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HYBRID DEEP LEARNING INTEGRATION ON ADVERSIAL NETWORK FOR AN ACCURATE AGRICULTURAL SEQUENCE DATA PREDICTION

ARUMAI RUBAN J[1], SUNDAR SANTHOSHKUMAR *[2], A. SUMATHI [3], J.JEGATHESH AMALRAJ[4], R. BHAGAVATHI LAKSHMI [5]

[1] Research Scholar, Computer Science, Alagappa University, Karaikudi, Tamil Nadu, India.
[2] Computer Science, Alagappa University, Karaikudi, Tamil Nadu, India
[3] Computer Science Engineering, SASTRA University, Kumbakonam, Tamil Nadu, India
[4] Assistant Professor, Department of Computer Science, Government Arts and Science College, Tittagudi, Cuddalore, Tamil Nadu, India
[5] Department of Computer Applications, SRM Institute of Science and Technology, Chennai, Tamil Nadu, India
E-mail: [1]rubsjoe@gmail.com, [2]santhoshkumars@alagappauniversity.ac.in, sumathi@src.sastra.edu, amal.jas@gmail.com, tbagavathi.scs@vistas.ac.in

ABSTRACT

In the Drip Irrigation system, Water scarcity and inefficient irrigation practices are major challenges that are faced in smart agriculture. To overcome these issues lot of Deep Learning (DL) methods are processed for prediction. Though there are lot of inefficiency and inaccurate in evaluation, an effective prediction is required in modern agriculture. To attain higher accuracy and robust prediction, this work presents an advanced sequence of Generative Adversarial Networks (SeqGAN) to generate and predict agricultural data that is specifically used to optimize irrigation practices and manage water resources effectively. The proposed seqGAN architecture consists of a generator and a discriminator. The generator involves a DL method of Long Short-Term Memory (LSTM) networks to create realistic agricultural text sequences by learning from previous data and it also has controlled variability through noise injection. The discriminator includes a Gated Recurrent Unit (GRU) and a CatBoost classifier to differentiate between real and generated sequences. The CatBoost integration enhances the model's ability to handle categorical data efficiently which enhances the accuracy and robustness of sequence classification. This proposed method is particularly beneficial for agricultural datasets augmenting and effective predictive sequences in agricultural fields. This proposed work not only improves data availability but also supports innovative solutions in agricultural research that ultimately contribute to more sustainable and efficient farming tasks than conventional methods.

Keywords: *Agricultural data, SeqGAN, LSTM Generator, GRU Discriminator, CatBoost classifier, Error Rate Analysis.*

INTRODUCTION

India is mainly an agrarian economy that heavily depends on efficient irrigation methods to optimize water usage and ensure sustainable agricultural activities [1]. Drip irrigation has gained importance due to its numerous benefits like overcoming severe water scarcity. Drip irrigation delivers water directly to the plant roots through a network of valves, pipes and emitters that minimize water wastage enhance soil moisture retention and boost crop yields [2]. In spite of its benefits, the implementation of drip irrigation systems must be coupled with accurate prediction models to address water scarcity issues effectively.

Water scarcity is a main concern all over the world, especially in India and affects both rural and urban populations [3]. Factors like erratic rainfall patterns, groundwater over-extraction and inefficient water management are worsening the situation of irrigation. As agriculture consumes approximately 80% of the country's freshwater resources enhancing irrigation practices is crucial [4]. Drip irrigation with its potential to save up to 50-70% of water offers a viable solution. However, its precise water usage prediction effectiveness can be significantly enhanced through advanced technologies like the Internet of Things (IoT) and DL methods [5].

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Usually, farmers depend on methods like flood irrigation which is highly inefficient and leads to significant water wastage and soil erosion [6]. Also, furrow and basin irrigation is slightly better than flood but still falls short in terms of water use efficiency. To overcome these limitations, the Internet of Thighs (IoT) integration in agriculture has arisen as a game-changer. IoT devices include soil moisture sensors, weather stations and aerial imagery from drones that make real-time data on various environmental parameters [7]. These data are used to analyze and provide an effective real-time prediction. So that advanced DL techniques are processed to achieve accurate predictions of water requirements and irrigation schedules.

Some of the popular DL methods used in agricultural fields [8] such as Convolutional Neural Networks (CNN) are used to extract spatial features that can help to estimate crop health and soil moisture levels. Recurrent Neural Networks (RNN) and LSTM networks are employed to capture temporal dependencies in time-series data namely weather forecasts and historical irrigation patterns. GRU is a variant of LSTMs that offers computational efficiency and is particularly useful for training sequential data. Additionally, GAN can be utilized to generate synthetic data for training to attain a robust model performance even with limited real-world data [9].

Most existing irrigation prediction models based on conventional DL techniques like LSTM and CNN, which face challenges in handling limited or imbalanced agricultural data. This models failed to achieve data augmentation and robust sequence learning. To address this gap, our research introduces a SeqGAN-based model that generates realistic data and increases prediction accuracy through a combined LSTM generator and GRU-CatBoost discriminator. The Generator uses LSTM layers to process input sequences and introduce noise for variability, creating new, reasonable agricultural data sequences [11]. The Discriminator employs GRU and dense layers to differentiate between real and generated sequences using a CatBoost classifier to evaluate their robust prediction among all the traditional methods.

The rest of the work is followed by the related works given in section 2 and the preliminaries of this work are presented in section 3. Section 4 contributes the materials and methods that have details of dataset samples and proposed methodology. Section 5 describes the result evaluation and finally, section 6 concludes the work.

2. RELATED WORKS

Several recent studies have explored the application of DL techniques in agricultural fields that enhance irrigation management and crop yield estimation. Abioye et al [12] presented a review based on DL methods to facilitate sustainable irrigation management among farmers. It emphasizes digital farming integration such as mobile and web frameworks to enable smart irrigation processes. These technologies offer remote monitoring and control capabilities that alleviate the challenges of farmers and researchers in managing irrigation efficiently.

Katimbo et al [13] evaluated the DL method to estimate Crop Water Stress Index (CWSI) and Crop Evapotranspiration (ETc). The CatBoost and Stacked Regression are used to perform predictions effectively and suggest their potential use to enhance its decision support systems in water management.

Sinwar et al [14] addressed issues of crop productivity and overcame them using a DL method. It is used to transform traditional farming activity into more innovative and eco-friendly methods with IoT and DL technologies. This method is used to enhance precision farming techniques for real-time purposes.

Baswaraju et al [15] introduced a Dense Convolutional Network (DenseNet) with LSTM to analyse production. It optimizes the LSTM weight using Arithmetic and Rider Optimization Algorithms (AOA and ROA) to estimate its potential to attain an accurate data analysis in agricultural activities.

Kadu et al [16] applied LSTM and CNN with a comparison of traditional methods to attain a prediction effectively. It supports small-scale farmers to make an informed decision about crop yield by using a CNN showing superior performance in their evaluations.

Godara et al [17] presented multi-DL methods like Support Vector Regression, Multi-layer Perceptron (MLP), LSTM and GRU to provide an

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automated system linked with agricultural data servers.

Godara et al [18] conducted a regional analysis to identify key wheat yield across different zones in India. Using DL models of XGBoost, MLP, GRU and 1-D CNN, the estimated wheat yield variations successfully achieve a superior importance of precise agricultural prediction.

Meghraoui et al [19] explored an LSTM and CNN to focus on cereals like wheat and corn production. This study achieves an efficient crop yield to emphasize accurate input data and model selection.

Suebsombut et al [20] developed an LSTM model to predict soil moisture based on sensor data. Their sensor-based real dataset in Thailand validates the model's effectiveness in predicting soil moisture levels placing the groundwork for future applications in precision agriculture.

Krishna et al [21] presented a crop prediction with the support of DL methods like Attention with Bidirectional LSTM and the MayFly method for a higher prediction. It focuses on major Indian crops like rice, sugarcane, wheat and maize that showcase the DL potential in agricultural optimization.

Devi et al [22] discussed weather forecasting systems by using a DL-based RNN method. This method is used to automate agricultural management and also enhances soil quality and weather monitoring. This work achieves higher accuracy in weather prediction than all other conventional methods and is also validated as highly advancing smart agriculture practices.

Water scarcity and inefficient irrigation practices remain critical challenges in modern agriculture, especially in regions heavily dependent on farming. Existing deep learning models often fail to provide accurate and robust predictions due to limited data, lack of augmentation, and inadequate handling of sequential patterns. There is a pressing need for an advanced predictive model that can generate realistic agricultural data and optimize irrigation practices for sustainable water management.

Preliminaries

GRU Model

The GRU architecture (Figure 1) comprises the Update Gate (zt), Reset Gate (rt), Current Memory Content (h't) and Hidden State Update (ht). These elements work has zt determines the relevance of past information for the present data while the rt controls the forgetting of historical data. The h't participates new sequence data into the h't and ht where Update combines both old and new data to update the ht. This design enables the GRU to long-term dependencies in sequential data effectively to make it highly suitable to achieve a time-series analysis and natural language processing.

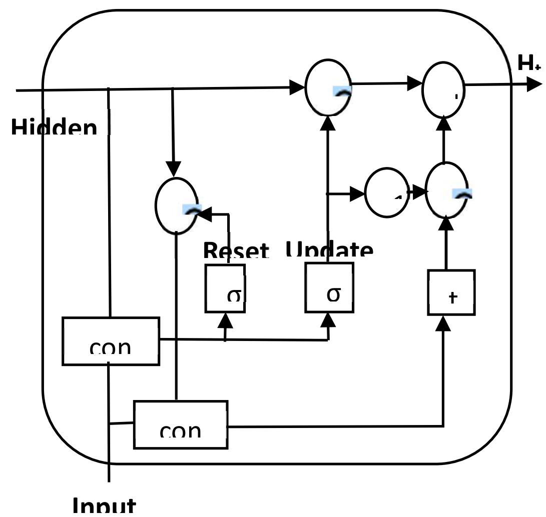

Figure 1: GRU Architecture

The GRU is considered by its gating mechanisms that control the data flow through the network that is given below equation (1-4).

$$zt = \sigma(Wz \cdot [ht-1, xt]) \quad (1)$$

$$rt = \sigma(Wr \cdot [ht-1, xt]) \quad (2)$$

$$h't = \tanh(W \cdot [rt \odot ht-1, xt]) \quad (3)$$

$$ht = (1-zt) \odot ht-1 + zt \odot h't \quad (4)$$

Unlike the more complex LSTM network, the GRU offers an efficient method that maintains effectiveness across sequential data processing. The equations (1-4) describe how the GRU processes sequential data to utilize weight matrices Wz, Wr, and W for gate process, sigmoid (σ) for activation and element-wise multiplication (⊙) to update hidden states. These mechanisms enhance the GRU's capability to capture and utilize relevant information over extended sequences that have practical advantages in modelling complex temporal dependencies.

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LSTM Model

The LSTM model is based on the RNN model and that solves long-term dependencies capturing in sequential data. It processes data over extended sequences and enables an effective sequential data analysis. It has a memory cell that regulates data flow and also has a forget gate, an input gate and an output gate. The input gate manages the new data in the memory cell, the forget gate controls the data retention and an output gate is used to control the data selection to a memory cell. By managing the data flow using these gates, LSTM captures and remembers an intricate dependency within sequential data. This model has a capability to sequential pattern process that has proven valuable. It is used to enhance LSTM architectures and explore their potential in DL and data analysis in various areas.

CatBoost Model

It is also known as the Categorical Boosting model or gradient boosting method is designed to handle categorical features in learning activities specifically. It handles categorical features that are sorted in a numerical order in every category based on the target variable's statistics. It enables CatBoost to access categorical data effectively during the training process. It is also integrated with a decision tree for weak learners to create a stronger predictive model. It also builds a decision tree ensemble where every subsequent tree corrects the mistakes made by the previous trees. By using a gradient optimization method, the CatBoost ensures efficient and accurate model training.

This method has the ability to handle missing values within the data automatically. It can handle missing data points effectively during the training phase without requiring explicit imputation or handling tactics. Also, it has the ability to handle categorical features with its high predictive accuracy and also makes a popular choice to tackle a real-world DL issue.

Materials And Methods

Dataset collection

In 2023, a dataset consisting of 619 samples exactly collected from a town of Batlagundu that is situated in the Nilakottai within the Dindigul district of Tamil Nadu, India (Figure 2). This dataset is focused on jasmine crop cultivation from June to September which is collected to gather the factors that prompt jasmine growth in this specific region. The data is captured using an agricultural sensing or monitoring system, recording essential data related to jasmine cultivation. This dataset serves as a valuable resource to offer environmental conditions, agricultural practices and crop responses specific to jasmine cultivation during the specified period.

Figure 2: Dataset collected from this Jasmine Farming

3. PROPOSED METHODOLOGY

The proposed SeqGAN architecture is designed to generate realistic agricultural sequences. Figure 3 shows both the Generator and the Discriminator where every component has a specific role in the GAN network and it works together to make and assess new data sequences.

LSTM based Generator

Parent Sequence:

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The generator begins with a parent sequence that is an agricultural data series. Each element in this sequence (x0, x1, ..., xt) represents data such as crop names, farming techniques, weather conditions, etc. This sequence helps as the input that the generator will use to create a new sequence. It represents the real agricultural sequence patterns and structures the generator aims to learn and repeat.

LSTM + Embedding Layers:

This layer is used to process an input sequence. The embedding layer is used to transfer input data into dense vectors that provide a continuous vector space where semantically similar sequence words are closer together. It is capable of training a long-term dependency in sequential data and provides suitable data sequences. In this sequence, LSTMs can capture complex patterns like seasonal trends, common agriculture data sequences and related relationships between terms.

Noise Injection:

In the generator, a random noise vector is presented in the representation after encoding the input sequence. It is crucial to create a diverse sequence. The noise vector assures that the generator produces mixed outputs rather than duplicating an exact input sequence. In data generation, this variability can lead to providing a new sequence of data that is reasonable within the agricultural tasks but not in the training data.

LSTM + Embedding Layers (Decoder):

On the decoder side, the noisy encode is fed into an LSTM layer with embeddings. The decoder generates a new sequence from the encoded representation. It produces a new sequence of data that should logically follow from the input sequence which enriches a noise-induced variability.

Generated Sequence (Ŷ = {ŷ0, ŷ1, ..., ŷt}):

The new output sequence of a generator (Ŷ) is used to resemble the real agricultural data. This generated sequence represents synthetic agricultural data which is indistinguishable from real data. The goal is to make sequences that could naturally occur in agricultural communication.

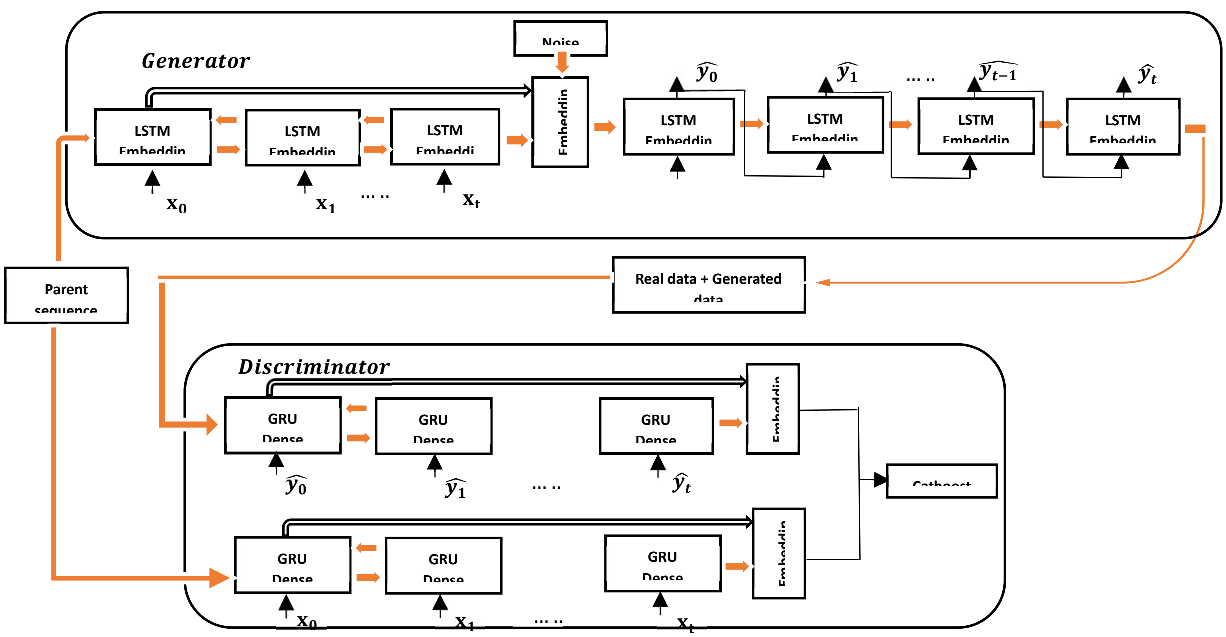

Figure 3: Hybrid Sequence GAN Architecture

GRU based Discriminator

Input Sequences (Real and Generated):

The discriminator receives two types of input sequences namely real sequences (Y) from the agricultural data and generated sequences ($\hat{Y}$) from the generator. The discriminator's process is to distinguish between these two types of sequences. It serves as a binary classifier that learns to estimate the subtle differences between real and generated data.

GRU + Dense Layers:

The discriminator uses GRU layers followed by dense layers. It is computationally less intensive than LSTMs while still capable of processing temporal dependencies. The GRU layers process the input sequences to learn temporal dependencies much like the LSTM layers in the generator. The dense layers that used to transform the GRU outputs into a suitable form for classification.

Encoding:

Both the real and generated sequences are encoded through a set of encoding layers. This encoding is used to transform data sequences into a fixed-size vector that is necessary to classify a subsequent step. It also helps to abstract the data contained in the sequences into a compact form that validates an essential feature.

CatBoost Classifier:

The encoded sequences are fed into a CatBoost classifier. Then it handles categorical data from encoded sequences effectively and efficiently. The classifier determines whether a given sequence is real or generated. It evaluates the agricultural text sequences accurately and attains a high benefit from encoded data of GRU layers and that attains an accurate classification.

Therefore, the proposed SeqGAN is effective and accurate in prediction. It has special features of Generator provides a new sequence of agricultural data and attains learning the patterns as real data. It also has special features of random noise to produce variability. This process involves multiple LSTM layers and embeddings to capture and generate complex sequences. The Discriminator evaluates both the real and generated sequences to classify them correctly by using CatBoost model. Therefore, the proposed method is highly capable of providing the best sequence data and attaining an effective prediction than conventional methods.

Results And Discussion

The evaluation of the proposed model has both training and testing on a dataset of 619 jasmine samples with a 70% training and 30% testing split. After training, the model's performance is compared with an existing model using various metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Bias Error (MBE), Standard Deviation (SD), T-Statistic (Tstat), Uncertainty with 95% Confidence Level (U95) and Nash-Sutcliffe Efficiency (NSE). The formulation of all these metrics is given below in Equation (5-12):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |O_i - P_i| \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (P_i - O_i)^2} \tag{6}$$

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n} (O_i - P_i) \tag{7}$$

$$\mathrm{SD} = \frac{\mathrm{RMSE}}{\bar{O}} \tag{8}$$

$$\mathrm{Tstat} = \sqrt{\frac{(1-n)\mathrm{MBE}^2}{\mathrm{RMSE}^2 - \mathrm{MBE}^2}} \tag{9}$$

$$\mathrm{U95} = 1.96\sqrt{\mathrm{SD}^2 + \mathrm{RMSE}^2} \tag{10}$$

$$\mathrm{NSE} = 1 - \frac{\sum (P_i - O_i)^2}{\sum (\bar{O_i} - O_i)^2} \tag{11}$$

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{(\sum_{i=1}^{n}(O_i - \bar{O_i}))^{\wedge}2\ (\sum_{i=1}^{n}(P_i - \bar{P})^{\wedge}2\ )}}\right]^2 \tag{12}$$

Where n indicates the Total number of observations, O_i denotes the Observed (actual) value for the i-th data point, P_i denotes the Predicted value for the i-th data point and |x| indicates an Absolute value of x, $\bar{O}$ denotes Mean of the observed values. $\bar{P}$ indicates the Mean of the predicted values. The real versus predicted plot of the proposed model is shown in Figure 7.

Table 1: Performance Analysis

Model	MAE	RMSE	SD	Tstat	U95	NSE	R^2
Proposed	3.70	5.90	1.92	1.90	4.65	0.65	0.60
GAN	5.30	7.50	2.90	1.40	6.10	0.55	0.58
CNN-LSTM	6.80	8.10	4.35	1.85	8.25	0.78	0.69
Optimised GRU	8.88	10.25	4.86	1.26	9.83	0.68	0.69

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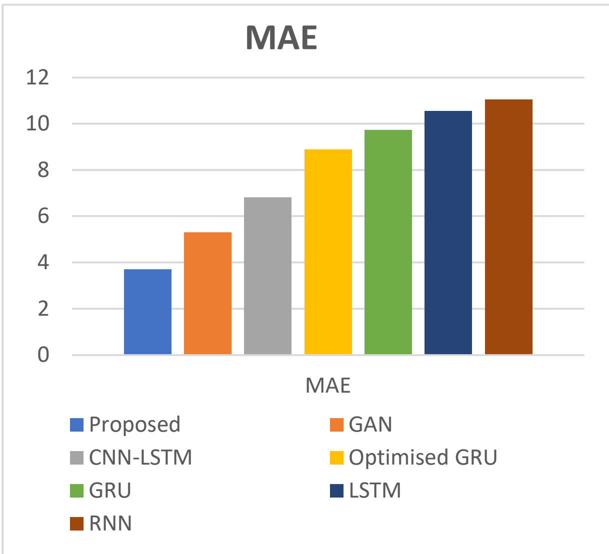
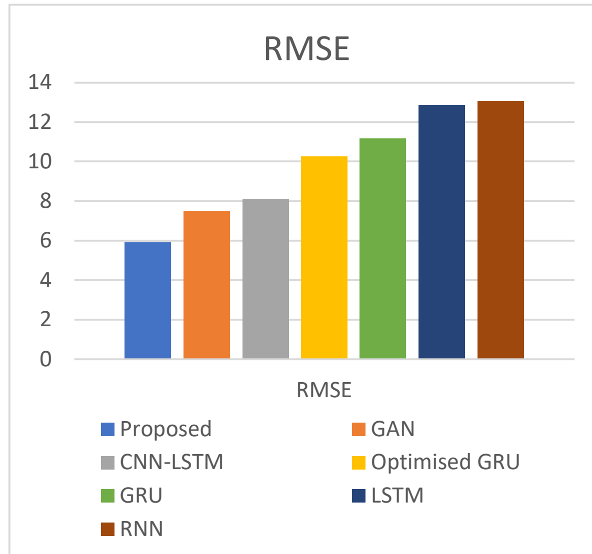
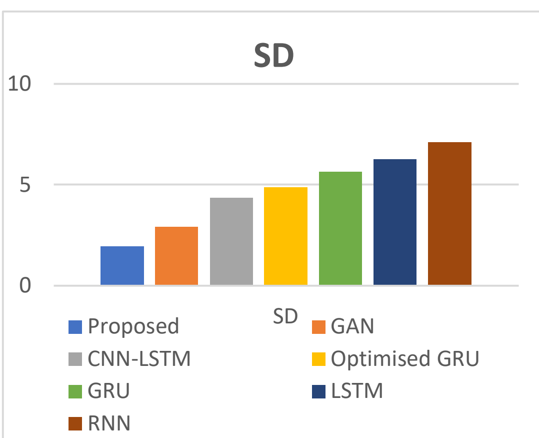
GRU	9.73	11.15	5.65	1.35	9.35	0.72	0.65
LSTM	10.55	12.85	6.25	0.85	10.22	0.65	0.60
RNN	11.04	13.05	7.09	0.70	11.25	0.55	0.58

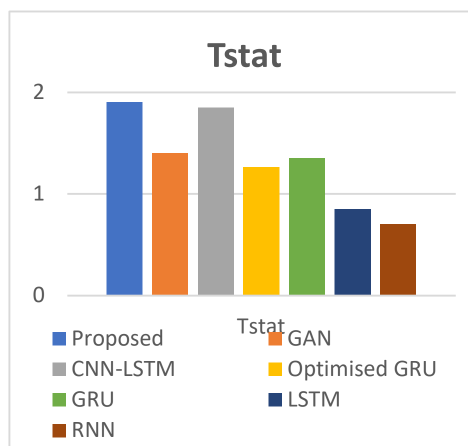


(a)

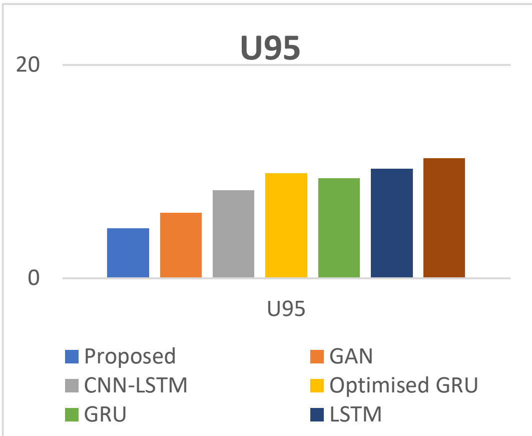


(b)

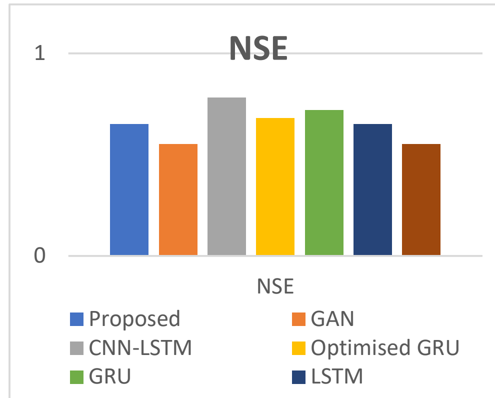




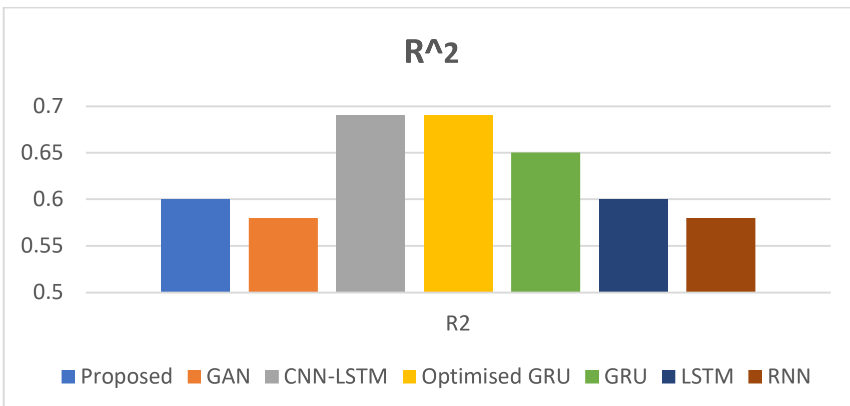
(c) **(d)**



(e)



(f)



(g)

Figure 4: Performance Of Proposed And Traditional Models Based On Error Rate Analysis (A) MAE Analysis, (B) RMSE Analysis, (C) SD Analysis, (D) Tstat Analysis, (E) U95 Analysis, (F) NSE Analysis And (G) R^2 Analysis

In Figure 4 and Table 1, Among the models evaluated, the Proposed model stands out with superior performance across key metrics. It achieves the lowest MAE of 3.70 (figure 4a) and RMSE of 5.90 (figure 4b) indicating minimal prediction errors and high accuracy. The model also exhibits the lowest SD of 1.92 (Figure 4c) which has consistent and reliable predictions. With a T-stat of 1.90 (Figure 4d), the Proposed model shows statistically significant results. Additionally, it maintains a competitive U 95 of 4.65 (Figure 4e), NSE of 0.65 (Figure 4f) and R^2 of 0.60 (Figure 4g) that attains robust predictive power and effective variability explanation. Overall, these findings highlight the Proposed model's effectiveness in bringing precise and reliable predictions compared to other models evaluated.

Table 2: Comparison With Other Models

Model	METHOD	MAE	RMSE	SD	Tstat	U95	NSE	R^2
Proposed	SeqGAN	**3.70**	**5.90**	**1.92**	**1.90**	**4.65**	**0.65**	**0.60**
Kadu et al [16]	LSTM and CNN	4.10	6.70	2.20	1.75	5.20	0.58	0.55
Godara et al [18]	Ensmeble	4.00	6.50	2.05	1.80	5.00	0.60	0.57
Krishna et al [21]	Bidirectional LSTM and the MayFly method	3.95	6.20	2.00	1.85	4.85	0.63	0.59
Devi et al [22]	DL-based RNN	4.20	6.80	2.25	1.70	5.30	0.55	0.52

The comprsion with other models are given in Table 2. The proposed SeqGAN model outperforms all existing methods across key evaluation metrics such as MAE, RMSE, and NSE, indicating superior prediction accuracy and reliability. Compared to methods like LSTM-CNN, Ensemble, Bi-LSTM with MayFly, and DL-based RNN, SeqGAN achieves the lowest error rates and the highest efficiency scores.

4. CONCLUSION

In this proposed work, the real-time dataset of jasmine samples is used which has 619 samples that is collected from June to September 2023. This dataset provides important factors of jasmine growth under specific regional and temporal conditions by using sensors for data collection. The proposed SeqGAN method is used to achieve an exact agricultural data prediction. This proposed work effectively generates realistic agricultural data sequences by using an LSTM and embedding layers that include noise injection for variability and also processed Discriminator features of GRU and CatBoost to classify a sequence. This method significantly advances agricultural data capabilities. The validation of the proposed SeqGAN model carried a better and superior performance than all other methods where the proposed attains an MAE of 3.70, RMSE of 5.90, SD of 1.92, T-stat of 1.90, U95 of 4.65, NSE of 0.65, and R^2 of 0.60 respectively. Therefore the proposed method demonstrated the model's precision, reliability and suitability and also enhanced agricultural decision-making and productivity. In the future, this work can be extended by integrating real-time IoT sensor data to further enhance the accuracy of irrigation predictions. Advanced hybrid models combining reinforcement learning with SeqGAN can be explored to optimize water usage dynamically. Additionally, deploying the model on edge devices can support on-field decision-making for smart and scalable agricultural systems.

REFERENCES

[1] Umutoni, L., & Samadi, V. (2024). Application of machine learning approaches in supporting irrigation decision making: A review. Agricultural Water Management, 294, 108710.
[2] Jiang, Z., Yang, S., Dong, S., Pang, Q., Smith, P., Abdalla, M., ... & Xu, Y. (2023). Simulating soil salinity dynamics, cotton yield and evapotranspiration under drip irrigation by ensemble machine learning. Frontiers in plant science, 14, 1143462.
[3] Ahmed, Z., Gui, D., Murtaza, G., Yunfei, L., & Ali, S. (2023). An overview of smart irrigation management for improving water productivity under climate change in drylands. Agronomy, 13(8), 2113.
[4] Uma Maheswari, P., Praveen Raj, U. S., & Dinesh Kumar, S. (2022, November). IoT-Based Automated Drip Irrigation and Plant Health Management System. In Proceedings of the International Conference on Intelligent Computing, Communication and Information Security (pp. 31-47). Singapore: Springer Nature Singapore.
[5] Elbeltagi, A., Deng, J., Wang, K., Malik, A., & Maroufpoor, S. (2020). Modeling long-term dynamics of crop evapotranspiration using deep learning in a semi-arid

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

environment. Agricultural Water Management, 241, 106334.

[6] Skhiri, A., Ibrahimi, K., & Arfaoui, A. (2024). A bibliometric analysis on artificial intelligence-based irrigation modeling techniques over the period of 1997-2023. African Journal of Advanced Pure and Applied Sciences (AJAPAS), 49-57.

[7] Araújo, S. O., Peres, R. S., Ramalho, J. C., Lidon, F., & Barata, J. (2023). Machine learning applications in agriculture: current trends, challenges, and future perspectives. Agronomy, 13(12), 2976.

[8] Dash, S., Priyadarshini, S., & Priyadarshini, S. (2024). An In-Depth Review on Machine Learning Infusion in an Agricultural Production System. How Machine Learning is Innovating Today's World: A Concise Technical Guide, 253-270.

[9] Agrawal, N., Govil, H., & Kumar, T. (2024). Agricultural land suitability classification and crop suggestion using machine learning and spatial multicriteria decision analysis in semi-arid ecosystem. Environment, Development and Sustainability, 1-38.

[10] Zhang, Q., Liu, Y., Gong, C., Chen, Y., & Yu, H. (2020). Applications of deep learning for dense scenes analysis in agriculture: A review. Sensors, 20(5), 1520.

[11] Berman, D. S., Howser, C., Mehoke, T., Ernlund, A. W., & Evans, J. D. (2023). MutaGAN: A sequence-to-sequence GAN framework to predict mutations of evolving protein populations. Virus Evolution, 9(1), vead022.

[12] Abioye, E. A., Hensel, O., Esau, T. J., Elijah, O., Abidin, M. S. Z., Ayobami, A. S., ... & Nasirahmadi, A. (2022). Precision irrigation management using machine learning and digital farming solutions. AgriEngineering, 4(1), 70-103.

[13] Katimbo, A., Rudnick, D. R., Zhang, J., Ge, Y., DeJonge, K. C., Franz, T. E., ... & Duan, J. (2023). Evaluation of artificial intelligence algorithms with sensor data assimilation in estimating crop evapotranspiration and crop water stress index for irrigation water management. Smart Agricultural Technology, 4, 100176.

[14] Sinwar, D., Dhaka, V. S., Sharma, M. K., & Rani, G. (2020). AI-based yield prediction and smart irrigation. Internet of Things and Analytics for Agriculture, Volume 2, 155-180.

[15] Baswaraju, S., Maheswari, V. U., Chennam, K. K., Thirumalraj, A., Kantipudi, M. P., & Aluvalu, R. (2023). Future food production prediction using AROA based hybrid deep learning model in agri-sector. Human-Centric Intelligent Systems, 3(4), 521-536.

[16] Kadu, A. V., & Reddy, K. T. V. (2023, December). Agriculture Yield Forecasting via Regression and Deep Learning with Machine Learning Techniques. In International Conference on Communication and Intelligent Systems (pp. 219-233). Singapore: Springer Nature Singapore.

[17] Godara, S., & Toshniwal, D. (2022). Deep Learning-based query-count forecasting using farmers' helpline data. Computers and Electronics in Agriculture, 196, 106875.

[18] Godara, S., Birthal, P. S., Avinash, G., Ahmad Faiz, M., Bana, R. S., Jhajhria, A., ... & Marwaha, S. (2024). Quantifying effects of climate change and farmers' information demand on wheat yield in India: a deep learning approach with regional clustering. Frontiers in Sustainable Food Systems, 8, 1357201.

[19] Meghraoui, K., Sebari, I., Pilz, J., Ait El Kadi, K., & Bensiali, S. (2024). Applied Deep Learning-Based Crop Yield Prediction: A Systematic Analysis of Current Developments and Potential Challenges. Technologies, 12(4), 43.

[20] Suebsombut, P., Sekhari, A., Sureephong, P., Belhi, A., & Bouras, A. (2021). Field data forecasting using LSTM and Bi-LSTM approaches. Applied Sciences, 11(24), 11820.

[21] Krishna, M. V., Swaroopa, K., SwarnaLatha, G., & Yasaswani, V. (2024). Crop yield prediction in India based on mayfly optimization empowered attention-bi-directional long short-term memory (LSTM). Multimedia Tools and Applications, 83(10), 29841-29858.

[22] Devi, T., Deepa, N., Gayathri, N., & Rakesh Kumar, S. (2024). AI-Based Weather Forecasting System for Smart Agriculture System Using a Recurrent Neural Networks (RNN) Algorithm. Sustainable Management of Electronic Waste, 97-112.