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Digital twin driven federated multi-agent intelligence for autonomous renewable forecasting and smart grid optimization

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ABSTRACT

The rapid growth of renewable energy integration has increased the complexity of smart grid operation due to the intermittent nature of distributed energy resources and continuously varying load demand. Existing approaches often rely on centralized control or combine only selected intelligent technologies, limiting scalability, data privacy, and autonomous decision-making. This paper proposes a digital twin-driven federated multi-agent intelligence (DT-FMAI) framework that integrates virtual system synchronization, privacy-preserving distributed learning, and cooperative multi-agent control within a unified architecture. Digital twins continuously mirror physical grid assets, federated learning enables collaborative forecasting without sharing raw data, and intelligent agents coordinate energy management in real time. The framework was implemented in MATLAB/Simulink with TensorFlow Federated and evaluated using renewable generation, weather, battery, and load datasets. Results demonstrate a 15-25% reduction in forecasting error, 10-18% improvement in voltage regulation, 92-96% load-matching efficiency, and 12-20% higher energy efficiency. These outcomes demonstrate the potential of the proposed framework for scalable, secure, and intelligent renewable-integrated smart grid operation.

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1. INTRODUCTION

The rapid transition toward low-carbon power systems has accelerated the integration of renewable energy sources (RESs), distributed energy resources (DERs), battery energy storage systems (BESSs), and electric vehicles (EVs) into modern smart grids. Although these technologies improve sustainability and operational flexibility, their intermittent generation characteristics and continuously varying load demand introduce significant uncertainty in grid operation, making voltage regulation, power balancing, frequency control, and energy scheduling increasingly challenging [1]. Consequently, conventional centralized energy management approaches experience limitations related to communication bottlenecks, computational burden, scalability, and data privacy as the number of distributed resources increases. To address these challenges, advanced cyber-physical technologies have been introduced for intelligent grid operation. Digital twin (DT) technology provides synchronized virtual representations of physical assets for predictive monitoring, system analysis, and operational planning [2]-[11]. Recent developments have further demonstrated the application of digital twins in renewable forecasting, energy management, and smart microgrid automation, improving system visibility and operational reliability [12]-[15]. In parallel, artificial intelligence techniques have significantly enhanced forecasting capability through data-driven modelling and adaptive learning, enabling more reliable operation of renewable-integrated power systems [16]-[23].

Despite these advances, current research primarily investigates digital twins, FL, and MAS independently or combines only two of these technologies for specific applications. Digital twin-based approaches mainly focus on virtual modelling and predictive monitoring, while federated learning emphasizes privacy-preserving distributed model training without directly supporting coordinated grid control. Similarly, multi-agent systems improve decentralized decision-making but generally operate without continuously synchronized virtual system models or collaborative learning mechanisms. Consequently, existing frameworks cannot simultaneously provide real-time digital twin synchronization, privacy-preserving distributed forecasting, autonomous agent coordination, and adaptive control within a unified intelligent architecture. Furthermore, limited attention has been given to analysing the relationship between forecasting accuracy and grid control performance, distributed model convergence, communication efficiency, scalability under increasing numbers of intelligent agents, and coordinated optimization in renewable-rich smart grids [20]-[25]. These limitations indicate the need for an integrated framework capable of combining predictive modelling, distributed intelligence, secure collaborative learning, and autonomous energy management.

To overcome these limitations, this paper proposes a digital twin-driven federated multi-agent intelligence (DT-FMAI) framework for autonomous renewable forecasting and smart grid optimization. Unlike previous studies integrating only digital twins with federated learning or multi-agent systems, the proposed framework establishes a closed-loop cyber-physical architecture in which digital twins continuously synchronize physical and virtual grid states, federated learning collaboratively updates forecasting models without exchanging raw operational data, and intelligent agents cooperatively perform renewable scheduling, battery energy management, demand response, and voltage regulation. This integrated framework enhances forecasting accuracy, operational resilience, communication efficiency, and scalability while preserving data confidentiality. Comprehensive simulation studies are conducted using renewable generation, weather, battery state-of-charge, and load demand datasets to evaluate forecasting accuracy, voltage stability, energy efficiency, communication overhead, convergence behaviour, and distributed scalability. The proposed DT-FMAI framework provides a practical and scalable solution for next-generation renewable-integrated smart grids by combining predictive digital representations, privacy-preserving distributed intelligence, and autonomous multi-agent control within a single unified architecture.

2. METHOD

The proposed DT-FMAI framework integrates digital twin (DT), federated learning (FL), and multi-agent systems (MAS) to enable autonomous renewable energy forecasting and predictive smart grid optimization. The framework consists of five functional layers: physical layer, digital twin layer, federated learning layer, multi-agent layer, and decision layer, as illustrated in Figure 1 Real-time measurements collected from photovoltaic (PV) systems, wind turbines, BESS, EVs, and smart loads are synchronized with their corresponding digital twins. Each intelligent agent performs local forecasting using its own operational data, while only model parameters are exchanged with the federated server to preserve data privacy. The updated global model is redistributed to all agents for coordinated energy management.

2.1. Dataset and data pre-processing

The framework was evaluated using historical renewable generation, electrical load demand, battery state-of-charge (SOC), and weather variables including solar irradiance and ambient temperature. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets. Missing samples were removed, and numerical features were normalized using min-max normalization,

$$X_{\mathrm{norm}} = \frac{X - X_{\mathrm{min}}}{X_{\mathrm{max}} - X_{\mathrm{min}}} \quad (1)$$

Where x_{min} and x_{max} denote the minimum and maximum values of each feature.

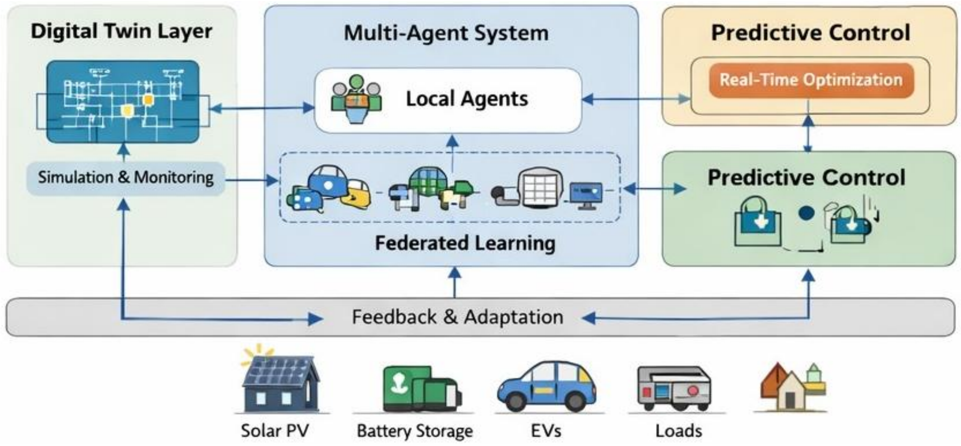

Figure 1. Digital twin driven federated multi agent smart grid framework

2.2. Mathematical formulation

The smart grid dynamic state is represented by (2).

$$\dot{x}(t) = Ax(t) + Bu(t) + Dw(t) \tag{2}$$

Where $x(t)$ denotes the system state vector, $u(t)$ is the control input, and $w(t)$ represents renewable generation uncertainty. Each physical asset is associated with a digital twin that predicts future operating conditions according to (3).

$$e_{\mathrm{DT}}(t) = x(t) - \hat{x}(t) \tag{3}$$

Where $x(t)$ represents the physical system state and $\hat{x}(t)$ denotes the corresponding digital twin state. The synchronization error is continuously minimized to maintain consistency between the physical and virtual systems.

$$\theta_i^{(r+1)} = \theta_i^{(r)} - \eta \nabla L_i(\theta_i) \tag{4}$$

Where $\theta_i^{(r)}$ denotes the local forecasting model parameters of agent i at communication round r, η is the learning rate, and $\mathcal{L}_i$ is the local loss function.

$$\theta_G^{(r+1)} = \sum_{i=1}^{N} \frac{n_i}{\sum_{j=1}^{N} n_j} \theta_i^{(r+1)} \tag{5}$$

Where $\theta_G^{(r+1)}$ is the updated global forecasting model, n_i is the number of local training samples at agent i, and N is the total number of participating agents.

2.3. Predictive smart grid optimization

The forecasting outputs are used to determine optimal scheduling of renewable resources, batteries, and EV charging. The optimization objective is formulated as (6).

$$minJ = C_{op} + \lambda_1 P_{loss} + \lambda_2 \Delta V \tag{6}$$

Where C_{op} denotes the operating cost, P_{loss} is the network power loss, and ΔV represents voltage deviation. The optimization is subject to the following constraints:

$$P_{PV} + P_{WT} + P_{BESS} + P_{GRID} = P_{LOAD} + P_{EV} + P_{LOSS} \tag{7}$$

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{8}$$

The optimized control actions are distributed to all intelligent agents for renewable dispatch, battery scheduling, demand response, and voltage regulation.

2.4. Implementation procedure

The implementation of the DT-FMAI framework consists of the following steps: i) Acquire real-time measurements from distributed smart grid assets; ii) Synchronize digital twin models with physical operating states; iii) Preprocess local datasets and train forecasting models; iv) Upload local model parameters to the federated server; v) Aggregate local models using the FedAvg algorithm; vi) Redistribute the updated global model; vii) Forecast renewable generation and electrical demand; viii) Optimize battery scheduling, EV charging, and power dispatch; and ix) Execute control actions and continuously update digital twin states.

2.5. Simulation setup and performance evaluation

The proposed framework was implemented using MATLAB/Simulink R2024a integrated with Python 3.11 and TensorFlow 2.16. Federated learning was implemented using TensorFlow Federated. Simulations were conducted on an Intel Core i7 workstation with 32 GB RAM under Windows 11. The principal simulation parameters are summarized in Table 1.

The proposed DT-FMAI framework was compared with centralized machine learning, Digital Twin-based forecasting, and federated learning-based forecasting under identical operating conditions. Forecasting accuracy was evaluated using mean absolute error (MAE) and root mean square error (RMSE):

$$V_{min} \leq V_i \leq V_{max} \tag{9}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{10}$$

Additional performance indicators included voltage deviation, communication overhead, energy efficiency, operating cost, and peak load reduction to comprehensively evaluate forecasting performance and grid operation.

Table 1. Simulation parameters

Parameter	Value	Parameter	Value
Learning rate	0.001	Optimizer	Adam
Batch size	64	Number of agents	10
Training epochs	100	Sampling interval	5 min
Communication rounds	50	Simulation duration	24 h
Local epochs	5	Aggregation method	FedAvg

3. RESULTS AND DISCUSSION

Figure 2 compares the forecasting performance of the proposed DT-FMAI framework with centralized machine learning, digital twin-only, and federated learning-based methods. The proposed framework achieved the lowest forecasting error, reducing RMSE by 15–25% through continuous digital twin synchronization, collaborative federated model updating, and decentralized agent learning. These results demonstrate that integrating predictive virtual modelling with privacy-preserving distributed intelligence improves forecasting reliability under varying renewable generation and load conditions.

Figure 3 illustrates the voltage regulation performance under dynamic operating conditions. The proposed framework reduced voltage deviation by 10–18% compared with conventional approaches. This improvement is mainly attributed to the predictive capability of the digital twin, which estimates future operating conditions before significant voltage fluctuations occur. Based on these predictions, the intelligent agents perform coordinated corrective actions through battery scheduling and renewable power regulation. The distributed control strategy therefore maintains acceptable voltage profiles even during rapid renewable generation changes and peak demand periods.

3.1. Load matching efficiency

The proposed DT-FMAI framework achieved a load-matching efficiency of 92–96%, demonstrating effective coordination among renewable generation, battery storage, and consumer demand. As shown in Figure 4, predictive scheduling reduced generation–load mismatch and increased overall energy efficiency by 12–20% compared with conventional methods. These improvements resulted from coordinated multi-agent control supported by digital twin forecasting and federated learning.

3.2. Operating cost and communication performance

The proposed DT-FMAI framework reduced operating cost by optimally scheduling renewable resources, battery storage, and EV charging based on forecasted demand. The federated learning strategy exchanged only model parameters, thereby reducing communication overhead while preserving data privacy. Consequently, the framework maintained forecasting accuracy with lower network traffic than centralized energy management approaches.

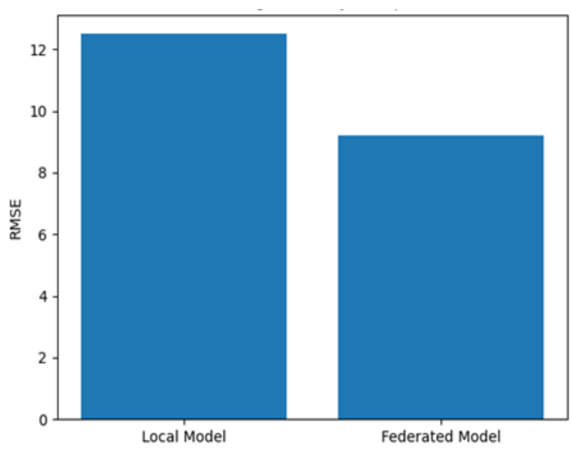

Figure 2. Forecasting accuracy comparison

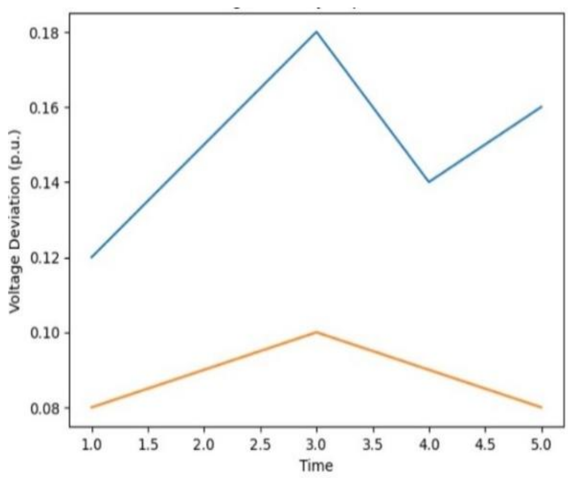

Figure 3. Voltage stability improvement

3.3. Peak load management

The proposed predictive scheduling strategy effectively shifted flexible loads away from peak demand periods, reducing peak loading and improving the load profile. Coordinated control of renewable generation, battery storage, and demand response enhanced resource utilization and maintained stable grid operation. These results indicate that proactive scheduling is more effective than conventional reactive energy management.

3.4. Scalability and communication performance

Figure 5 shows that the DT-FMAI framework maintained stable computational performance as the number of intelligent agents increased, demonstrating good scalability. The exchange of only model parameters during federated learning reduced communication overhead while preserving data privacy, as shown in Figure 6. Consequently, the proposed framework achieved secure distributed learning without degrading forecasting accuracy, making it suitable for large-scale smart grid deployment.

3.5. Convergence and adaptive control

Figure 7 indicates that the proposed DT-FMAI framework converged within 10–20 communication rounds, confirming stable federated optimization and efficient parameter aggregation. Figure 8 demonstrates that continuous digital twin synchronization enabled rapid adjustment of battery dispatch, renewable scheduling, and load management. These adaptive control actions reduced transient oscillations and improved overall system stability under dynamic operating conditions.

3.6. Comparative performance analysis

Table 2 compares the proposed DT-FMAI framework with centralized machine learning, digital twin-based, and federated learning-based approaches. The proposed framework achieved superior forecasting accuracy, voltage regulation, load-matching efficiency, energy utilization, scalability, and convergence through the integrated operation of synchronized digital twins, privacy-preserving federated learning, and coordinated multi-agent control. These results confirm the effectiveness of the proposed architecture for renewable-integrated smart grid operation.

Table 3 quantitatively confirms these improvements. The proposed framework achieved the lowest RMSE (9.2), the smallest voltage deviation (0.09 p.u.), and the highest operational efficiency (88%). In comparison, centralized machine learning produced an RMSE of 12.5, a voltage deviation of 0.15 p.u., and an efficiency of 75%. These results demonstrate that integrating digital twins with federated learning and multi-agent systems improves both prediction accuracy and operational performance, making the framework suitable for large-scale renewable-integrated smart grids.

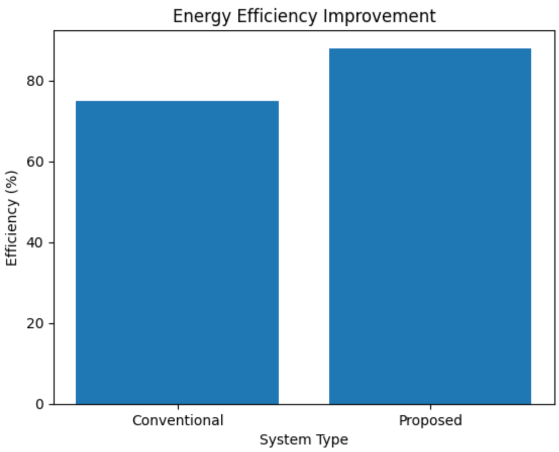

Figure 4. Energy efficiency improvement

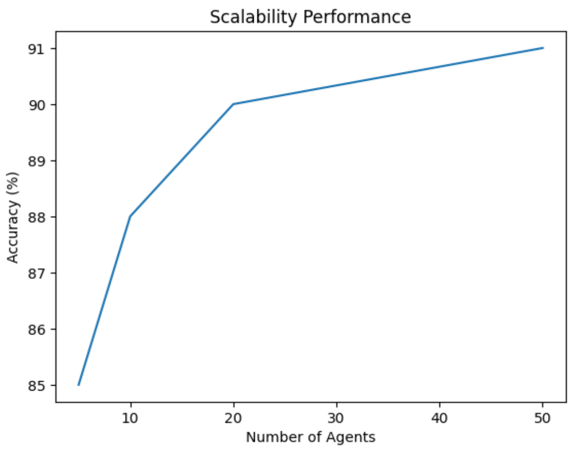

Figure 5. Scalability performance

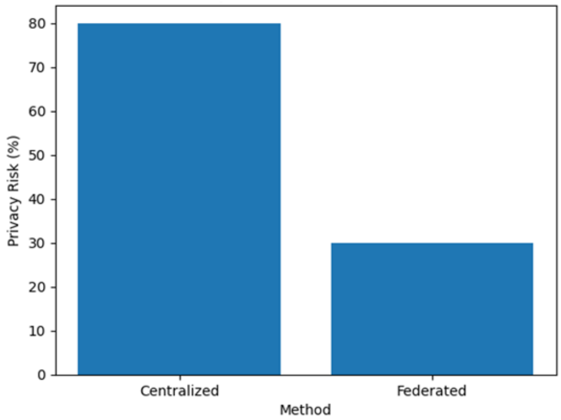

Figure 6. Privacy preservation comparison

Table 2. Comparative performance evaluation of conventional, digital twin, federated learning, and proposed DT–FL–MAS framework in smart grid applications

S. No.	Performance metric	Conventional ML (centralized)	Digital twin only	FL-based models	Proposed DT–FL–MAS framework	Key improvement
1	Forecasting Accuracy	Moderate (high error under variability)	Improved prediction with simulation	Good due to distributed learning	High accuracy (15–25% RMSE reduction)	Combines spatial learning + predictive modeling
2	Voltage stability	Reactive control, slower response	Predictive but limited coordination	Limited control integration	Proactive and coordinated (10–18% improvement)	Prediction + adaptive control integration
3	Load matching	Poor during peak variations	Moderate performance	Improved but not fully coordinated	High (92–96% matching efficiency)	Multi-agent coordination with forecasting
4	Energy efficiency	Energy losses due to poor scheduling	Better utilization via simulation	Moderate improvement	12–20% higher efficiency	Optimal dispatch using predictive intelligence
5	Scalability	Limited due to central processing	Moderate	High (distributed training)	Very high (fully decentralized)	No central bottleneck
6	Data privacy	Low (data sharing required)	Moderate	High (no raw data sharing)	Very high (secure + distributed)	Privacy-preserving learning
7	Convergence speed	Slow with large datasets	Moderate	Faster than centralized	Fast (10–20 rounds)	Parallel local training
8	Control strategy	Reactive	Predictive (limited scope)	Not control-focused	Fully adaptive and predictive	Closed-loop intelligent control
9	System intelligence	Static models	Semi-dynamic	Learning-based	Self-learning and self-adaptive	Continuous feedback loop
10	Practical deployment	Difficult at scale	Limited	Feasible	Highly feasible for smart grids	Integration of all layers

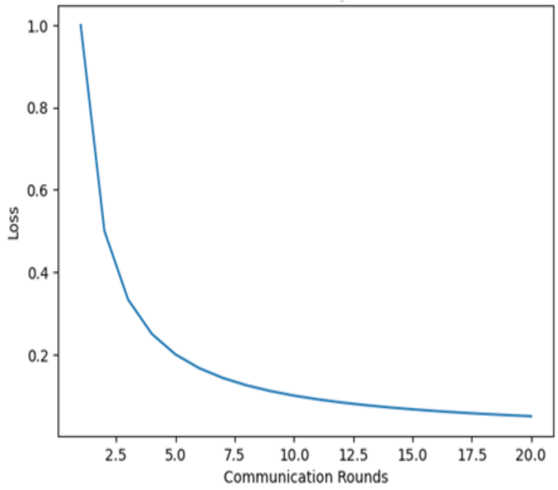

Figure 7. Model convergence

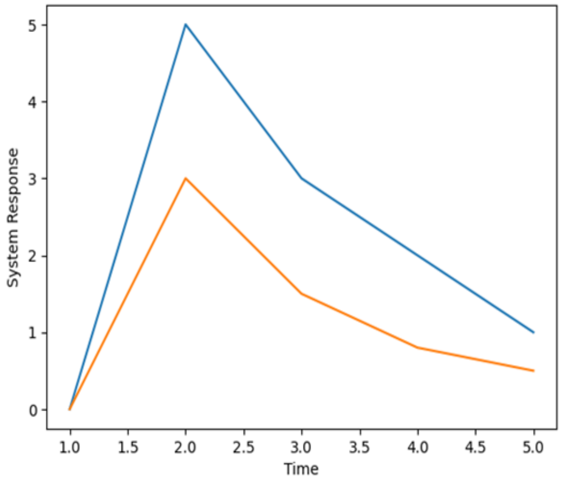

Figure 8. Adaptive control performance

Table 3. Gives the comparative analysis of forecasting error, voltage stability, and energy efficiency for different smart grid methods

Method	MAE	RMSE	Voltage deviation	Efficiency (%)
Centralized ML	9.8	12.5	0.15	75
FL only	8.2	10.5	0.12	82
DT only	8.6	11.0	0.11	80
Proposed DT-FMAI	7.1	9.2	0.09	88

4. CONCLUSION

This study proposed a DT-FMAI framework for autonomous renewable energy forecasting and smart grid optimization. The proposed architecture integrates digital twin technology, federated learning, and multi-agent systems to provide predictive control, decentralized decision-making, and privacy-preserving collaborative learning for renewable-integrated smart grids. The framework enables distributed energy resources to operate cooperatively while maintaining data confidentiality through parameter-based model aggregation. Simulation results demonstrated that the proposed framework improved forecasting performance and grid operation compared with conventional centralized, digital twin-based, and federated learning-based approaches. The framework achieved lower forecasting error, enhanced voltage regulation, improved load matching, higher energy efficiency, faster model convergence, and better scalability under varying renewable generation and load conditions. The distributed learning strategy also reduced communication requirements while preserving forecasting accuracy, making the framework suitable for large-scale smart grid applications.

The present study is limited to a simulation-based evaluation under predefined operating scenarios. Practical issues such as communication latency, packet loss, cyberattacks, and hardware implementation were not considered and may influence real-world performance. Future work will focus on hardware-in-the-loop validation, real-time deployment on edge computing platforms, integration of reinforcement learning for adaptive energy management, and evaluation under large-scale distribution networks with high renewable penetration and electric vehicle participation.

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Pushpa Sreenivasan	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
K. Gattaiah		✓				✓		✓	✓	✓	✓	✓		
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Radhey Shyam Meena	✓		✓	✓			✓			✓	✓		✓	✓
Mallareddy Adudhodla					✓		✓			✓		✓		✓
V. S. Bhagavan					✓		✓			✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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