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Comparative Analysis of Deep Learning Architectures for Short-Term Solar Power Forecasting

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Abstract: The increasing use of renewable energy sources, where solar power, has introduced a challenge in maintaining grid stability due to their intermittent and dependent on nature weather. Accurate forecasting of solar power generation is essential for efficient energy management and reliable power system operation. This paper presents a comparative analysis of traditional statistical and deep learning models for short-term solar power forecasting using a dataset. The ARIMA model is used as a baseline and compared with advanced deep learning models like, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid CNN-LSTM architecture. The models are evaluated using performance metrics such as MAE, RMSE, MAPE, and R^2, along with computational efficiency. The results show that deep learning models perform better than the traditional method, where the ARIMA model in capturing nonlinear and temporal patterns. Among them, the CNN-LSTM model achieves the highest prediction accuracy, while the GRU model offers a better trade-off between accuracy and computational cost. The findings highlight the importance of advanced data-driven techniques in improving renewable energy forecasting and supporting sustainable energy systems.

Keywords: Renewable Energy Forecasting, Solar Power Prediction, Deep Learning, LSTM, GRU, CNN-LSTM, ARIMA, Time-Series Analysis, Smart Grid, Energy Analytics

I. INTRODUCTION

Now the world is moving toward the renewable energy such as solar and wind, which play has significantly transformed the modern electricity systems, reduced carbon emissions and supporting sustainable development. This shift accelerated by growing of environmental concerns, strict regulatory policies, and rapid technological advancements. The conventional energy systems, renewable energy generation is highly dependent on natural weather conditions and difficult to control [1]. The power output from these sources can fluctuate, making accurate forecasting essential for maintaining grid stability, minimizing operational risks, and enabling informed market decisions.

Conventional power plants, those based on fossil fuels, can be regulated according to demand, ensuring consistent energy supply. In contrast, renewable sources such as solar and wind depend on external environmental factors like sunlight intensity, temperature, cloud cover, and wind speed where the sudden variations or change in these factors can lead to imbalances between energy generation and demand, potentially causing voltage instability, increased reliance on backup systems, and economic losses due to energy curtailment [2]. To address these challenges, system operators and energy planners increasingly dependent on forecasting techniques to get correct data so that they can optimize the resource management.

The forecasting approaches primarily utilized statistical models such as ARIMA and SARIMA due to their simplicity and strong mathematical foundation. However, renewable energy data show the nonlinear and complex patterns that limit the effectiveness of such linear models where the recent research has shifted toward machine learning and deep learning techniques, which are better suited for handling large-scale and noisy time-series data, the models like RNNs, LSTM networks, and GRUs have demonstrated strong capabilities in capturing temporal dependencies other than simple model we can also go for hybrid architectures like, combining CNNs with LSTM, as well as transformer-based models leveraging attention mechanisms, have shown improved forecasting performance [3]. These advancements, challenges remain, including high computational requirements, limited reproducibility, and lack of generalization across different regions. This paper addresses these gaps and providing a comparative analysis of traditional time-series and deep learning models under consistent conditions, highlighting their respective strengths and limitations [4].

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Table 1 summarized the importance of forecasting across various operational aspects of renewable energy systems. Table 2 presents the categories along with their respective durations and key applications in power system management and Table 3 summarizes the key properties and highlighting the challenges with respect to solar and wind energy data.

TABLE I
IMPORTANCE OF FORECASTING IN RENEWABLE ENERGY SYSTEMS

Sr.no	Area	Role of Forecasting
1	Grid Stability	Maintains balance between supply and demand and ensures frequency control
2	Energy Storage	Optimizes charging/discharging cycles of storage systems
3	Reserve Management	Reduces need for spinning reserves and improves allocation
4	Market Operations	Supports price prediction and strategic bidding decisions
5	Maintenance Planning	Helps in predictive maintenance and risk reduction
6	Curtailment Control	Minimizes energy wastage due to overproduction
7	Decentralized Integration	Facilitates integration of rooftop solar and distributed systems

TABLE II
FORECASTING TIME HORIZONS AND THEIR APPLICATIONS

Sr.no	Time Horizon	Duration	Key Applications
1	Short-Term	Minutes to Hours	Real-time operations, load balancing, dispatch decisions
2	Medium-Term	Hours to Days	Market planning, scheduling, energy trading
3	Long-Term	Weeks to Months	Policy making, infrastructure planning, resource allocation

TABLE IIII
CHARACTERISTICS OF RENEWABLE ENERGY TIME-SERIES DATA

Sr.no	Characteristic	Description
1	Nonlinearity	Complex relationships between variables
2	Seasonal Patterns	Daily and yearly cycles in solar and wind data
3	Abrupt Variations	Sudden changes due to weather conditions
4	Multivariate Dependency	Influence of multiple environmental factors
5	Noise	Errors from sensors and environmental disturbances

II. LITERATURE REVIEW

The world global energy sector is undergoing a major transformation with the rapid integration of renewable energy sources (RES) into modern power systems. Although this transition supports decarbonisation goals, it introduces challenges related to grid stability and supply–demand balance. Solar and wind energy are highly dependent on unpredictable weather conditions, making their output variable and difficult to control. As a result, accurate forecasting has become essential for reliable system operation [5]. This chapter reviews existing research in renewable energy forecasting, highlighting the shift from traditional statistical models to advanced deep learning techniques. The table 4 disused about the traditional vs, Modern foresting approaches. The deep learning models like, RNN, LSTM, and GRU are more effective in detecting the temporal dependencies [6]. The paper also explores hybrid and transformer-based models that improve forecasting performance. The table 5 summarizes research gaps and study contribution of the other author the Renewable energy sources such as solar and wind are non-dispatch able and depend on environmental conditions, leading to variability in power generation [7-10]. This intermittency causes challenges in maintaining grid stability, including frequency deviations and supply–demand imbalance. Accurate forecasting is therefore essential for reliable system operation and efficient resource management.

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TABLE IIIV
SUMMARY OF TRADITIONAL VS. MODERN FORECASTING APPROACHES

Approach	Key Models	Strengths	Limitations
Statistical	ARIMA, SARIMA, ETS	Interpretable, computationally light, effective for linear trends.	Fails with high volatility, assumes stationarity, cannot map complex non-linear interactions.
Machine Learning	SVR, Random Forest	Handles non-linearity better than ARIMA, robust to noise.	Requires manual feature engineering, limited memory of long-term sequences.
Deep Learning	LSTM, GRU, CNN	Automatic feature extraction, captures long-term dependencies, high accuracy.	Computationally expensive, requires large datasets, "black box" nature.

TABLE V
SUMMARY OF IDENTIFIED RESEARCH GAPS AND STUDY CONTRIBUTIONS

Sr. No.	Identified Research Gap	Supporting Literature	How This Study Fulfils the Gap
1	**Lack of Rigorous Benchmarking:** Few studies compare ARIMA, GRU, and CNN-LSTM side-by-side on high-frequency (15-min) solar data under identical pre-processing conditions.	Hossain et al. (2025). Chodakowska et al. (2024)	Implements a unified experimental pipeline to test all three architectures on the same 15-minute interval dataset to ensure fair comparison.
2	**Neglect of Computational Efficiency:** Research often focuses solely on error minimisation, ignoring the training time and resource consumption required for deployment.	Teixeira et al. (2024). Zameer et al. (2023)	Introduces "Training Time" and "Convergence Speed" as key evaluation metrics alongside RMSE/MAE to assess the trade-off between accuracy and cost.
3	**Ambiguity of Hybrid Model Efficacy:** Limited evidence exists on whether CNN-LSTM hybrids offer tangible benefits over simpler GRUs for short-term horizons.	Guermoui et al. (2025). Abumohsen & Owda (2024)	Specifically isolates the performance of the CNN feature-extraction layer to determine if it improves prediction stability for short-term horizons.

The integration of renewable energy sources into modern grid systems is supported by energy storage and smart grid technologies, which enable efficient power management and improved stability [5-11], and the interaction between technological advancements, policy frameworks, and electricity markets plays a vital role in facilitating renewable energy adoption.

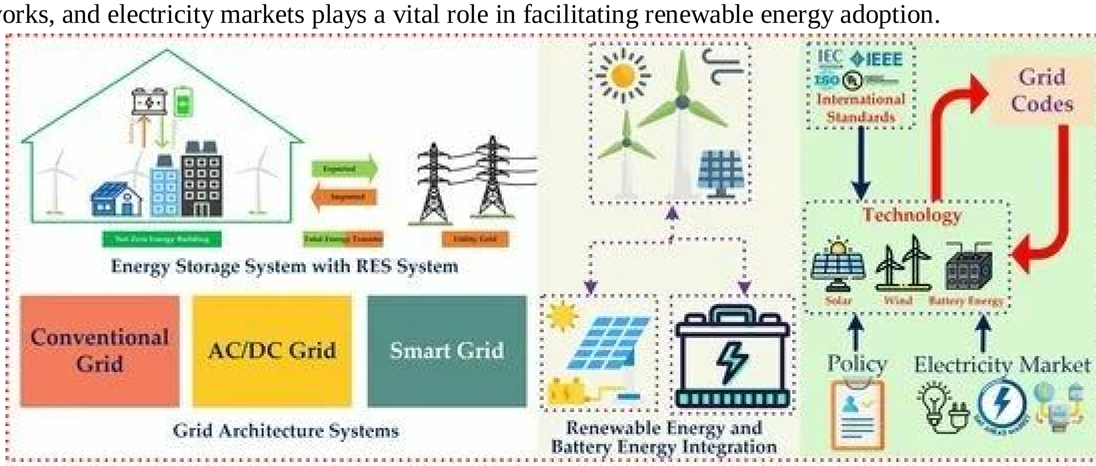

Fig. 1 Solar PV Integration

AI plays a significant role in renewable energy forecasting by enhancing the advanced data-driven approaches [12]. ML, a subset of AI, includes supervised, unsupervised, reinforcement, and deep learning techniques [13]. These approaches support tasks such as regression, classification, clustering, and feature extraction, thereby improving forecasting accuracy and system efficiency.

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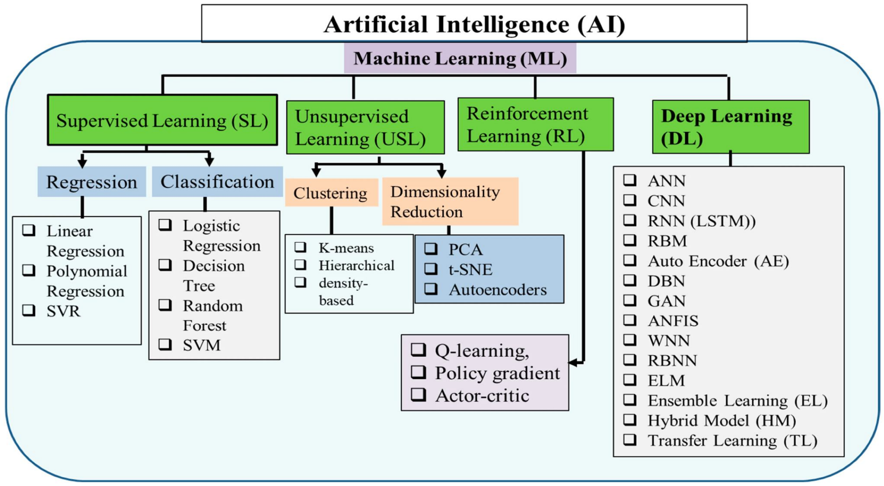

Fig. 2 Type of AI

III.METHODOLOGY

Here we, used to compare traditional statistical models vs. deep learning techniques for short term solar power forecasting. Where it compares with LSTM [22], Hybrid CNN-LSTM [24] and GRU [23] models to determine the best balance between prediction accuracy and computational efficiency.

A. Research Design

The quantitative experimental approach based on a philosophy, where objective data such as meteorological variables and power generation are analysed. The approach is adopted to test the hypothesis where deep learning models perform the statistical models in non-linear time-series forecasting [14].

B. Data Acquisition

The dataset is from the Kaggle, Table VI show the column detail of, Solar Power Generation dataset, containing real-time solar plant data from India. It includes both power generation and environmental parameters recorded at 15-minute intervals of time.

TABLE VI
IMPACT OF INTERMITTENCY

Sr. No.	Category	Variable	Unit	Description	Role
1	Target	DC_POWER	kW	Generated power output	Dependent
2	Feature	AMBIENT_TEMPERATURE	°C	Surrounding temperature	Independent
3	Feature	MODULE_TEMPERATURE	°C	Panel temperature	Independent
4	Feature	IRRADIATION	W/m²	Solar intensity	Independent

C. Data Pre-processing

Table VII show the step which are done for data pre-processing.

TABLE VII
PRE-PROCESSING STEPS

Sr. No.	**Step**	**Purpose**
1	Missing Value Handling	Maintain time-series continuity
2	Feature Engineering	Add temporal information
3	Differencing	Achieve stationary
4	Normalization	Scale data for DL models

D. Data Splitting and Model Architecture

The dataset is divided into training (70%), validation (15%), and testing (15%) sets for model evaluation. ARIMA model is used as a statistical baseline, with its parameters (p, d, q) determined for the ACF and PACF analysis. For deep learning approaches, an LSTM model is developed consisting of two layers with 50 units each, followed by a dropout layer (0.2) to prevent over fitting and a dense output layer. A GRU model is also implemented with a similar structure but fewer parameters, where we enabling faster training with comparable performance. Additionally, hybrid CNN-LSTM model is proposed, where the CNN layer extracts local patterns, max-pooling reduces dimensionality, and the LSTM layer captures temporal dependencies. The architecture of this hybrid model is illustrated in Fig. 3.

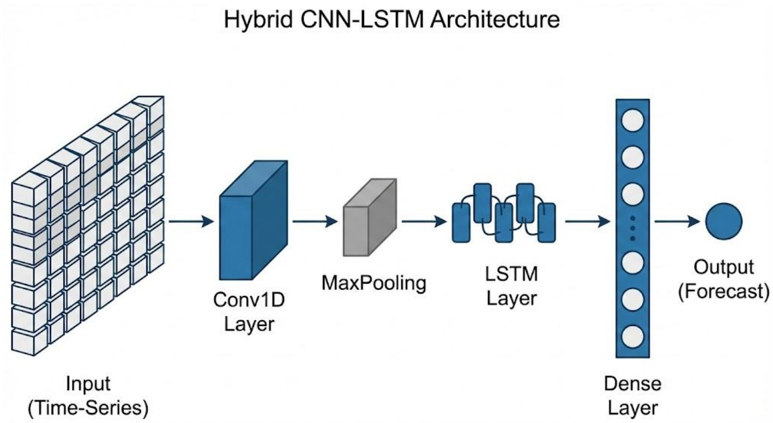

Fig. 3. Proposed Hybrid CNN-LSTM Architecture

E. Experimental Setup

The implementation of the proposed models is done in Python using like Pandas and NumPy, for Deep learning models, including LSTM, GRU, and CNN-LSTM, are developed using Tensor Flow/Keras. The experiments are run on Google Colab with GPU support to reduce training time as compare to the CPU support.

F. Evaluation Metrics

The performance of the models is evaluated using multiple statistical metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and R-squared (R^2) score is used to evaluate proposed model [26].

IV. RESULTS AND ANALYSIS

The performance of different models was evaluated using MAE, RMSE, MAPE, and R^2 metrics. The ARIMA model showed limited performance with higher error values and lower accuracy, indicating its inability to capture nonlinear patterns in solar data. In contrast, deep learning models such as LSTM, GRU, and CNN-LSTM demonstrated significantly improved performance. Among them, the CNN-LSTM model achieved the lowest error values and highest R^2 score, followed by LSTM and GRU.

TABLE VIII
CORRELATION MATRIX OF SOLAR POWER GENERATION VARIABLES

Variables	DC_POWER	IRRADIATION	MODULE_TEMPERATURE	AMBIENT_TEMPERATURE
DC_POWER	1.00	0.92	0.88	0.81
IRRADIATION	0.92	1.00	0.79	0.74
MODULE_TEMPERATURE	0.88	0.79	1.00	0.84
AMBIENT_TEMPERATURE	0.81	0.74	0.84	1.00

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TABLE IX
CORRELATION MATRIX OF SOLAR POWER GENERATION VARIABLES

Model	MAE	RMSE	MAPE	R^2	Training Time
ARIMA	205.87	340.12	32.6%	0.71	~32 sec
LSTM	Low	Low	Low	High	~215 sec
GRU	Moderate	Moderate	Moderate	High	~160 sec
CNN-LSTM	Lowest	Lowest	Lowest	Highest	~278 sec

V. CONCLUSIONS

This paper shows the comprehensive comparison of models for solar power forecasting using a real-world dataset. The results, indicate that traditional models such as ARIMA are limited in their ability to capture the nonlinear and dynamic nature of renewable energy data. Where deep learning models shows the effectively learning temporal dependencies and complex relationships among variables. Among the evaluated models, the hybrid CNN-LSTM achieved the highest accuracy due to its ability to combine feature extraction with temporal learning.

The GRU model emerged as a practical alternative, offering a good balance between prediction accuracy and computational efficiency, making it suitable for real-time and resource-constrained applications. The LSTM model also showed strong performance, particularly in capturing abrupt variations in solar power generation. Overall, the findings emphasize that deep learning approaches are more suitable for modern renewable energy forecasting tasks. Future work can focus on incorporating larger datasets, real-time deployment, and advanced architectures such as transformer-based models to further enhance forecasting accuracy and scalability.

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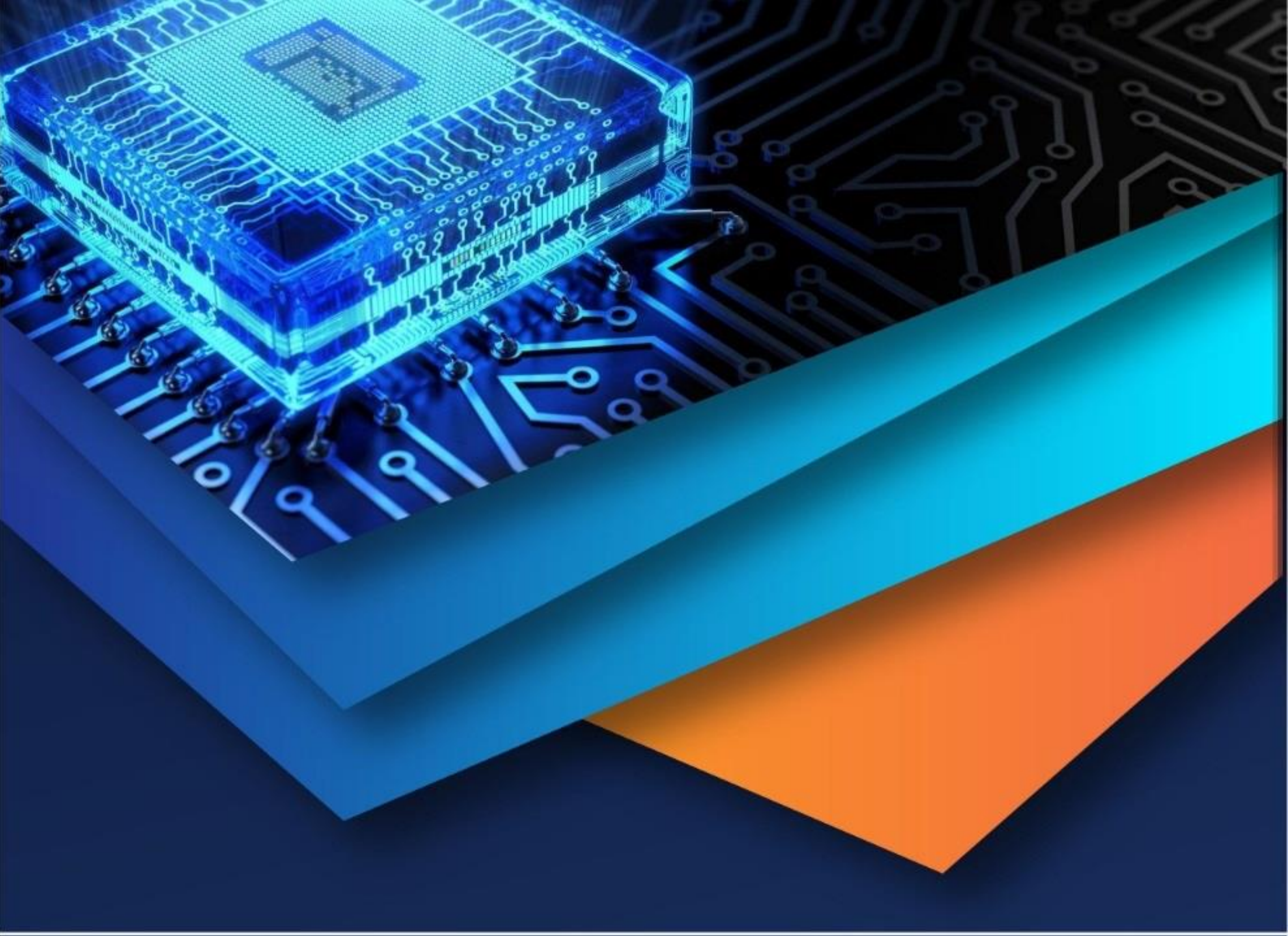

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