Solar Power Prediction Using LSTM & RNN

R. Indhuja[1]; Sivakami G.[2]; Syamala Devi S.[3]; Sowndarya A. K.[4]

[1,2,3,4]Department of Artificial Intelligence & Data Science Kamaraj College of Engineering and Technology
(An Autonomous Institution - Affiliated to Anna University, Chennai)
K. Vellakulam, Virdhunagar – 626 001

Publication Date: 2025/03/31

Abstract: Solar power prediction using Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) in Python is a crucial application of deep learning for renewable energy optimization. This study focuses on leveraging time-series forecasting capabilities of LSTM and RNN to predict solar power generation based on historical data, including temperature, sunlight intensity, humidity, and other meteorological factors. By preprocessing data, normalizing inputs, and training models using TensorFlow and Keras, the study enhances prediction accuracy. The comparative analysis of LSTM and standard RNN highlights the superior performance of LSTM in capturing long-term dependencies and mitigating vanishing gradient issues. The results demonstrate that deep learning models can effectively forecast solar energy output, aiding energy grid management and sustainable resource planning.Solar power is one of the most promising renewable energy sources, playing a crucial role in sustainable energy solutions. However, its efficiency depends on various meteorological factors, such as sunlight intensity, temperature, humidity, and cloud cover, making accurate prediction a challenging task.

This study explores the application of LSTM and RNN models for predicting solar power generation using Python-based machine learning frameworks such as TensorFlow and Keras. By leveraging historical meteorological data, the proposed models aim to improve forecasting accuracy, aiding energy management systems in optimizing solar energy utilization and grid stability. The research also includes a comparative analysis of RNN and LSTM to assess their effectiveness in predicting solar power generation.

Keywords: *Solar Power Prediction, Time Series Forecasting, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Renewable Energy, Deep Learning, Energy Management, AI in Forecasting, Flask Web Application.*

How to Cite: R. Indhuja; Sivakami G.; Syamala Devi S.; Sowndarya A. K. (2025) Solar Power Prediction Using LSTM & RNN. *International Journal of Innovative Science and Research Technology*, 10(3), 1545-1548. https://doi.org/10.38124/ijisrt/25mar1047.

I. INTRODUCTION

Solar power prediction is essential for efficient energy management, grid stability, and optimizing the use of renewable resources. Solar energy generation depends on various environmental factors like temperature, humidity, and cloud cover, making accurate forecasting a challenge. Traditional statistical models often fail to capture the nonlinear patterns in solar power generation. Advanced deep learning techniques, particularly Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, are highly effective in handling time-series data, learning temporal dependencies, and improving prediction accuracy.

This project utilizes RNN and LSTM models to forecast solar power generation based on historical weather and solar energy data. By analyzing past trends, the model predicts future energy output, aiding in efficient energy distribution and planning. A Flask web application is integrated to provide an interactive user interface for inputting data and visualizing predictions. This system benefits energy providers, researchers, and policymakers by improving decision-making in renewable energy management.

A. Overview

Solar power prediction is crucial for optimizing energy management and ensuring grid stability, especially as renewable energy adoption increases. Our AI-driven forecasting system enhances energy planning by:

- Improving Prediction Accuracy using deep learning models like RNN and LSTM.
- Aiding energy providers in balancing supply and demand efficiently.
- Offers a user friendly flask Web-Application for real time solar power forecasting.

The integration of AI in renewable energy forecasting helps maximize efficiency, reduce reliance on non-renewable sources, and support sustainable energy management for a greener future.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1047

B. Objective

- **To analyze** historical solar power generation data along with meteorological factors such as sunlight intensity, temperature, humidity, and cloud cover.
- **To develop and implement** RNN and LSTM-based models for time-series forecasting of solar power generation using Python frameworks such as TensorFlow and Keras.
- **To compare the performance** of RNN and LSTM models based on evaluation metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).
- **To optimize the model parameters** to improve prediction accuracy and efficiency.

C. Social Impact

- **Sustainable Energy Management:** Enhances the efficiency of solar power utilization, reducing dependence on fossil fuels.
- **Optimized Grid Stability:** Helps balance energy supply and demand, preventing power shortages or wastage.
- **Support for Remote Areas:** Enables better energy planning in regions with limited access to reliable electricity sources.
- **Cost-Effective Energy Solution:** AI-driven forecasting reduces energy costs by improving resource allocation and minimizing inefficiencies.

II. REALTED WORK

"A Novel Approach Based Deep RNN Using Hybrid NARX-LSTM Model For Solar Power Forecasting",Mohamed Massaoudi, Ines Chihi, Lilia Sidhom, Mohamed Trabelsi, Shady S. Refaat, Fakhreddine S. Oueslati,Year 2022,This paper proposes a hybrid model combining Nonlinear Autoregressive Exogenous (NARX) models with LSTM networks to address the challenges of solar power forecasting. The study demonstrates that integrating LSTM with NARX enhances prediction accuracy by effectively capturing long-range dependencies in time-series data.

"Short-Term Power Prediction for Renewable Energy Using Hybrid Graph Convolutional Network and Long Short-Term Memory Approach",Wenlong Liao, BirgitteBak-Jensen, Jayakrishnan Radhakrishna Pillai, Zhe Yang, Kuangpu Liu,Year 2023.This study introduces a hybrid model that combines Graph Convolutional Networks (GCN) with LSTM networks to capture both spatial and temporal correlations in renewable energy data. The proposed approach outperforms traditional models in short-term power prediction, demonstrating the effectiveness of integrating spatial and temporal features.

Esteva, A., et al. [3] (2017): "Dermatologist-level classification of skin cancer with deep neural networks." Published in *Nature*, this study explored the application of CNNs for detecting skin cancer from images, achieving accuracy comparable to dermatologists. While focused on skin conditions, the methodology of leveraging deep learning for image-based medical diagnosis is closely related to pneumonia detection from chest X-rays.

"Sequence to Sequence Deep Learning Models for Solar Irradiation Forecasting",Bhaskar PratimMukhoty, Vikas Maurya, Sandeep Kumar Shukla,Year 2023.This paper explores the application of sequence-to-sequence deep learning models, particularly LSTM networks, for short-term forecasting of Global Horizontal Irradiance (GHI).

The study demonstrates that LSTM models effectively capture temporal dependencies in solar irradiation data, leading to improved forecasting accuracy compared to traditional methods.

"An Integrated Multi-Time-Scale Modeling for Solar Irradiance Forecasting Using Deep Learning",Sakshi Mishra, Praveen Palanisamy,Year 2022.This research proposes a unified architecture combining RNN and LSTM for multi-time-scale solar irradiance forecasting. The study demonstrates that the integrated model achieves lower root-mean-square prediction error compared to existing methods, highlighting its effectiveness for intra-day and intra-hour forecasting horizons.

III. DESIGN ARCHITECTURE

A. Design Architecture

This section illustrates a Flask-based web application that integrates deep learning for solar power prediction. The system architecture comprises four main components:

- **User Input & Flask Server:** Users upload historical solar power data in CSV format through a web-based interface. The Flask server receives the request and temporarily stores the file in a predefined folder (e.g., /uploads). The user's input parameters, such as location and weather conditions, are recorded in the Flask server for further processing.
- **Preprocessing & Model Inference:** The system retrieves the uploaded dataset and applies preprocessing steps, including missing value handling, feature scaling, and time-series formatting. The preprocessed data is then passed into the pre-trained deep learning models (RNN and LSTM, saved in .h5 format). The model predicts future solar power generation based on historical trends.
- **Database Storage (SQLite):** The prediction results, along with the uploaded dataset's metadata, are stored in an SQLite database. This allows users to retrieve past predictions and analyze long-term energy trends for better planning.
- **Output & User Interface:** The forecasted solar power output is sent back to the Flask server, which processes and displays the results on the web interface. Users can view visualized graphs of predicted power generation

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1047

trends, helping them make informed energy management decisions.

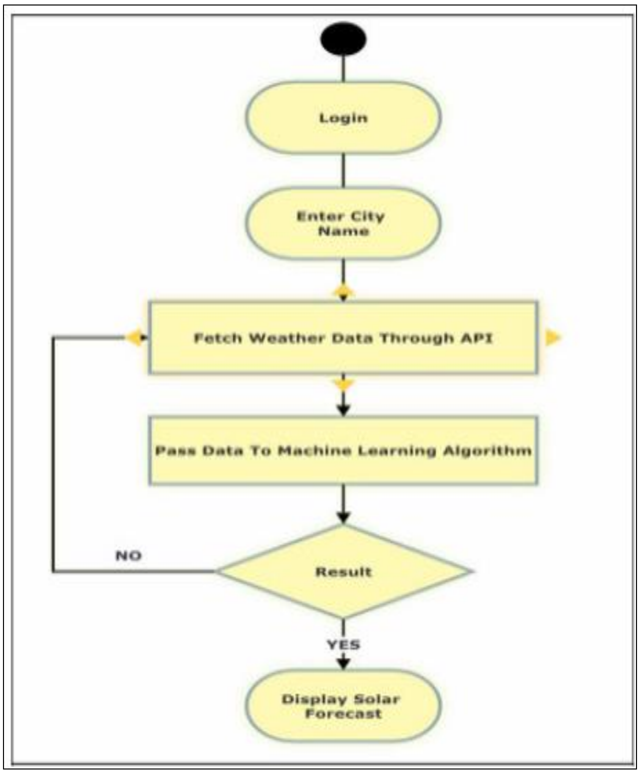

Fig 1: Flow Chart

B. Model Mechanism

The model mechanism for solar power prediction is designed to provide accurate and real-time forecasting through a Flask-based web application. The process starts with user login, where users authenticate themselves to access the platform securely. Once logged in, they **enter the city name**, which acts as an input for retrieving real-time weather data. The system then **fetches weather data through an API** (such as Open Weather Map or NASA's POWER API), gathering key meteorological parameters like solar radiation, temperature, humidity, wind speed, and cloud cover. This data is essential for predicting solar energy output.

After fetching the weather data, the system performs **data preprocessing**, handling missing values, normalizing inputs, and structuring them for time-series analysis. The preprocessed data is then fed into a **deep learning model** based on Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) algorithms. These models are trained to learn complex temporal dependencies and patterns in historical solar power data, improving forecasting accuracy.

The prediction results are **stored in an SQLite database**, allowing users to track past forecasts and compare them with actual energy generation data.

Finally, the **predicted solar power output** is displayed on the web interface, where users can visualize trends through interactive graphs and numerical values. This AI-driven forecasting system helps energy providers, researchers, and policymakers make informed decisions about solar energy utilization, ultimately contributing to sustainable energy management and optimized grid stability.

IV. RESULTS

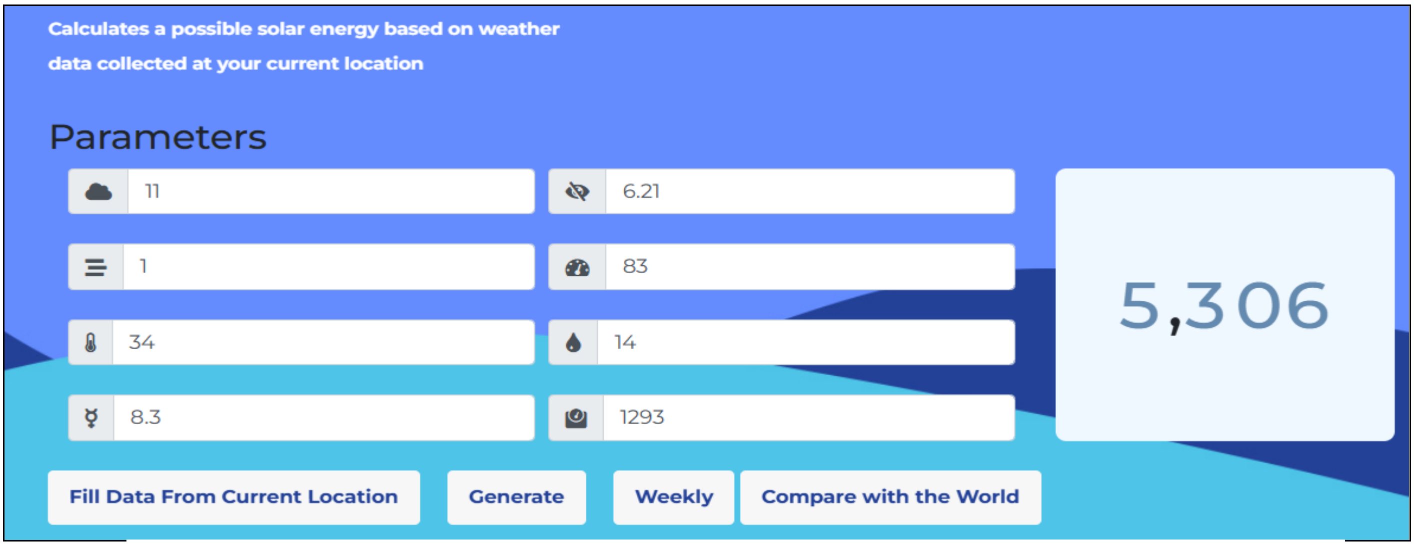

Fig 2: The **Solar Energy Prediction Output** Provides Forecasted Power Generation Based on Historical and Real-Time Weather Data, Enabling Users to Optimize Energy Planning, Manage Grid Stability, and Enhance Renewable Energy Utilization Efficiently

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25mar1047

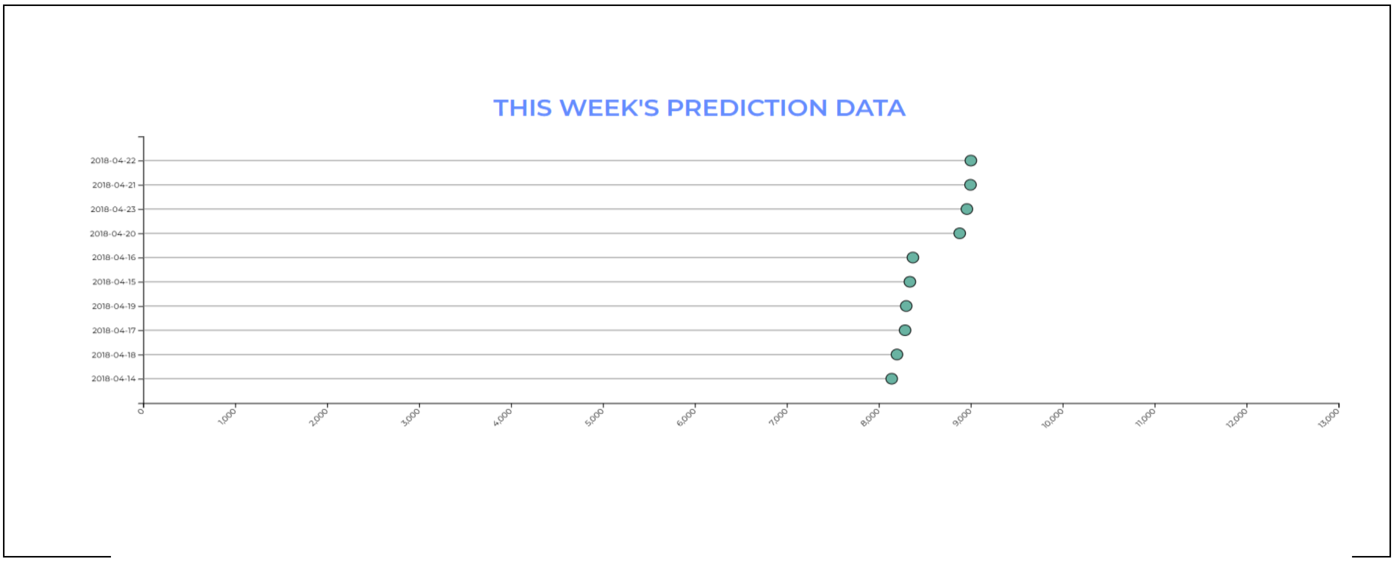

Fig 3: The Weekly Solar Power Prediction Provides Forecasted Energy Generation Trends using RNN and LSTM Models, Helping Users Analyze Patterns, Optimize Energy Usage, and Plan Efficient Resource Allocation for Sustainable Power Management

V. CONCLUSION & FUTURE WORK

In summary, this study explored the use of Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) for predicting solar power generation. The results demonstrated that LSTM models effectively capture long-term dependencies in time-series data, outperforming traditional forecasting techniques in accuracy and reliability.

The implementation of deep learning-based models provided significant improvements in short-term solar power prediction, reducing errors and enhancing decision-making for energy management. Despite the promising outcomes, challenges such as model complexity, data quality, and computational requirements were identified. Addressing these limitations through feature selection, hybrid models, and improved training techniques can further enhance prediction accuracy.In conclusion, LSTM and RNN models present a powerful approach for solar power forecasting, contributing to efficient renewable energy integration. Future research could focus on combining deep learning with external factors like satellite data, weather forecasts, and hybrid AI techniques to refine predictions and support sustainable energy solutions.

In future work, transfer learning can be explored to develop models that generalize well across different geographic locations. To optimize computational efficiency, techniques such as model pruning, quantization, and lightweight architectures can be implemented, enabling faster and more efficient predictions suitable for deployment on low-power devices. Ensemble learning approaches, such as stacking or boosting multiple deep learning models, may also improve forecast stability and reliability.

REFERENCES

[1]. U. K. Das, K. S. Tey, M. Seyed mahmoudian, S. Mekhilef, M. Y. I. Idris, W. V. Deventer, B. Horan, and A. Stojcevski, "Forecasting of photovoltaic power generation and model optimization: A review," Renewable and Sustainable Energy Reviews, vol. 81, pp. 912 – 928, 2023.

[2]. M. Abuella and B. Chowdhury, "Solar power probabilistic forecasting by using multiple linear regression analysis," in Southeast Con 2021. IEEE,2022, pp. 1–5.

[3]. A. Gensler, J. Henze, B. Sick, and N. Raabe, "Deep learning for solarpowerforecastingâ ˘A˘Tan approach using autoencoder and lstmneuralnetworks," in Systems, Man, and Cybernetics (SMC), 2023 IEEE Inter-national Conference on. IEEE, 2023, pp. 002 858–002 865.

[4]. J. Zeng and W. Qiao, "Short-term solar power prediction using a support vector machine," Renewable Energy, vol. 52, pp. 118–127, 2023.

[5]. S. Ferrari, M. Lazzaroni, V. Piuri, L. Cristaldi, and M. Faifer, "Statistical models approach for solar radiation prediction," in Instrumentation and Measurement Technology Conference (I2MTC), 2013 IEEE International. IEEE, 2023, pp. 1734–1739.