PLANT SCIENCE TODAY
ISSN 2348-1900 (online)
Vol x(x): xx–xx
https://doi.org/10.14719/pst.7412

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REVIEW ARTICLE

A novel approach for predicting net irrigated area in India using hybrid deep learning architectures

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OPEN ACCESS

ARTICLE HISTORY
Received: 30 January 2025
Accepted: 28 February 2025
Available online
Version 1.0 : 07 March 2025

Check for updates

Additional information

Peer review: Publisher thanks Sectional Editor and the other anonymous reviewers for their contribution to the peer review of this work.

Reprints & permissions information is available at https://horizonepublishing.com/journals/index.php/PST/open_access_policy

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Indexing: Plant Science Today, published by Horizon e-Publishing Group, is covered by Scopus, Web of Science, BIOSIS Previews, Clarivate Analytics, NAAS, UGC Care, etc
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CITE THIS ARTICLE
Palanichamy NV, Kalpana M, Balakrishnan N, Suresh A, Balamurugan V, Rajavel M, Dhivya R, Santhosh Kumar M. A novel approach for predicting net irrigated area in India using hybrid deep learning architectures. Plant Science Today (Early Access). https:/doi.org/10.14719/pst.7412

Abstract

Studying irrigation systems is crucial to ensuring efficient freshwater utilization and conservation. This study examines the efficacy of forecasting the net irrigated area for future generations to create a model of prediction that can efficiently exchange water demand. To improve the forecast, we generate a model using two-hybrid deep learning techniques to predict irrigation demands: Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) and Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU). These models effectively capture complex variables from diverse data sources, including rainfall patterns, irrigated area statistics and various irrigation system parameters. The main ideas, noteworthy contributions and crucial quantitative results from our study on net irrigated area projection are outlined in this publication. Our main contribution is the development of unique hybrid deep learning approaches that effectively integrate the CNN-LSTM and CNN-GRU architectures. Better predictions are made possible by the models' design, which consists of parallel CNN layers that independently interpret certain input features. Thorough examinations of these situations validated the models' effectiveness and led to notable decreases in important evaluation parameters, such as the RMSE, MSE, MAE and R^2. Regarding excellent accuracy in predicting and overall performance, our CNN-GRU hybrid deep learning model outperformed the other models in the present research.

Keywords

deep learning; India; irrigation; prediction; water resources

Introduction

Climate change increases variability in rainfall patterns, reduces groundwater recharge and intensifies droughts. These factors significantly impact water availability for irrigation, requiring advanced predictive models for sustainable management. When irrigation becomes increasingly important due to climate change, the water used by the agriculture sector directly affects food security. Irrigation systems impact agricultural productivity, the environment, sustainable development, soil health and water resources (1). The bulk of the water extracted and consumed is primarily irrigated agriculture. Incorporating evaluations of irrigation water usage and requirements facilitates the assessment of the influence of irrigation on the existing water resources. To ensure summer output, a profitable crop grown without irrigation is created (2).

Irrigation is the process of artificially adding water to the soil. It is employed in dry climates or areas with little rainfall to cultivate crops, preserve landscapes and restore degraded soils. For over 5000 years, irrigation has been vital to agriculture. Artificial constructions such as tanks, wells, canals and rivers are primary irrigation sources in India.

Additionally, groundwater extraction from springs and wells supports irrigation in many regions. India relies on irrigation for several reasons, such as encouraging irrigation during the monsoon season, having access to water from rivers or tube wells all year round and irrigating for three crops yearly (3). No matter how often a crop is irrigated, the area of agricultural land that is irrigated once a year for that crop is known as Net Irrigated Area (NIA) (4-6). For example, the Indira Gandhi Canal has transformed arid lands into fertile agricultural regions in Rajasthan, significantly improving food production and livelihoods. The quantity of water required by crops varies based on growth conditions, soil moisture levels and seasonal cropping schedules. The total area of irrigated regions significantly impacts the social-ecological implications of irrigated agriculture, which is the most efficient agriculture method on the basis of labour and output per area unit (4). Agriculture absorbs around 80 % of the countrys' water resources, making it a vital resource. The net irrigated area of the nations' total sown land comprises about 49 %. About 40 % of this is irrigated via canal systems; the remaining 60 % uses groundwater (5). Indias' net irrigated area for the 2022 fiscal year is depicted in Fig 1.

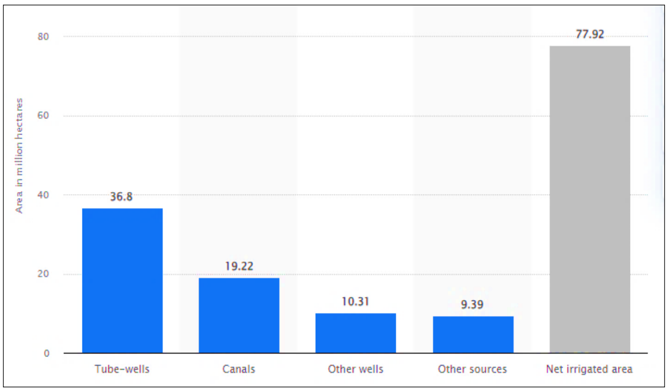

Fig. 1. Indias' net irrigated area for the 2022 fiscal year (in million hectares). *(Data source: Statista, 2024)*

The term "deep" refers to the quantity of hidden layers found in Deep Learning (DL) algorithms, which makes them significantly more intricate than Machine Learning (ML) algorithms. Deep neural networks gather features from data with multiple hidden layers, enabling them to solve increasingly difficult issues. Deep learning models do not rely on feature engineering, unlike machine learning techniques. Instead, they automatically extract valuable properties from the raw data during training (6). Compared to ML methods, DL models require significantly more data to train and their training periods are more extended.

On the other hand, DL models operate more quickly and accurately after training. These factors have contributed to their rising popularity in recent times. Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) stand out as the two most well-known and significant subfields of deep learning. Nowadays, CNN models are being applied for localization, identification and classification. AlexNet won the Large Scale Visual Recognition Challenge (LSVRC) 2012 classification challenge, demonstrating a breakthrough in deep learning accuracy and efficiency (7).

According to Sermanet and Overfeat, excellent results were obtained when applying deep learning algorithms for localization, recognition and classification (8). Deep learning methodologies have demonstrated remarkable success in addressing many practical challenges, including object recognition, picture captioning, processing natural language, analysis of text in computer vision and image categorization. By using the backpropagation technique to find intricate patterns in the data set, deep neural networks can connect the input to the output while learning a function (9). Recurrent neural networks are commonly utilized to handle both continuous and sequential data. Examples of these networks include Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) (10). CNN can use LSTM networks to handle raw data, including time-series data, location data and aerial pictures. The effectiveness of a hybrid Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model for soybean yield prediction. Their model leveraged CNNs' ability to extract spatial features from agricultural data. At the same time, LSTM captured temporal patterns in crop growth, resulting in more accurate yield forecasts than traditional prediction methods (11). The analysis shows that the model outperforms both the CNN and LSTM models when considered individually. In contrast to current remote sensing-based techniques, a novel method was developed that adds a Gaussian Process component to a CNN (12). This approach can yield a 30 % reduction in root-mean-squared error (RMSE). In two distinct scenarios, tomato yield was forecasted and predicted the growth of the stem of *Ficus benjamina* using the LSTM under controlled greenhouse circumstances (13). While CNNs extract at analyzing spatial patterns, LSTMs are better suited for capturing temporal or sequential patterns in data (14). In several studies, long-distance dependability was assessed using long short-term memory (LSTM) and local spatial information was extracted using convolutional neural networks (CNNs). Since these studies consider CNN output as LSTM input, they deal with CNNs and LSTMs independently. Convolutional LSTM (ConvL STM) integrates convolutional structures into the LSTM cell. The GRU, LSTM and RNN were studied using three different approaches. Each approach was individually evaluated for effectiveness using metrics including MAPE, MSE, R^2 and MAE. The LSTM network serves as a framework for RNNs in tools that include nonlinear sequential prediction and RNNs can learn order reliance (16). According to the results, the GRU strategy functioned better than the other two. In terms of rates of convergence and accuracy of predictions, the hybrid CNN-GRU model outscored the GRU or CNN algorithm in terms of standalone accuracy (17). The Conv1D-GRU deep learning model was built (18). Its purpose is to predict the water demand. Their model revealed higher accuracy in forecasting (MAPE of 1.677 %) in contrast to GRU and ANN. The CNN-GRU model demonstrated superior performance compared to using either the CNN or GRU model separately, based on accurate forecasting and convergence rate (19). It was showed that integrating CNN and GRU was a valuable and effective method to enhance yield calculation, offering significant potential for estimating crop yields worldwide (19). While deep learning models have been widely used for crop yield prediction, their application in net irrigated area forecasting remains limited. This study bridges this gap by integrating CNN and LSTM/GRU architectures for enhanced predictive accuracy. Future research should explore real-time irrigation data integration and model optimization for practical field implementation.

Materials and Methods

According to research, combining prediction models adds a bias, reduces variation and produces better performance than single models (20). Consequently, we propose two CNN-based hybrid models (CNN-GRU & CNN-LSTM) to forecast Indias' agricultural net irrigated area.

Data collection

Since the availability of the data is essential to the other procedures, gathering the data is an important first step. Data collection aims to collect all pertinent data from accessible sources. Before utilization, it is essential to filter and clean the data. The Indian Statistics Department (21) and other government websites provided the data for this study on irrigation resources (such as tanks, canals, tube wells and other wells), gross sown area, net irrigated area, net sown area and yearly rainfall (22). The information gathered between 1950 and 2021 was analyzed to identify long-term trends in irrigation patterns and water availability.

Data preparation

After data collection, preparation comes next. The primary objective of this stage is to prepare raw data for transformation into a format compatible with the deep learning algorithm employed. All deep learning models require data pre-processing since it enhances the input datas' reliability and extracts essential details, raising the models' accuracy.

Data splitting

We integrated historical irrigation data with advanced deep-learning techniques to build and assess a forecasting model to improve predictive accuracy. The collected data was pre-processed using several cleaning steps to ensure accuracy and consistency. First, missing values were handled using interpolation and statistical imputation techniques. Outliers were identified using standard deviation and necessary corrections were applied. The data was then normalized to a standard scale for better compatibility with deep learning models. Duplicate data were removed. After cleaning the data, it was divided into training and test sets. There is no perfect proportion for the splitting ratio.

Nevertheless, the dataset can be divided in several ways. For example, 90 % of it can be allocated to training and 10 % to testing (23). Alternatively, it can be divided into 75 % training and 15 % testing (24). However, this study considers a scenario where 80 % of the data is used for training while the remaining 20 % is allocated for testing (25). Following the suggested methodology, we split the dataset into two groups based on the parameters and size. This study aimed to analyze the contribution of the research and measure how varying data regarding irrigation resources might influence the proposed DL models in predicting the net irrigated area.

Method of selection

LSTM and GRU use modern deep-learning methods for prediction. This approach has been widely studied in deep learning, with significant applications in time-series prediction, image recognition and agricultural forecasting. Research indicates its effectiveness in modelling complex relationships in irrigation systems. Over time, there has been improvement and diversity in the LSTM and GRU techniques. Because of their demonstrated effectiveness in managing dependence over time-series data modelling and long-term data, this study has chosen to use GRU and LSTM for net irrigated area forecasting. This is important because temporal trends in the irrigated area persist. The model selection process, which carefully suits the areas' unique requirements under irrigation forecast work, improves the accuracy of the research findings.

Proposed deep learning models

Convolutional Neural Network (CNN): CNNs are widely utilized in time-bound series categorization, image processing and video forecasting due to their effective information collection and reorganization capabilities (26). The CNN model is a powerful deep-learning technique capable of addressing challenging issues (27). CNNs' architecture is shown in Fig. 2. The CNN structure, which is proposed as a solution to this problem, consists of an input layer, a convolutional layer, a pooling layer and a fully connected layer. Convolutional layers will be used in the feature extraction process. Data samples are inputted into the pooling layer, situated below the convolutional layer, with the results displayed in the output layer. A sizeable computational burden during the whole linked neural network computation frequently leads to erroneous predictions at the end of the process.

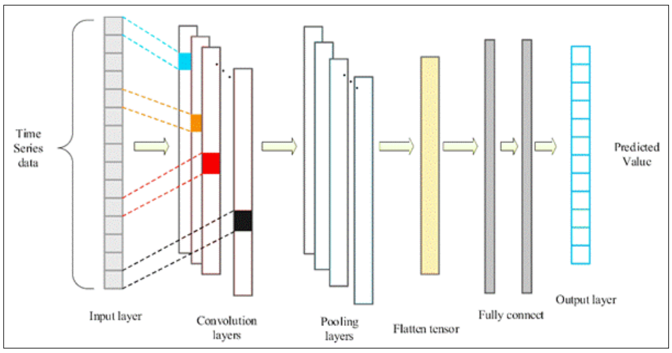

Fig. 2. The architecture of the Convolutional Neural Network (CNN) model comprises several essential components.

Long short-term memory (LSTM): The original use of the LSTM model aimed to illustrate long-range dependencies and ascertain an appropriate time gap for time series challenges (28). The following three levels comprise an LSTM network: input, output and recurrent hidden. The memory block is the fundamental component of the concealed layer (29). It has two movable, multiplicative gated units that regulate the data flow inside this block and self-organizing memory cell networks that monitor its temporal state. The memory cell functions as a Constant Error Carousel (CEC), characterized by a linear unit with continuous self-connections. The activation of the CEC represents the cell condition. The model learns when to activate and deactivate the gates, optimizing the information flow (13). If the network fault is maintained constant, LSTM can prevent gradient vanishing. A forgotten gate is incorporated into the memory cell to suppress the gradient blow-up further while learning large time series. Fig. 3 below represents the basic structure of LSTM.

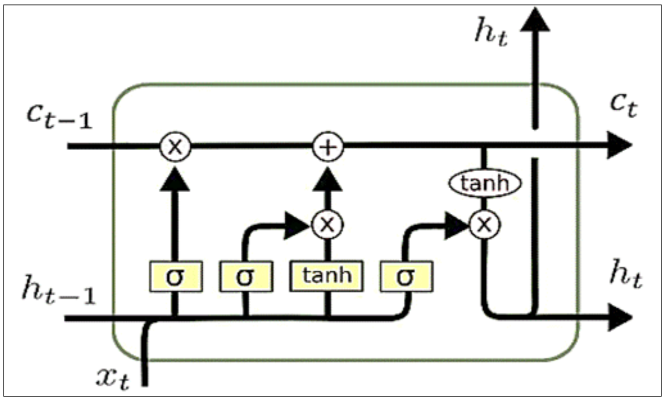

Fig. 3. Basic structure of LSTM.

***Gated recurrent unit (GRU)*:** The GRU branchs' purpose in this process is to find the temporal change and long-term dependency components in the input sequences by applying the recurrent pattern and GRU filtering technique. Sophisticated in architecture, the GRU network maximizes three distinct LSTM gate functions. The input and recall algorithm gates are unified within a single update gate structure, while the obscured and neuron states are integrated. The GRU network might successfully resolve the "gradient disappearance" issue with the RNN network. Additionally, it can shorten training periods and lower the LSTM network units' variable count (30). The following Fig. 4 depicts the fundamental design of the GRU network.

***The hybrid model of CNN-GRU*:** Multidimensional time series data, including details on canals, tanks, tube wells, other wells, annual rainfall, gross irrigated area and net irrigated area, are displayed on the left side of the CNN-GRU hybrid structure diagram. The time series for the net irrigated area has a significant level of connection because it includes historical range data. Consequently, the convolution kernel uses a sliding window to obtain the raw data from CNNs' sources stratum by stratum. The CNN ascertains the level of correlation between many data sets while simultaneously extracting the distinctive characteristics of each data set. The

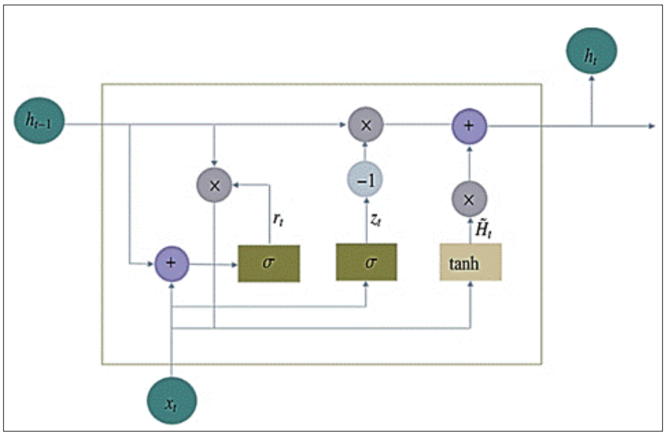

Fig. 4. Fundamental design of the GRU network.

main CNN framework and the main fine-tuning element for transfer learning are included in the central portion. The main body continuously refines the parameters of each layer by using the vast amount of accessible net irrigated area data. Following this, the layer is immobilized to uphold the optimal weight parameters for the subsequent prediction of the net irrigated area (31). The following Fig. 5 represents the Structural diagram of CNN-GRU.

***The hybrid model of CNN-LSTM*:** The CNN-LSTM structure integrates CNN and LSTM to ascertain the net irrigation area for agricultural purposes. The suggested approach can store irregular trends and retrieve complex elements from previous data. Processing the data and extracting relevant information, the first signal is integrated using CNN, while the second stream employs LSTM to extract temporal features. The four layers comprising the well-known CNN deep learning architecture are the convolutional neural network, pooling, fully connected and predictive layers (32). The multiple convolution filters in the convolutional layers execute convolutional processes involving convolution neuron weights and the volume of input-linked areas, leading to the development of a feature map (33). The task of storing temporal data for essential irrigation sources falls to the LSTM design. It preserves long-term memory and offers a solution by merging memory units with the capacity to restore the prior hidden state (34). This function will aid in comprehending the temporal links in a long-term chain. The CNN layers, which appeared previously, provide the gate units with their outcome values here. Vanishing and ballooning gradients are issues that the LSTM network tackles when

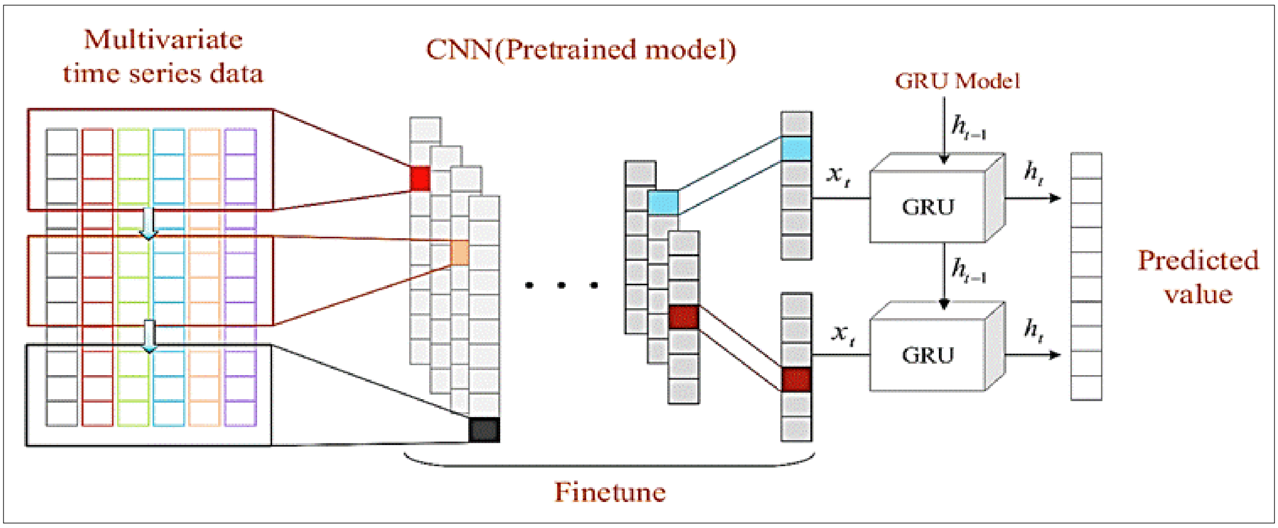

Fig. 5. Structural diagram of CNN-GRU.

learning simple RNNs. It is possible to ascertain the condition of every memory cell using each gate units' function. The input represents the gate unit, forget and output gates. The following Fig. 6 illustrates the fundamental structure of CNN-LSTM (35).

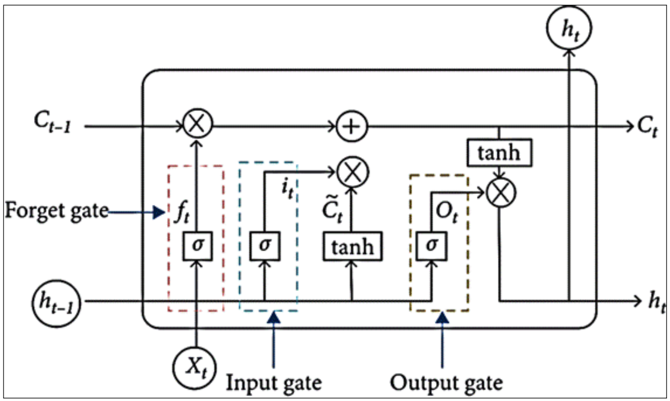

Fig. 6. Fundamental structure of CNN-LSTM.

***Tools used*:** Python 3.7.3 (64-bit) was used to build the hybrid CNN architecture that was discussed. It was built using TensorFlow, an open-source deep learning model and Keras version 2.3.1 as the frontend interface.

***Performance analysis*:** The effectiveness of the hybrid models is assessed using conventional evaluation criteria like MAE, R^2, RMSE and MSE. The research applies these standards to determine the predictions for agriculture for the net irrigated area. The following is the mathematical equation for these metrics, which can be found in the Equations 1-4:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |\hat{y}_i - y_i| \quad \text{(Eqn. 1)}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad \text{(Eqn. 2)}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2} \quad \text{(Eqn. 3)}$$

$$R^2 = 1 - \frac{\left(\sum_{i=1}^{n} (y_i - \hat{y}_i)^2\right)/n}{\left(\sum_{i=1}^{n} (\bar{y}_i - t\hat{y}_i)^2\right)/n} \quad \text{(Eqn. 4)}$$

Where yi and $\hat{y}i$ represent the predicted and actual outcomes, respectively. 'n' indicates the number of data points, while $\bar{y}$i indicates the average values. A lower MAE, MSE and RMSE values indicate better forecasting accuracy, while an R^2 value closer to 1 indicates a higher degree of fitting for the model.

Results and Discussion

CNN, GRU and LSTM are trained using the training set data that has been processed. The CNN-GRU and CNN-LSTM models are employed to predict the test set data, each respectively, after training and the expected and actual outcomes are compared as depicted in Fig. 7, 8. The test set forecasts from the models provided are shown as predicted vs. actual graphs in Fig. 7, 8. The diagrams showing projected and actual values demonstrate that the two models minimized error and effectively suited the dataset. The CNN-GRU charts, which nearly resemble straight lines, indicate a strong correlation (R^2 = 0.94), suggesting a strong relationship between predicted and

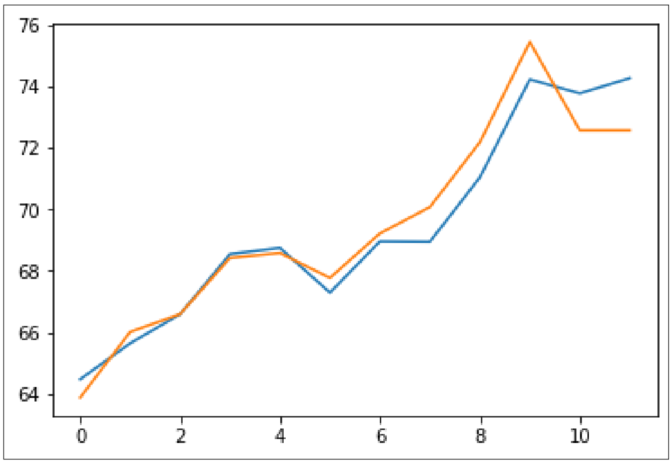

Fig. 7. Compare the actual value for CNN-GRU with the predicted value.

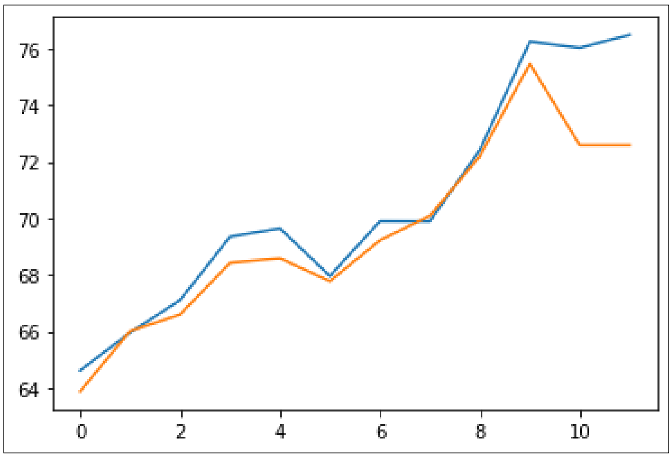

Fig. 8. Compared the actual value for CNN-LSTM with the predicted value.

actual values. While the CNN-LSTM model also performs well, minor deviations at specific data points suggest potential anomalies within the dataset.

The heat map displayed in Fig. 9 indicates that the intensity of the squares is relatively low, suggesting weak correlations between 'Net Irrigated Area' and other numerical variables. Therefore, this visualization alone cannot establish a strong dependency between these variables, necessitating further statistical analysis such as regression modelling or feature importance evaluation.

The models' performance was evaluated concerning those objectives using commonly employed performance metrics.: MSE, RMSE, MAE and R-square (R^2). The training and testing performance parameters for the net irrigated area forecasting process MSE, RMSE, MAE and R^2 are shown in Fig. 10, 11. Excellent results are obtained from the performance measures of both hybrid models in the training phase. The model performance is optimal when MAE and RMSE values are minimal (closer to 0) and R^2 values are maximal (closer to 1). The results show MAE = 0.023, RMSE = 0.031 and R^2 = 0.94, indicating substantial predictive accuracy. These findings all indicate robust and effective performance over various measurement criteria. Tables 1 and 2 show how well the CNN-GRU and CNN-LSTM hybrid algorithm predicted net irrigated area. The CNN-GRU model surpassed all other models.

According to the data, CNN-GRU performs better than the two hybrid deep learning approaches. The CNN-GRU prediction model, with an accuracy of 0.713, an MSE of 0.89 and an RMSE of 0.946, exhibits the lowest level of accuracy among

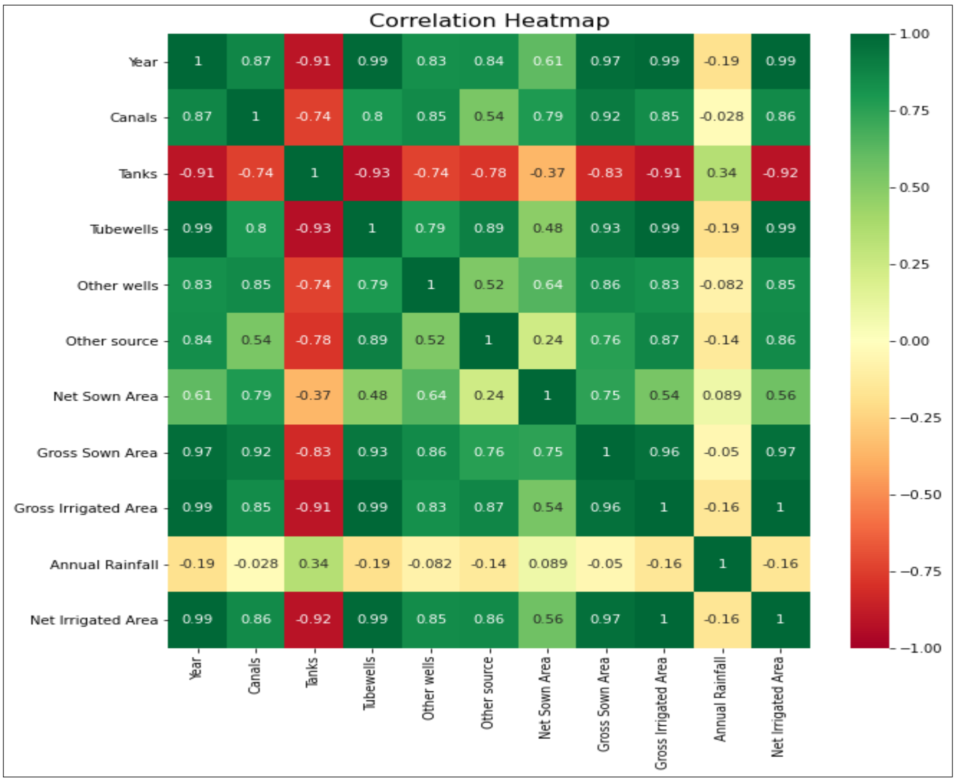

Fig. 9. Heat map depicting the relationship between the data sets' numerical properties.

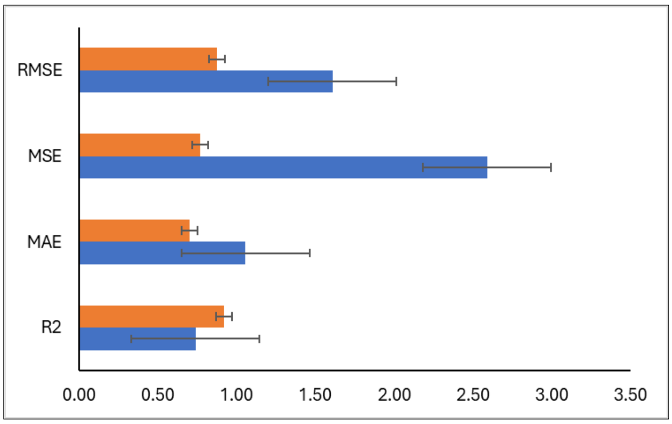

Fig. 10. Comparative train performance metric analysis of hybrid deep learning models.

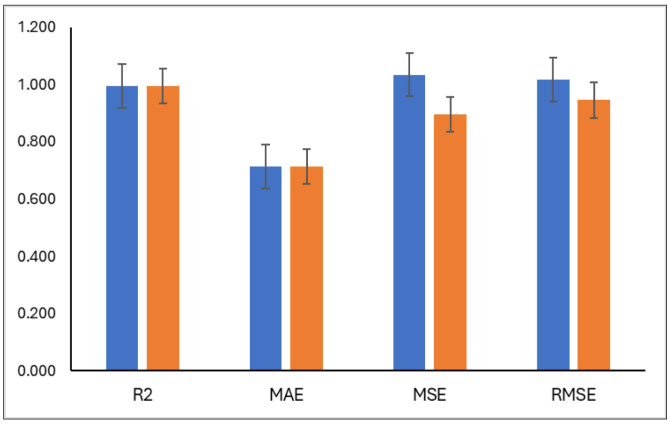

Fig. 11. Analysis of performance metrics for hybrid deep learning models in a comparative test.

Table 1. Training performance metrics of the deep learning hybrid models

	R^2	MAE	MSE	RMSE
LSTM	0.994	0.714	1.034	1.017
GRU	0.995	0.713	0.895	0.946

the models evaluated. Its R^2 of 0.995 indicates that it outperforms the other approaches in forecasting. The CNN-GRU algorithm presented in this paper thus outperforms the CNN-LSTM algorithm in terms of fitting points and error level.

Fig. 12 shows the projected results of the model. The x-axis represents the years, while the y-axis indicates the net irrigated area in million hectares. Using models from 2022 to 2033, we estimated the net irrigated area during the research period. This sections' graph shows the total data sets' actual net irrigated area for the years 1990 to 2021, together with the values predicted by the best hybrid deep learning model. We also have projected values for the years 2022 through 2033. The following Table 3 compiles the appropriate tables from the papers that were reviewed.

Table 2. Test performance metrics of the deep learning hybrid models

	R^2	MAE	MSE	RMSE
LSTM	0.74	1.06	2.59	1.61
GRU	0.92	0.70	0.77	0.88

Table 3. Compilation of the key findings from the reviewed papers, presented in the appropriate tables

Models	Result	Reference
CNN-GRU & CNN-LSTM	CNN-GRU: R^2=0.995	Our study
CNN-GRU & Conv-LSTM	MSE=0.5092, MAE=0.4172 and R^2=0.9460	(36)
LSTM	R^2 =0.910	(37)
CNN-LSTM	R^2=0.865	(38)
CNN-GRU	R^2=0.62	(19)
RNN, LSTM, CNN-LSTM, GRU Wave Net & CNN-GRU	CNN-LSTM and CNN-GRU	(39)
BPNN, GRU, CNN, &GRU-CNN	CNN-GRU performed well	(40)

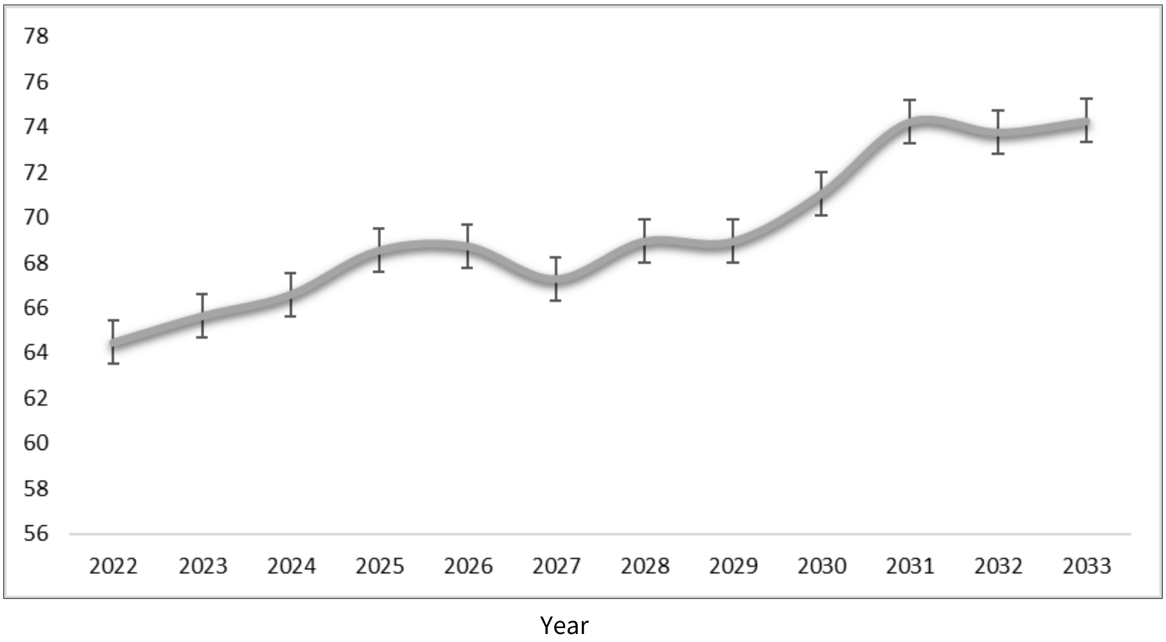

Fig. 12. Predicted net irrigated area for upcoming years (2022 to 2033).

Conclusion

This study aimed to create a novel deep-learning architecture by integrating Convolutional Neural Networks with LSTM and GRU networks to predict net irrigated areas using data on irrigated areas and water resources. The basic tenet of this inventive architecture is that combining CNNs' potent feature recognition powers with GRU and LSTMs' proficiency in data analysis significantly increases prediction accuracy. The study demonstrates the advantages of the proposed approach over traditional methods, validating the efficacy of the recently developed CNN-LSTM and CNN-GRU hybrid models in predicting net irrigated areas from univariate data. The datasets used in this research span from 1950 to 2021. The input data was transformed into a monitored framework and divided into training (80 %) and testing (20 %) sets. The performance of these hybrid models was evaluated using the testing data based on statistical criteria such as R^2, RMSE, MAE and MSE. Among the models, CNN-GRU outperformed the other hybrid deep learning techniques. Its R^2 of 0.995 indicates that it outperforms the different approaches in forecasting. Accordingly, the CNN-GRU presented in this paper exceeds the CNN-LSTM algorithm regarding fitting degrees and error values. This finding will significantly impact agricultural research in the future, especially in studies of water supplies, irrigated areas and rainfall. Future enhancements can be made by incorporating more historical datasets, integrating external climatic and geographical factors and exploring attention mechanisms to improve prediction accuracy. Additionally, real-time data processing and deploying these models in operational irrigation planning systems could provide more robust decision-making support for agricultural resource management.

Acknowledgements

The authors thank the Tamil Nadu Agricultural University for supporting their research.

Authors' contributions

NV contributed to the conceptualization, framing of the methodology, obtaining resources, carrying out the investigation, analysis and writing of the original draft. MK helped with the statistical analysis, investigation, methodology formulation, software use and writing the original draft. NB has assisted with the study, investigation, methodological framework, software application and writing. AS participated in writing, reviewing and editing the manuscript. VB took part in framing the methodology, utilizing software, writing, reviewing and editing. BR is involved in writing, reviewing and editing. VP, MR, SK and RD contributed to writing, reviewing and editing the manuscript. All authors have read and agreed to the published version of the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare

Ethical issues: None

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