A Deep Learning CNN-GRU-RNN Model for Sustainable Development Prediction in Al-Kharj City

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Received: 12 October 2024 | Revised: 29 October 2024 | Accepted: 3 December 2024

ABSTRACT

This study introduces an advanced Deep Learning (DL) framework, the Convolutional Neural Network-Gated Recurrent Unit-Recurrent Neural Network (CNN-GRU-RNN). This model is engineered to forecast climate dynamics extending to the year 2050, with a particular focus on four pivotal scenarios: temperature, air temperature dew point, visibility distance, and atmospheric sea level pressure, specifically in Al-Kharj City, Saudi Arabia. To address the data imbalance problem, the Synthetic Minority Over-Sampling Technique was employed for Regression along with the Gaussian Noise (SMOGN). The efficacy of the CNN-GRU-RNN model was benchmarked against five regression models: the Decision Tree Regressor (DTR), the Random Forest Regressor (RFR), the Extra Trees Regressor (ETR), the Bayesian Ridge Regressor (BRR), and the K-Nearest Neighbors Regressor (KNNR). The models were evaluated using five distinct metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), Median Absolute Error (MedAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). The experimental outcomes demonstrated the superiority of the CNN-GRU-RNN model, which surpassed the traditional regression models across all four scenarios.

Keywords-climate change; deep learning; temperature; air temperature dew point; visibility distance; atmospheric sea level pressure

I. INTRODUCTION

Climate change denotes alterations in typical atmospheric conditions, encompassing factors like precipitation, temperature, humidity, and wind patterns [1]. Additionally, it entails modifications in the occurrence and severity of these meteorological phenomena. The terrestrial climate is undergoing substantial transformations, a trajectory anticipated to persist and possibly intensify over the coming century and beyond [2]. The magnitude of these future climatic shifts is contingent primarily upon the volume of the greenhouse gases released and the Earth's responsiveness to such emissions. Should robust measures be undertaken to curtail greenhouse gas outputs, it is conceivable to confine global warming to within 2 degrees Celsius [3]. Conversely, a failure to enact these mitigations could precipitate an escalation in mean global temperatures by 5 degrees Celsius or greater by the end of the century. The current velocity of climate change surpasses any other epoch in the annals of Earth's climatological history [4]. Clear signs of a warming planet, such as the rising global temperatures, rising sea levels, warming of the upper layers of the oceans, melting ice on land, shrinking Arctic Sea ice, and deeper seasonal thawing of soils, are witnessed [5]. These trends are well documented and confirmed by many independent research groups around the world. The rising average temperatures denote that the heat waves are now more frequent and tend to be hotter. Some of the extreme heat waves being experienced nowadays would likely not have occurred if the planet had not been recently warming [6-10]. In this context, Artificial Intelligence (AI) emerges as a pivotal tool, focusing on predictive analysis and the use of datasets of climate change and weather data [11]. The versatility of AI allows it to be used in a variety of ways to reduce the harmful effects of climate change [12]. These AI methods include increasing energy efficiency, improving carbon capture and storage, forecasting renewable energy production, managing energy grids, designing sustainable buildings, improving transportation systems, advancing smart agriculture, improving industrial processes, reducing deforestation, and creating resilient cities. AI has revolutionized climate modeling by processing complex multidimensional data to produce more accurate and detailed climate predictions [13-17].

The motivation for this study stems from the need to enhance climate change prediction models by addressing the limitations of the existing approaches. Current research primarily relies on traditional Machine Learning (ML) or basic hybrid models, which often focus on short-term forecasts, single climate variables, and specific geographic regions. There is a clear demand for more sophisticated DL models capable of delivering accurate, multi-scenario, and long-term predictions, particularly for understudied regions like Al-Kharj city, Saudi Arabia. By developing a CNN-GRU-RNN model that outperforms traditional techniques in predicting various climate parameters up to 2050, this study aims to provide valuable insights for improved climate adaptation and mitigation strategies.

II. LITERATURE REVIEW

Authors in [18] demonstrated the impact of climate change on the rain rate distribution in a Malaysian city using hydro-estimator data for the period 2011-2020. The study found an increasing trend in rainfall rates, indicating the effects of climate change, which may exacerbate rainfall fading and impact signal performance for high-frequency communication systems, such as 5G. Authors in [19] employed a technique known as prophetic forecasting to project annual temperatures in Myitkyina for the period from 2010 to 2017. This method, a variant of parametric regression, integrated distinctive holidays and seasonal trends, facilitating intricate time series predictions with a minimal parameter set. The precision of their forecasts was evaluated using the RMSE, which was found to be 5.7573 for the years 2012 and 2013. Authors in [20] presented three models to predict temperatures using the high-resolution operational model GRAPES-3km. Their dataset included records from Shaanxi Province, China, covering the years 2019 and 2020. LightGBM was the most effective method, delivering a prediction accuracy surpassing 84%. Authors in [21] devised the WD-SARIMAX model to predict temperatures in Delhi. The model's efficacy was assessed through multiple metrics, including MSE, MAE, MedAE, RMSE, Mean Absolute Percentage Error (MAPE), and R^2. The WD-SARIMAX model exhibited commendable results, with respective values of 2.80, 1.13, 0.76, 1.67, 4.90, and 91%.

Authors in [22] investigated the prediction of sea levels utilizing Genetic Programming (GP) and Artificial Neural Networks (ANNs). Rather than directly forecasting sea levels, they concentrated on Sea Level Anomalies (SLAs). The study involved analyzing hourly data on local wind shear speed components over the previous 12 hours at four coastal locations in the USA. Their findings indicated that the GP algorithm surpassed the ANN in accuracy, achieving notable results: a maximum correlation coefficient of 0.998, a MAE of 0.106 meters, a dispersion index of 0.031, and an efficiency coefficient of 0.995 for an one-day forecast.

Authors in [23] developed a forecasting model utilizing six ML regression techniques to predict global temperatures. Their findings revealed that the CBR model excelled, surpassing the performance of the other regression models with an R^2 value of 92.4%. Authors in [24] demonstrated a hybrid CNN-BRNN model to predict temperature, air temperature dew point, visibility distance, and atmospheric sea level pressure. The experimental results demonstrated that the CNN-BRNN model achieved the best results among other models for predicting climate change scenarios. Authors in [25] performed a comparative analysis employing 10 ML regression models alongside an ensemble model. The ensemble model outperformed the individual models. For humidity, the ensemble model recorded MAE, RMSE, MSE, and R^2values of 4.0126, 29.9885, 5.4428, and 93.35%, respectively. Regarding the minimum temperature, the ensemble model achieved MAE, RMSE, MSE, and R^2 values of 0.7908, 1.0515, 1.1329, and 90.18%. For the maximum temperature, the ensemble model yielded MAE, RMSE, MSE, and R^2 values of 1.2515, 1.6591, 2.8038, and 82.05%. In the context of rainfall, the model demonstrated MAE, RMSE, MSE, and R^2 values of 0.2142, 0.4100, 0.1681, and 77.33%.

Authors in [26] first preprocessed and cleaned air pollution data from 23 Indian cities over six years, including missing values and outliers. Skewed features were logarithmically transformed, while major pollutants impacting the Air Quality Index (AQI) were identified using a correlation-based feature selection. According to exploratory data analysis, the pollution levels dropped significantly in 2020. The dataset is balanced and separated into training and testing sections using SMOTE. ML models predict AQI, with XGBoost being the most accurate and SVM being the least accurate. The models are evaluated using accuracy, precision, recall, and F1-score, with XGBoost performing the best. The study implies that DL could improve AQI prediction in future air quality studies in India. Authors in [27] forecast PM_{10} air quality in Battaramulla and Kandy, Sri Lanka, utilizing twelve air quality metrics and five models: XGBoost, CatBoost, LightBGM, LSTM, and GRU. The LightBGM algorithm predicted PM_{10} levels most accurately in both sites, according to multiple indicators. The study found that customized forecasting models are needed for distinct locations and that seasonal fluctuations increased PM_{10} levels in both areas.

A. Research Gap and Contribution

There is a significant gap in the development of advanced DL models that can effectively handle multi-scenario, long-term climate predictions for specific regions, such as the city of Al-Kharj, Saudi Arabia. While previous studies have examined individual variables, such as temperature or rainfall, they lack a comprehensive approach that considers multiple climate factors simultaneously. Additionally, the comparative analysis between DL and traditional models remains underexplored, particularly over extended time periods up to 2050. This study aims to fill these gaps by introducing a novel CNN-GRU-RNN model that outperforms conventional regression techniques across various metrics, providing a more robust predictive capability for climate change adaptation. Specifically, the study aims to predict climate change in Al-Kharj, Saudi Arabia, up to the year 2050 using four different scenarios: temperature, air temperature dew point, visibility distance, and atmospheric sea level pressure. It compares the performance of the proposed CNN-GRU-RNN model with five traditional regression models: the DTR, RFR, ETR, BRR, and KNNR. To assess these models, various metrics, including MSE, MAE, MedAE, RMSE, and R^2, are utilized. The findings reveal that the CNN-GRU-RNN model surpasses conventional regression models across all four scenarios, yielding remarkable R^2 values of 98.64% in the first scenario, 98.13% in the second, 98.71% in the third, and an impressive 98.85% in the fourth.

III. METHODOLOGY

This research utilizes a sophisticated DL framework, the CNN-GRU-RNN architecture, to predict climate variations in Al-Kharj, Saudi Arabia, up to the year 2050. The methodology unfolds as follows:

- Identification of dataset features.
- Applying the Synthetic Minority Over-Sampling Technique for Regression with Gaussian Noise (SMOGN) to address dataset imbalance.
- Normalization of data using Min-Max normalization.
- Partitioning of the dataset into training (70%), validation (15%), and testing (15%).
- Training the CNN-GRU-RNN model.
- Leveraging a suite of performance evaluation metrics, including MSE, MAE, MedAE, RMSE, and R^2.
- Assessing the performance of the proposed model in predicting climate change in Al-Kharj City across the four scenarios: temperature, air temperature dew point, visibility distance, and atmospheric sea level pressure.

A. Dataset

The dataset employed in this study originates from [28], it was issued from 2019 encompassing 7 unique attributes and comprising a total of 51,358 records. Its features include wind direction angle, wind speed rate, sky ceiling height, visibility distance, temperature, air temperature dew point, and atmospheric sea level pressure. It entails 4 classes, Temperature, Visibility distance, Air temperature dew point and Atmospheric sea level pressure, for prediction. A detailed statistical analysis of these features is provided in Table I. Figure 1 depicts the heatmap analysis of the dataset features, offering a visual representation of the interrelationships and correlations among the variables. The heatmap analysis is an effective way to visually represent how different features in the dataset are related to each other. It is often used in exploratory data analysis to uncover relationships and patterns between the variables.

TABLE I. STATISTICAL ANALYSIS FOR THE DATASET FEATURES

Feature Name	Mean	Std	Min	50%	Max
Wind direction angle	277.67	291.06	10	180	999
Wind speed rate	6.6688	49.721	0.0	4.1	999.9
Sky ceiling height	669280	399381	15	99999	99999
Visibility distance	881341	269274	0.0	9900	99999
Temperature	28.9671	37.3852	1.6	28	999.9
Air temperature dew point	3.63588	51.4667	25	0.0	999.9
Atmospheric sea level pressure	9999.55	56.0842	1004	9999.9	9999.9

Fig. 1. Heatmap analysis for the dataset features.

B. Synthetic Minority Over-Sampling for Gaussian Noise Regression (SMOGN)

SMOGN is a technique designed to deal with imbalanced datasets in regression tasks. Unlike classification tasks, where the objectives are categorical, regression deals with continuous objectives [29-31].

C. Min-Max Normalization

Normalization is a prevalent preprocessing method in ML, designed to address the challenge of datasets with varied scales [32]. This technique ensures that all data points are treated equally by applying specific mathematical transformations, thus enabling fair comparisons. It achieves this by converting disparate metrics into a standardized format [33]. The process involves adjusting the minimum and maximum values to normalize the data range. The goal is to map the smallest data point to 0 and the largest to 1, with all other values being proportionally distributed within this normalized interval of 0 to 1 [34]. The Min-Max normalization formula is detailed as:

$$z = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

where z signifies the normalized data, x denotes the original input data, $max(x)$ indicates the maximum value within the input dataset, and $min(x)$ represents the minimum value within the same dataset.

D. Convolutional Neural Network (CNN)

CNN is a distinct DL architecture class engineered specifically for handling structured network data [35]. Modeled after the human visual system, CNN is employed for various tasks, including both classification and regression. These networks consist of multiple foundational layers that methodically process and transform input data to produce predictions [36]. The principal layers in CNN are convolutional layers, activation function, pooling layers, fully connected layers, and output layer.

E. Gated Recurrent Unit (GRU)

GRU is a specialized neural network architecture specifically engineered for processing sequential data [37]. As a variant of Recurrent Neural Networks (RNNs), GRUs address several challenges associated with traditional RNNs, such as the vanishing gradient problem, which hinders effective learning across long sequences. Although GRUs are akin to Long Short-Term Memory (LSTM) networks in their use of gating mechanisms to manage information flow [38], GRUs represent a more recent innovation, featuring a streamlined and efficient architectural design compared to LSTMs.

F. Recurrent Neural Network (RNN)

RNNs represent a distinct category of ANNs engineered to process data with temporal or sequential dependencies [39]. Unlike conventional feed-forward neural networks, RNNs incorporate self-recurrent connections that allow them to preserve memory of previous inputs. This unique architectural feature equips RNNs with the capability to handle tasks, where maintaining contextual continuity or managing input sequences is essential. While the basic unit of an RNN is a neuron, like those found in other neural network frameworks [40], each neuron in an RNN is linked to its output from the previous time step. This recurrent connection supports the retention of a hidden state that integrates information from past inputs, thereby enabling the network to effectively capture and leverage temporal dependencies.

G. The Proposed CNN-GRU-RNN Model

The architecture of the proposed CNN-GRU-RNN model is detailed through the following stages:

- Input layer: The model processes the input as a sequence of vectors, each with a dimension of 7, formatted as (1, 7, 1).
- Convolutional layers: The network consists of four convolutional layers. The first layer employs 256 filters with a kernel size of 10, the second layer utilizes 128 filters with a kernel size of 7, the third layer incorporates 32 filters with a kernel size of 5, and the fourth layer applies 16 filters with a kernel size of 3. Each convolutional layer is activated through the ReLU function.
- Max pooling layer: After the convolutional layers, a max pooling operation with a 3×3 window is applied to diminish the spatial dimensions of the feature maps.
- GRU layer: The processed output of the max pooling layer is routed through a GRU layer featuring 256 hidden units.
- RNN layer: This output is then channeled into an RNN layer with 128 hidden units.
- Fully connected layer: The concluding layer is a fully connected layer comprising 64 neurons, activated by ReLU.
- Output layer: The final output layer employs a linear activation function and consists of a single neuron.

The model is configured with a batch size of 128, a learning rate of 0.001, and utilizes the Adam optimizer, with a total of 50 epochs.

H. Evaluation Metrics

To evaluate the efficacy of the proposed CNN-GRU-RNN model in comparison to other models examined in this study, the latter utilized a range of assessment metrics [41-42]. These metrics include MSE, MAE, MedAE, RMSE, and R^2. The mathematical formulations for these evaluation criteria are given by:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Act_i - pre_i)^2 \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Act_i - pre_i| \quad (3)$$

$$MedAE = median(|pre_i - Act_1|, \dots, |pre_i - Act_i|) \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Act_i - pre_i)^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Act_i - pre_i)^2}{\sum_{i=1}^{n}\left((\sum_{i=1}^{n} Act_i) - Act_i\right)^2} \quad (6)$$

where, n represents the dataset sample size, and Act_i, pre_i are the i^{th} actual and predicted values, respectively.

IV. RESULTS AND DISCUSSION

This study's experiments were carried out using Jupyter Notebook version 7.2.1, an esteemed platform for Python-based data analysis and visualization. Jupyter Notebook provides an ideal environment for code development, execution, and documentation, alongside the creation of visual data representations. It supports a range of programming languages, including Python 3.10, and is operated through a web browser interface. The experiments were conducted on a PC running Microsoft Windows 10, featuring an Intel Core i7 processor, 32GB of RAM, and an Nvidia RTX 2080 GPU. The hyperparameter settings for the ML regression models used in this study are detailed in Table II.

TABLE II. HYPERPARAMETERS FOR THE FIVE TRADITIONAL ML REGRESSION MODELS

Models	Hyperparameters
DTR	Max_depth = 50, criterion = "squared_error".
RFR	N_estimators = 150, max_depth = 30.
ETR	N_estimators = 100, max_depth = 20.
BRR	Max_iter = 100, tol = 0.01.
KNNR	N_.neighbors = 20, weights = "distance".

Tables III-VI present the performance metrics for the CNN-GRU-RNN model alongside five conventional ML regression models, DTR, RFR, ETR, BRR, and KNNR, for predicting temperature, air temperature dew point, visibility, and atmospheric sea level, respectively, evaluated using the metrics specified in (2)-(6). The CNN-GRU-RNN model demonstrated superior performance across all evaluated metrics, recording the minimal values for MSE, MAE, MedAE, RMSE, and the highest R^2. Conversely, the KNNR model exhibited the least favorable performance, with elevated values for MSE, MAE, MedAE, and RMSE, and the lowest R^2.

TABLE III. EVALUATION OF THE EFFICACY OF THE PROPOSED CNN-GRU-RNN MODEL COMPARED TO TRADITIONAL REGRESSION MODELS IN PREDICTING TEMPERATURE

Model	MSE	MAE	MedAE	RMSE	R^2(%)
CNN-GRU-RNN	0.0102	0.0805	0.0676	0.1010	98.64
DTR	0.0215	0.0921	0.0745	0.1466	96.94
RFR	0.0263	0.0987	0.0791	0.1621	96.27
ETR	0.0374	0.1362	0.0854	0.1933	94.85
BRR	0.0586	0.3748	0.1736	0.2420	93.76
KNNR	0.0862	0.7942	0.4681	0.2935	91.85

TABLE IV. EVALUATION OF THE EFFICACY OF THE PROPOSED CNN-GRU-RNN MODEL COMPARED TO TRADITIONAL REGRESSION MODELS IN PREDICTING AIR TEMPERATURE DEW POINT

Model	MSE	MAE	MedAE	RMSE	R^2(%)
CNN-GRU-RNN	0.0141	0.0952	0.0813	0.1187	98.13
DTR	0.0247	0.1054	0.0962	0.1571	96.83
RFR	0.0374	0.2536	0.1392	0.1933	95.79
ETR	0.0562	0.4714	0.3543	0.2370	94.04
BRR	0.0826	0.6825	0.5839	0.2908	92.68
KNNR	0.0984	0.8403	0.7582	0.3136	91.27

TABLE V. EVALUATION OF THE EFFICACY OF THE PROPOSED CNN-GRU-RNN MODEL COMPARED TO TRADITIONAL REGRESSION MODELS IN PREDICTING VISIBILITY DISTANCE

Model	MSE	MAE	MedAE	RMSE	R^2(%)
CNN-GRU-RNN	0.0099	0.0799	0.0683	0.0999	98.71
DTR	0.0147	0.0894	0.0752	0.1212	96.93
RFR	0.0263	0.1052	0.0917	0.1621	95.75
ETR	0.0574	0.3965	0.2841	0.2395	93.42
BRR	0.0736	0.5842	0.4792	0.2712	91.85
KNNR	0.0951	0.7594	0.7251	0.3083	90.73

TABLE VI. EVALUATION OF THE EFFICACY OF THE PROPOSED CNN-GRU-RNN MODEL COMPARED TO TRADITIONAL REGRESSION MODELS IN PREDICTING ATMOSPHERIC SEA LEVEL PRESSURE

Model	MSE	MAE	MedAE	RMSE	R^2(%)
CNN-GRU-RNN	0.0100	0.0803	0.0651	0.1004	98.85
DTR	0.0292	0.0931	0.0759	0.1708	97.19
RFR	0.0438	0.1362	0.0974	0.2092	95.82
ETR	0.0757	0.3732	0.1638	0.2751	93.78
BRR	0.0936	0.5826	0.3829	0.3059	91.92
KNNR	0.2758	0.8072	0.6475	0.5251	90.02

Figures 2-5 demonstrate the future forecasting from 2015 to 2050 using the proposed CNN-GRU-RNN model for the temperature, air temperature dew point, visibility, and atmospheric sea level, respectively.

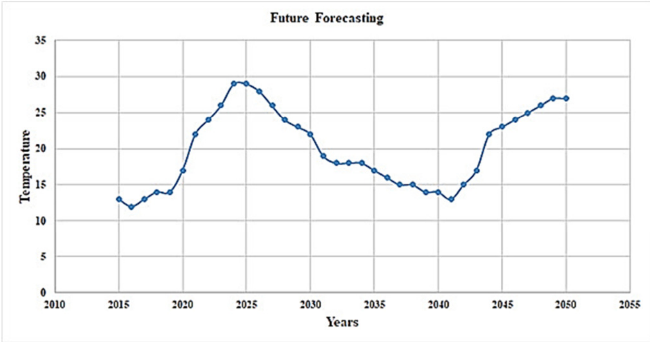

Fig. 2. Future forecasting for the temperature from 2015 to 2050 using the proposed CNN-GRU-RNN model.

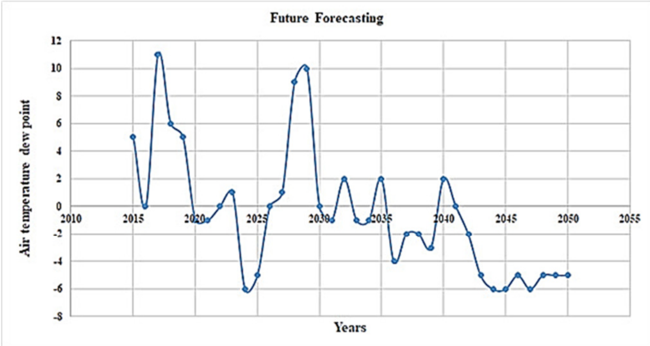

Fig. 3. Future forecasting for air temperature dew point from 2015 to 2050 using the proposed CNN-GRU-RNN model.

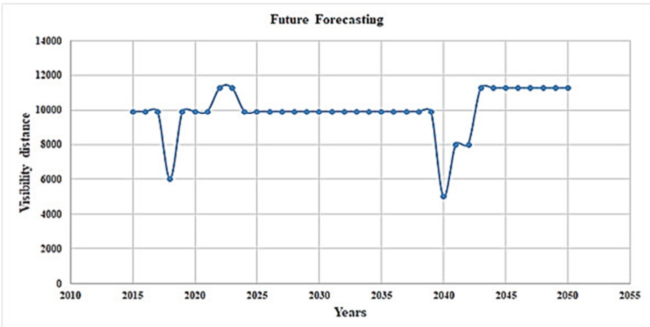

Fig. 4. Future forecasting for visibility distance from 2015 to 2050 using the proposed CNN-GRU-RNN model.

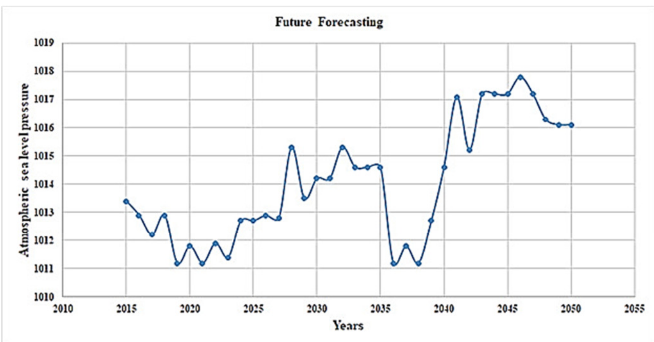

Fig. 5. Future forecasting for atmospheric sea level pressure from 2015 to 2050 using the proposed CNN-GRU-RNN model.

Figure 2 demonstrates the future prediction of the temperature from 2015 to 2050 using the proposed CNN-GRU-RNN model. From approximately 2015 to 2025, there is a rise in temperature, peaking at around 30 ^{o}C. After 2025, the temperature drops significantly, reaching its lowest level around 2035. Between 2035 and 2040, the temperature remains stable with slight fluctuations. From 2040 to 2050, the temperature shows an increase, reaching around 25 ^{o}C by 2050. Figure 3 showcases the future forecasting for the air temperature dew point from 2015 to 2050 using the proposed CNN-GRU-RNN model. From 2015 to 2020, the dew point shows large fluctuations, with notable peaks in the period between 2015 and 2020, reaching values above 10 ^{o}C. After 2020, the dew point trends downward, reaching a low near 2025, followed by a period of relative stability. Between 2025 and 2035, the dew point rises again, peaking near 12 ^{o}C around 2030, and then fluctuates. From 2035 to 2050, the dew point shows a gradual decrease with slight fluctuations, reaching a lowest level near 7 ^{o}C around 2045, then stabilizing with slight changes towards 2050. Figure 4 portrays the future forecasting for the visibility distance from 2015 to 2050 using the proposed CNN-GRU-RNN model. The visibility distance remains constant around 10,000 m in 2015. A sharp decline to approximately 6,000 m is observed around 2015, followed by a return to stability. Between 2020 and 2025, oscillations appear in visibility, peaking slightly above 10,000 m before stabilizing. From 2025 to 2035, the visibility distance consistently hovers around 10,000 m. Around 2040, another sharp decline occurred, with visibility dropping to around 4,000 m. After this decline, visibility gradually recovers, stabilizing at around 12,000 m from 2045 to 2050. Figure 5 depicts the future forecasting for the atmospheric sea level pressure from 2015 to 2050 using the proposed CNN-GRU-RNN model. The atmospheric sea level pressure starts at approximately 1013 hPa in 2015, it shows a decreasing trend until approximately 2018. During the period from 2018 to 2025, the pressure exhibits large fluctuations characterized by many prominent peaks and troughs. After 2025, the pressure displays a marked upward trajectory that peaks around 2035. After 2035, the pressure continues to fluctuate periodically, with significantly higher peaks occurring around 2040 and 2045. When this period ends, the pressure stabilizes slightly above 1016 hPa.

V. CONCLUSION AND FUTURE WORK

This study underscores the critical necessity of addressing climate change through the precise prediction of its future impacts via advanced modeling techniques. The proposed Convolutional Neural Network-Gated Recurrent Unit-Recurrent Neural Network (CNN-GRU-RNN) model exhibits exceptional performance in forecasting climate change indicators, such as temperature, air temperature dew point, visibility distance, and atmospheric sea level pressure in Al-Kharj city, Saudi Arabia. It outperformed traditional regression models, like Decision Tree Regressor (DTR), Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Bayesian Ridge Regressor (BRR), and K-Nearest Neighbors Regressor (KNNR). The model evaluations, utilizing metrics, such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Median Absolute Error (MedAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2), demonstrate that the CNN-GRU-RNN model markedly outperforms the other approaches, consistently achieving R^2 values exceeding 98% across all scenarios. These findings highlight the potential of Deep Learning (DL) models to provide accurate climate predictions, which are pivotal for devising effective planning and mitigation strategies against the adverse impacts of climate change. Moving forward, the generalizability and robustness of the proposed model could be enhanced by incorporating more diverse and extensive datasets from various geographical regions. Additionally, investigating the influence of supplementary climate and environmental variables on model performance will be crucial for augmenting prediction accuracy and developing real-time prediction systems capable of providing updated climate forecasts to facilitate real-time decision-making.

ACKNOWLEDGMENT

The authors extend their appreciation to Prince Sattam bin Abdulaziz University for funding this research work through the project number (PSAU/2024/01/28539).

REFERENCES

[1] O. Adedeji, O. Reuben, and O. Olatoye, "Global Climate Change," *Journal of Geoscience and Environment Protection*, vol. 2, no. 2, pp. 114–122, Apr. 2014, https://doi.org/10.4236/gep.2014.22016.

[2] M. Noor *et al.*, "Climate Change and Costal Plant Lives," in *Environment, Climate, Plant and Vegetation Growth*, S. Fahad, M. Hasanuzzaman, M. Alam, H. Ullah, M. Saeed, I. Ali Khan, and M. Adnan, Eds. Cham, Switzerland: Springer International Publishing, 2020, pp. 93–108.

[3] M. C. Urban *et al.*, "Improving the forecast for biodiversity under climate change," *Science*, vol. 353, no. 6304, Sep. 2016, Art. no. aad8466, https://doi.org/10.1126/science.aad8466.

[4] W. Thuiller, "Climate change and the ecologist," *Nature*, vol. 448, no. 7153, pp. 550–552, Aug. 2007, https://doi.org/10.1038/448550a.

[5] F. J. Doblas-Reyes *et al.*, "Initialized near-term regional climate change prediction," *Nature Communications*, vol. 4, no. 1, Apr. 2013, Art. no. 1715, https://doi.org/10.1038/ncomms2704.

[6] B. A. Yerlikaya, S. Ömezli, and N. Aydoğan, "Climate Change Forecasting and Modeling for the Year of 2050," in *Environment, Climate, Plant and Vegetation Growth*, S. Fahad, M. Hasanuzzaman, M. Alam, H. Ullah, M. Saeed, I. Ali Khan, and M. Adnan, Eds. Cham, Switzerland: Springer International Publishing, 2020, pp. 109–122.

[7] C. Huntingford, E. S. Jeffers, M. B. Bonsall, H. M. Christensen, T. Lees, and H. Yang, "Machine learning and artificial intelligence to aid climate change research and preparedness," *Environmental Research Letters*, vol. 14, no. 12, Nov. 2019, Art. no. 124007, https://doi.org/10.1088/1748-9326/ab4e55.

[8] J. Abdullahi and G. Elkiran, "Prediction of the future impact of climate change on reference evapotranspiration in Cyprus using artificial neural network," *Procedia Computer Science*, vol. 120, pp. 276–283, Jan. 2017, https://doi.org/10.1016/j.procs.2017.11.239.

[9] M. A. Haq, "CDLSTM: A Novel Model for Climate Change Forecasting," *Computers, Materials & Continua*, vol. 71, no. 2, pp. 2363–2381, Dec. 2021, https://doi.org/10.32604/cmc.2022.023059.

[10] S. M. Petrea *et al.*, "A Forecasting and Prediction Methodology for Improving the Blue Economy Resilience to Climate Change in the Romanian Lower Danube Euroregion," *Sustainability*, vol. 13, no. 21, Oct. 2021, Art. no. 11563, https://doi.org/10.3390/su132111563.

[11] R. A. Ramadan and S. Boubaker, "Predictive Modeling of Groundwater Recharge under Climate Change Scenarios in the Northern Area of Saudi Arabia," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13578–13583, Apr. 2024, https://doi.org/10.48084/etasr.7020.

[12] W. Leal Filho *et al.*, "Deploying artificial intelligence for climate change adaptation," *Technological Forecasting and Social Change*, vol. 180, Jul. 2022, Art. no. 121662, https://doi.org/10.1016/j.techfore.2022.121662.

[13] Z. Liu, C. Peng, W. Xiang, D. Tian, X. Deng, and M. Zhao, "Application of artificial neural networks in global climate change and ecological research: An overview," *Chinese Science Bulletin*, vol. 55, no. 34, pp. 3853–3863, Dec. 2010, https://doi.org/10.1007/s11434-010-4183-3.

[14] A. M. Elshewey, S. M. Tawfeek, A. A. Alhussan, M. Radwan, and A. H. Abed, "Optimized Deep Learning for Potato Blight Detection Using the Waterwheel Plant Algorithm and Sine Cosine Algorithm," *Potato Research*, May 2024, https://doi.org/10.1007/s11540-024-09735-y.

[15] M. Y. Shams, Z. Tarek, E.-S. M. El-kenawy, M. M. Eid, and A. M. Elshewey, "Predicting Gross Domestic Product (GDP) using a PC-LSTM-RNN model in urban profiling areas," *Computational Urban Science*, vol. 4, no. 1, Jan. 2024, Art. no. 3, https://doi.org/10.1007/s43762-024-00116-2.

[16] D. Chakraborty, A. Alam, S. Chaudhuri, H. Başağaoğlu, T. Sulbaran, and S. Langar, "Scenario-based prediction of climate change impacts on building cooling energy consumption with explainable artificial intelligence," *Applied Energy*, vol. 291, Jun. 2021, Art. no. 116807, https://doi.org/10.1016/j.apenergy.2021.116807.

[17] E. Tapoglou, I. C. Trichakis, Z. Dokou, I. K. Nikolos, and G. P. Karatzas, "Groundwater-level forecasting under climate change scenarios using an artificial neural network trained with particle swarm optimization," *Hydrological Sciences Journal*, vol. 59, no. 6, pp. 1225–1239, Jun. 2014, https://doi.org/10.1080/02626667.2013.838005.

[18] H. Basarudin *et al.*, "Evaluation of Climate Change Effects on Rain Rate Distribution in Malaysia using Hydro-Estimator for 5G and Microwave Links," *Engineering, Technology & Applied Science Research*, vol. 13, no. 4, pp. 11064–11069, Aug. 2023, https://doi.org/10.48084/etasr.5552.

[19] Z. Z. Oo and S. Phyu, "Time Series Prediction Based on Facebook Prophet: A Case Study, Temperature Forecasting in Myintkyina," *International Journal of Applied Mathematics Electronics and Computers*, vol. 8, no. 4, pp. 263–267, Dec. 2020, https://doi.org/10.18100/ijamec.816894.

[20] H. Zhang, Y. Wang, D. Chen, D. Feng, X. You, and W. Wu, "Temperature Forecasting Correction Based on Operational GRAPES-3km Model Using Machine Learning Methods," *Atmosphere*, vol. 13, no. 2, Feb. 2022, Art. no. 362, https://doi.org/10.3390/atmos13020362.

[21] A. M. Elshewey *et al.*, "A Novel WD-SARIMAX Model for Temperature Forecasting Using Daily Delhi Climate Dataset," *Sustainability*, vol. 15, no. 1, Jan. 2023, Art. no. 757, https://doi.org/10.3390/su15010757.

[22] S. P. Nitsure, S. N. Londhe, and K. C. Khare, "Prediction of sea water levels using wind information and soft computing techniques," *Applied Ocean Research*, vol. 47, pp. 344–351, Aug. 2014, https://doi.org/10.1016/j.apor.2014.07.003.

[23] M. Y. Shams, Z. Tarek, A. M. Elshewey, M. Hany, A. Darwish, and A. E. Hassanien, "A Machine Learning-Based Model for Predicting Temperature Under the Effects of Climate Change," in *The Power of Data: Driving Climate Change with Data Science and Artificial Intelligence Innovations*, A. E. Hassanien and A. Darwish, Eds. Cham, Switzerland: Springer Nature, 2023, pp. 61–81.

[24] F. Aljuaydi, B. K. Behera, A. M. Elshewey, and Z. Tarek, "A Deep Learning Prediction Model to Predict Sustainable Development in Saudi Arabia," *Applied Mathematics & Information Sciences*, vol. 18, no. 6, pp. 1345–1366, Nov. 2024, https://doi.org/10.18576/amis/180615.

[25] C. Nyasulu, A. Diattara, A. Traore, A. Deme, and C. Ba, "Towards Resilient Agriculture to Hostile Climate Change in the Sahel Region: A Case Study of Machine Learning-Based Weather Prediction in Senegal," *Agriculture*, vol. 12, no. 9, Sep. 2022, Art. no. 1473, https://doi.org/10.3390/agriculture12091473.

[26] K. Kumar and B. P. Pande, "Air pollution prediction with machine learning: a case study of Indian cities," *International Journal of Environmental Science and Technology*, vol. 20, no. 5, pp. 5333–5348, May 2023, https://doi.org/10.1007/s13762-022-04241-5.

[27] L. Mampitiya *et al.*, "Machine Learning Techniques to Predict the Air Quality Using Meteorological Data in Two Urban Areas in Sri Lanka," *Environments*, vol. 10, no. 8, Aug. 2023, Art. no. 141, https://doi.org/10.3390/environments10080141.

[28] "Saudi Arabia Hourly Climate Integrated Surface Data." Kapsarc, [Online]. Available: https://datasource.kapsarc.org/explore/dataset/saudi-hourly-weather-data/information/.

[29] .X. Y. Song, N. Dao, and P. Branco, "DistSMOGN: Distributed SMOGN for Imbalanced Regression Problems," in *Proceedings of the Fourth International Workshop on Learning with Imbalanced Domains: Theory and Applications*, Grenoble, France, 2022, pp. 38–52.

[30] P.-H. Kuo, Y.-T. Chen, and H.-T. Yau, "SMOGN, MFO, and XGBoost Based Excitation Current Prediction Model for Synchronous Machine," *Computer Systems Science and Engineering*, vol. 46, no. 3, pp. 2687–2709, Apr. 2023, https://doi.org/10.32604/csse.2023.036293.

[31] M. Arteaga, M. J. Gacto, M. Galende, J. Alcalá-Fdez, and R. Alcalá, "Enhancing soft computing techniques to actively address imbalanced regression problems," *Expert Systems with Applications*, vol. 234, Dec. 2023, Art. no. 121011, https://doi.org/10.1016/j.eswa.2023.121011.

[32] Z. Tarek *et al.*, "Soil Erosion Status Prediction Using a Novel Random Forest Model Optimized by Random Search Method," *Sustainability*, vol. 15, no. 9, Apr. 2023, Art. no. 7114, https://doi.org/10.3390/su15097114.

[33] A. M. Elshewey *et al.*, "Optimizing HCV Disease Prediction in Egypt: The hyOPTGB Framework," *Diagnostics*, vol. 13, no. 22, Nov. 2023, Art. no. 3439, https://doi.org/10.3390/diagnostics13223439.

[34] S. A. Alzakari, A. A. Alhussan, A.-S. T. Qenawy, and A. M. Elshewey, "Early Detection of Potato Disease Using an Enhanced Convolutional Neural Network-Long Short-Term Memory Deep Learning Model," *Potato Research*, Jul. 2024, https://doi.org/10.1007/s11540-024-09760-x.

[35] M. Shujaat, A. Wahab, H. Tayara, and K. T. Chong, "pcPromoter-CNN: A CNN-Based Prediction and Classification of Promoters," *Genes*, vol. 11, no. 12, Dec. 2020, Art. no. 1529, https://doi.org/10.3390/genes11121529.

[36] S. Kareem, Z. J. Hamad, and S. Askar, "An evaluation of CNN and ANN in prediction weather forecasting: A review," *Sustainable Engineering and Innovation*, vol. 3, no. 2, pp. 148–159, Oct. 2021, https://doi.org/10.37868/sei.v3i2.id146.

[37] G. Shen, Q. Tan, H. Zhang, P. Zeng, and J. Xu, "Deep Learning with Gated Recurrent Unit Networks for Financial Sequence Predictions," *Procedia Computer Science*, vol. 131, pp. 895–903, 2018, https://doi.org/10.1016/j.procs.2018.04.298.

[38] Z. Tarek *et al.*, "An Optimized Model Based on Deep Learning and Gated Recurrent Unit for COVID-19 Death Prediction," *Biomimetics*, vol. 8, no. 7, Nov. 2023, Art. no. 552, https://doi.org/10.3390/biomimetics8070552.

[39] W. Fang, Y. Chen, and Q. Xue, "Survey on Research of RNN-Based Spatio-Temporal Sequence Prediction Algorithms," *Journal on Big Data*, vol. 3, no. 3, pp. 97–110, 2021, https://doi.org/10.32604/jbd.2021.016993.

[40] S. Khaki, L. Wang, and S. V. Archontoulis, "A CNN-RNN Framework for Crop Yield Prediction," *Frontiers in Plant Science*, vol. 10, Jan. 2020, https://doi.org/10.3389/fpls.2019.01750.

[41] A. M. Elshewey, M. Y. Shams, Z. Tarek, M. Megahed, E.-S. M. El-kenawy, and M. A. El-dosuky, "Weight Prediction Using the Hybrid Stacked-LSTM Food Selection Model," *Computer Systems Science and Engineering*, vol. 46, no. 1, pp. 765–781, Jan. 2023, https://doi.org/10.32604/csse.2023.034324.

[42] E. H. Alkhammash, A. F. Kamel, S. M. Al-Fattah, and A. M. Elshewey, "Optimized Multivariate Adaptive Regression Splines for Predicting Crude Oil Demand in Saudi Arabia," *Discrete Dynamics in Nature and Society*, vol. 2022, no. 1, 2022, Art. no. 8412895, https://doi.org/10.1155/2022/8412895.