Fuzzy Systems and Soft Computing
ISSN : 1819-4362

A CNN-CNN-LSTM HYBRID DEEP NEURAL NETWORK FOR FORECASTING WATER QUALITY OF THE GANGA RIVER

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Abstract—**Large population of India lives on the bank of Ganga River. These people use the water of the Ganga River for different purposes in your daily life. Water pollution of Ganga River is the main problem to these people. Base stations funded by government is available to find the Water Quality of the Ganga River. Forecasting of pollution of Ganga River water using Water Quality data available from these base stations can help the government to take necessary actions in advance. A large number deep learning algorithms available now days which can process the data easily & forecast Water Quality Index (WQI). These deep learning models can be used by the government to take the necessary actions to prevent the pollution of Ganga River water & save the lives of human beings and living organisms depends on the Ganga River. In this paper, Convolutional Neural Network-Convolutional Neural Network-Long Short-Term Memory (CNN-CNN-LSTM) deep learning-based hybrid model is developed to forecast the water quality of the river Ganga. Various deep learning models like NN, LSTM, CNN, CNN-LSTM, BiLSTM, RNN, NN-LSTM, NN-CNN, LSTM-CNN, NN-CNN-LSTM, LSTM-CNN-LSTM, NN-Bi-LSTM, LSTM-Bi-LSTM, CNN-Bi-LSTM and CNN-LSTM-Bi-LSTM have been designed as baseline models to compare the outcome to the proposed model. Water Quality data collected from ten base stations of Uttarakhand Pollution Control Board is used for training & testing of the model developed in this paper. Water quality parameters like BOD (Biochemical Oxygen Demand), pH (potential of Hydrogen), DO (Dissolved Oxygen), temperature is used for calculating WQI (Water Quality Index). The proposed CNN-CNN-LSTM model provides better forecasting results for Water Quality Index (WQI).**

Index Terms— **Ensemble Learning, Ganga River, Water Quality Index (WQI), Deep Learning**

I. INTRODUCTION

Good Quality water is not available for more than 30% population of the world [1]. 80% water available on earth is not suitable for humans [2]. Water Quality of the Ganga River is decreasing due to sewage, fertilizers used in agriculture field, industrial waste [12]. A large population of India can suffer from disease like cancer depends on Ganga River water due to killer pollutants available in Gana River water. Water quality parameters like BOD (Biochemical Oxygen Demand), pH (potential of Hydrogen), DO (Dissolved Oxygen), temperature etc. are used to find the Water Quality. Each water quality parameter has their unique contribution in Water quality [12]. WQI is calculated to shows the contribution of each parameter in Water Quality [3]. The methods available in literature for finding the water quality is very costly & not gives the accurate data. The Machine & Deep Learning algorithms can easily read the dependency of different parameters available & forecast the future data based on trained data [1].

Forecasting water quality can be done using Time series analysis methods [17]. Time series analysis methods like Prophet, ARIMA, SARIMA is discussed for forecasting the water quality parameters like DO and BOD of Water & Water Quality Index of the river ganga in Uttar Pradesh. Best model is finding by doing comparative study based on values of performance metrices such as square root of Mean Squared Error (RMSE) and Mean Absolute Error (MAE) [2]. CNN-BiLSTM-SVR is developed an efficient deep learning model to forecast DO and BOD of Ganga River in Uttar Pradesh (UP). Developed model has been compared to other models like LSTM, Bi-LSTM, CNN-LSTM based on performance parameters like MSE & RMSE [3]. To find the temporal and spatial variations in water quality parameters of the river ganga in UP. Unsupervised machine learning methods like cluster analysis, PCA (Principal Component Analysis) & correlation is introduced. The study finds that pH, DO water quality parameters had correlation with season [4]. To get the concentrations of different optical & non-optical parameters from satellite images, machine learning based framework is implemented [1]. Research given in the paper finds the relations of Advanced Space Borne

Thermal Emission and Reflection Radiation data and finds parameters of water quality using regression analysis. Values of parameters predicted using regression analysis is same as the parameters calculated from ASTER reflectance bands [5]. Statistical methods-based water quality analysis has done of Semenyih River [6]. In this paper, we have used the deep learning models like NN, LSTM, CNN, CNN-LSTM, BiLSTM, RNN, NN-LSTM, NN-CNN, LSTM-CNN, NN-CNN-LSTM, LSTM-CNN-LSTM, NN-Bi-LSTM, LSTM-Bi-LSTM, CNN-Bi-LSTM and CNN-LSTM-Bi-LSTM for training & testing of Water Quality parameters data available on UPCB (Uttarakhand Pollution Control Board) website. Study used total four parameter’s data such as pH, DO, temperature & BOD in our study.
We have implemented CNN-CNN-LSTM model to predict accurate WQI of the River Ganga. The paper is divided in five sections. Section II discusses the motivation of the research. Section III is discussed the methodology used to develop the efficient deep learning model. The discussion on result is done in Section IV. The model comparisons based on performance metrices such as MSE, RMSE & R2 score is done in Section V. Section VI contains the conclusion of the research.

II.MOTIVATION FOR RESEARCH

Water pollution is a major problem at various places in Uttarakhand. Future water quality prediction using deep learning algorithms can helps the individuals and the government to take necessary actions on time.
The Paper implemented deep learning models using ensemble learning for analysis and forecasting of Water Quality Index. For finding the best model comparative analysis is held to find the best model.

III.STEPS FOR METHODOLOGY

Methodology used for developing the efficient deep learning model is given below-

A. *Study Area*

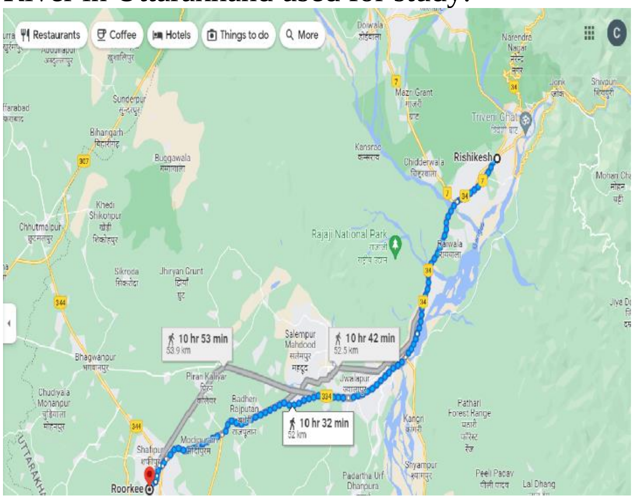
A Large number of studies are available in literature for quality prediction of the Ganga River water in UP. Uttarakhand state is also suffered from water pollution due to industrial area. This paper has chosen the area of Uttarakhand for research. Fig.1 shows the geographical location of the Ganga River in Uttarakhand used for study.


Fig. 1: Part of the Ganga River flows from Rishikesh to Roorkee

B. Preprocessing of Water Quality Parameters

Water Quality data set is used for research have been taken from Uttarakhand Pollution Control Board website. Data set available from 10 base stations is used for study. The points of base stations are- P1: Rishikesh at Bairaj Near Pashulok, Uttarakhand, P2: Lakshmanjhula Rishikesh, P3: Raiwala Dehradun, P4: Bindughat Dudhiyabad, Haridwar, P5: Balkumari Mandir, Ajeetpur, Haridwar, P6: Lalita Rao Bridge, Haridwar, P7: Rishikul Bridge D/S Harkipouri Haridwar, P8: Harkipouri Haridwar (Damkothi), P9: Harkipouri Haridwar, P10: Roorkee Haridwar. Total 1440 samples of four water quality parameters like BOD, Temperature, DO, pH from year 2011 to 2022 is used for training & testing models. Water quality is also impacted by temperature of water & it shows water chemistry, biological activities [8].
pH defines the basic or acidic property of water [10]. Quantity of DO can harm the living organism & changes the water quality. Organic quantity of matters can increase the level of BOD in water [4].

Collected data have some null values. Filling to these null values, backward fill method is utilized. Min-max normalization technique is used to fit the data in range from 0 to 1. Scaled data has been separated in training & test set.

C. Formula of WQI Calculation [3][16]

Individual water quality parameter is affecting the water quality & have their unique importance in WQI calculation. This unique importance in WQI is counted by assigning a unique value to these parameters [7]. WQI is calculated using four parameters like pH, DO, temperature and BOD. The value of *q* shows the value of individual parameters in the range 0-100. Eq.1 shows the calculation of WQI [11].

$$WQI = \sum_{i=1}^{n} Wi * Qi \qquad (1)$$

In Eq.1 W_i defines assigned weight to i^{th} water quality parameter, *n* defines count of water quality parameters, Q_i defines *q*-value associate with i^{th} water quality parameter. Weight assigned to each parameter for WQI calculation is shown in Table I.

TABLE I: Contribution of various parameters in WQI Calculation

Parameters	**Assigned Weight**
Temperature	0.10
BOD (mg/L)	0.11
DO (mg/L)	0.17
pH	0.11

D. Proposed Hybrid Model

Proposed deep hybrid model is designed using ensemble modelling technique to forecast the univariate time series data. The flow diagram of the developed model is shown in Fig. 2.

Convolutional Neural Network (CNN): This Feedforwards Neural Network can forecast the time series using spatial features available in the time series data. [13]-[15].

CNN-LSTM: Forecasting the water quality parameters is a tedious task. Individual deep learning models is not sufficient to read the seasonal and time variations of data. It can be done using hybrid models easily. Here, CNN-LSTM Hybrid deep learning model is designed by combining CNN and LSTM neural networks in a special manner. First CNN is constructed using ReLU activation function and kernel size is equal to 1. Second a MaxPooling layer is connected and pool size is set to 2. Now the features extracted from second layer is forwarded to the LSTM layer to find the predicted values of DO and BOD after adding a flatten layer to CNN. Next, the dense layer is used to find the output.

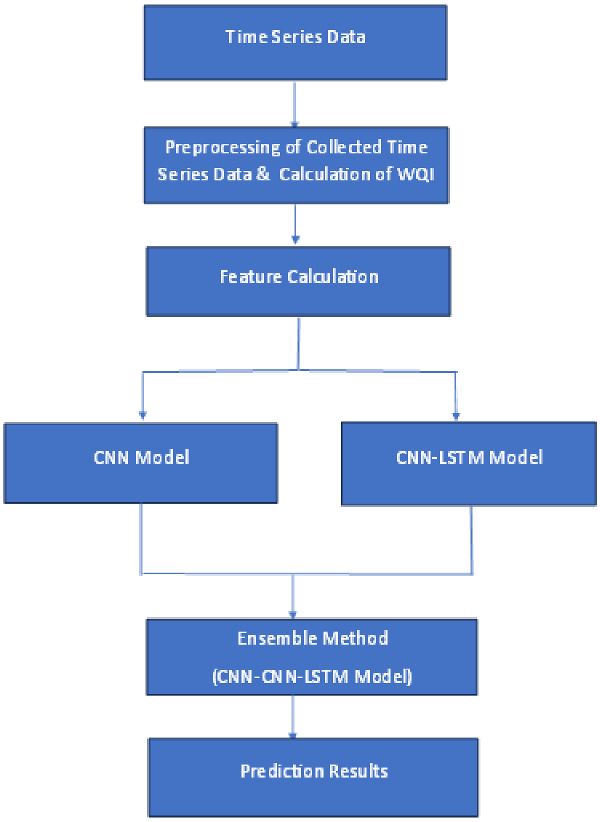


Fig.2: Flow diagram of the CNN-CNN-LSTM proposed hybrid model

E. Calculation of Performance matrices [4][16]

We can easily find the accuracy of deep learning models using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) performance metrices. MSE can be calculated by finding the deviation between the predicted and the original values. RMSE is equal to square root of MSE. Error is the deviation between actual and predicted values e_i, for i = 0,1,2,3...n. The model which has smallest MSE & RMSE values will be worked as best model.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}|e_i| \qquad (2)$$

$$RMSE=\sqrt{MSE} \qquad (3)$$

F. Model parameter

For designing the deep learning models, parameter values of various hyper parameters are set as per detail given in Table II.

Parameter	**Value**
Count of Convolution layer filters	64
Loss function	MSE
Padding of Convolution layer	same
Size of MaxPooling layer	2
Optimizer	Adam
Padding used at MaxPooling layer	same
Activation Function	ReLU
Batch size	64
Epochs	100
Kernel size	1

TABLE II: Parameter of Hybrid CNN-CNN-LSTM deep hybrid model

IV. THE DISCUSSION OF RESULTS

Multiple baseline models like NN, LSTM, CNN, CNN-LSTM, BiLSTM, RNN, NN-LSTM, NN-CNN, LSTM-CNN, NN-CNN-LSTM, LSTM-CNN-LSTM, NN-Bi-LSTM, LSTM-Bi-LSTM, CNN-Bi-LSTM and CNN-LSTM-Bi-LSTM has been implemented in this paper. The proposed CNN-CNN-LSTM model is compared with the baseline models to shows that it is the best model. Data set is divided in training & test data set. 80% of data set have been used for training of models & 20% of data set is used for testing. Prediction have been done on test data set. Performance matrices such as MSE, RMSE and R2 Score is used to decide the best model.

A. Baseline Models Development

The system configuration used for developing all the models is as follows: Operating system: Windows 64-bit Operating System, x64-based processor, CPU-Intel® Core™ i5-10210U @ 1.60GHz 2.11 GHz, RAM-4 GB. Deep learning packages like pandas, NumPy, Keras, TensorFlow, and matplotlib is used for developing all models. Epochs is set to 100. Adam optimizer is used whereas the batch size set to 64. Loss and activation functions are used as MSE and ReLU (Rectified Linear Unit) respectively. Development steps of the baseline models is given below.

1)NN Model- In ANN (Artificial Neural Network), the input parameters is passed in forward direction. Hidden layers are used to extract features. Comparative analysis shows that this model is less powerful than CNN and LSTM. In this paper, ten one-dimensional ReLU activated dense layer is used to design NN Model & kernel size is equal to 1. Next, To get the output of the model a dense layer is added.

2) LSTM Model- Forecasting of univariate time series can be done using LSTM model. Next value in the series based on past observations can be easily predicted using LSTM model. LSTM is accepting a three-dimensional input and generate a two-dimensional output based on feature extraction done from the sequence. The LSTM model try to find a function by which output observations can easily be find by using the past observations of the input. In this paper, LSTM is designed using LSTM layer with dimension of output vector=16, input shape= (1,1) with ReLU activation. The next layer is a dense layer is used in this model to get the output.

3) CNN Model-A Convolutional Neural Network (CNN) is a neural network used for working with two-dimensional image data. Extracting features from univariate time series data can be done easily. In this, CNN is designed using an input_shape= (1,1), Convolution layer with ReLU activation function & the kernel size is set to 1. Next the MaxPooling layer is added with pool size of 2. Then, the extracted features are inputted to the flatten layer. Now dense layer with dimension of output vector=50, is added with ReLU activation. Lastly, the dense layer with dimension of output vector=1, is added to get the output.

4) CNN-LSTM Model-

Forecasting the water quality parameters is not an easy task. Individual models such as CNN & LSTM is not sufficient to read the seasonal or temporal information from a time series data. This can be done easily using hybrid models. A hybrid mode of CNN model with an LSTM backend where the CNN is used to interpret hidden features of input & output of CNN model is provided to LSTM model to interpret. This hybrid model is called a CNN-LSTM model. Here, CNN model is designed with a one-dimensional ReLU activated convolution layer and kernel size is set to 1. Next layer is MaxPooling with a pool size of 2. Next, flatten layer is added & the extracted features are inputted to LSTM layer to get the forecasted values of WQI. Next, the dense layer is used to get the output.

5) BiLSTM Model- LSTM model is used to read the input features both in forward & backward direction & concatenate both results. This model is called the Bidirectional LSTM. A Bidirectional LSTM can be designed by wrapping the first hidden layer in a wrapper layer called Bidirectional for univariate time series forecasting. In this, three bidirectional LSTM layers with output shape (None, 1, 256), (None, 1, 128), (None, 64) respectively is designed. Then five dense layers is added with output shape (None, 128), (None, 64), (None, 32), (None, 1) respectively.

6) RNN Model-Due to the implicit memory of previous inputs, the temporal relations of data can be easily understood by Recurrent Neural Networks (RNN) model. This paper, creates a RNN with four layers of basic RNNs and a dense output layer. ReLU activation function is used. A dropout layer is added to avoid overfitting with a rate of 0.2. Adam is used as optimizer & MSE is used as error function and accuracy as the evaluation metric. Epochs is set equal to 100 & batch size is set to 64.

7) NN-LSTM Model-Ensemble learning techniques have the better performance on deep learning problems. In ensemble technique, the final output can be obtained by combining results from several baseline models. Final prediction can be obtained by using ensemble techniques like averaging, voting and stacking. In this, Basic ensemble learning technique, averaging, the final output is an average of all predictions is used for developing ensembling models to improve the performance of various base models. Averaging ensembling technique is used to develop NN-LSTM Model.

8) NN-CNN Model- Averaging ensembling technique is used to develop NN-CNN Model. Average of all predictions is used to get the final output for developing ensembling models to improve the performance of various base models.

9) LSTM-CNN Model- Averaging ensembling technique is used to develop LSTM-CNN Model.

10) NN-CNN-LSTM Model- Averaging ensembling technique is used to develop NN-CNN-LSTM Model.

11) LSTM-CNN-LSTM Model- Averaging ensembling technique is used to develop LSTM-CNN-LSTM Model.

12) NN-Bi-LSTM Model- Averaging ensembling technique is used to develop NN-Bi-LSTM Model.

13) LSTM-Bi-LSTM Model- Averaging ensembling technique is used to develop LSTM-Bi-LSTM.

14) CNN-Bi-LSTM Model- In this, Averaging ensembling technique is used to develop LSTM-Bi-LSTM.

15) CNN-LSTM-Bi-LSTM Model- Averaging ensembling technique is used to develop CNN-LSTM-Bi-LSTM.

B.Comparative Analysis

The values of performance metrices like MSE, RMSE & R2 score is compared with other baseline models in Table III.

Model	Performance metrices	WQI
NN	MSE	0.04
	RMSE	0.201
	R2 score	0.71
LSTM	MSE	0.039
	RMSE	0.198
	R2 score	0.717
CNN	MSE	0.037
	RMSE	0.193
	R2 score	0.734
CNN-LSTM	MSE	0.036
	RMSE	0.191
	R2 score	0.739
Bi-LSTM	MSE	0.094
	RMSE	0.307
	R2 score	0.323
RNN	MSE	0.092
	RMSE	0.304
	R2 score	0.336
NN-LSTM	MSE	0.04
	RMSE	0.2
	R2 score	0.712
NN-CNN	MSE	0.038
	RMSE	0.194
	R2 score	0.73
LSTM-CNN	MSE	0.038

	RMSE	0.195
	R2 score	0.727
NN-CNN-LSTM	MSE	0.037
	RMSE	0.193
	R2 score	0.732
LSTM-CNN-LSTM	MSE	0.037
	RMSE	0.192
	R2 score	0.736
CNN-CNN-LSTM	**MSE**	**0.035**
	RMSE	**0.188**
	R2 score	**0.747**
NN-Bi-LSTM	MSE	0.06
	RMSE	0.245
	R2 score	0.568
LSTM-Bi-LSTM	MSE	0.058
	RMSE	0.24
	R2 score	0.585
CNN-Bi-LSTM	MSE	0.052
	RMSE	0.227
	R2 score	0.629
CNN-LSTM-Bi-LSTM	MSE	0.051
	RMSE	0.225
	R2 score	0.635

TABLE III: Parameter of hybrid CNN-CNN-LSTM deep model

Lowest values of MSE & RMSE are shows that the model can forecast the better result than other models.

R2 Score can be described as the proportion of the variance in the dependent variable given by the independent variables in the model. It has the values from 0 to 1, where 0 shows that the model does not explain any variability, and 1 represents that it explains all the variability. Higher values of R2 Score shows that model predict better result but it does not necessary that the model is a good predictor in an absolute sense.

The Table III shows that the developed CNN-CNN-LSTM deep hybrid model have the smallest values of MSE & RMSE and higher value of R2 score compared to another basic models. Hence, CNN-CNN-LSTM deep hybrid model forecast the values of WQI more accurate compared to other basic models used in this paper.

Here, In Fig.12, the developed model, i.e., CNN-CNN-LSTM, predict the more accurate values of time series. The proposed model has the capability to read the accurate features that are hidden in the collected water pollution data.

Fig.3 shows the temporal representation of WQI data from 2015 to 2019. Fig4. represents the division of train & test sets used for training & testing of the models. Fig5. shows results of prediction of NN Model. Fig6. shows results of prediction of LSTM model. Fig8. represents the results of prediction of CNN model. Fig8. represents the results of prediction of CNN model. Fig9. represents the results of prediction of Bi-LSTM Model. Bi-LSTM Model gives the following values of performance metrices-the MSE 0.094, RMSE 0.307, R2 score 0.323 which shows that Bi-LSTM model have not predict the better result on the data set used in this paper.

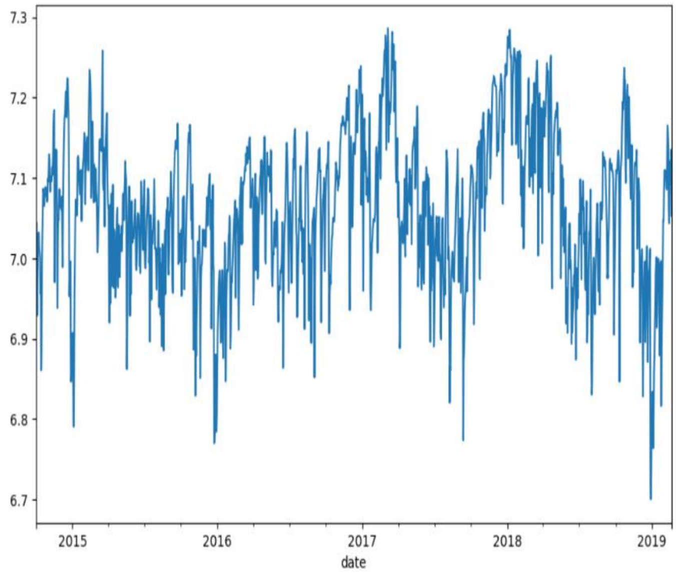


Fig.3: Temporal representation of WQI

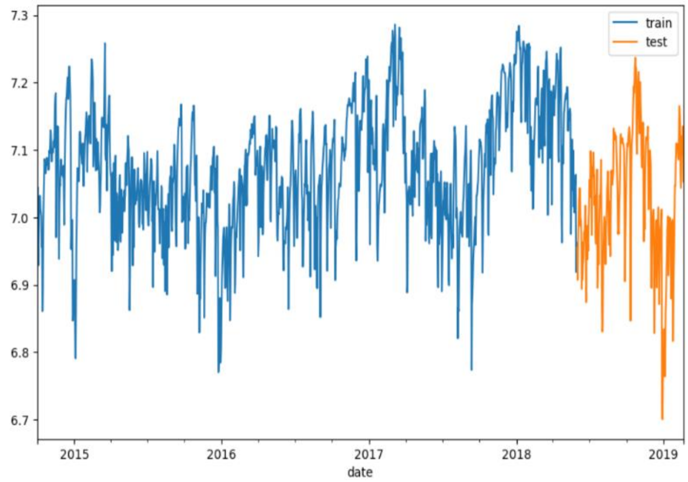


Fig.4: Temporal representation of trained & test data

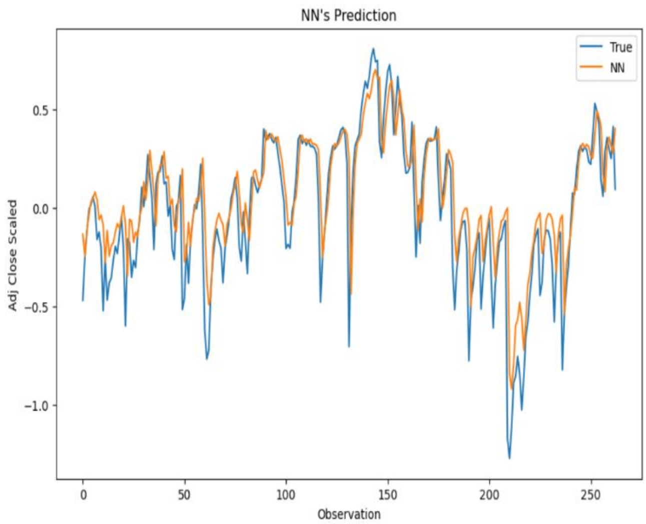


Fig.5: Results of prediction done by NN Model

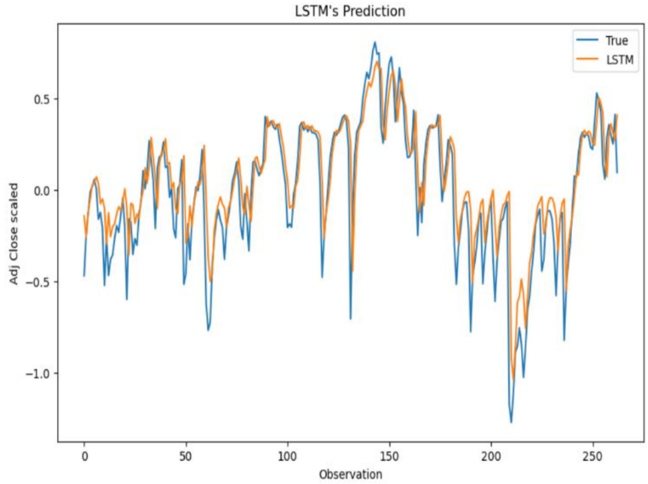


Fig.6: Results of prediction done by LSTM Model

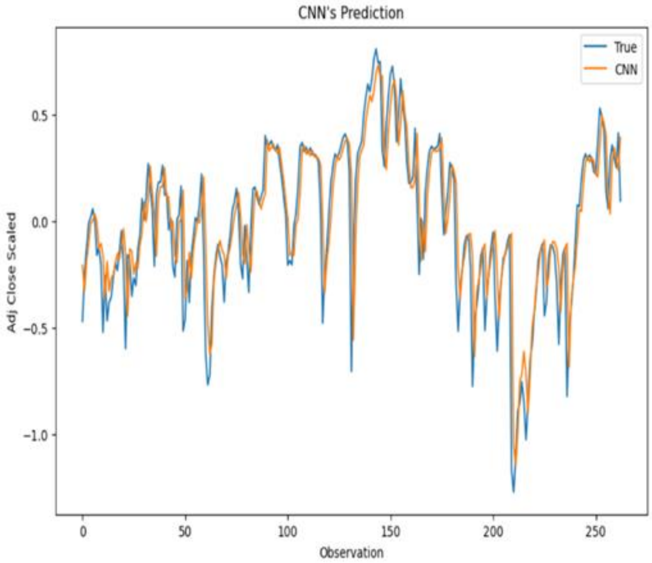


Fig.7: Results of prediction done by CNN Model

Fig10. shows results of prediction of RNN Model. MSE, RMSE & R2 score values of RNN shows that the predicted values of WQI from this model have the higher difference compare to actual values of WQI.

Fig12. shows results of prediction of NN-CNN model. Fig13.shows results of prediction of LSTM-CNN model. Results predicted by NN-CNN-LSTM Model is shown in the Fig14. Results predicted by LSTM-CNN-LSTM Model is shown in the Fig. 15. Results predicted by CNN-CNN-LSTM Model is shown in the Fig.16. CNN-CNN-LSTM Model have done the better prediction compare to other models. This designed model has the MSE 0.035, RMSE 0.188, R2 score 0.747. Lower values of MSE & RMSE & higher value of R2 score shows this model prediction ability. Fig17.shows the prediction results of NN-Bi-LSTM Model. Fig18.shows the prediction results of LSTM-Bi-LSTM Model. Fig19.shows the results of prediction of CNN- Bi-LSTM Model.

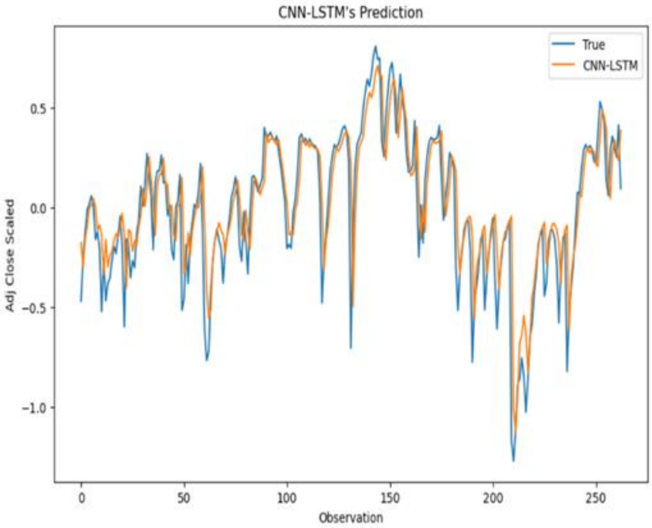


Fig.8: Results of prediction done by CNN-LSTM Model

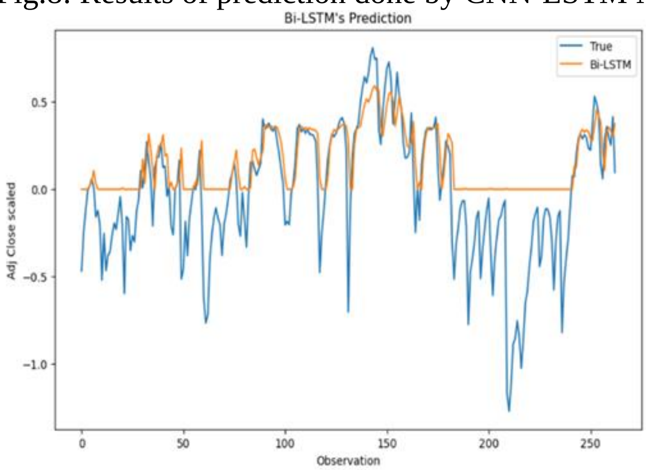


Fig.9: Results of prediction done by Bi-LSTM Model

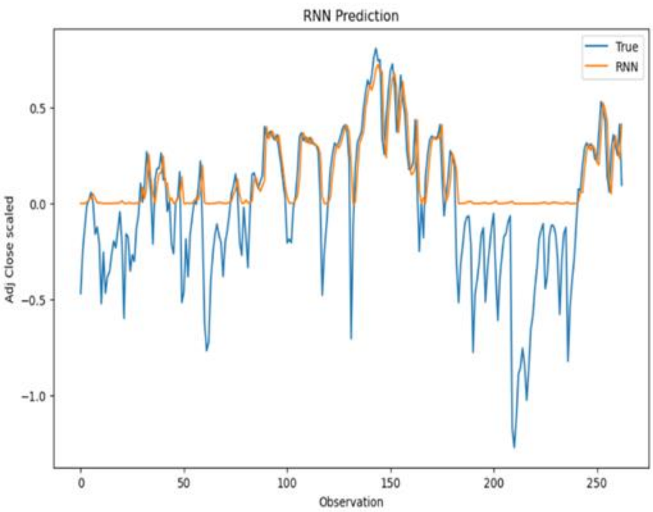


Fig.10: Results of prediction done by RNN Model

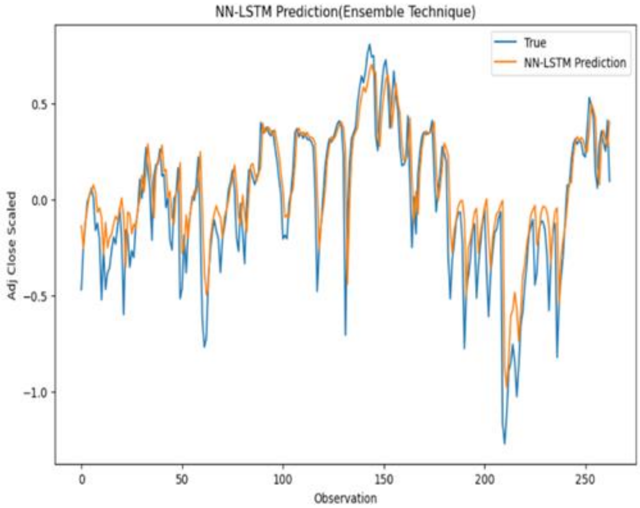


Fig.11: Results of prediction done by NN-LSTM Model (Ensemble Technique)

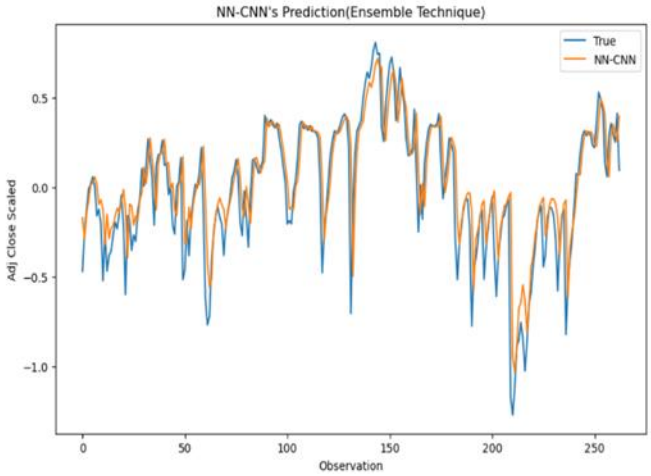


Fig.12: Results of prediction done by NN-CNN Model (Ensemble Technique)

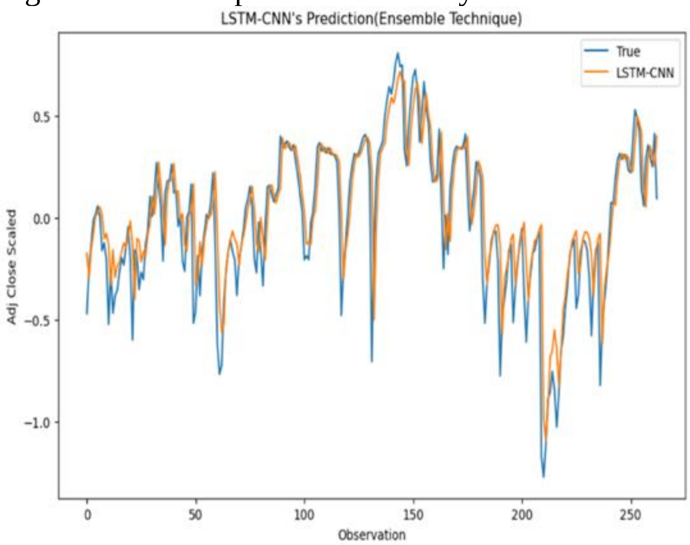


Fig.13: Results of prediction done by LSTM-CNN Model(Ensemble Technique)

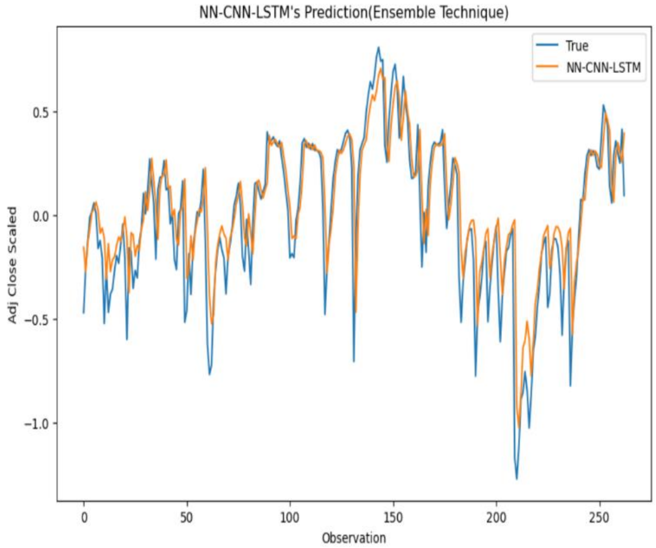


Fig.14: Results of prediction done by NN-CNN-LSTM Model (Ensemble Technique)

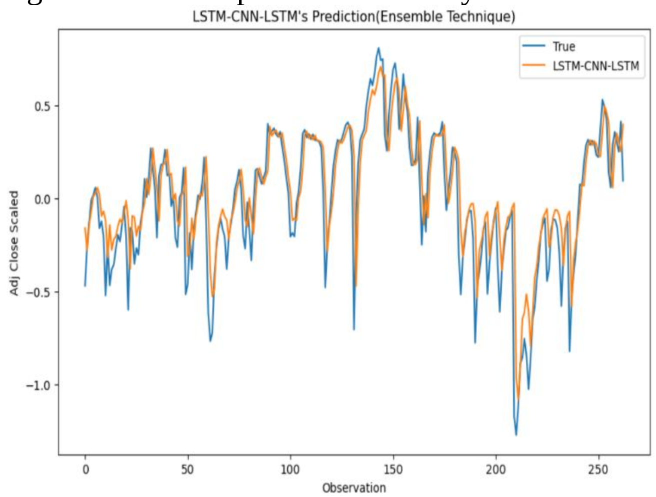


Fig.15: Results of prediction done by LSTM-CNN-LSTM Model (Ensemble Technique)

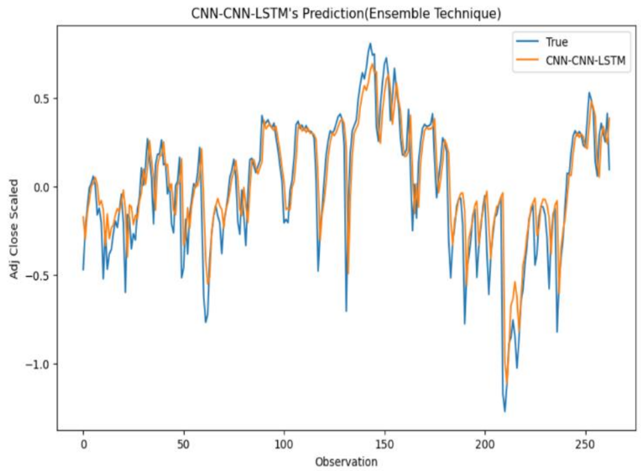


Fig.16: Results of prediction done by CNN-CNN-LSTM Model (Ensemble Technique)

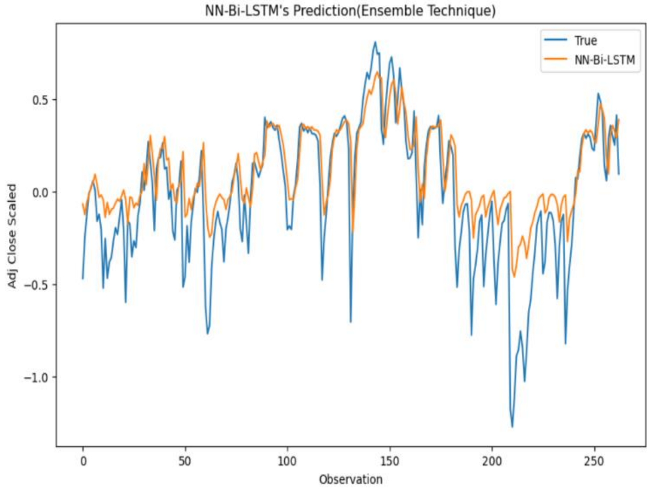


Fig.17: Results of prediction done by NN-Bi-LSTM Model (Ensemble Technique)

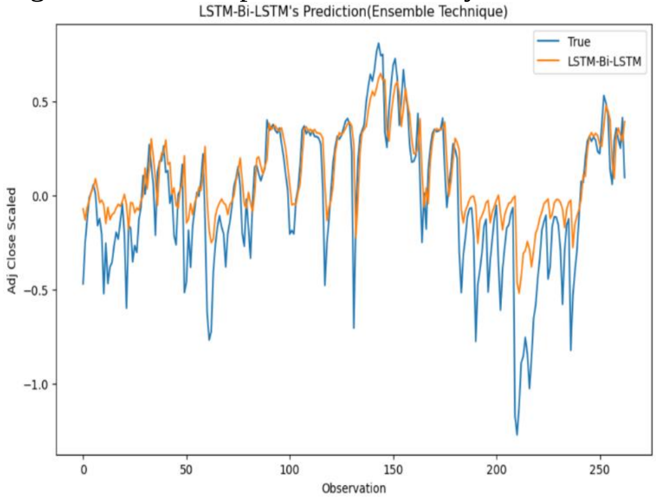


Fig.18: Results of prediction done by LSTM-Bi-LSTM Model (Ensemble Technique)

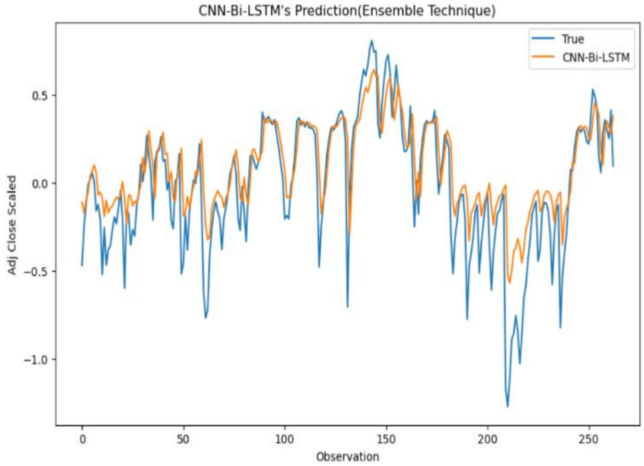


Fig.19: Results of prediction done by CNN- Bi-LSTM Model (Ensemble Technique)

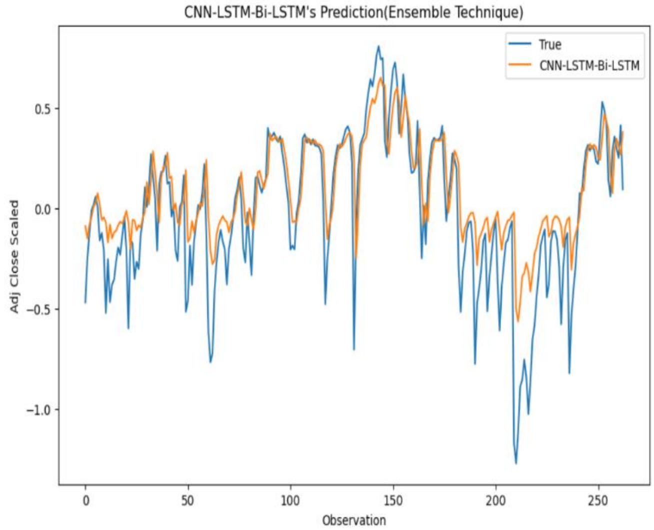


Fig.20: Results of prediction done by CNN-LSTM-Bi-LSTM Model (Ensemble Technique)

Fig20.shows results of prediction done by CNN-LSTM-Bi-LSTM Model.

V. CONCLUSIONS

In this paper, Ensemble technique is used to develop an efficient CNN-CNN-LSTM deep hybrid model. The proposed model can easily forecast the Water Quality Index for the River Ganga using collected pollution data. Using the proposed model water quality is predicted with lower values of MSE, RMSE & higher value of R2 Score, which shows that the proposed model is the best model when compared with the baseline models. Further, the research study may be extended by hybrid the different deep learning models using various ensemble techniques.

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