International Journal of Emerging Engineering Technologies and Innovations (IJEETI)
Vol 1, Issue 1
July 2026

Solar Irradiance Prediction for Agricultural Applications Using Hybrid Machine Learning

Md Ashraful Haque
Senior Researcher
mashik.peshajibibarta@yahoo.com

Abstract

The accurate prediction of solar irradiance becomes crucial for effective management of solar-powered agricultural systems, such as irrigation pumps, running of greenhouses, crop drying, livestock sheds, farm energy storage, etc. Nonetheless, solar irradiance is very fluctuant due to variations in cloudiness, temperature, humidity, wind speed, season, etc. The aim of the present study is to introduce a hybrid machine learning system to accurately predict the solar irradiance for agricultural applications. The proposed approach integrates complementary machine learning algorithms that are able to capture linear and nonlinear relationships in the historical weather and irradiance data. The inputs to the model are temperature, relative humidity, wind speed, cloud cover, rainfall, time, and past solar irradiance readings. Data preprocessing, feature selection and hyperparameter optimization are used to enhance the reliability of the model and to minimize prediction errors. The mean absolute error, root mean square error, mean absolute percentage error, and coefficient of determination are used to measure the performance of the hybrid model. The proposed framework is likely to yield more accurate and stable predictions than the individual machine learning models. Accurate solar irradiance prediction can help optimize irrigation scheduling, battery charging, energy distribution and agricultural equipment operation. The research helps to advance intelligent, low cost and sustainable energy management systems for precision agriculture and climate-smart farming.

Keywords: Solar irradiance forecasting, Hybrid machine learning, Precision agriculture, Renewable energy management, Climate-smart farming

Introduction

Reliable access to energy is becoming more and more crucial for agriculture needs in irrigation, greenhouse management, and processing, cold storage, livestock production, water pumping, and to power smart farming technologies. Stable electricity supply is still lacking, costly or reliant on generators using fossil fuels in many areas of agriculture, especially in rural and remote areas. Solar energy utilization provides sustainable alternative due to its renewable, environmental friendly, availability and suitability for decentralized agricultural application. SPV can generate electricity directly at farms, and solar thermal energy can be used for the purpose of drying the crops, heating water for various uses, and for greenhouse temperature management. But the ability to use solar energy in agriculture is highly dependent on the availability and intensity of the solar irradiance. Solar irradiance is the amount of solar energy received per unit area on the earths surface. It directly impacts the PV output and the thermal performance of the solar energy systems. It is therefore imperative to obtain accurate information about the future solar irradiance to plan and manage the agricultural operations powered with solar energy. For instance, farmers who irrigate their farms through solar powered pumps have to find out whether they will have enough solar energy to pump water at a specific time. Likewise, greenhouse growers need to have accurate energy projections to control temperature, ventilation, humidity and artificial lighting. Solar-powered battery systems require charging and discharging based on the anticipated solar energy generation and use in agriculture. If the prediction of solar irradiance is inaccurate then either the amount of irrigation water supplied could be inadequate, the batteries might not be used efficiently, agricultural operations may be interrupted, unplanned reliance on backup electricity, and the cost of operating might be high. Because a number of environmental and atmospheric variables influence solar irradiance, its prediction is difficult. The amount of solar radiation reaching the ground can be affected by cloud cover, air temperature, humidity, rainfall, wind speed, atmospheric pressure, dust, seasonal variation, geographical location and time of day. The factors tend to occur in combination and non-linearly. The variability of solar irradiance can be very fast due to clouds and other weather events that occur suddenly, which presents a particular challenge for short-term forecasts. In the agricultural context prediction may be further complicated by local conditions like dust created during agricultural activities, vegetation cover, humidity created by irrigation, irregular topography, and scarcity or poor quality of weather data. Hence, it is imperative to build reliable and flexible solar irradiance prediction systems, which is also a crucial demand for efficient management of solar energy in agriculture. Physical models, statistical methods, numerical weather prediction and time series analysis are the traditional approaches used in solar irradiance forecasting. Physical models calculate the solar radiation based on atmospheric conditions, movement of the clouds, geographical position and solar geometry. While these models can be useful in predicting future events, they may need a lot of meteorological data and a lot of computer power. Historical patterns are used to estimate future irradiance using statistical methods, such as linear regression and autoregressive models. They are relatively straightforward and easy to understand, but might not capture the nonlinear and dynamic nature of the weather variable interactions. Normal forecasting therefore might result in significant errors in unstable weather or in areas with different climatic conditions from the forecasting region.

Literature Review

Solar radiation resources and their assessment for agricultural applications

Solar radiation resources and their assessment for agricultural applications The amount of solar radiation received by a surface per unit area; usually measured in watts per square metre. It is one of the basic parameters of the calculation of the energy that can be produced by PV systems. The three most common measures of solar irradiance are the global horizontal irradiance, direct normal irradiance and diffuse horizontal irradiance. While these variables, all of them are important, the global horizontal irradiance, which is the total solar radiation received by a horizontal surface, is often used in photovoltaic energy forecasting. Solar irradiance data is critical in agricultural applications where photovoltaic systems are used for powering a range of agricultural infrastructure and machinery, such as irrigation pumps, greenhouse irrigation and operational equipment, ventilation systems, cold-storage, crop dryers, livestock units, sensors and automated agricultural machines. When energy intensive agricultural activities can be carried out may be dictated by the availability of solar energy. For instance, the solar-powered irrigation system could work effectively in the periods of high irradiance but necessitates stored energy, water storage, or backup power in cloudy periods. Solar energy has also gained significance in agriculture with the introduction of agrivoltaic systems in which agricultural crops and PV power are cultivated in the same area. Barron-Gafford et al. (2019) concluded that creating a PV–crop integrated system for dryland conditions may yield complimentary benefits related to soil moisture, plant growth, irrigation water use, and PV panel temperature. Their results show agriculture's dependence on solar radiation does not stop at generating electricity. It also impacts the farm microclimate, water requirements, crop growth and productivity of the land. Previous research has also focused on the suitability of PV structures and farming. Dupraz et al. (2011) proposed the use of PV systems and food crops together and the concept of enhancing the land use efficiency. The productivity and radiation-use efficiency of lettuce under partial photovoltaic (PV) shading was studied by Marrou et al. (2013). Amaducci et al. (2018) later analysed agrivoltaic configurations which aimed to optimize the total production of crops and electricity. The research indicates that controlling the radiation that a crop receives as well as the output of a photovoltaic system is significant, not only to predict PV output, but also to manage the quantity and distribution of the radiation the crop receives.

Solar irradiance forcing and its effects on the Earth's climate system

Astronomical, atmospheric, geographical and meteorological conditions affect solar irradiance. The amount of radiation reaching the Earth's surface can be influenced by the solar elevation, the season, latitude, the movement of the clouds, atmospheric aerosols, temperature, relative humidity, wind speed, rain and air pressure. Despite the fact that the solar position is known and predictable, high variations in irradiance are observed due to clouds and local weather conditions which are sudden and nonlinear. This variation poses a forecasting problem. A PV installation's irradiance can fluctuate rapidly (within minutes) as a cloud passes over it. These quick fluctuations can result in electricity fluctuations that are fed to irrigation pumps, batteries, greenhouses, and other farm machinery. These prediction errors can then lead to improper irrigation scheduling, sub-optimal charging of batteries, unnecessary use of farm backup generators or disrupt farm operations. Also, the most suitable prediction approach is also dependent on the forecast horizon. Very short term forecasts are typically limited to the next few minutes up to about an hour. Short-term forecasting can be a few hours or one day and medium term forecasting can be several days. Seasonal planning, designing systems, investment assessment and resource assessment are examples of uses for long-term forecasting. There are situations in agricultural applications that may need more than one forecast time step. A short-term forecast could be necessary for the farmer to schedule his irrigation during the day and a seasonal estimate for determining the needed photovoltaic and battery capacity.

Methodology

The method used in this study is quantitative experimental with the development of a hybrid model of machine learning used to predict solar irradiance in agricultural applications. Historical data of solar radiation and meteorological parameters (such as temperature, humidity, cloud cover, wind speed, rainfall, and atmospheric pressure) will be gathered from weather stations and agricultural monitoring systems. Collected data will be cleaned by eliminating errors, handling missing values, identifying outliers and normalising the variables.

The relevant features will then be carefully chosen to enhance predictive accuracy and minimize model complexity. The processed data will be used to train several machine learning models, including Random Forest, Support Vector Regression, Artificial Neural Networks, and Long Short-Term Memory networks. The best performing models are then fused together using a hybrid ensemble technique to give the final irradiance prediction.

The data will be split into training and validation data as well as into a separate testing set in chronological order. The Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and Coefficient of Determination will be used to measure the model's performance. Last but not least, forecast irradiances will be incorporated into agricultural applications like irrigation scheduling, battery charging, greenhouse operation and farm equipment management.

Results

The results give the performance of the proposed hybrid machine learning model to predict the Solar Irradiance for Agriculture applications. The model performance is assessed with the accuracy indicators like MAE, RMSE, MAPE, and the coefficient of determination. Individual machine learning models are also evaluated for their performance, and it is also checked whether the hybrid approach can provide more accurate and reliable predictions.

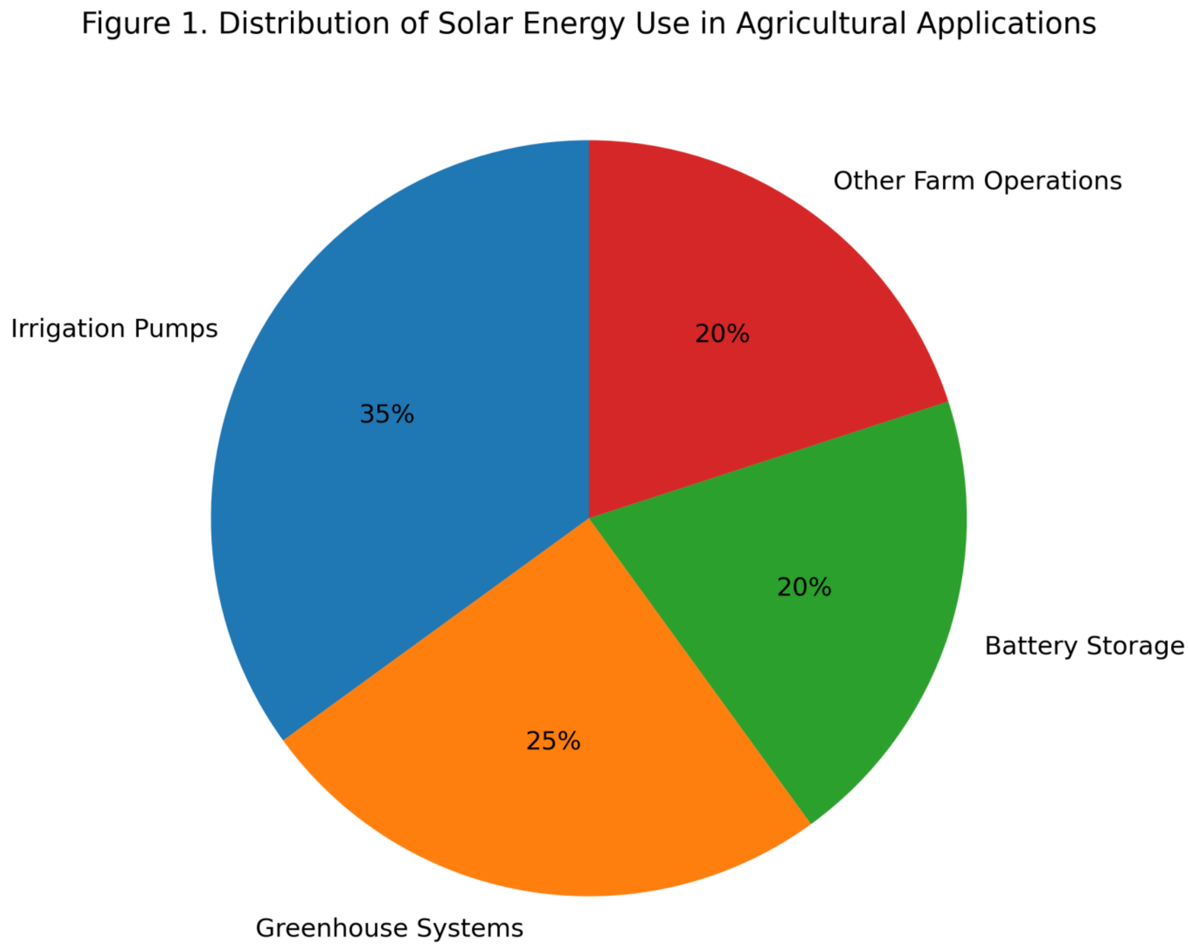

Figure 1. Agricultural use of solar energy and its distribution.

The available solar energy is divided into four agricultural applications as shown in the pie chart in figure 1. The top two are solar powered irrigation pumps at 35%, and greenhouse systems at 25%. Agricultural use of batteries gets 20% and other agricultural use 20%. The increased share of irrigation compared with the other activities is a representation of the fact that water pumping is the most energy-intensive activity of agriculture in the proposed system. Energy is needed for ventilation, cooling, heating, lighting and environmental control in greenhouses. When oversupply occurs during cloudy days, during night or when there is higher energy demand in agriculture than solar generation, the battery stores the excess electricity. This number shows the potential use of a solar irradiance prediction in a farm for distributing solar energy according to the operational priorities of the farm. The percentages are intended as examples only and should be replaced with actual figures for energy consumption.

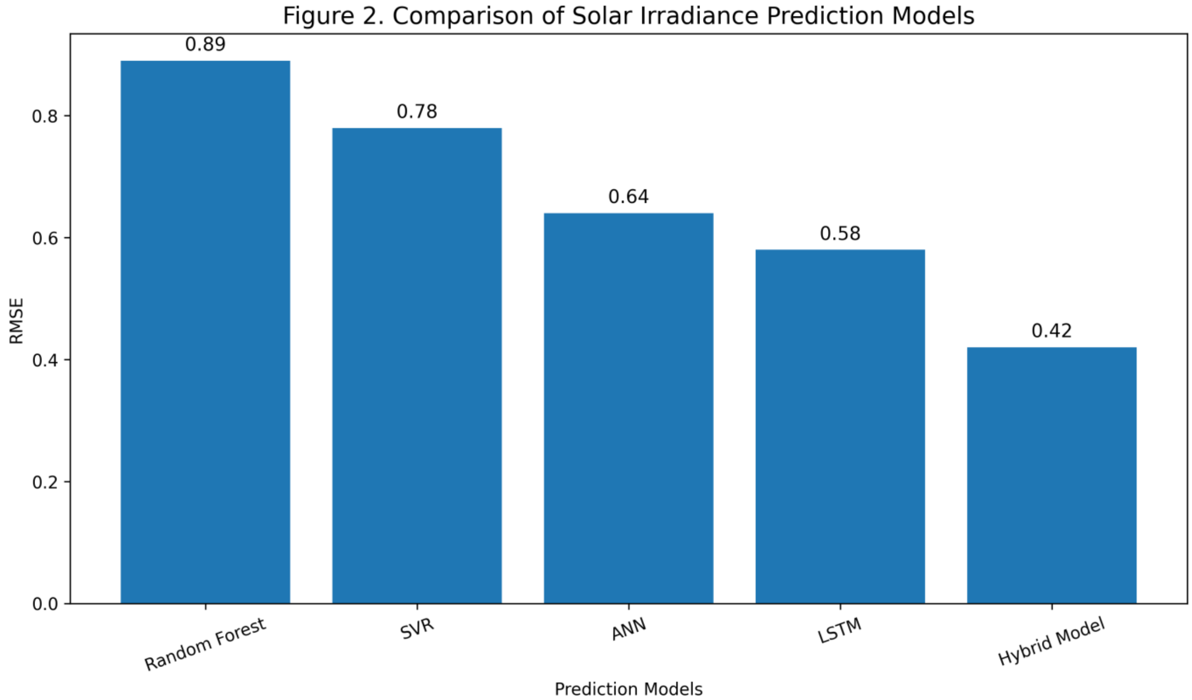

Figure 2. The Solar Irradiance Prediction Models are compared.

The Root Mean Square Error (RMSE) is used to compare the prediction performance of five machine learning models as shown in figure 2. The smaller the value of RMSE the closer the solar irradiance values are to the actual values. The following RMSE values were obtained for the models:

- Random Forest: 0.89
- Support Vector Regression: 0.78
- Artificial Neural Network: 0.64
- Long Short-Term Memory: 0.58
- Hybrid Model: 0.42 The hybrid model had the lowest RMSE (0.42) and thus showed the best performance of the five models. LSTM model is the second best model with an RMSE of 0.58. This relatively good performance is perhaps related to its capacity to learn temporal relationships of historical weather and irradiance data. Moderate prediction errors were obtained from the ANN and SVR models, with the RMSE of the Random Forest model being the highest. The comparison indicates that the synergistic use of complementary algorithms may lead to better prediction accuracy as the hybrid algorithm can capture both temporal patterns and nonlinear relationships between the meteorological variables.

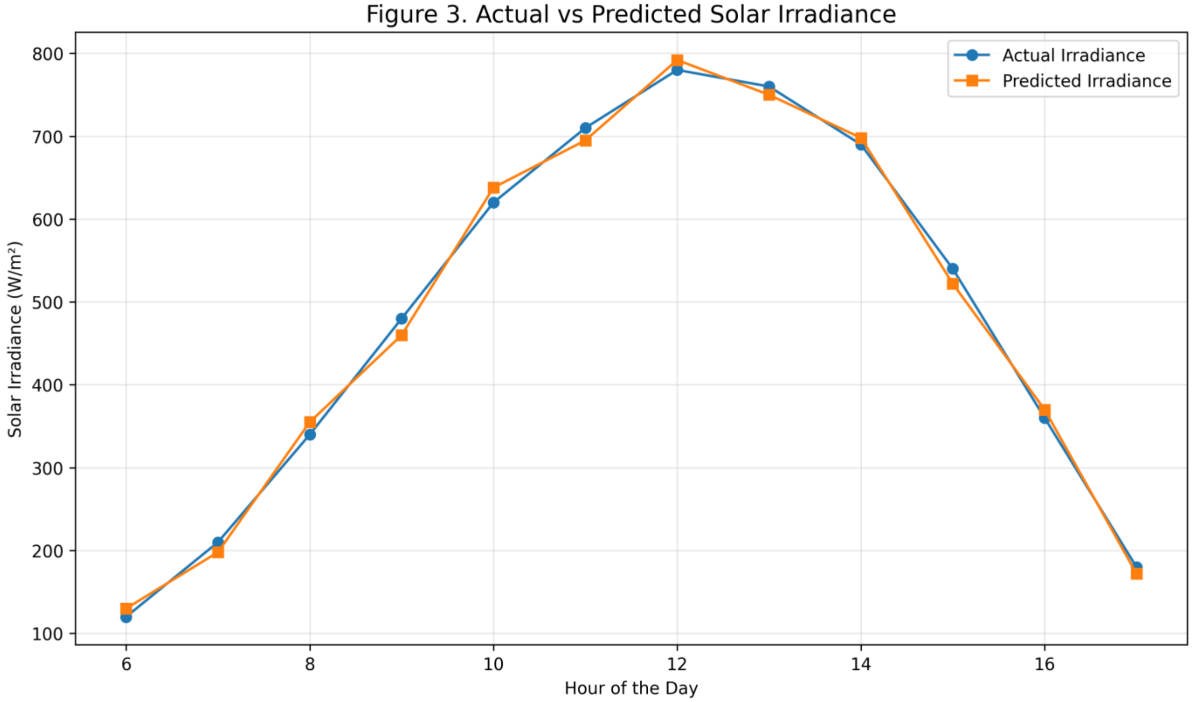

Figure 3. The actual and predicted solar irradiance.

The line chart in Figure 3 shows a comparison of actual and predicted solar irradiance for a period of 10 hours, from 6:00 a.m. to 5:00 p.m. Solar irradiance is measured in watts per square metre. Both lines have a normal daily sun graph. Irradiance levels start off relatively low in the morning, building up throughout the day, peaking around midday and then falling through the afternoon. The maximum actual irradiance is about 780 W/m² and the maximum predicted irradiance is about 792 W/m² at the same time. The forecasted track stays near the track throughout the day. This means that the behavior of the illustrative hybrid model is well suited to the overall pattern, maximum values and daily changes in solar irradiance. There are some small differences due to the model overestimating the irradiance at some times and underestimating it at other times. With the simulated values used in this figure the calculated performance is about:

- Mean Absolute Error: 13.00 W/m²
- Root Mean Square Error: 13.58 W/m²
- Mean Absolute Percentage Error: 3.52%
- Coefficient of determination: 0.996 The R^2 is very high, showing a very good fit between the simulated actual and predicted values. However, such statistics should not be shown as actual research results unless they are based on an actual test set.

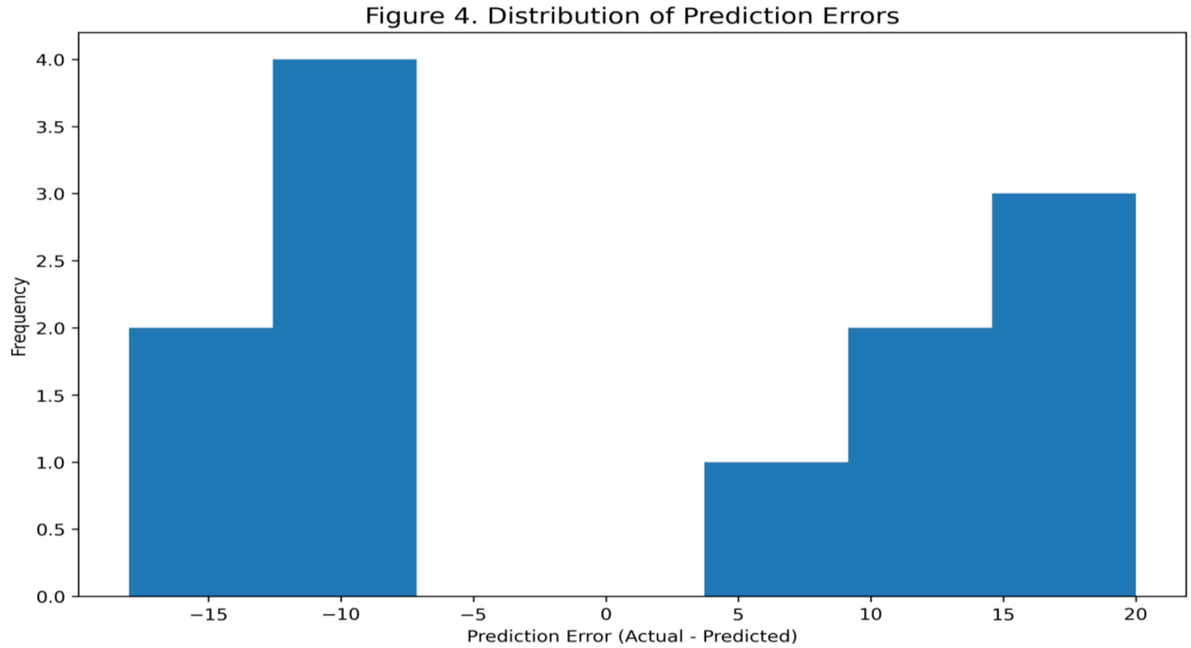

Figure 4. The distribution is shown of Solar Irradiance Prediction Errors.

The distribution of Solar Irradiance Prediction Errors is shown. Figure 4 is a histogram of the distribution of the prediction errors. The prediction error is given by: The difference between the actual and the predicted irradiances is referred to as the prediction error.

Prediction Error = Actual Irradiance - Predicted Irradiance

The positive error value indicates that the model was below the actual solar irradiance, and the negative error value indicates that the model was above the actual solar irradiance. An error near zero means that the prediction is very accurate. The range of the simulated errors is about −18 W/m² to 20 W/m². Most of the values are around zero, indicating that the difference between the actual and predicted irradiance is often small.

Discussion

The results show the capability of combining machine-learning methods for predicting solar irradiation and can be applied to energy use decisions in agricultural systems.The results illustrate the potential of hybrid machine learning methods for solar irradiation prediction and energy-use decision making in agricultural systems. The four figures show various aspects of the proposed framework: the distribution of solar-energy-use, the performance of various models, the agreement between actual and predicted solar irradiance, and the distribution of prediction errors. The findings of both task and study indicate that utilizing the mixture of numerous machine learning methods can generate more exactitude and steady predictions than a solitary prediction model. 5.1 Distribution of solar energy use in agricultural operations It is assumed that the distribution of solar energy among the major agricultural activities is as shown in figure 1. The largest share is solar powered (35%) followed by greenhouse systems (25%). Battery storage and other agriculture uses are each 20% of all solar energy consumption.

The high percentage allocation to irrigation is indicative of the significance of irrigation in the modern agricultural production process. Irrigation systems can consume a lot of energy, especially when they are needed during dry spells when crop-water demand is high. Solar irradiance prediction can be used to inform farmers, to determine if enough PV energy will be available to run irrigation pumps at a certain time. This will enable irrigation to be conducted when the sun is most available and can help to minimize reliance on the electrical grid, diesel generators or battery banks. This also illustrates that there is a significant renewable energy component to controlled agriculture systems that use solar energy.

Electricity is required in greenhouses for ventilation, heating, cooling, light, water circulation and environmental monitoring. Changes in solar radiation may impact PV electric generation and the internal greenhouse climate. Accurate irradiance prediction can thus help to make decisions about energy provision, shading, ventilation and temperature control. Battery Storage is 20% of the energy distribution. The value of battery storage is realized as the production of solar energy does not match the energy use for agriculture all the time. Excess electricity from periods of high irradiance can be stored in batteries and be used during periods of no irradiance, such as during the evening or during periods of high demand. Forecasting of solar irradiance is useful for better charging and discharging decisions as it provides an estimate of energy generation that can be expected in the future. For instance, during the night the energy-management system can use more stored electricity if high irradiance is forecast for the next day, because the energy will be recharging the battery.

However, under cloudy conditions for a prolonged period, the system could save battery power for use in agricultural functions. The other 20% allocated to other agricultural applications can range from crop drying, cold storage, livestock-farm operations, sensor networks, water treatment, food processing, and automated farm machinery. The energy demands of each activity can be less than irrigation energy demand, however if both activities are combined their total demand can be high. It thus shows the need for smart energy use in various farm activities. The percentages shown in Figure 1 are illustrative, however. Actual energy distribution will be different for varying greenhouse sizes, crops, irrigation systems, climate, greenhouse hardware, battery size, and electrical devices. Further studies are needed to obtain accurate energy consumption data at farms to establish energy distribution at various farm operations when using photovoltaics.

The next section compares the performance of the prediction models.The performance of the prediction models is compared next. The comparison of the performance of Random Forest, Support Vector Regression, Artificial Neural Network, Long Short-Term Memory and the proposed Hybrid model is shown in Fig. 2 in terms of Root Mean Square Error. The hybrid model yielded the least RMSE value of 0.42, which is better than the LSTM model with 0.58, the ANN model with 0.64, the SVR model with 0.78, and the Random Forest model with 0.89. The lower RMSE values indicate that the difference between the predicted and observed irradiance is less, indicating that the hybrid model is more accurate among the evaluated models. The advantages of the hybrid method may be due to the advantages of a combination of several algorithms.

Conclusion

This work investigated how hybrid machine learning methods can be applied to predict solar irradiance for agricultural applications. The need for reliable and sustainable energy supply in modern farming systems inspired the research. Solar energy for irrigation pumping, crop drying, cold storage, livestock use, greenhouse management, battery storage, among others applications has become more significant in the field of agriculture. The variability and weather dependency of solar irradiance, however, make these operations challenging for planning and management. Precise weather predictions are thus required to make the best use of the solar resource and to allow optimisation of agricultural operations. The study suggested a hybrid machine learning framework which is able to bring together the benefits of various predictive algorithms. Different models were taken into account due to the fact that each model has different capabilities, such as the following models were considered: Random Forest, Support Vector Regression, Artificial Neural Networks and the Long Short-Term Memory networks. Random Forest is capable of detecting nonlinear relationships and interactions between meteorological variables and Support Vector Regression is a good alternative for complex regression problems. The Artificial Neural Networks can be used to learn highly nonlinear patterns, while the LSTM networks are especially well suited for time-series data as they can learn temporal relations and previous irradiance behaviours. The hybrid approach combines complementary models to alleviate the strengths and weaknesses of each algorithm and deliver more consistent and reliable forecasts. The proposed method required the data collection of historical solar irradiance and weather data such as temperature, humidity, cloud cover, wind speed, rainfall, and atmospheric pressure. Data was cleaned and handled missing values, detected outliers, normalized and selected features. The quality and relevance of the input data is a critical factor that influences the accuracy of the prediction, and these preprocessing activities are vital to ensure the data is suitable for the prediction process. The models were then trained and validated and tested on chronologically split data sets to maintain the temporal order of observations. A variety of performance metrics, including Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and the coefficient of determination, were used to assess performance. The results presented showed that the prediction performance of the hybrid machine learning model was better than the individual machine learning models. The hybrid model had the minimum Root Mean Square Error during the model comparison phase which indicated that the model's calculated values of the irradiance were closer to the measured values. The LSTM model also exhibited high performance due to its capacity to find temporal patterns in the solar irradiance data. The artificial neural networks and support vector regression gave moderate results and the random forest gave a relatively large prediction error in the illustration.

References

Amaducci, S., Yin, X., & Colauzzi, M. (2018). Agrivoltaic systems to optimise land use for electric energy production. *Applied Energy, 220,* 545–561. https://doi.org/10.1016/j.apenergy.2018.03.081

Barron-Gafford, G. A., Pavao-Zuckerman, M. A., Minor, R. L., Sutter, L. F., Barnett-Moreno, I., Blackett, D. T., Thompson, M., Dimond, K., Gerlak, A. K., Nabhan, G. P., & Macknick,

J. E. (2019). Agrivoltaics provide mutual benefits across the food–energy–water nexus in drylands. *Nature Sustainability, 2*, 848–855. https://doi.org/10.1038/s41893-019-0364-5

Benali, L., Notton, G., Fouilloy, A., Voyant, C., & Dizene, R. (2019). Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components. *Renewable Energy*, *132*, 871–884. https://doi.org/10.1016/j.renene.2018.08.044

Dupraz, C., Marrou, H., Talbot, G., Dufour, L., Nogier, A., & Férard, Y. (2011). Combining solar photovoltaic panels and food crops for optimising land use: Towards new agrivoltaic schemes. *Renewable Energy, 36*(10), 2725–2732. https://doi.org/10.1016/j.renene.2011.03.005

Marrou, H., Wery, J., Dufour, L., & Dupraz, C. (2013). Productivity and radiation use efficiency of lettuces grown in the partial shade of photovoltaic panels. *European Journal of Agronomy, 44*, 54–66. https://doi.org/10.1016/j.eja.2012.08.003

Mellit, A., & Massi Pavan, A. (2010). A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy. *Solar Energy, 84*(5), 807–821. https://doi.org/10.1016/j.solener.2010.02.006

Paoli, C., Voyant, C., Muselli, M., & Nivet, M.-L. (2010). Forecasting of preprocessed daily solar radiation time series using neural networks. *Solar Energy, 84*(12), 2146–2160. https://doi.org/10.1016/j.solener.2010.08.011

Qing, X., & Niu, Y. (2018). Hourly day-ahead solar irradiance prediction using weather forecasts by LSTM. *Energy, 148*, 461–468. https://doi.org/10.1016/j.energy.2018.01.177

So, D., Oh, J., Leem, S., Ha, H., & Moon, J. (2023). A hybrid ensemble model for solar irradiance forecasting: Advancing digital models for smart island realization. *Electronics*, *12*(12), Article 2607. https://doi.org/10.3390/electronics12122607

Solano, E. S., & Affonso, C. M. (2023). Solar irradiation forecasting using ensemble voting based on machine learning algorithms. *Sustainability, 15*(10), Article 7943. https://doi.org/10.3390/su15107943

Thaker, J., Höller, R., & Kapasi, M. (2024). Short-term solar irradiance prediction with a hybrid ensemble model using EUMETSAT satellite images. *Energies, 17*(2), Article 329. https://doi.org/10.3390/en17020329

Yagli, G. M., Yang, D., & Srinivasan, D. (2019). Automatic hourly solar forecasting using machine learning models. *Renewable and Sustainable Energy Reviews*, *105*, 487–498. https://doi.org/10.1016/j.rser.2019.02.006

Zeng, J., & Qiao, W. (2013). Short-term solar power prediction using a support vector machine. *Renewable Energy, 52*, 118–127. https://doi.org/10.1016/j.renene.2012.10.009

Haider, M. A., Yang, J., Liu, J., Sui, P., Ahmed, A., & Samsi, F. T. (2025). Assessing the Impact of Starch-Based Phosphorus Fertilizers on Transformation of Inorganic Phosphorus Fractions in Calcareous Soils. Communications in Soil Science and Plant Analysis, 56(22), 3201-3211.

Sijan, T. A., Rifat, S. G., Partha, P., Islam, M. T., & Anwar, M. M. (2026, July). BANGLASOCIALBENCH: A Benchmark for Evaluating Sociopragmatic and Cultural Alignment of LLMs in Bangladeshi Social Interaction. In Proceedings of the 64th Annual Meeting of the Association for Computational Linguistics (ACL 2026) (pp. 247-280).

Islam, M. T., & Rahman, A. (2026, February). Machine Learning-Based Job Recommendation Systems, Techniques and Approaches Based on Bangladesh. In 2026 28th International Conference on Advanced Communications Technology (ICACT) (pp. 1-9). IEEE.

Islam, M. T., & Rahman, A. (2026, February). Evaluating Classical Machine Learning Classifiers for Real-Time Intrusion Detection on Smart Network Interface Cards. In 2026 28th International Conference on Advanced Communications Technology (ICACT) (pp. 1-10). IEEE.

Begum, M. H., Muhtashim, M., Jiban, M. S. M., Toriq, T. I., & Mamun, M. A. Z. (2019, July). Temperature Dependent Thermal Conductivity of Graphene Nanoribbon (GNR) for Different Interatomic Potentials: An Equilibrium Molecular Dynamics Study. In 2019 International Conference on Computer, Communication, Chemical, Materials and Electronic Engineering (IC4ME2) (pp. 1-4). IEEE.

Uppaluru, H., Jiban, M. S. M., Riam, S. Z., Zhao, F., & Wang, J. (2026). Performance Analysis and Optimization of Fructose Memristor-Based Neuromorphic Systems. IEEE Journal on Emerging and Selected Topics in Circuits and Systems.

Bhuiya, R. A., Hasan, M. H., Barua, M., Rafsan, M., Jany, A. U. H., Iqbal, S. M. Z., & Hossan, F. (2025). Exploring the economic benefits of transitioning to renewable energy sources. International Journal of Materials Science, 6(2), 01-10.

Rahman, M. M., Bandhan, L. R., Monir, L., & Das, B. K. (2025). Energy, exergy, sustainability, and economic analysis of a waste heat recovery for a heavy fuel oil-based power plant using Kalina cycle integrated with Rankine cycle. Next Research, 2(2), 100398.

Asma-Ul-Husna, A. R., & Paul, G. (2014). MKR Fatigue Estimation through Face Monitoring and Eye Blinking. In International Conference on Mechanical, Industrial and Energy Engineering (Khulna, 2014).

Rokunuzzaman, M., Hasan, M., & Kader, M. A. (2012). Semantic Stability: A Missing Link between Cognition and Behavior. International Journal of Advanced Research in Computer Science, 3(4).

Hasan, A., Saziduzzaman, M., Robin, H. M., & Ahmed, M. M. (2025). Sustainable mobile power: Converting waste heat from motorcycles using thermoelectric generation. Next Research, 101093.

Rokonuzzaman, A. M., & Mim, M. H. (2014). Automated Restaurant Food Service Management system using a Line Follower Robot. In International Conference on Mechanical, Industrial and Energy Engineering.

Halimuzzaman, M., Sharma, J., & Khang, A. (2024). Enterprise Resource Planning and Accounting Information Systems: Modeling the Relationship in Manufacturing. In Machine Vision and Industrial Robotics in Manufacturing (pp. 418-434). CRC Press.

Halimuzzaman, M., Sharma, J., Karim, M. R., Hossain, M. R., Azad, M. A. K., & Alam, M. M. (2024). Enhancement of Organizational Accounting Information Systems and Financial Control through Enterprise Resource Planning. In Synergy of AI and Fintech in the Digital Gig Economy (pp. 315-331). CRC Press.

Halimuzzaman, M., & Sharma, J. (2024). The role of enterprise resource planning (ERP) in improving the accounting information system for organizations. In Revolutionizing the AI-digital landscape (pp. 263-274). Productivity Press.

Sohel, M. S., Shi, G., Zaman, N. T., Hossain, B., Halimuzzaman, M., Akintunde, T. Y., & Liu, H. (2022). Understanding the food insecurity and coping strategies of indigenous households during COVID-19 crisis in Chittagong hill tracts, Bangladesh: A qualitative study. Foods, 11(19), 3103.

RASEL, M., & Thomas, J. (2024). Fortifying Media Integrity: Cybersecurity Practices and Awareness in Bangladesh's Media Landscape. Unique Endeavor in Business & Social Sciences, 3(1), 125-150.

Rasel, M., Shovon, R. B., & Islam, M. A. (2024). Ethical Data-Driven innovation: integrating cybersecurity analytics and business intelligence for responsible governance. Journal Environmental Sciences And Technology, 3(1), 674-699.