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Article

High-Resolution Short-Range Weather Forecasting Using Data Driven BDCL-Net Forecasting Model

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Abstract: Recent developments in computational techniques have significantly increased interest in probabilistic weather forecasting. Despite these advancements, accurately predicting weather remains a complex task because atmospheric processes are highly nonlinear and involve numerous interacting variables. Even minor variations in the initial atmospheric conditions can result in considerable differences in forecast outcomes, making reliable prediction a challenging problem. Conventional forecasting approaches, including persistence methods, climatology-based models, linear regression, Markov models, and Auto-Regressive Integrated Moving Average (ARIMA), have demonstrated limited effectiveness in capturing the complex temporal relationships present in weather data. Artificial intelligence (AI)-based methods have surfaced as a viable substitute for weather prediction in order to overcome these constraints. These approaches are capable of learning complex nonlinear patterns directly from historical observations while providing increased computational effectiveness and forecasting accuracy. Motivated by these advantages, the present research proposes a deep learning-based forecasting framework trained on real-world meteorological datasets. The proposed Bidirectional Drop Connect-Regularized LSTM Network (BDCL-Net) has been developed using meteorological information gathered from Jaipur, Delhi, and Chandigarh. The effectiveness of the proposed model is assessed through comprehensive experimental evaluation using multiple performance measures, including the Coefficient of Determination (R^2), Mean Squared Error (MSE), and Root Mean Square Error (RMSE), to determine its forecasting accuracy and overall predictive capability.
Keywords: Short-Range Weather Forecasting, Deep Model, LSTM.

1. Introduction

Historically sky observation served as the main forecasting method before people developed weather forecasting instruments such as the hygrometer and anemometer (Salman et al., 2015). Further the establishment of dedicated meteorological satellites (Haupt & Delle Monache, 2014) together with radars has enabled scientists to achieve precise weather monitoring through advanced observational methods and forecasting systems. Meteorological satellites enable countries to rapidly share weather data through modern telecommunication networks which results in highly accurate weather predictions (Mass & Mass, 2011). The private sector now offers weather forecasting services which compete with government meteorological services and observation stations because people can access forecasting services through contemporary smart devices. In spite of that the process of predicting weather conditions for particular locations remains difficult because it requires using multiple meteorological variables to achieve accurate forecasts (World Meteorological Organization, 2021). For this, era of big data has arrived in weather forecasting, and traditional computational intelligence algorithms (such as machine learning and NWP models) have felt out of step when it comes to producing precise weather forecasts (Bauer et al., 2015).

Big data is defined by five primary characteristics: variety, variability, volume, velocity, and value (Gao & Chiu, 2012), whereas 'volume' refers to the total size of the dataset, and 'variety' refers to the presence of data in various formats from distinct sources, i.e., sensor devices, web logs, web pages, emails, documents, and social networking sites. Therefore, processing such vast and diverse data necessitates sophisticated infrastructure that goes beyond conventional systems that are unable to effectively handle big data. Consequently, research requires advanced tools and innovative analytical techniques for managing enormous datasets, since it offers an AI-based methodology that uses big data analysis to produce accurate findings (Weyn et al., 2021). AI's deep learning approaches, which are focused on data visualization methods that allow precise prediction of weather and climate conditions using big data (Ham et al., 2019); hence, the same is proposed in the present work.

Additionally deep learning model, over the traditional forecasting methods which include statistical models such as linear regression ARIMA and Markov models together with standard machine learning techniques face limitations because they use fixed assumptions which enforce linear restrictions that stop their ability to model complex nonlinear patterns. In contrast deep learning models demonstrate better performance when they need to analyze nonlinear relationships and multidimensional data (Siami-Namini & Namin, 2018) (Houssein et al., 2025). The advancements in the fields of AI, ML and Deep learning have revolutionized weather prediction as it provides variety of tools to model intricate connections and highly nonlinear dynamics within the atmosphere (Lata & Verma, 2024).

The current study has created, Bespoke Deep Forecasting Model for High-Resolution Short-Range Weather Forecasting. The meteorological data is gathered from the publicly available domain and preprocessed according to the forecasting mode. i.e., whether the input is a univariate or multivariate time series, which means that the former uses temperature data as input while the latter accepts all four features as input. The proposed BDCL-Net generates 10 days advance predictions which represent the output of the system. The outcomes of the experiment demonstrate that adaptive bidirectional predictions, BDCL-Net learning demonstrates substantial performance enhancement over the adaptive model because it achieves a 77.87% MAE reduction and a 75.13% RMSE reduction, which results in decreased prediction errors. The model improves the coefficient of determination (R^2) by 1.64% to reach 0.9971 which shows it can explain almost all variance. The findings demonstrate that, in comparison to alternative strategies, the suggested strategy offers superior prediction performance and increased dependability. The study presents three main contributions, which include.

1. The researchers developed a weather prediction model which uses bidirectional LSTM technology to produce high accuracy results which reach an R^2 value of 0.9971 and show minimal errors with MAE reaching 0.1452 and RMSE reaching 0.2149.
2. The researcher implemented a systematic data collection process to obtain actual meteorological data from three Indian cities (Chandigarh, Jaipur, and Delhi) which provided public access to their data through open data portals. The researcher conducted data extraction and feature engineering and sampling procedures to assess data quality and system durability which enabled them to apply their work in real-world situations while improving the accuracy of their forecasting model.
3. The research presents a new adaptive bidirectional LSTM framework named BDCL-Net which enhances meteorological forecasting through its advanced prediction capabilities significantly lower mistake rates in comparison to deep learning and conventional approaches.

The next sections of the paper are organized as follows: Section 2 reviews the recent literature. Section 3 describes the methods used and proposed for this study. Section 4 shows the results and emphasizes the most important discoveries. The 5th section of this paper presents the main points of the research study and offers recommendations for future work.

2. Related work

The expansion of sensor-generated weather data has increased research interest in data-driven modeling techniques which predict meteorological time-series patterns. The recent advancements in machine learning and artificial intelligence technologies have improved data analysis processes by making them more efficient and flexible and creating reliable solutions.

2.1 Weather forecasting

Lee et al. (2025) created a deep learning-based system which improves precipitation forecast accuracy through high-resolution radar data and their framework uses data normalization together with physics-based feature extraction to outperform conventional statistical techniques. Guo et al. (2025) developed FuXi-TC, a generative diffusion-based model which uses WRF simulation data and reanalysis information to improve tropical cyclone intensity predictions, resulting in lower RMSE values through its multi-day forecasting capabilities. Huang et al. (2025) created FuXi-RTM, a physics-based deep learning system that merges radiative transfer modeling to increase its capability of forecasting atmospheric conditions. Linander et al. (2025) introduced PEAR as a transformer-based system that works on equal-area spherical grids to improve medium-range forecasting by using global reanalysis data. Shi et al. (2025) conducted a detailed study which classified three weather prediction models, namely transformer, graph neural network, and foundation models, while showing the methods of dataset preparation and testing standards. Cao et al. (2025) created a five-day regional deep learning forecasting system which uses ERA5 data for training and achieves better temperature and wind forecasting results. Yasavoli et al. (2025) developed a temperature forecasting system that combines CNN and LSTM deep learning methods, which outperformed individual models in terms of MAE and RMSE. Allen et al (2025) developed an end-to-end weather forecasting system which uses multiple observational data sources to predict global weather patterns at accuracy of an operational numerical weather prediction system that offers quicker forecast times. Bhuskute et al. had to develop deep learning models for the Weather4Cast 2025 competition, which efficiently predicted precipitation through their use of spatio-temporal convolutional architectures while showing effective performance across unknown weather conditions.

2.2 Adaptive models

Recent improvements in adaptive and deep learning-based forecasting Systems perform better when handling several meteorological data types which exhibit changing patterns across different time durations. He et al. (2025) introduced MSPT, a transformer-based architecture that captures multiscale periodic patterns for 10–30 days subseasonal sea surface temperature prediction, which enhances the modeling of long-term time dependencies. Miao et al. (2025) created a single architecture for federated continuous learning that permits spatiotemporal prediction on streaming data through adaptive updates without requiring centralized data sharing. Liu et al. (2025) developed the TripFormer model to enhance short-term precipitation forecasting by refining temporal attention mechanisms. Devkota et al. (2025) used graph neural networks for spatiotemporal weather prediction, effectively modeling spatial correlations between observation stations. Qiao et al. (2025) created a hybrid CNN-Transformer network which uses weighted loss functions to enhance global sea surface wind speed retrieval from GNSS-R observations. Liu et al. (2025) presented MMF-RNN, a multimodal fusion recurrent model which combines radar and ground station data for precipitation nowcasting. Nikraftar et al. (2025) proposed Season-Net, a deep learning–based bias correction framework for improving seasonal forecast reliability. Mengistu et al. (2026) used Bayesian deep learning to measure environmental prediction uncertainty while demonstrating the advantages of probabilistic modeling. Feng et al. (2025) used reinforcement learning to create adaptive climate risk management systems that optimized strategies in uncertain conditions. Nikseresht et al. (2025) concentrated on demand forecasting but their hybrid ensemble framework enables them to solve non-stationarity problems that occur in weather forecasting systems. The studies demonstrate that adaptive transformers, graph-based learning, multimodal fusion, Bayesian inference, and reinforcement learning represent new development paths which will create weather forecasting systems that can handle uncertainty and adapt to new information.

Table 1: Performance evolution of recent existing work

Study	**Problem**	**Method**	**ML/DL Model(s)**	**Prediction Approach**	**Dataset(s)**	**Metrics**	**Pros**	**Cons**
He et al., 2025	Subseasonal SST forecasting (10–30d)	Multiscale periodic modeling	Transformer (MSPT)	Long-range time-series	Sea surface temperature datasets	RMSE, MAE	Captures periodic cycles effectively	High computational cost
Miao et al., 2025	Streaming spatio-temporal prediction	Federated continuous learning	Adaptive DL framework	Online/streaming	Distributed spatio-temporal datasets	RMSE, Accuracy	Privacy-preserving & adaptive	Communication overhead

Liu et al., 2025 (TripFormer)	Short-term precipitation	Enhanced attention transformer	TripFormer	Sequence modeling	Radar-based precipitation data	RMSE, CSI	Improved temporal focus	Data-intensive
Devkota et al., 2025	Spatio-temporal weather modeling	Graph learning	GNN	Spatial-temporal prediction	Station-based weather data	MAE, RMSE	Captures spatial dependency	Limited scalability
Qiao et al., 2025	Sea surface wind retrieval	Hybrid deep learning	CNN-Transformer	Regression retrieval	GNSS-R satellite data	MSE, RMSE	Weighted loss improves accuracy	Requires large labeled data
Liu et al., 2025 (MMF-RNN)	Precipitation nowcasting	Multimodal fusion	RNN + Radar fusion	Short-term nowcasting	Radar + ground station	RMSE, POD	Integrates multi-source data	Complex preprocessing
Nikraftar et al., 2025	Seasonal bias correction	DL bias adjustment	Season-Net	Post-processing correction	Seasonal forecast outputs	RMSE, Skill Score	Reduces systematic bias	Depends on baseline model quality
Mengistu et al., 2026	Environmental uncertainty prediction	Bayesian inference	Bayesian DL	Probabilistic prediction	Environmental datasets	NLL, RMSE	Quantifies uncertainty	Higher training complexity
Feng et al., 2025	Climate risk adaptation	Reinforcement learning	RL-based adaptive model	Policy optimization	Coastal flood datasets	Reward, Risk metrics	Dynamic decision-making	Application-specific tuning
Nikseresht et al., 2025	Non-stationary forecasting	Hybrid ensemble learning	Ensemble ML/DL	Adaptive regression	Time-series datasets	MAE, RMSE	Handles uncertainty & drift	Not weather-specific

3. Materials and methods

This paper presents the methodology adopted for the proposed BDCL-Net model. The overall workflow of the system is illustrated in Figure 1, which outlines the sequential steps from data preprocessing to final prediction. It includes data preparation, feature transformation using PCA, sequence generation, model training using a bidirectional LSTM architecture, and performance evaluation based on multiple metrics.

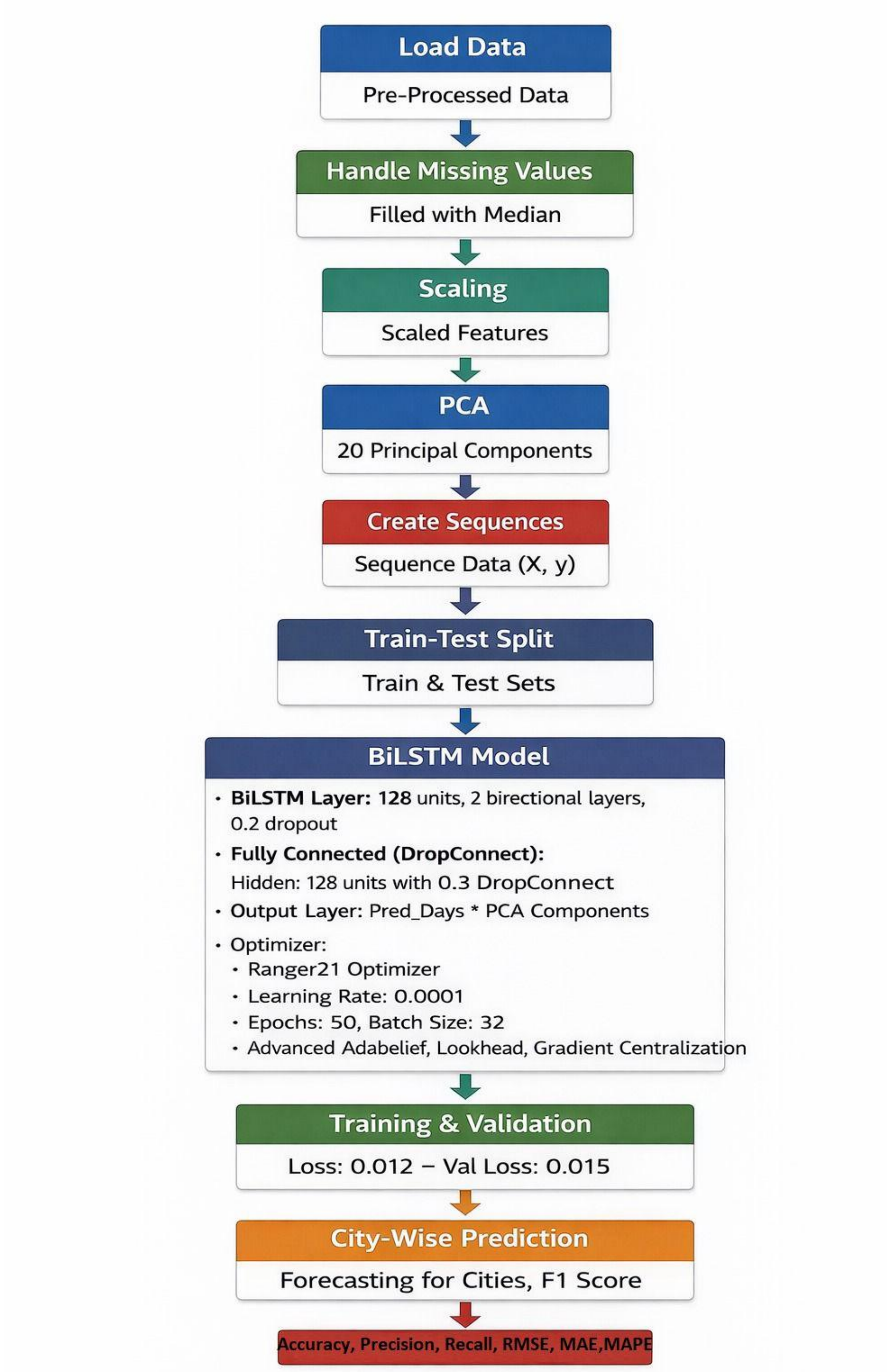


Figure 1: Workflow of the proposed BDCL-Net forecasting model.

3.1 Materials

For the present work, the Historical Weather Data for Indian Cities dataset is used. It is an extensive collection of daily weather data from January 1, 2023, to January 1, 2025, which spans of two years. It offers insightful information on climatic trends, which makes it an essential tool for data-driven research, climate change studies, and weather forecasting. To ensure region-specific climate data availability, the dataset is gathered from a variety of weather stations throughout India, including cities in North India like Delhi, Jaipur, and Chandigarh. Reputable meteorological organizations and APIs that routinely check atmospheric conditions are the sources of the data.

Essential meteorological factors such as daily precipitation, wind speed, humidity, and maximum and lowest temperatures are included in this dataset. Because the data is organized in CSV format, researchers, data analysts, and machine learning practitioners can easily access and process it. For deep learning models like LSTMs (Long Short-Term Memory Networks) and RNNs (Recurrent Neural Networks), which are excellent at spotting long-term dependencies in weather patterns, this dataset is especially helpful because it is time-series in nature. Furthermore, the well-structured content of the dataset makes it possible to comprehend seasonal fluctuations and climate shifts through trend analysis, statistical modeling, and exploratory data analysis (EDA).

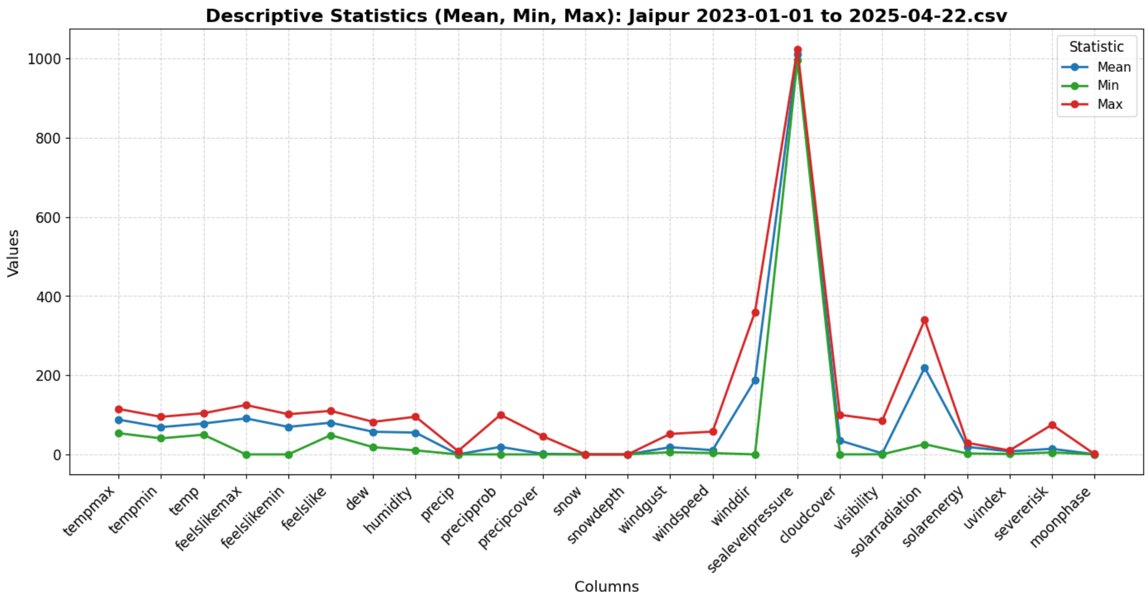
This dataset's broad temporal coverage and granularity, which allow for accurate analysis of past weather trends, are among its primary features. It records every day, which gives machine learning-based weather forecasting algorithms enough data points. Using this dataset, researchers may create predictive models that examine heat waves, rainfall patterns, weather variations, and the impacts of climate change in various Indian cities. More precise weather forecasts can be produced by combining this dataset with additional meteorological data sources, such as satellite imaging and Internet of Things-based real-time weather monitoring systems.

The description of the dataset in term of various parameters like link for the dataset sources, composition, format and characteristics are given table 2.

Table 2: Dataset description

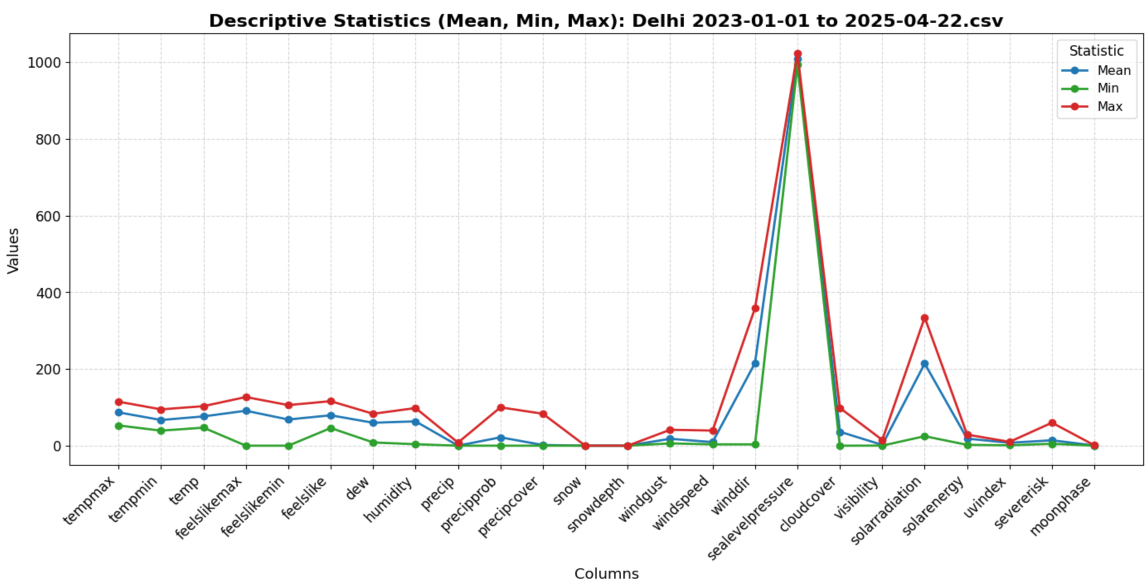
Attribute	**Details**
Dataset Name	Historical Weather Data
Link for Dataset	https://www.visualcrossing.com/weather-query-builde
Sources	Weather Query Builder
Composition	The dataset consists of daily weather records for multiple Indian cities, including Jaipur, Delhi, and Chandigarh covering temperature, precipitation, and other meteorological parameters.
Format	CSV format, containing structured data with columns representing date, location, temperature, humidity, wind speed, and precipitation.
Characteristics	The dataset spans from January 1, 2023, to January 1, 2025 and includes parameters such as maximum temperature, minimum temperature, daily precipitation, and humidity. It is structured to support time-series forecasting models and trend analysis for climate studies.

For each city in north India, their weather forecasting dataset's descriptive statistics analysis has been presented below.



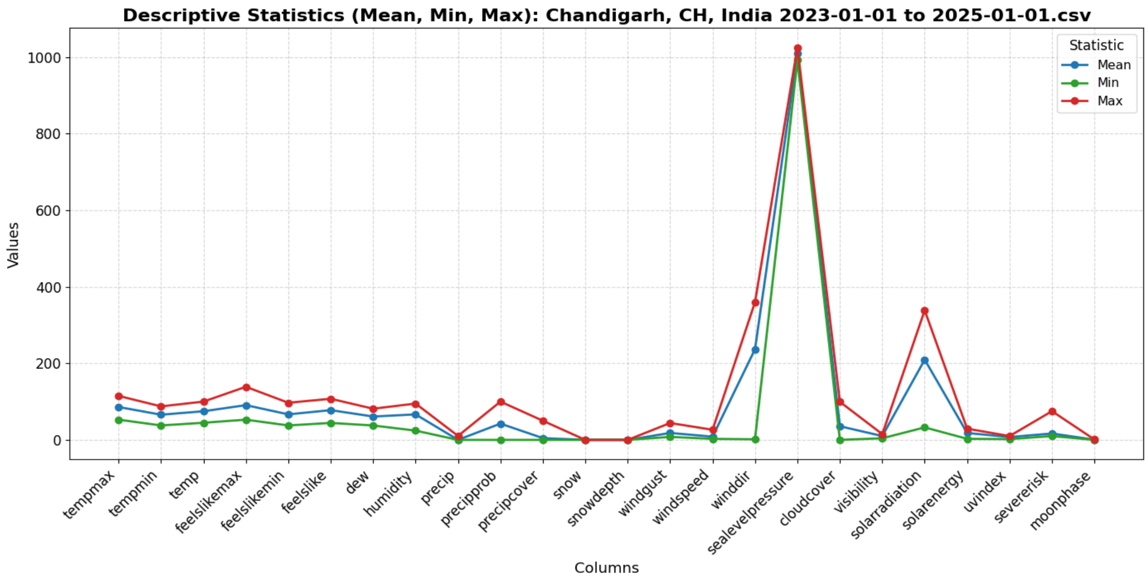
Mean	87.9	69.0	78.1	91.0	69.6	80.1	57.2	55.1	0.1	19.0	1.4	0.0	0.0	18.2	10.8	188.1	1011.0	35.1	2.6	219.3	18.9	7.7	14.2	0.5
Min	53.6	40.6	49.7	0.0	0.0	48.6	18.3	10.2	0.0	0.0	0.0	0.0	0.0	5.6	3.4	0.0	996.0	0.0	0.3	25.8	2.3	1.0	5.0	0.0
Max	114.8	95.0	104.0	124.8	101.6	110.0	82.2	95.2	8.4	100.0	45.8	0.0	0.0	51.9	57.5	359.9	1024.2	100.0	85.8	340.0	29.3	10.0	75.0	1.0

Figure 2: Descriptive statistics analysis for Jaipur



Mean	86.8	67.0	76.3	91.2	68.3	79.3	59.8	63.4	0.1	21.8	1.8	0.0	0.0	18.0	9.4	215.5	1009.8	36.4	2.0	214.2	18.5	7.5	14.1	0.5
Min	52.8	39.2	47.0	0.0	0.0	46.0	8.5	3.8	0.0	0.0	0.0	0.0	0.0	6.0	3.4	3.4	993.5	0.0	0.2	24.7	2.2	1.0	5.0	0.0
Max	114.8	94.7	103.1	126.9	105.9	116.1	83.2	98.2	8.0	100.0	83.3	0.0	0.0	41.4	39.4	358.7	1024.2	98.5	15.0	334.5	28.9	10.0	60.0	1.0

Figure 3: Descriptive statistics analysis for Delhi



Mean	85.9	65.7	74.8	90.7	66.6	77.7	61.0	66.6	0.1	42.5	4.6	0.0	0.0	18.1	8.4	236.8	1009.5	35.7	10.1	209.5	18.1	7.3	16.7	0.5
Min	52.8	37.7	44.7	52.8	37.7	44.3	37.6	24.2	0.0	0.0	0.0	0.0	0.0	7.8	2.7	1.5	992.9	0.0	4.2	32.6	2.8	2.0	10.0	0.0
Max	114.9	87.5	100.0	138.7	97.0	107.4	81.4	94.9	10.3	100.0	50.0	0.0	0.0	44.1	26.4	359.7	1025.0	99.5	15.0	338.4	29.3	10.0	75.0	1.0

Figure 4: Descriptive statistics analysis for Chandigarh

3.2 BDCL-Net

The development of the proposed **BDCL-Net** model for weather forecasting begins with the acquisition and preparation of historical meteorological data. Weather-related parameters, A time-series dataset is created by gathering data over a predetermined length of time, such as temperature, humidity, wind speed, rainfall, and other meteorological factors. Several preparation steps must be completed before the data is utilized to train the model are performed, such as removing inconsistencies, handling missing observations, and scaling the features. These preprocessing steps improve data quality and ensure that the dataset is suitable for deep learning applications.

The **BDCL-Net** model is It is highly suited for capturing temporal correlations found in consecutive weather measurements. for forecasting future weather conditions. By learning patterns from historical records, the model can estimate upcoming weather values based on previously observed data. A sliding window approach is adopted to generate input sequences, where a fixed number of past observations are used to forecast values in the future. The prepared dataset is split into training and testing subsets in order to properly assess the model. The testing data is used to evaluate the model's capacity for generalization and prediction accuracy, while the training data is used to discover the underlying temporal patterns. Figure 5 shows the suggested BDCL-Net model's architectural layout.

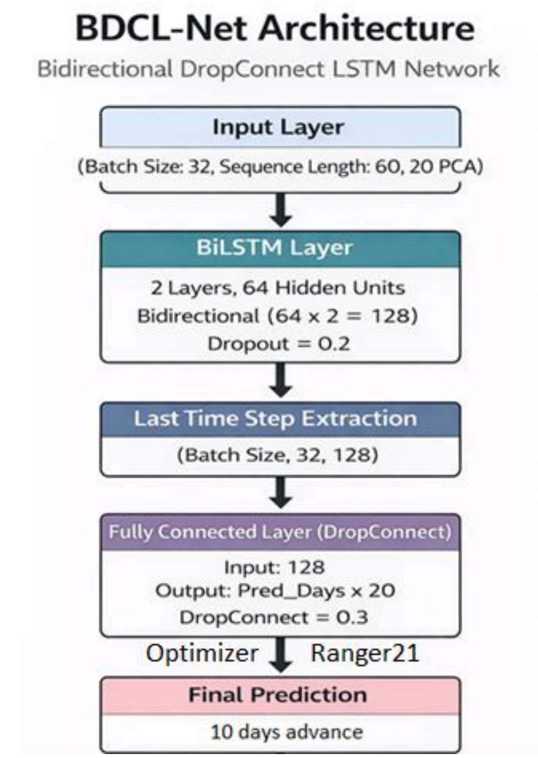


Figure 5: BDCL-Net Model's architecture

The input layer receives PCA-transformed sequential data with dimensions of (Batch Size, 60, 20), where 60 represents the time steps and 20 denotes the principal components extracted from the original features. A two-layer Bidirectional LSTM (BiLSTM) network captures both forward and backward temporal relationships by processing the input sequences enabling improved learning of short-term and long-term financial patterns. Each LSTM layer contains 64 hidden units, and due to bidirectional processing, the effective output dimension becomes 128 features per time step. The system implements a 0.2 dropout rate between LSTM layers to improve generalization capabilities. The model uses time step extraction to produce a feature vector which contains final time step representation of entire sequence. The system processes the condensed temporal representation through a fully connected linear layer which implements Drop Connect regularization with a drop connect rate of 0.3 to randomly mask weights during training in order to decrease overfitting while increasing robustness. The final output layer generates a multi-step prediction with dimensions (Batch Size, Pred_Days × 20), enabling simultaneous forecasting of multiple future time horizons and PCA-based feature projections. Final Prediction, ensuring efficient temporal feature extraction and regularized nonlinear mapping for improved predictive performance.

Table 3: Parameters selected for the LSTM models training

Parameters	**Value**
Input	60,20
Model	BiLSTMModel
hidden_dim	64
Loss Function	MSE
Optimizer	Ranger21
Metrics	MSE, RMSE, R2
Epochs	50

Batch Size	32
LR	1e-3

3.3. Data split and preparation

Data cleaning techniques eliminate errors, missing values, and distortion. Real-world data often contains missing values. It may be caused by data redundancy and other issues, such as undocumented values. Most forecasting algorithms do not accept partial information. As a result, imputation of missing values is necessary, and the missing data is usually replaced by means values.

Data de-noising techniques help remove noise from datasets by splitting the original data into distinct low- and high-frequency signals. Data de-noising techniques help remove noise from datasets by splitting the original data into distinct low- and high-frequency signals. One method of data decomposition that will significantly improve the forecasting model's prediction accuracy is the wavelet transform. In our case no denoising method has been employed as the is free from noise.

The objective of this stage is to transform the dataset into a uniform format that may be processed further while maintaining the integrity of the original information. Once the preprocessing steps are completed, the dataset is normalized using standardization or normalizing approach, it is converted into a format that can be processed. Data transformation techniques speed up model training and the prepared dataset is then utilized to enhance the performance and computational efficiency of the proposed learning model. The dataset must be divided into several subsets for model construction and performance assessment since neural networks learn patterns from previously collected data. As a result, a training set and a testing set are created from the dataset. The model can learn the underlying relationships thanks to the training set within the data, whereas the testing set is reserved for validating the model's predictive capability on unseen observations. Such data partitioning is a fundamental step in data science, as it helps assess the generalization ability of a learning model and reduces the risk of overfitting. For this research, the dataset is divided in an 80:20 ratio, where 80% of the records are allocated for training the model and the remaining 20% are used for testing and evaluating its prediction performance.

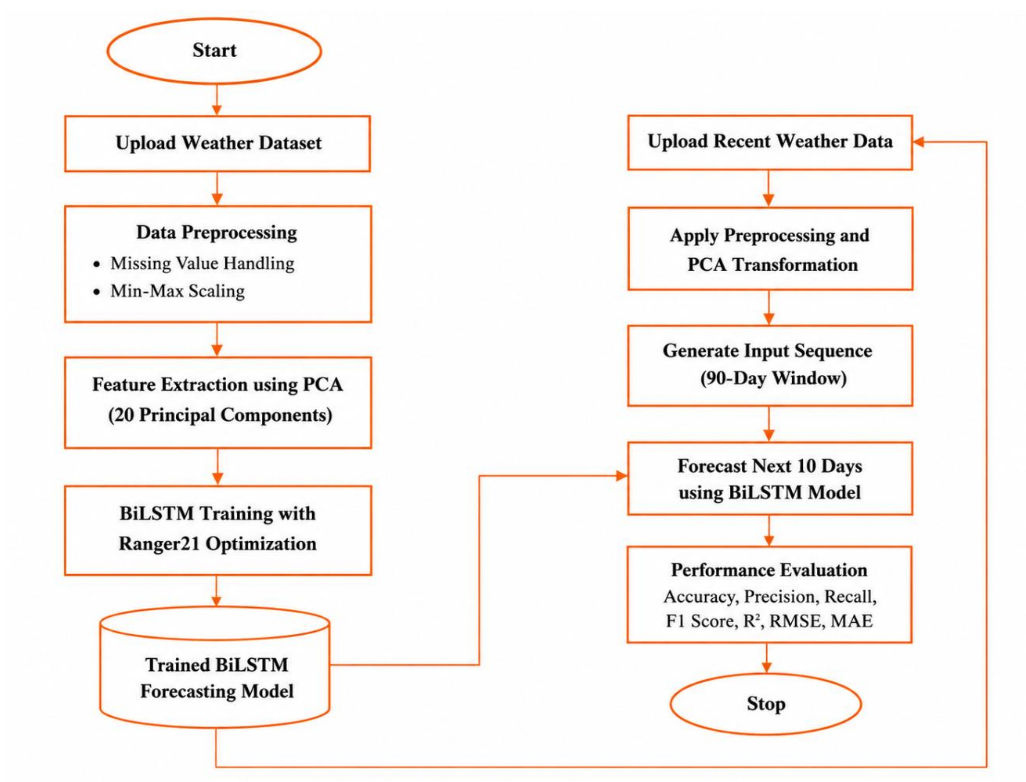


Figure 6: Workflow of the proposed BDCL-Net model for multi-step weather prediction

Figure 6 illustrates the complete workflow of the proposed BDCL-Net model for multi-step weather forecasting. The process begins with the collection of historical weather data from multiple Indian cities, followed by data preprocessing, which includes handling missing values, data cleaning, and normalization. After preprocessing, Principal Component Analysis (PCA) is applied to reduce dimensionality and extract the most relevant features from the dataset. The transformed data is then organized into sequential time windows and fed into the Bidirectional LSTM-based BDCL-Net model for training.

The predicted outputs are then evaluated using both regression metrics such as R^2, RMSE, and MAE, The incorporation of these evaluation metrics establishes a complete deep learning framework capable of delivering accurate multi-step weather predictions.

3.4 Performance evaluation parameters

The suggested BDCL-Net model's performance was assessed using the following evaluation metrics on the selected dataset.

1. Coefficient of determination
2. MSE
3. RMSE

3.4.1 Coefficient of determination

For predictive analysis, A statistical metric used to assess how effectively a regression model explains the variance in the dependent variable depending on the independent variable or variables is the Coefficient of Determination (R^2). A greater R2 value suggests that the model offers a more accurate match to the observed data by accounting for a greater proportion of the variability in the outcome. The Coefficient of Determination is calculated using Equation (1).

$$R^2 = 1 - \frac{RSS}{TSS} \quad (1)$$

Where RSS represents the Residual Sum of Squares, which measures the unexplained variation between the observed and predicted values, and TSS denotes the Total Sum of Squares, representing the total variation present in the observed data.

3.4.2 MSE

A popular regression performance indicator called Mean Squared Error (MSE) calculates the average squared difference between the actual values and the values that a model predicts. It shows how well the regression model matches the observed data. Larger mistakes are given more weight since the prediction errors are squared before averaging, which makes MSE especially helpful for assessing model accuracy. Better predictive performance is indicated by a lower MSE score. Equation (2) is used to get the Mean Squared Error.

$$\mathrm{MSE} = 1/n \sum_{i=1}^{n} (\mathrm{y_i} - y^{\wedge}{}_{i})^2 \quad (2)$$

3.4.3 RMSE

The Root Mean Square Error (RMSE) was used to assess the prediction error for quantitative quantities. The square root of the average of the squared discrepancies between the observed and model-estimated values is measured by this metric. Regression and forecasting models are frequently evaluated for accuracy using RMSE; a lower number denotes greater prediction ability. Equation (3) is used to get the Root Mean Square Error.

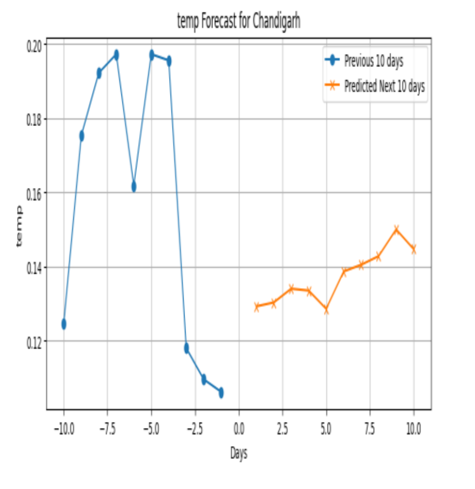
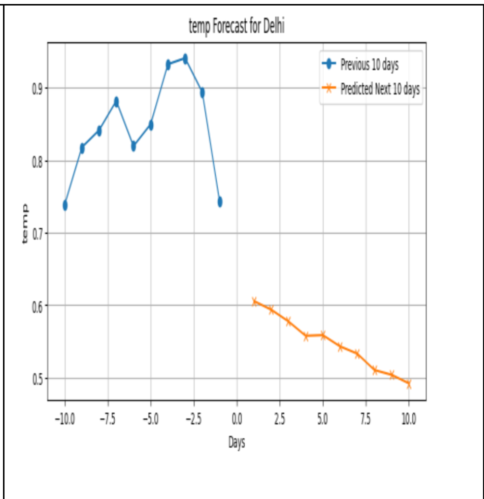
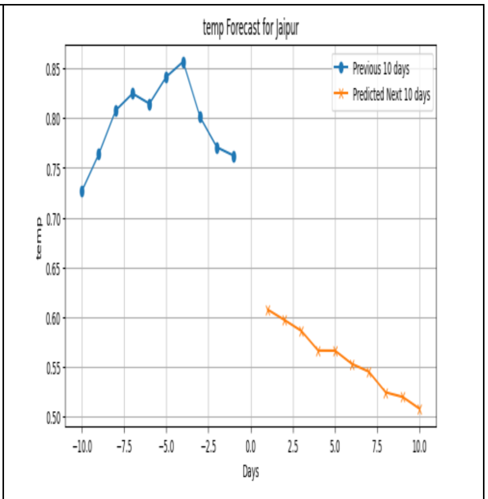
$$RMSE = \sqrt{\sum_{\mathrm{i=1}}^{\mathrm{n}} \frac{(\mathrm{y_i} - y^{\wedge}{}_{i})^2}{\mathrm{n}}} \quad (3)$$

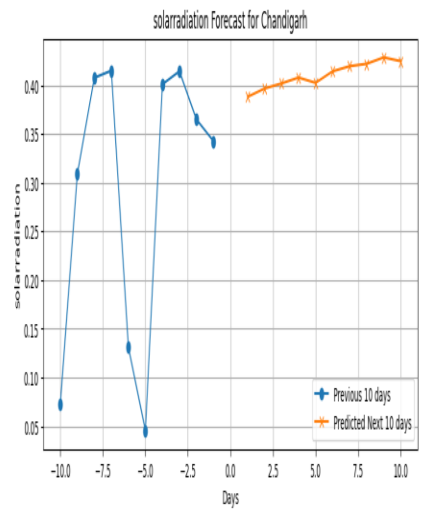
4. Results and discussion

The BDCL-Net model's training was conducted using the back-propagation technique on a small batch size of 32 and epochs of 50. To increase the precision, several parameters, including decay, dropout function, and learning rate, were set to 1e-6, 0.5, and 1e-3, respectively. A PC equipped with an Intel Core (TM) i5-6200U, 8 GB of RAM, a CPU operating at 2.30 GHz, and Python 3.6 software with Keras 2.2.4 and a Tensor flow 1.12.0 backend library was used for the various experiments. Additionally, the tests were carried out on a T4 GPU running Google Colab for up to 12 hours straight. Depending on the quantity of GPU traffic at the time, the training time changed with each epoch.

4.1 Weather feature comparison

The comparative analysis of multi-parameter forecasting across Chandigarh, Delhi, and Jaipur demonstrates that the proposed BDCL-Net model performs most effectively in regions with relatively stable climatic transitions. Chandigarh demonstrates the highest temperature prediction accuracy because its historical and projected temperature patterns show strong correlation which leads to consistent results. A similar pattern is observed for solar radiation prediction, where smoother atmospheric conditions in Chandigarh lead to more consistent forecasts, whereas Jaipur presents marginal deviations because of higher radiation intensity fluctuations. Chandigarh achieves the highest forecasting accuracy through its humidity predictions which show only minor changes, while Delhi and Jaipur demonstrate moderate forecasting accuracy differences. Precipitation forecasting remains comparatively more challenging across all three cities due to its stochastic and event-driven nature; however, the model maintains acceptable stability, particularly in Chandigarh and Delhi. The results demonstrate that the model performs well across various North Indian climate conditions although regional differences and atmospheric changes affect its performance.

		
(a_1)	**(a_2)**	**(a_3)**



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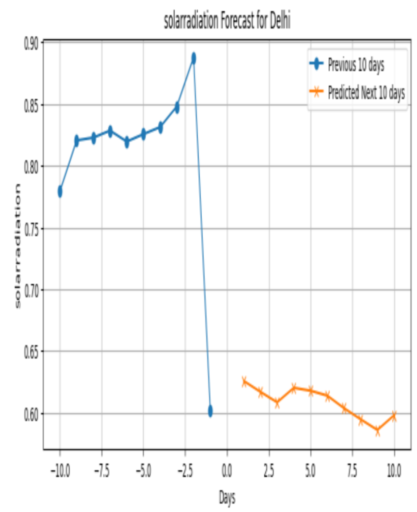

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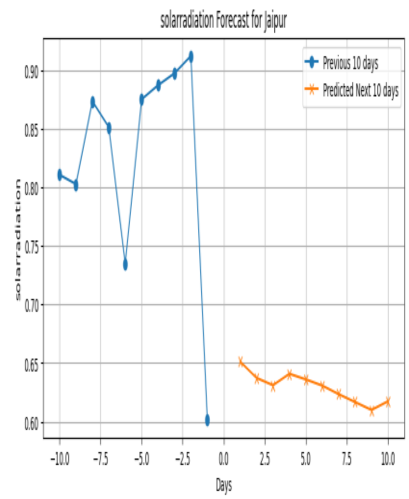
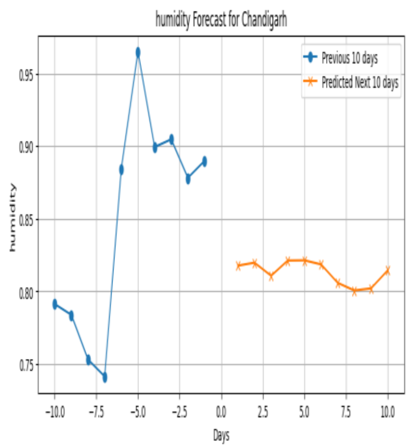
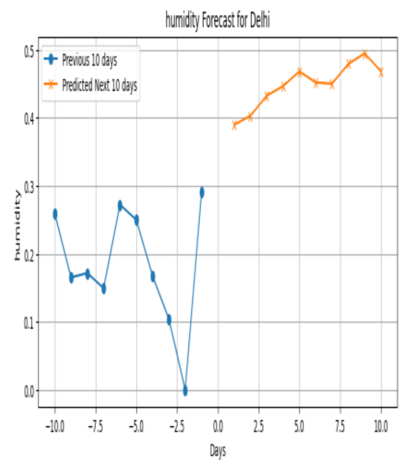


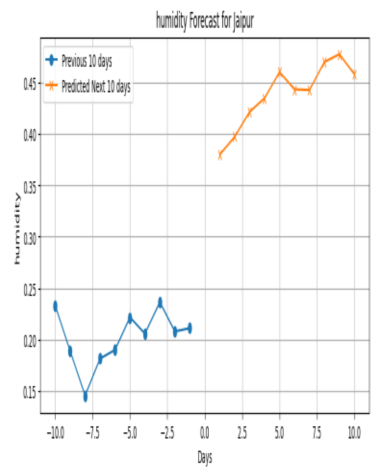
(b3)



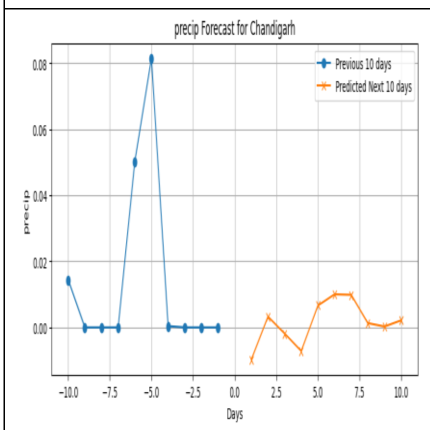
(C1)



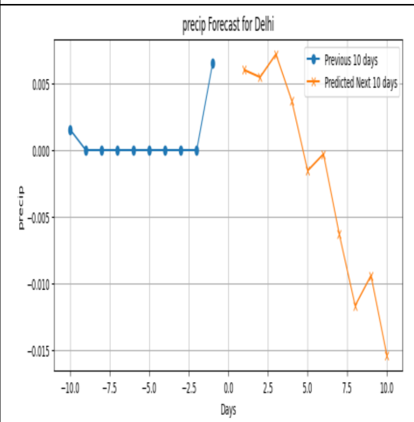
(C2)



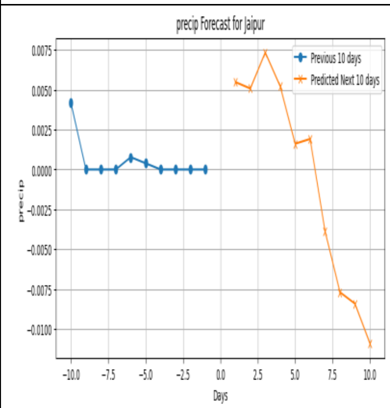
(C3)



(d1)



(d2)



(d3)

Figure 7: Temperature forecast (a1) Chandigarh (a2) Delhi (a3) Jaipur **,** Solar radiance forecast (b1) Chandigarh (b2) Delhi (b3) Jaipur, humidity forecast (c1) Chandigarh (c2) Delhi (c3) Jaipur, precipitation forecast (d1) Chandigarh (d2) Delhi (d3) Jaipur

4.2 Analysis of proposed BDCL-Net models

The figure 8 shows the training and validation loss results of the BDCL-Net through 50 training periods. The training and validation losses begin to decline at a slow pace because the system successfully learns to track time-based relationships in its sequential input. The first training period which lasts from 1 to 10 shows only small changes but it keeps moving towards its final state. The Ranger21 optimizer achieves its best results after completing its warmup period because learning rate stabilization improves performance to reduce validation loss. The model reached its highest performance level because both training and validation loss remained almost the same according to the results which showed both curves stopped increasing after 20 training periods. The BDCL-Net architecture demonstrates strong generalization capability through its training loss which decreases to 0.0179 and its validation loss which stays around 0.0198. The model exhibits regularization through its smooth convergence pattern which enables precise predictions of time-series data.

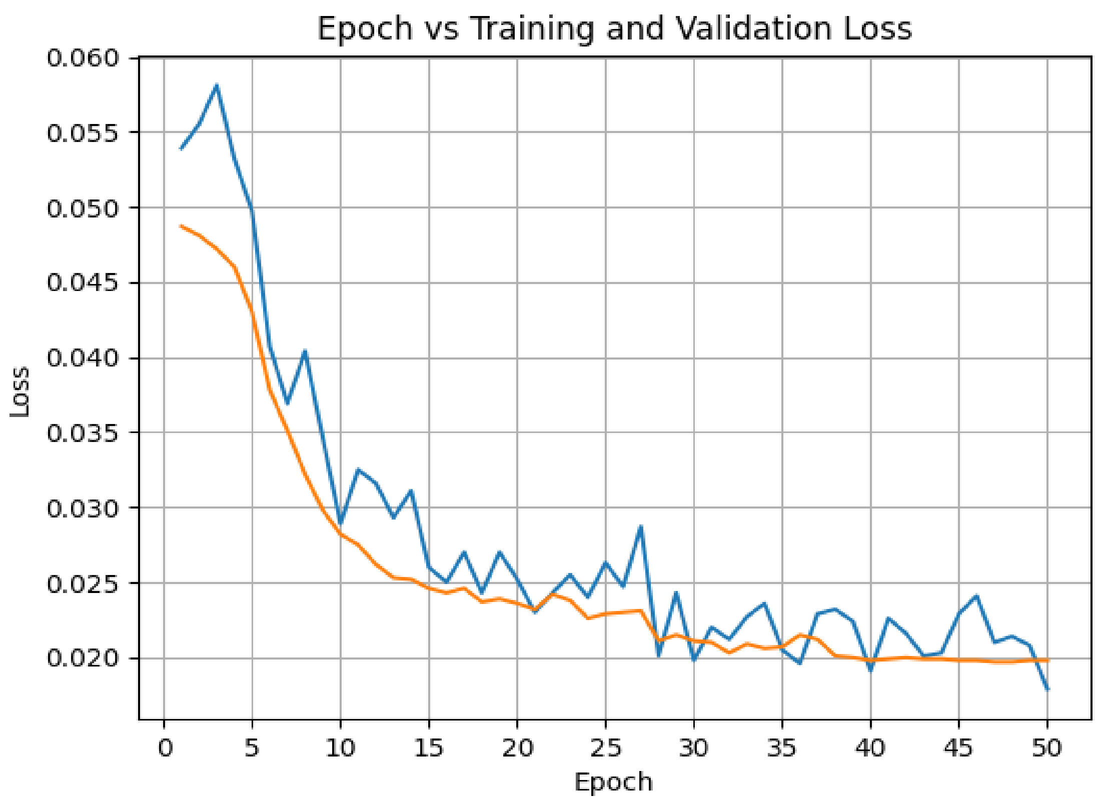


Figure 8: Training and validation loss graph

Table 4: Performance analysis of model

Category	Metric	Value
Classification Metrics	Accuracy	0.8619
	Precision	0.8408

	Recall	0.8929
	F1 Score	0.8661
Regression Metrics	R^2 Score	0.9971
	RMSE	0.2149
	MAE	0.1452

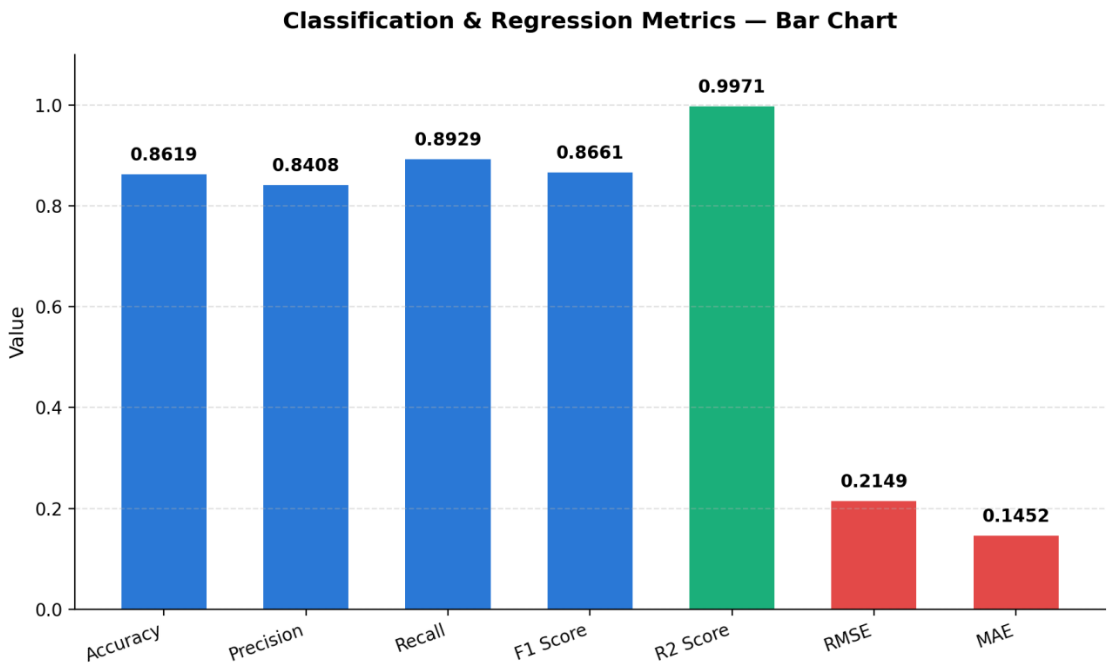


Figure 9: Bar chart representing classification (Accuracy, Precision, Recall, F1 Score) and regression (R^2, RMSE, MAE) performance metrics of the model.

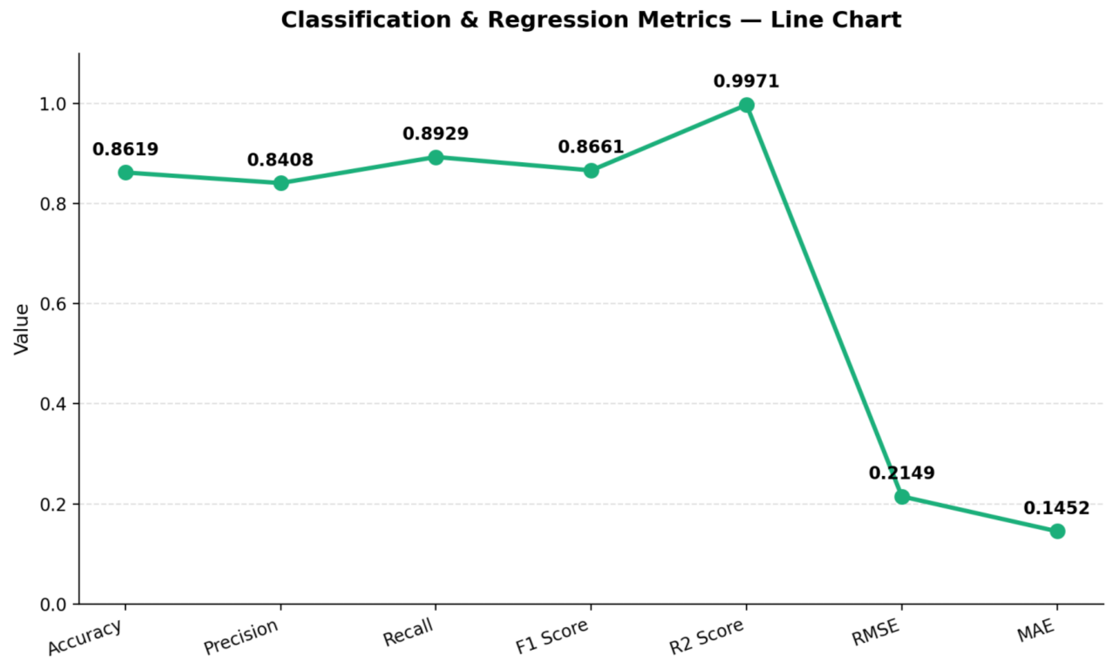


Figure 10: Line chart representing the trend of classification (Accuracy, Precision, Recall, F1 Score) and regression (R^2, RMSE, MAE) performance metrics of the model.

The classification metrics indicate high reliability, with an accuracy of 86.19%, precision of 84.08%, recall of 89.29%, and an F1-score of 86.61%, which reflects a balanced trade-off while maintaining a balanced rate of false positive and false negative predictions.

The model demonstrates higher recall value which indicates its ability to identify true positive instances, which holds particular significance for forecasting applications that require detection of critical events. The model demonstrates outstanding regression performance through its R^2 score of 0.9971 which shows that more than 99% of target variable variance is accounted for by the model. The low RMSE (0.2149) and MAE (0.1452) values demonstrate that prediction errors remain minimal while maintaining high numerical accuracy.

The bidirectional structure enables better temporal context learning through its ability to capture both past and future sequence dependencies, which results in stronger generalization performance and accurate forecasting results.

4.3 Comparative analysis with state of art models

The BDCL-Net demonstrates better results than all past studies when measured through its regression and classification performance. Abdulla, Demirci, and Ozdemir (2022) demonstrated that adaptive deep learning models work effectively for weather forecasting because the models achieved moderate predictive accuracy according to their tests. The study by Hewage et al. (2020, 2021) used Temporal Convolutional Networks (TCN) together with other deep learning models to obtain MAE results of 0.769 and 0.656 and RMSE results of 1.077 and 0.864 and R^2 results of 0.971 and 0.981 for baseline and adaptive models.

The BDCL-Net achieved an MAE value of 0.1452 and an RMSE value of 0.2149 and an R^2 value of 0.9971 together with excellent classification results which included 0.8619 accuracy and 0.8408 precision and 0.8929 recall and 0.8661 F1-score. The BDCL-Net demonstrates superior predictive performance to earlier methods while also delivering a dependable system for time-series analysis and classification activities.

Table 5: Comparative analysis

Model	**MAE**	**RMSE**	**R^2**	**Accuracy**	**Precision**	**Recall**	**F1-Score**

Baseline Model(Abdulla et al., 2022)	0.769	1.077	0.971	—	—	—	—
Adaptive Model(Abdulla et al., 2022)	0.656	0.864	0.981	—	—	—	—
Proposed BDCL-Net	**0.1452**	**0.2149**	**0.9971**	**0.8619**	**0.8408**	**0.8929**	**0.8661**

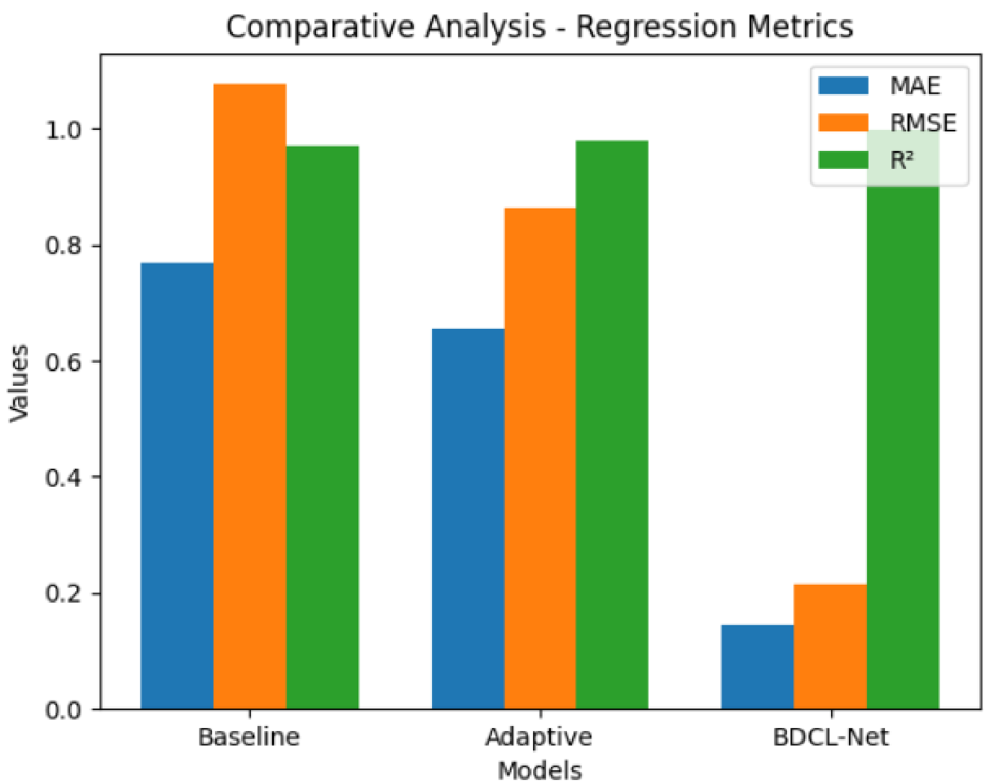


Figure 11: Regression performance comparison of Baseline, Adaptive, and BDCL-Net models.

4.5 Limitations of study

The BDCL-Net system exhibits strong predictive capabilities but currently holds multiple points which require additional development work. The model depends on historical weather information but its performance decreases in case it encounters missing data points or inconsistent data patterns or when data quality varies Preprocessing techniques address these problems effectively yet data dependency continues to impact the accuracy of all predictions. The model has only undergone testing for forecasting periods that range from short-term up to medium-term timespans. The forecasting accuracy declines as the prediction window extends to 10-day periods because atmospheric dynamics introduce higher levels of uncertainty. Time-series weather modeling faces this problem because climatic systems exhibit both stochastic behavior and highly non-linear patterns. This can affect its capacity to generalize under exceptional situations which involve significant changes in conditions. The upcoming enhancements should concentrate on acquiring bigger datasets which include The study incorporated data spanning several years and multiple geographical regions to enhance data diversity and improve the overall performance of the proposed system. The model's capability to predict future outcomes and maintain stability across various conditions will improve through the implementation of advanced techniques which focus on rare events and long-term forecasting.

5. Conclusion

In this research work we developed and tested BDCL-Net which stands for Bidirectional Drop Connect-Regularized LSTM Network to enhance weather forecasting accuracy through its ability to extract intricate time-based patterns that exist in historical weather data. The model uses bidirectional sequence learning because it needs to analyze both its previous and upcoming information to better understand weather patterns which exhibit both non-linear and dynamic behavior. The system performance assessment for BDCL-Net is tested with actual data and comparison of results against standard baseline methods has been demonstrated. The experimental findings demonstrate that BDCL-Net continuously performs better than comparable models. A wide range of performance indicators were used to evaluate the suggested model. Improved predictive ability was shown by the evaluation, as evidenced by the Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE). The findings indicate that the model achieved its best regression results through optimized training which produced MAE 0.1452 and RMSE 0.2149 and R^2 0.9971. The result showed the model's ability to predict with high accuracy while making only small errors and also The proposed model demonstrates reliable performance in both classification tasks and continuous forecasting applications. The evaluation results indicate that the model achieved better performance results because its technical capabilities enable it to learn long-term dependencies while its bidirectional processing prevents information loss and its advanced regularization techniques enable better generalization and prevent over-fitting. In this we found that combination of deep learning models with optimized training methods results in better model stability and more accurate predictions.

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