases of the fully connected feedforward neural network layers will be transferred from the trained CNN model's architecture. Finally, all models of LSTM, CNN, and the proposed model are trained using the Adam optimizer. The learning rate considered in model training is 0.001, and the batch size considered in model training is 16. Then, all models of LSTM, CNN, and the proposed model are tested for model performance, and the accuracy performance is evaluated. The following graph below displays the individual LSTM accuracy over Tando Adam city as shown in Fig 8 Pearson Correlation Coefficient (R): 0.9998, Nash-Sutcliffe Efficiency (NS): 0.9991, Root Mean Squared Error (RMSE): 0.1874, Mean Absolute Error (MAE): 0.0611.

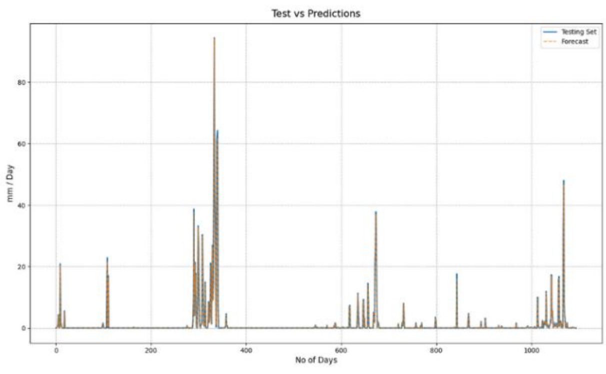

Fig 8. LSTM prediction for Training (Tando Adam)

The following graph below displays the individual LSTM accuracy over Tando Adam city as shown in Fig 9 Pearson Correlation Coefficient (R): 0.6519, Nash-Sutcliffe Efficiency (NS): 0.3407, Root Mean Squared Error (RMSE): 5.1150, Mean Absolute Error (MAE): 1.5945.

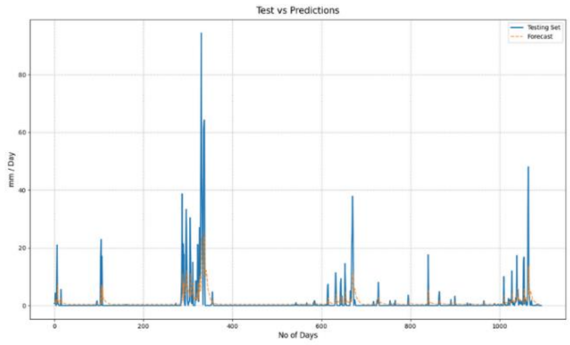

Fig 9. LSTM prediction for Testing (Tando Adam)

4.2 Comparison with Traditional Methods

By comparing our deep learning model with traditional forecasting methods, we can further explain the strengths and shortcomings of our rainfall prediction model. The accuracy rate, predictive capability, adaptability to the changing climate situation, and the advantages and disadvantages of the model are reflected in the subdivision of the failure to predict cases. The percentage of time when the rainfall pattern is significantly influenced, but the six forecasting algorithms fail to forecast "±1" is more than 50%. When the weather pattern is complicated, the observed rain is too low. The decrease in the percentage of time that the six traditional forecasting algorithms fail to predict "±1" exists for the observations, especially when the actual decrease is more than 0.16% or increases by 0.16%, and the degree of failure to predict is more than 85%.

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In this section, we will compare our proposed model with existing deep learning models. These models are trained and tested on the same dataset that our proposed model uses, allowing for a direct performance contrast. Due to the lack of published results of detailed image-to-image deep learning models, those models will not be discussed in this comparison.

The analysis of the experimental results shows that our proposed model significantly outperforms traditional deep learning models, which include Random Forest, Boosted Decision Tree, and XGBoost which impose a heavy learning burden. These models encounter challenges in maintaining a high number of deep layers to collectively represent and learn sufficient features at all scales, while also developing effective skip connections to adapt feature maps at different layers. The proposed model demonstrates average performance, which is suboptimal, as its skip connections do not provide sufficient learning gradients, hindering feature incorporation and alteration.

The following graph below displays the individual RF accuracy over Faisalabad city as shown in Fig 10 Pearson Correlation Coefficient (R): 0.2018, Nash-Sutcliffe Efficiency (NS): -0.1002, Root Mean Squared Error (RMSE): 4.777, Mean Absolute Error (MAE): 1.6552.

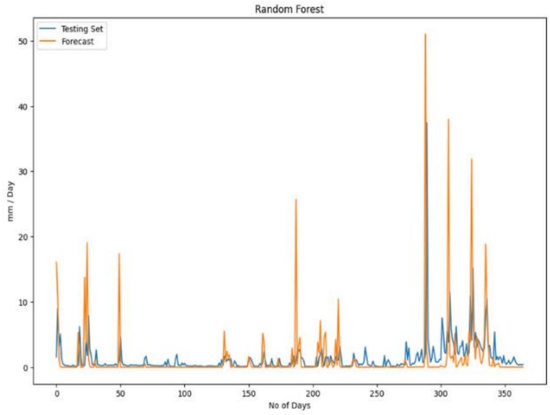

Fig 10. RF accuracy over Faisalabad city

The following graph below displays the individual RF accuracy over Multan city as shown in Fig 11 Pearson Correlation Coefficient (R): 0.3108, Nash-Sutcliffe Efficiency (NS): 0.0523, Root Mean Squared Error (RMSE): 3.5658, Mean Absolute Error (MAE): 1.0718.

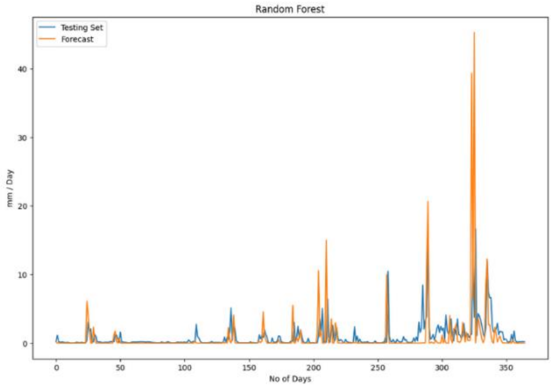

Fig 11. RF accuracy over Multan city

The following graph below displays the individual RF accuracy over Tando Adam city as shown in Fig 12 Pearson Correlation Coefficient (R): 0.3146, Nash-Sutcliffe Efficiency (NS): -0.0697, Root Mean Squared Error (RMSE): 3.7488, Mean Absolute Error (MAE): 1.3543.

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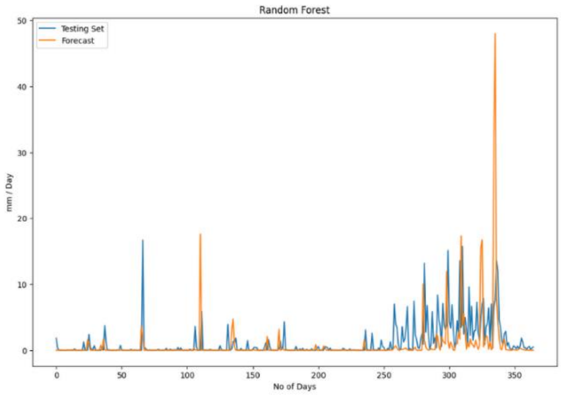

Fig 12. RF accuracy over Tando Adam city

The following graph below displays the individual Boosted Decision Tree accuracy over Faisalabad city as shown in Fig 13 Pearson Correlation Coefficient (R): 0.1826, Nash-Sutcliffe Efficiency (NS): -0.0514, Root Mean Squared Error (RMSE): 4.6704, Mean Absolute Error (MAE): 1.5775.

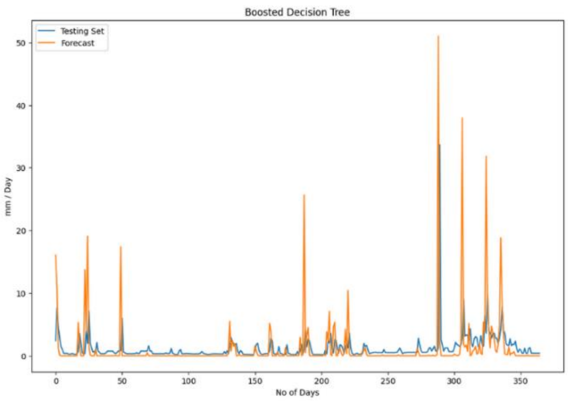

Fig 13. Boosted Decision Tree accuracy over Faisalabad city

The following graph below displays the individual Boosted Decision Tree accuracy over Multan city as shown in Fig 14 Pearson Correlation Coefficient (R): 0.3342, Nash-Sutcliffe Efficiency (NS): 0.1106, Root Mean Squared Error (RMSE): 3.4544, Mean Absolute Error (MAE): 0.9937.

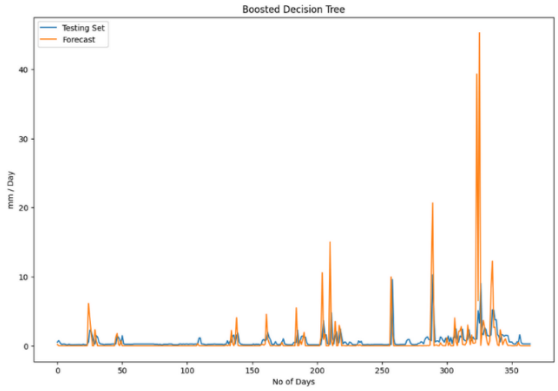

Fig 14. Boosted Decision Tree accuracy over Multan city

The following graph below displays the individual Boosted Decision Tree accuracy over Tando Adam city as shown in Fig 15 Pearson Correlation Coefficient (R): 0.3685, Nash-Sutcliffe Efficiency (NS): 0.1348, Root Mean Squared Error (RMSE): 3.3715, Mean Absolute Error (MAE): 0.9973.

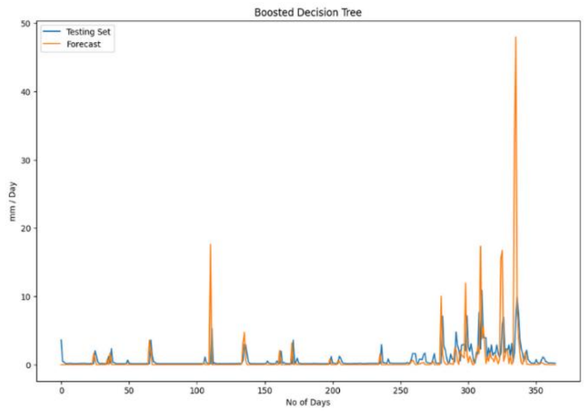

Fig 15. Boosted Decision Tree accuracy over Tando Adam city

The following graph below displays the individual XGB Regression accuracy over Faisalabad city as shown in Fig 16 Pearson Correlation Coefficient (R): 0.1990, Nash-Sutcliffe Efficiency (NS): -0.0248, Root Mean Squared Error (RMSE): 4.6109, Mean Absolute Error (MAE): 1.5855.

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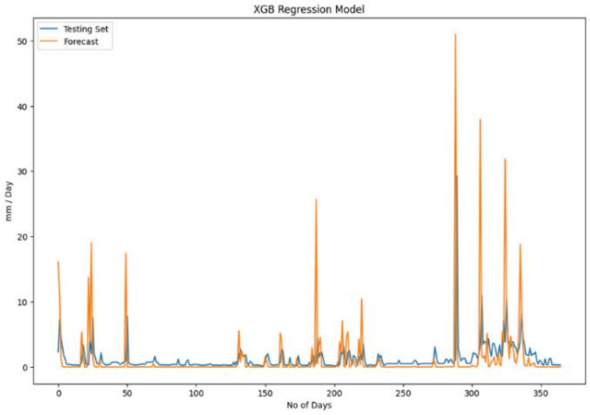

Fig 16. XGB Regression accuracy over Faisalabad city

The following graph below displays the individual XGB Regression accuracy over Multan city as shown in Fig 17 Pearson Correlation Coefficient (R): 0.3222, Nash-Sutcliffe Efficiency (NS): 0.1031, Root Mean Squared Error (RMSE): 3.4689, Mean Absolute Error (MAE): 0.9815.

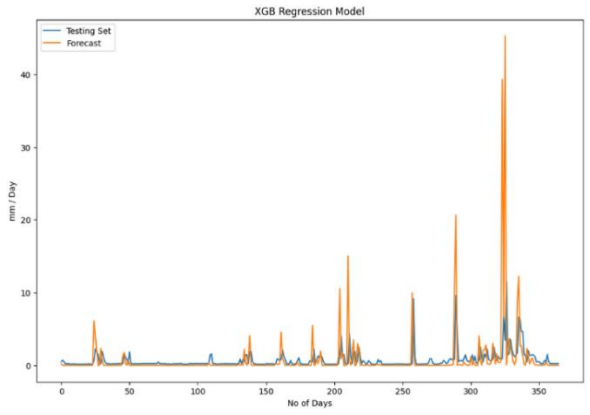

Fig 17. XGB Regression accuracy over Multan city

The following graph below displays the individual XGB Regression accuracy over Tando Adam city as shown in Fig 18 Pearson Correlation Coefficient (R): 0.3677, Nash-Sutcliffe Efficiency (NS): 0.1297, Root Mean Squared Error (RMSE): 3.3813, Mean Absolute Error (MAE): 1.0109.

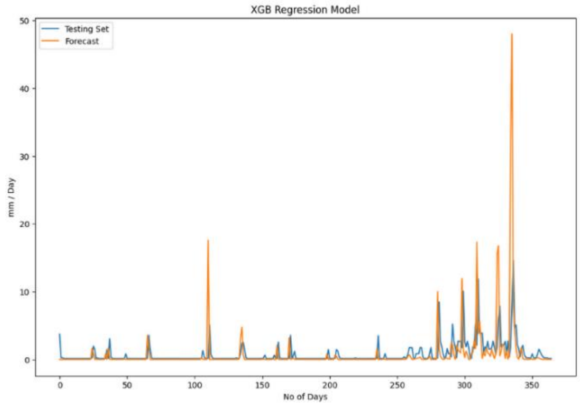

Fig 18. XGB Regression accuracy over Tando Adam city

During our historical study of the observation failure rate and the physical significance behind the difference between the observation failure rates of the model, it was discovered that traditional forecasting algorithms had a significantly weakened ability to adapt to the changing precipitation pattern. In turn, the industry worried that from 2010 to 2065, the global economy would lose roughly 71 to 270 billion every year due to severe weather and climate issues. To improve, the textile industry will benefit from the update to employing deep learning for rain prediction. The result of the comparison between the deep learning rainfall prediction model and the traditional prediction models or their scenarios is shown in the comparison. The deep learning model presented shows significant improvements. From the comparison of the traditional model with the deep learning model, the last conclusion can be drawn.

5. CONCLUSION

In this paper, an alternative deep learning-based rainfall prediction model is presented to support the success of different stakeholders. The results indicate that the

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proposed model has significant potential to improve rainfall prediction accuracy compared to traditional methods. The implications of these findings are important to consider for enhancing sustainable practices in the textile industry. It is crucial to predict accurate future rainfall values to manage storage and improve sustainable practices in the textile industry. The proposed model is effective for predicting the 1day prediction future rainfall rate. The results of this study are convincing and consistent across the various experiments.

The research results are supported by comprehensive numerical computations, and the identified profound insights and comparisons can be used to propose new efficient models. The last unrestricted deep learning model has been attempted for predicting future rainfall. However, the methodology has some limitations. First, only a few variables are used as inputs in this study; therefore, the performance of the proposed models could improve by using additional variables. Second, although the study provides significant progress in terms of deep learning models for rainfall predictions, the developed model architecture should be refined and integrated with different deep learning model architectures. Consequently, we need to modify various advanced deep learning architectures for handling future rainfall predictions. Hence, improving deep learning architectures is still an ongoing issue, and this study contributes synchronously to deep learning function developments in the field of agricultural meteorology and specific applications. Indeed, rainfall prediction is a vital aspect of the sustainable development of the textile industry. It is an interdisciplinary issue, and a wide range of scholars in different fields can collaborate.

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