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EVALUATION OF SOLAR POWER FORECASTING USING DEEP LEARNING: A CASE STUDY IN İZMIR, TÜRKIYE

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Abstract. Countries' ambition to achieve independence from foreign energy sources, coupled with the need for future energy production forecasts based on reliable information, not only enables the safe operation of electrical networks, but also enhances the economic efficiency of these systems designed to utilize energy resources. Therefore, the prediction of energy production from renewable energy sources has emerged as a highly researched topic of considerable interest. Deep learning algorithms, such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and One-Dimensional Convolutional Neural Networks (1D-CNN), have been demonstrated efficacy in diverse forecasting tasks, including economic time series and computer vision. However, their application to energy production forecasting from renewable energy plants has only recently seen a significant surge. This study examines LSTM, GRU, and 1D-CNN based time-series forecasting experiments for predicting solar power generation in İzmir, the third largest city in Türkiye. The predictions have undergone comparative analysis using various statistical calculations, and the results are depicted visually through graphs. The primary objective of these computations is to deliver an optimized academic outcome, potentially necessary for the development of new solar energy fields. This could significantly contribute to the amplified usage of solar energy, a sustainable and cleaner energy source, in Türkiye.

Keywords: Deep Learning, Photovoltaic Solar Energy Systems, Machine Learning, Renewable Energy.
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1 Introduction

Established in 1993 within the scope of the Technology Cooperation Program by the International Energy Agency (IEA), the Photovoltaic Power Systems Program includes Türkiye among its members. The mission of the IEA is to facilitate the role of photovoltaic solar energy as a fundamental component in the transition to sustainable energy systems through the development of international collaborative efforts IEA (2023). In this context, Photovoltaic Solar Energy is recognized globally as a significant potential source of clean energy IEA (2023). Annual, seasonal, daily, or hourly variations in solar radiation create an immeasurable uncertainty that jeopardizes the reliability and stability of solar energy systems, especially when considering large-scale renewable energy integration. This complicates the estimation of the amount of energy to be obtained from renewable energy sources compared with conventional energy sources. This complexity is cited as the reason why projects have increased installation costs and slow adoption globally. Therefore, it is incumbent upon industry professionals to develop appropriate digital designs, analysis methods, and estimation approaches tailored to each project. Electricity is produced from solar energy in two ways. One is with the help of photovoltaic (PV) cells that use the suns rays directly; the other is with the help of Concentrated Solar Energy (CSE) systems, which work in the form of indirectly rotating the generator tribunes of the steam obtained with the heat and temperature transfer fluids. Plataforma Solar de Almería in Spain is the best example of CSE systems. The ACUREX parabolic panel, under consideration here, has been examined through numerous studies Masero et al. (2023), and Ruiz-Moreno et al. (2021).

PV systems that can be installed on the roofs of small, medium, and large-scale factories and workplaces reduce electricity costs for the institutions where they are installed. For this purpose, especially in the industry sector, the use of grid-connected roof-integrated PV systems has been increasing over the last decade. In this way, both damages to the environment are minimized and the energy cost is reduced. Melikoğlu demonstrated that the use of solar energy in electricity generation is the most environmentally friendly option, with an annual greenhouse gas emission estimate of 0.17 million tons CO_2 equivalent Melikoğlu (2013).

Upon examining the studies, it is observed that the prediction of photovoltaic (PV) power production is typically conducted in various methods. Firstly, PV power production forecasts are made by estimating the amount of solar radiation, which has been proven to be directly proportional to the production amount Şen (2004). Secondly, the prediction is directly made using the actual amount of photovoltaic power production.

In their study of PV power forecasting via solar irradiance, Toğrul and Toğrul employed a variety of regression analyses to predict the monthly average solar radiation for six provinces in Türkiye: Antalya, İzmir, Ankara, Aydın (Yenihisar), Adana (Yumurtalık) and Elazığ. They aimed to develop some statistical relations of the latitude of cities, the climate of the site, and the season of the year Toğrul & Toğrul (2002). Çağlayan et al., emphasized that Türkiye s solar energy potential is very high and the use of grid-connected PV systems should be increased, used the RETScreen model to estimate energy production with 22 years of data for 135 locations across Türkiye Çağlayan et al. (2003). Demolli et al. used kNN, SVM, and LASSO regression algorithms to predict the power values to be received from solar panels for the next year the insolation intensity and temperature values recorded between 2013 and 2017 in the Niğde region Demolli et al. (2003). According to Jebli et al., solar radiation, temperature, wind conditions, wind speed, pressure, and humidity recorded between 2016 and 2018 in the Er-Rashidia province of Morocco, which has a semi-desert climate, were used as meteorological data. When the LR, RF, SVR, and MLP models are compared, the most effective performance in real-time and short-term PV power forecasting was shown by ANN Jebli et al. (2021).

On the other hand, for PV power forecasting by actual PV output, Kim et al. trained their two-step models with LR, SVR, CART, kNN, AdaBoost, RFR, and ANN algorithms using Yeongam Solar Power Generation data, which is publicly available in South Korea, and found that RFR was the best performing algorithm in PV power prediction for one day ahead Kim et al. (2019). Chaouachi et al., for the $20kW$ PV system at Tokyo University of Agriculture and Technology (TUAT), four different ANNs have estimated PV power generation for the next $24h$ Chaouachi et al. (2010). Huang et al. obtained real-time PV power data collected from PV panels installed on the roofs of Tong Feng secondary school in 2007 and Bai He library in 2009 in Taiwan, using the Evolution Programming Algorithm (EPA), with the independent variables of weather, solar radiation, and panel temperature Huang et al. (2013). Essam et al. used 43 different meteorological parameters for a year and the PV module power output in Cocoa, Florida, which was publicly shared by the National Renewable Energy Laboratory of the United States of America, as a dataset. When the prediction scores of the ANN, RF, DT, xGBoost, and LSTM models were compared, the study emphasized that the ANN model had the best performance Essam et al. (2022). Raj et al. created Ensemble-based models using data obtained from the Tenaga Suria Brunei (TSB) PV energy field located in Der es Salaam, Brunei, using Gradient Boosting Machine (GBM) and RF. They compared their new models with SVM and kNN performances. It was stated that Ensemble algorithms based on Desicion Tree and SVM had the best performance Raj et al. (2023). There are many studies that use ML and some statistical applications for forecasting solar power.

Deep learning has become a prediction mechanism that is increasingly used in different fields such as electricity load Tokgöz & Ünal (2018), energy consumption Bişkin & Çifci (2021), and energy policies of developing countries such as Türkiye Kural & Ara Aksoy (2020). Tokgöz and Ünal estimated the amount of electricity load in Türkiye by making time series forecasting with different RNN, LSTM, and GRU models that were created in the study, and stated that the best performance was achieved with the tree-layer GRU model Tokgöz & Ünal (2018). Nam et al. created a deep learning-based prediction model using MLR, SARIMA, GRU, LSTM, and DNN models. Electricity demand and renewable energy production through wind power and photovoltaic energy were used to find the best renewable energy scenarios to guide sustainable energy policy for Korea s Jeju island Nam et al. (2020). Kural and Ara aimed to reveal the optimal Feed-in Tariff (FIT) design for photovoltaic (PV) investments in Türkiye, which is the long-term agreement between governments and firms investing in solar energy, where governments guarantee to purchase the energy produced by firms. The authors mentioned that the solar energy market has a young and highly dynamic structure in Türkiye and is thought to be easily adaptable to innovations Kural & Ara Aksoy (2020). Gao et al. used a hybrid method called CEEMDAN-CNN-LSTM to forecast solar irradiance with greater robustness and accuracy Gao et al. (2020). Bişkin and Çifci focused on forecasting Türkiye s electrical energy consumption and for this purpose, LSTM and GRU models were used for time series data. The results of the study showed that GRU is better than LSTM for one-hour and three-hour ahead forecasting Bişkin & Çifci (2021). Neshat et al. proposed a new hybrid deep learning model to predict solar radiation one hour ahead based on real meteorological and Shortwave Radiation (SRAD1) data, which comprises GRU, LSTM, and BiLSTM Neshat et al. (2023).

Although it has become easier to access articles and theses on the subject being researched with the development of technology, the intensity of DL studies, the number of which is increasing day by day, has caused researchers to want to discover the similarities and deficiencies in the field. There are many review studies conducted for this purpose. In a survey by Alcaniz et al., it is mentioned that some DL methods such as LSTM intrinsically consider previous PV output values intrinsically Alcaniz et al. (2023). In Ajith et al. (2023), it is mentioned that both LSTM and GRU models have designs that are successful in solving the vanishing gradient problem in RNN, and can easily remember long-term dependencies in data such as time series. Emphasizing that the management and planning of solar energy resources such as solar power plants can be made more efficient with effective forecasts, Yuzer and Bozkurt stated that CNN has proven success in predicting solar radiation Yüzer & Bozkurt (2023). In particular, studies conducted for Türkiye solar energy forecasts have mostly created forecasting mechanisms with statistical or machine learning methods using meteorological data sets such as solar radiation amount. This study aims to contribute to research using a different approach by using both deep learning methods and a real solar energy production dataset that has never been used before.

Deep learning is an active area of research with various applications in renewable energy forecasting, mostly in solar energy, wind energy, and hybrid energy forecasting. Nevertheless, its application in the field of solar energy forecasting has notably advanced over the recent years. The aim of all these computations is summarized as fallows: the tendency to use wind and solar energy as renewable energy sources in Türkiye in recent years, and the concrete steps taken to reduce the use of nuclear power plants will lead to a further reduction in the amount of greenhouse gas emissions per unit of electricity production in the coming years Bakay & Ağbulut (2021). To contribute to the studies summarized above with a new dataset, this article presents the development of fifty different DL models, their comparative comparison with four different metrics (MAE, RMSE, R^2 and MAPE) and the resulting analysis. Furthermore, some hydrid models are proposed that can be used for prediction tasks regarding the harvested energy required for short-term prediction of photovoltaic power generation, taking into account data availability and reliability issues. The purpose of this study is to improve the integration of residential and industrial photovoltaic systems by strengthening various intermediate elements in the development of photovoltaic power generation estimation models in order to provide decision support based on the results obtained.

The contributions of this study are summarized as follows:

- First, this study provides a comprehensive comparison of three different deep learning models, namely, Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and One Dimension Convolution Neural Networks (1D-CNN), for solar energy forecasting in İzmir, Türkiye.
- In addition to these deep learning models, some hybrid models such as 1D-CNN-LSTM and 1D-CNN-GRU are introduced based on univariate time-series forecasting. The performance of these models is also compared and analyzed with other forecasting models.
- Finally, this study discusses the predictions made by the analyzed prediction models on the time series data set, and evaluates how these can be used for new decisions to be made in different systems that can be developed for the effective management and integration of PV energy production.

The rest of this paper is organized as follows: In Section 2, the methodology section is outlined, including the location where the study was conducted, how the data was collected, the data preparation processes, the Deep Neural Networks used in the article, the metrics used, and the predictions obtained. In Section 3, the obtained experimental results are discussed. Finally, in Section 4, the main findings of this article are summarized. The abbreviations and symbols used in this study can be found in Table 1.

Table 1: Acronyms Table

LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units
CNN	Convolution Neural Network
1D-CNN	One dimension Convolution Neural Network
MSE	Mean Squared Error
R^2	R-squared
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
DL	Deep Learning
ML	Machine Learning
IEA	International Energy Agency
PV	Photovoltaic
CSE	Concentrated Solar Energy
kNN	k-Nearest Neighbor
SVM	Support Vector Machine
RNN	Recurrent Neural Network
MAPE	Mean Absolute
SPP	Solar Power Panels
AC/DC	Alternative Current/ Direct Current
EDA	Exploratory Data Analysis
ReLU	Rectified Linear Unit
DNN	Deep Neural Network

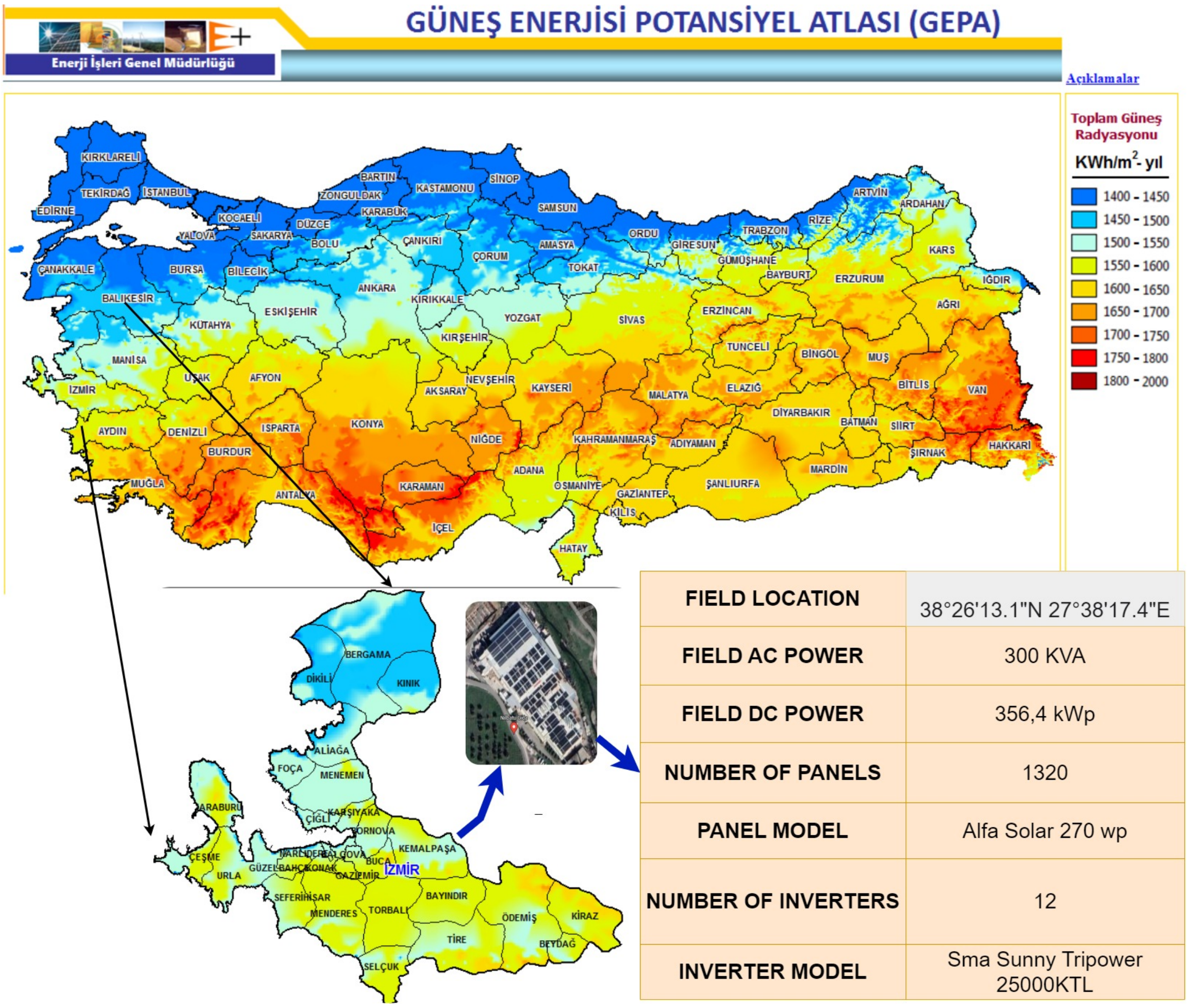
2 Methodology

The methodology developed in this study is categorized into five sections: (2.1) Location, which involves the geographical location and climatic characteristics of İzmir. (2.2) Time-series Data, which involves data collection, data preprocessing, and data visualizing. (2.3) Models, which are the proposed models. (2.4) Metrics, which are utilized for compering models by. (2.5) Forecasting, after the PV power output time series data is split into training, validation, and test sets, each of the proposed models are developed and the models performances are determined using various error metrics.

2.1 Location

The geographical location of Türkiye can meet most of the annual energy demand for electricity generation from solar energy. According to the Solar Energy Potential Atlas (GEPA) of Türkiye GEPA (2023), prepared by the Ministry of Energy and Natural Resources, the average annual total sunshine duration is $2,741h$ and the average annual total radiation value is calculated as $1,527.46kWh/m^2$ ETKB (2023). Figure 1 shows the solar energy map of Türkiye.

This study focuses on forecasting solar power production in İzmir, Türkiye. Due to the geographical location of İzmir, similar climatic characteristics are seen almost everywhere within the borders of the province. It is in the middle latitude zone and is open to marine influences, as shown in Figure 1.



FIELD LOCATION	38°26'13.1"N 27°38'17.4"E
FIELD AC POWER	300 KVA
FIELD DC POWER	356,4 kWp
NUMBER OF PANELS	1320
PANEL MODEL	Alfa Solar 270 wp
NUMBER OF INVERTERS	12
INVERTER MODEL	Sma Sunny Tripower 25000KTL

Figure 1: İzmir's Solar Energy Potential Atlas GEPA (2023)

The Mediterranean climate character is dominant in the city, which is located in the coastal Aegean. Summers are hot and dry, winters are warm and rainy, and spring months are transitional. Figure 2 shows İzmir average monthly temperature and rainfall.

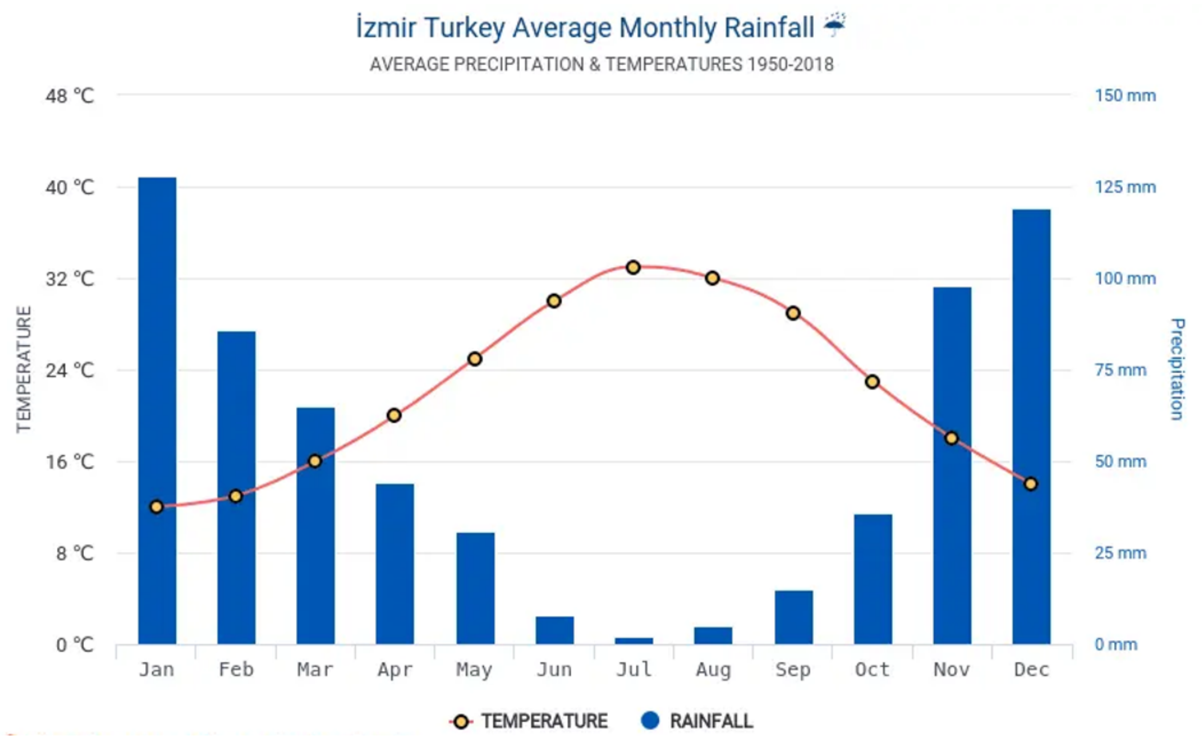


Figure 2: İzmir's average monthly temperature and rainfall Hikersbay (2023)

As illustrated in Figure 1, the province of İzmir possesses considerable potential for sunbathing. While the average duration of sunshine in İzmir is $8.0h$, the average number of clear days reaches up to 27 days in July and August. However, this figure decreases to approximately 5 days in the months of December, January, and February. While no off days are observed during the summer, approximately six off days are noted in December and January.

2.2 Time Series Data

A time series is a collection of values with evenly spaced time intervals that are analyzed to determine the underlying pattern for making predictions. Time series data may vary because of time-based dependency and seasonality trends. Time series, which are called univariate or multivariate depending on time, are a dataset used to create forecast models related to many fields of finance, medicine, and meteorology. Univariate time series forecasting, which will also be used in this study, is the process of predicting the future values of a single variable using past values.

Univariate time series data defined as x_t consists of k samples and is forecasted for a time horizon T. The correlation between past and future samples x_{k+T} can be used to define the parametric function, as shown in Eq. (1):

$$x_{k+T} = f(x_k) + e_k \tag{1}$$

where x_k is a column vector consisting of one frame of T previous values of a particular time series, and e_k is the error during the forecast period.

Time series have several key features such as trend, seasonality, and noise. If the raw data is examined in general in Figure 3; it has been observed that features of time series data are easily observed.

After plotting the time series graph, the following three features can be seen in Figure 3

1. *Trend:* There is an increase in values in summer and a decrease in values in winter.

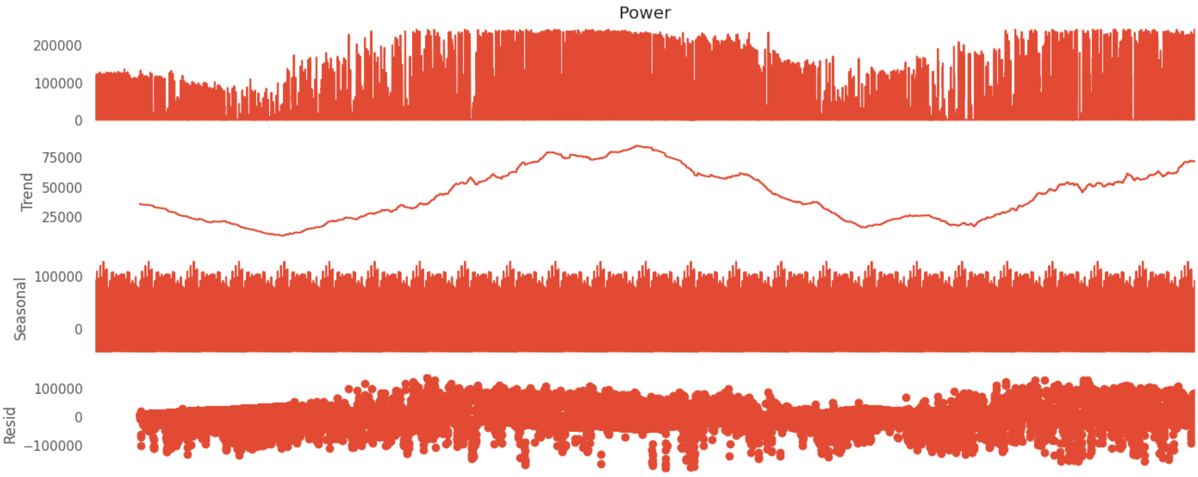


Figure 3: Power production trends, seasonality and residual

2. *Seasonality:* High or low values are repeated in daily, weekly, monthly, or annual periods because of different sunshine durations at different times of the year.

3. *Noise:* Especially on rainy or cloudy days, the production amount creates a value far away from other values in the dataset.

2.2.1 Data Collection

Input data, which is an important factor in determining the performance of the prediction model to be created, has a direct effect on prediction accuracy. This demonstrates that the data employed in the study will affect the originality and economy of the research. Many studies have used open-source data stores for PV power generation forecasting. Examples of these studies can be given as Kim et al. (2019), Raj et al. (2023), Gensler et al. (2016). The fact that the data are recorded at certain time intervals with the help of appropriate sensors and smart systems is a factor that increases the originality of the study. Therefore, many studies have used their own PV power data because of their originality. Huang et al. (2013), Essam et al. (2022), Yılmaz & Şahin (2023), Suri et al. (2008), and Marion et al. (2014) are examples of some of these articles.

The most accurate and high-quality data for the estimation of the amount of solar energy production, which varies according to the seasons, months, and even the hours of the day; should be collected from inverters, which are electrical power converters that convert direct current (DC) from PV panels to alternating current (AC), located on an installed solar energy system.

In this study, data from the Nilbatu facility in Kemalpaşa, İzmir whose features and location are shown in Figure 1, were used. The solar energy system, whose installation was completed in 2021, is a grid-connected roof integrated system. As a univariate time series dataset, 18816 inverter PV power kW values recorded hourly between 22.08.2021 (00:00) and 14.10.2023 (23:00) were used.

2.2.2 Data Visualizing

The data were visualized and evaluated with the help of Matplotlib (2023), a drawing library that allows visualization of numerical mathematical calculations as 2D or 3D visual outputs using the Python programing language for data science studies.

Although the durability of the materials used in solar energy systems has increased with the development of technology, the efficiency of the systems installed in open air conditions and operating continuously starts to decrease by 0.8% after the first year Akbarzadeh & Wadowski

(1996). Many reasons can be given, including the panel surfaces that become polluted over time and begin to collect less solar radiation, the annual wear of the used panel and inverter, and even the heating of the inverter depending on the daily working amount and the decrease in the efficiency in the AC/DC conversion Sornek et al. (2022). The observed decrease can be comprehensively understood by analyzing the annual production amount, commencing from the installation date and onwards as depicted in Figure 4.

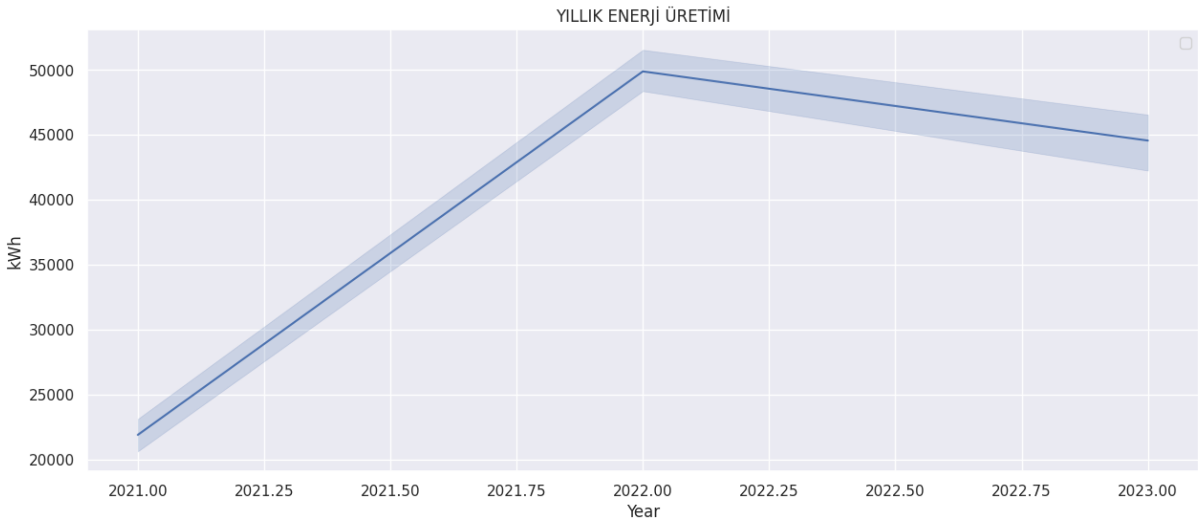


Figure 4: Annual Production Amount

When the annual production amount is examined, it is seen that after the facility, which was established in 2021, reached maximum efficiency in the first year, its efficiency decreased as of 2022, albeit with a low acceleration. Upon examining the production volumes of the facility depicted in Figure 5, it is evident that these values correlate appropriately with the amount of solar radiation, differentiated by the months of the year.

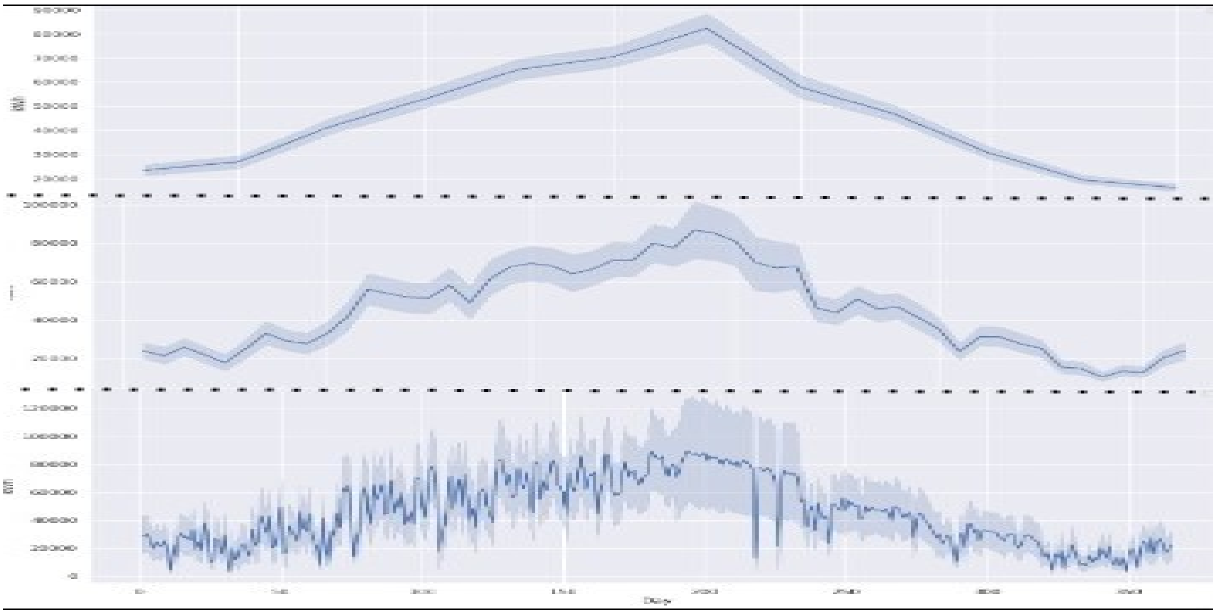


Figure 5: Daily, Weekly, and Monthly Production Amount

The analysis reveals that in a Mediterranean climate, such as that found in İzmir, the distribution of energy production by month peaks in July, correlating to an increase in duration of sunshine starting from February. Upon examination, it can be observed that Figure 5 closely resembles Figure 2. The decrease experienced between July and August is due to both the August rains experienced in the city every year and the fact that the panels do not continue production when they reach very high temperatures Bigorajski & Chwieduk (2018). The same seasonality can be observed equivalently in both the weekly and daily energy production graphs, as depicted in Figure 5.

When the daily energy production graph within a year is analyzed, many fluctuations are observed. Considering the energy production for a day, it can be seen that daily PV output reaches peak values at noon, as shown in Figure 6.

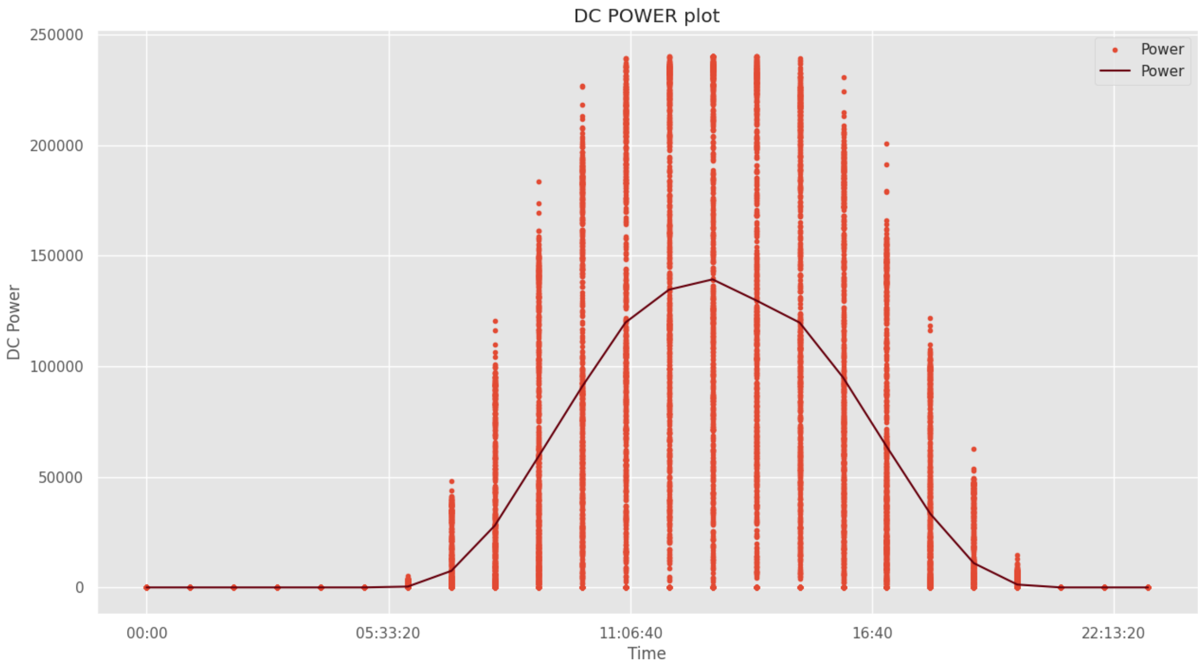


Figure 6: Daily Mean Power Production

Despite the fluctuations in Direct Current (DC) Power that correspond with the varying sunrise and sunset times across different seasons, it tends to achieve peak levels during the afternoon. Typically, production commences around 05:33 and terminates post sundown.

2.2.3 Data Preprocessing

In general, the selection of raw data collected as input can cause estimation errors that increase time delay, cost, and computation. With preprocessing methods, the data should be made available so that it can be used in the next stages. The performance and quality of the information extracted by data mining are not only dependent on the design and performance of the model. Negative factors such as noise, missing values, inconsistent and redundant data, and numerous samples and features greatly affect the quality of datasets used for learning and knowledge extraction Garcia et al. (2016).

In this study, data processing and visualization were conducted using several libraries written in the Python programming language. These libraries included TensorFlow (2023), Pandas (2023), and Keras (2023). Additionally, the Matplotlib (2023) was utilized for graphical representations.

Prior to the development of a variety of deep learning and hybrid models, it was necessary to preprocess the dataset to enhance the performance of the proposed models. Missing values were cleaned and replaced, outliers were identified and the dataset was denoised, and the necessary exploratory data analyses (EDA) were performed. Because the PV production amount shows hourly, daily and annual seasonality, data set normalization was performed to be between -1

and 1. The univariate time series with input (X) and corresponding output (Y) variables were reconstructed with a sliding window size of 8. That is, the model to be created will attempt to predict the next hour by using 8 consecutive hours of data at each step. Considering the time-dependent change of the time series to be used after standardization is made on the converted new dataset, the dataset was divided into three subsets: the first 70% as the training set, the next 15% as the validation set, and the last 15% as the test set.

2.3 Models

Deep learning represents a method within the sphere of machine learning that utilizes multi-layer neural network architectures. The first scientific research involving the concept of deep learning was conducted by Ivakhnenko & Lapa (1965). Although the concept of deep learning emerged in the 1960s, the lack of sufficient data and the necessary computational power to train deep architectures at that time constituted a significant obstacle to the development of the concept of deep learning. Today, due to the rapid advancement in digitalization, a significant volume of data is now accessible. Consequently, the essential infrastructure for deep learning is increasingly available, given that the computation of this data has become less complex. Its application has significantly increased in usage in recent researches. Many areas such as natural language processing, translation, computer vision, and time series estimation can be given as examples of areas where deep learning is used. RNN cells are shown in Figure 7(a).

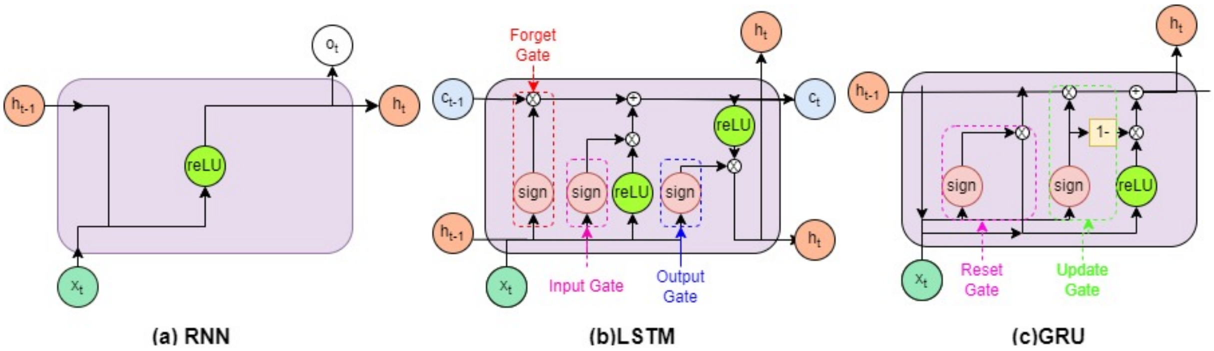


Figure 7: (a) RNN, (b) LSTM, and (c) GRU cells

2.3.1 Long Short-Term Memory Networks

A Recurrent Neural Network(RNN) is a specialized paradigm of neural networks, characterized by single or multiple feedback loops, offering either local or global scope. The application of feedback empowers the Recurrent Neural Network (RNN) to acquire state representations, which establishes its appropriateness for nonlinear prediction and modeling Haykin (1999). Long Short-Term Memory (LSTM), a unique variant of Recurrent Neural Networks (RNN), was first proposed by Hochreiter & Schmidhuber (1997). LSTM networks possess the capability to learn both long-term and short-term dependencies within a dataset. LSTMs are structurally similar to the chain of repeating units identified as cells. The introduction of gate mechanisms into the system strategically determines the data transferred to the cell, the proportion utilized in output calculation, and the portion to be deleted. This method effectively addresses the issue of vanishing and exploding gradients, while ensuring information is transferred with precision. The system is comprised of three gates: the forget gate, which determines the quantity of past information to be incorporated into new data; the input gate, which manages the addition of information into the cell memory; and the output gate, which controls the utilization of information stored in the memory for output computation. This method can be leveraged for the classification, processing, and prediction of data based on time series. The LSTM network maintains long-range dependencies, which are useful for making predictions at both current and future time steps. LSTM cells are shown in Figure 7(b).

2.3.2 Gated Recurrent Units

Gated Recurrent Units(GRU) is also a special case of RNN like LSTM, which was introduced by Cho et al. (2014). Unlike LSTM, GRU combines the input and forget gates in LSTM into a single update gate and adds a reset gate. In other words, GRU is a simplified version of LSTM, is less complex than standard LSTM models, and can perform better than LSTM in various subjects. GRU cells are shown in Figure 7(c).

2.3.3 One Dimension Convolutional Neural Networks

Originally designed for modeling 2D image data, CNNs can now be used for prediction, solving time series prediction problems by applying 1D convolutions to the time series to learn more patterns from the sequence. A 1D-CNN model consists of a convolutional layer that processes time series data. If the input data are very long, a second convolutional layer follows. The architecture of the 1D-CNN model developed in this research, with a kernel size of 2 and two dense layers, is illustrated in Figure 8.

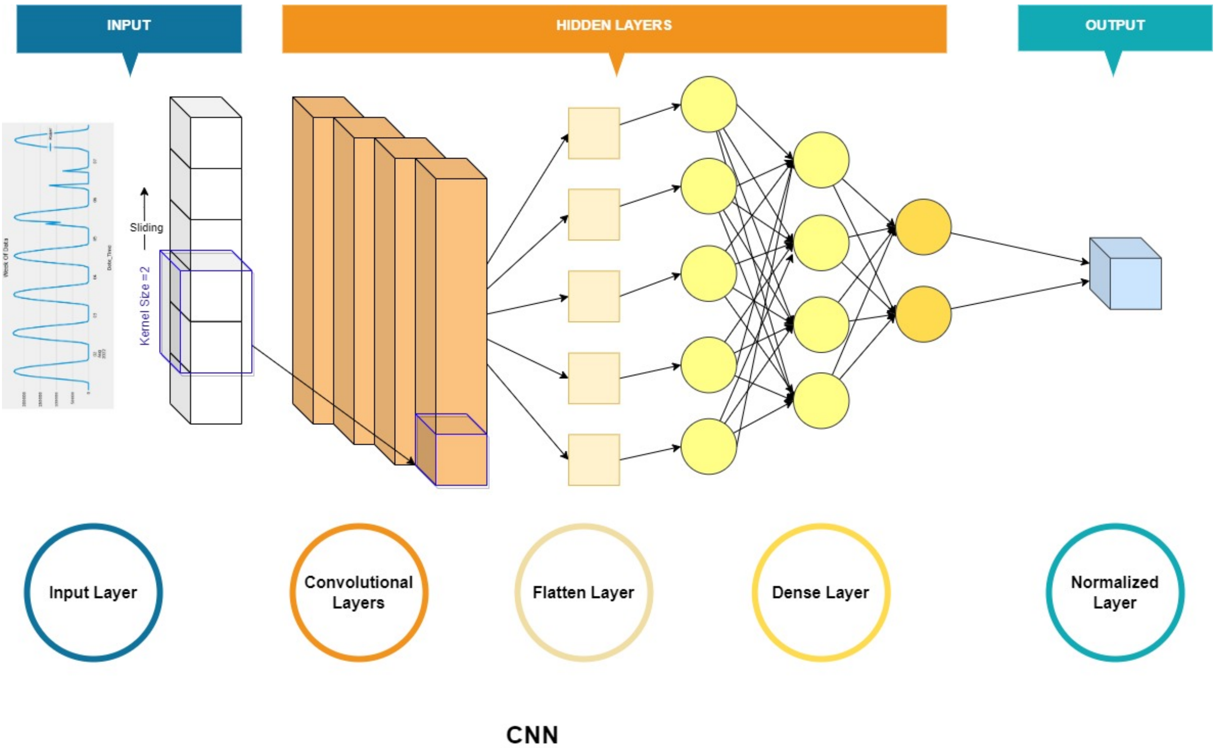


Figure 8: 1D-CNN Architecture

2.4 Metrics

After the evaluations, it is important to find the insights of the selected model, draw conclusions, and determine the predictive performance of the results. For this purpose, Mean Absolute Error (MAE), R-squared (R^2), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) statistical calculations, which calculate the error rates between real values and predicted values, were used. Each of these metrics provides different information about the type of error performed.

Thus, the performance metrics equations are given as follows in Eq.(2), Eq.(3), Eq.(4) and Eq.(5):

$$MSE = \frac{1}{n}\sum_{i=0}^{n}(y_i - \widehat{y}_i)^2 \tag{2}$$

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(y_i - \widehat{y}_i)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=0}^{n}|y_i - \widehat{y}_i| \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=0}^{n}(y_i - \widehat{y}_i)^2}{\sum_{i=0}^{n}(y_i - \overline{y}_i)^2} \tag{5}$$

Let a vector y be the future values of the sequence x such that $y = \widetilde{x} = [x_T, \ldots, x_{T+k}]$. Then, y_i represent actual value of y, $\widehat{y}_i$ represent predicted value of y and $\overline{y}_i$ represent mean value of y respectively.

Various metrics are utilized to decide which model performs better and to measure the reliability of the predictions made. The following can be said about the metrics used in the study. The R-squared metric measures the correlation between the values predicted by the model and the actual values encountered with the test set. The consistency of the prediction is directly proportional to the closeness of the resulting measurement to 1.0. It can also be said that it shows the percentage of the real data set that can be found with estimated values. The mean absolute error (MAE) is calculated as the average of the differences between the actual and predicted values in the test set.The superiority of the estimate is directly proportional to the proximity of the measurement to zero. Mean squared error (MSE) is a calculation similar to mean absolute error but takes the average of the square of the difference between the actual and predicted values. Therefore, large forecast deviations are more noticeable than small deviations. The root mean square error is basically obtained by taking the square root of the measurement, which MSE enlarges by squaring the errors.

2.5 Forecasting

In this study, the Colab (Collaborative) Platform offered by Google was used for calculations and visualizations, and the GPU provided by the platform was also used to accelerate model training. Figure 9 summarizes the applied computational framework of this study.

Following the data preparation stages, the training and validation sets of the solar energy production dataset, which was divided into three groups as training, validation, and test sets, were used to train the models to be created. To obtain a model that recognizes dependencies in univariate time series, multilayer model structures with a hierarchical structure consisting of an input layer, an output layer, and multiple hidden layers were created. In this formation, fifty different models were created by blending one to five LSTM/GRU/1D-CNN layers. Table 2 shows the hyperparameters configured in the network models created for time series forecasting using Keras (2023). All models were built using different LSTM/GRU/1D-CNN layers consisting of 4, 8, 16, 32, 64, 128, and 256 neurons.

To overcome the problem of the vanishing gradient and overfitting, the Dropout layer with a coefficient of 0.2, Flatten and Dense layers have been added. The Rectified Linear Unit (ReLU) function, which is used in hidden layers, was used as the activation function. ReLU is a piecewise

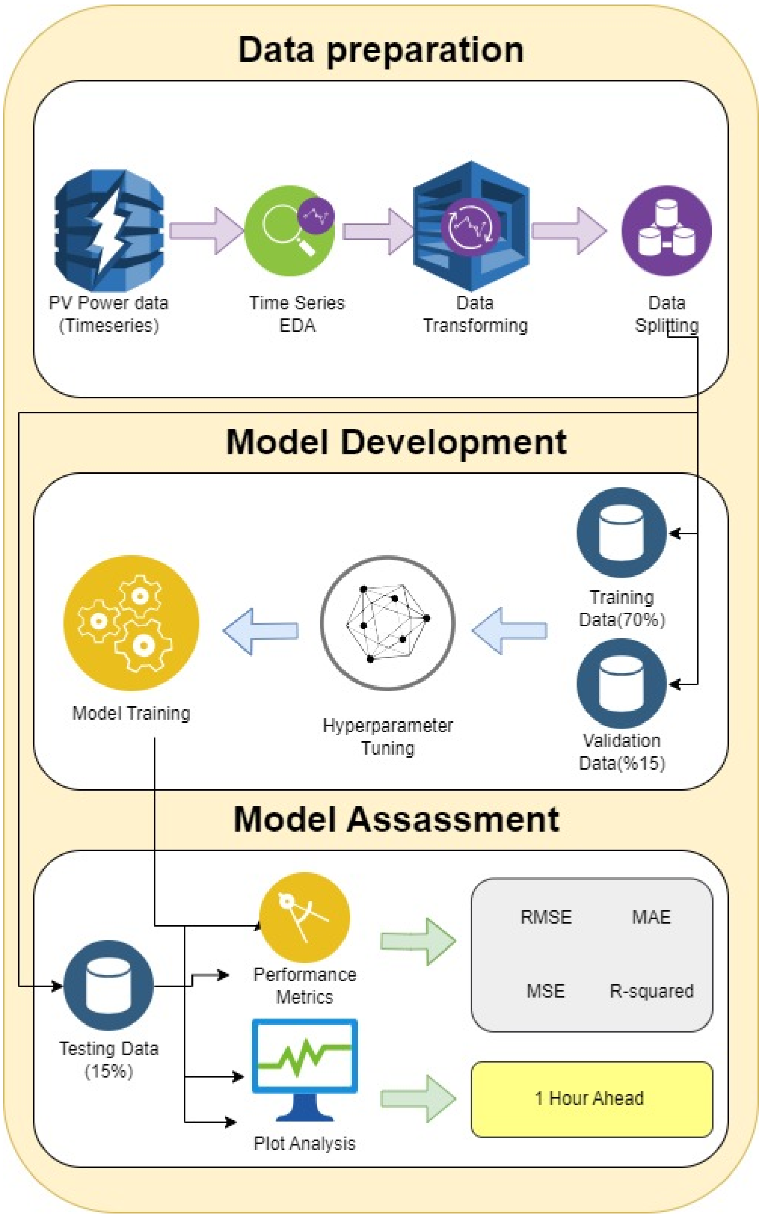


Figure 9: Computational framework of this study

Table 2: Models Hyperparameters

	Hyperparameters	Value
	Hidden Layers	LSTM, GRU, 1D-CNN, Dropout, Dense, Flatten
	Units	4, 8, 16, 32, 64, 128, 256
MODELS	Learning rate	0.001
	Activation functions	ReLu, Linear
	Optimizer	Adam
	Loss Metrics	RMSE, MSE, MAE, R-square
	Epoch	100

linear function that works to give direct output to positive inputs and zero output to negative inputs, thus preventing the gradient from vanishing. Dropout can overcome the problem of overfitting by randomly dropping units from hidden layers when calculating activations. Using ReLU as an activation function has become a standard activation function for many types of neural networks because it makes the models in which it is used easier to train and generally provides better performance Tan & Lim (2019). Gensler et al., especially mentioned that choosing a Rectified Linear Unit (ReLU) instead of a tanh activation function as the activation function for the neural network will contribute to the elimination of erroneous prediction data. In particular, the tanh activation function may learn during the winter months when production is low on the training set, causing the prediction to be lower. However, it can solve this problem better by making predictions only for positive inputs Gensler et al. (2016). In all configured models, the training epoch was 100, and Adaptive moment optimization (Adam) with a learning rate of $0,001$ was selected as the optimizer.

After the hyperparametric selections mentioned above, all models created to predict the next hour's production value with eight hours of PV power data were trained using the training set, and training errors were calculated with error metrics after each training iteration on the validation set. The model with the lowest error discovered by the training error calculations made on the validation set was selected to be run on the test data set to make a final performance evaluation.

In this study, 40 different single and multilayer LSTM/GRU/1D-CNN models and 11 different hybrid models were developed. To compare the performances of the created models, measurements were made with four different error metrics: R-squared, MSE, MAE, and RMSE, which are introduced in Section 2.4 by equations. In the Results and Discussion section, the error rates calculated for all models are given with the help of tables and graphs.

3 Results and Discussion

This section discusses the experimental results of the single-layer, multi-layer, and hybrid deep learning models. Forecast models are trained using an input dataset consisting only of hourly intervals of historical PV output power to obtain improved forecasting results. These results will be discussed in three parts: single layers, multilayers, and hybrids.

Starting from August 22, 2021, two years of winter, two years of autumn, one year of spring, and one year of summer were used as the training set in PV power data. The winter and spring seasons of 2023 were used as the validation set. Finally, summer data from 2023 and autumn data until October 14, 2023 were used in the test set. In line with this information, the accuracy values of the models trained on the training set are expected to be lower in the validation set.

The names of the models in the table are given as Method and number of neurons. In other words, the letters "L" for LSTM, "G" for GRU, and "C" for 1D-CNN are given together with the number of neurons of the model. During the experiment, RMSE, MSE, MAE, and R-square errors were calculated for each model, and the best results for the test set are shown in bold in Table 3, Table 4 and Table 5.

In the study, 18 distinct models were created using single-layer LSTM, GRU, and 1D-CNN by altering the number of neurons. The change in the accuracy of the univariate PV power production estimation of these formations with different numbers of neurons can be examined. The data obtained when the different error scores of the created single-layer models were calculated are given in Table 3. When the values in this table are examined according to the methods, the error rates of the L8, L16, L32, L64, L128 and L256 LSTM models increase as the number of neurons increases. However, the predictions made with the L8 and L16 models were found to have equivalent errors. In the G8, G16, G32, G64, G128 and G256 single-layer models created with GRU, a simplified version of LSTM, error rates increase as the number of neurons increases, similar to LSTM models; It has been observed that the G16 model, created with a GRU layer with 16 neurons, can make the highest accurate predictions with the least error. Finally, apart from these two methods with similar working mechanisms, single-layer models with different numbers of neurons have been created with 1D-CNN, which is increasingly used in time series. Although these CNN models created with the numbers of 8, 16, ..., 256 neurons gradually reduced the prediction errors up to the model created with 64 neurons, it was observed that the prediction errors in the models created with 128 and 256 neurons, on the contrary, increased. With this change, it has been shown that a method used in image processing, such as CNN does not need high neuron numbers when used in the prediction of univariate time series and that the best prediction with the least error can be obtained with the single 1D-CNN layer C64 model with 64 neurons.

Table 3: Single-type models results

Model	R-squared	MSE	RMSE	MAE
L8	**0.910**	**0.138**	**0.371**	**0.137**
G8	**0.907**	**0.142**	**0.377**	**0.148**
C8	0.905	0.146	0.382	0.153
L16	**0.910**	**0.138**	**0.372**	**0.137**
G16	**0.910**	**0.137**	**0.371**	**0.138**
C16	0.905	0.146	0.382	0.153
L32	0.896	0.160	0.400	0.161
G32	0.901	0.152	0.390	**0.148**
C32	**0.906**	**0.145**	0.380	0.162
L64	0.896	0.159	0.399	0.153
G64	0.893	0.164	0.405	0.161
C64	**0.911**	**0.137**	**0.370**	**0.139**
L128	0.887	0.173	0.416	0.157
G128	0.886	0.176	0.419	0.155
C128	0.897	0.158	0.398	0.163
L256	0.880	0.184	0.429	0.165
G256	0.880	0.184	0.429	0.160
C256	0.898	0.157	0.396	0.169

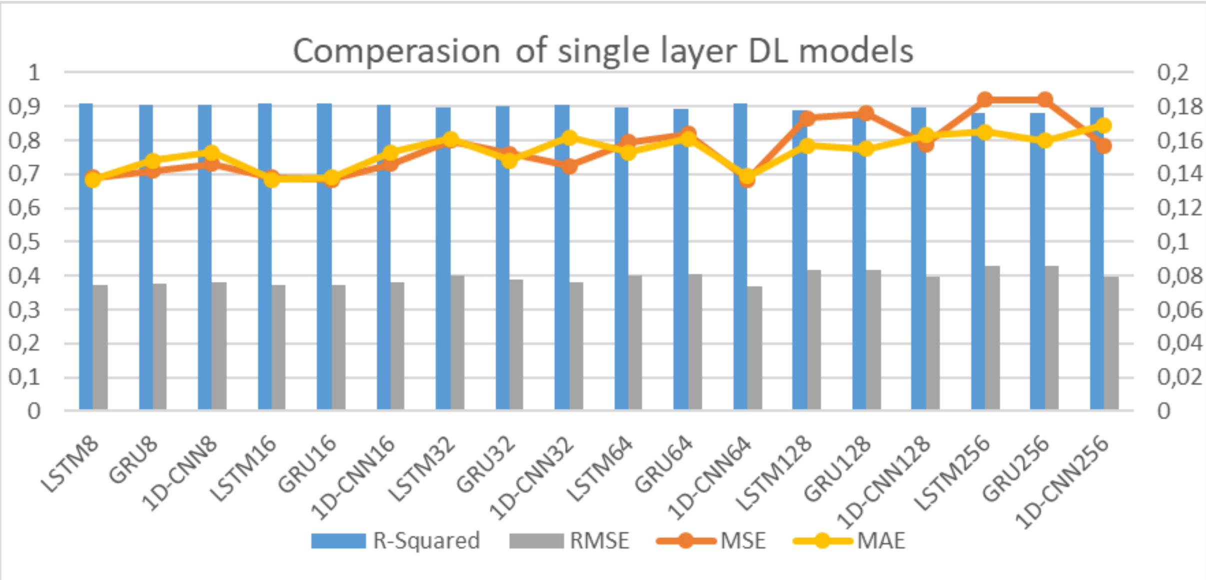


Figure 10: Metrics chart of single-type DL models

Upon graphing the data from Table 3, a clearer representation of the change in error metric values for each model can be observed in Figure 10. When single-layer models are examined holistically, regardless of the model and number of neurons, the most successful single-layer model is C64. This is subsequently followed by L8, L16, and G16.

In this study, multilayer models were created after single-layer models, and the prediction errors of the models were calculated using RMSE, MSE, MAE, and R-squared metrics. The values obtained after the error calculations of the predictions made on the test set are given in Table 4.

Table 4: Multiple Layer Models based on a Unique Network

Model	R-squared	MSE	RMSE	MAE
L44	0.886	0.174	0.418	0.219
G44	**0.907**	**0.143**	**0.378**	**0.148**
L88	**0.910**	**0.138**	**0.372**	**0.145**
G88	**0.910**	**0.137**	**0.371**	0.149
C88	**0.910**	**0.138**	**0.371**	0.150
L1616	**0.908**	**0.141**	**0.375**	**0.134**
G1616	**0.907**	**0.143**	**0.378**	**0.132**
C1616	**0.906**	0.145	0.380	**0.145**
L3232	0.888	0.173	0.416	0.153
G3232	0.884	0.179	0.423	0.158
C3232	0.888	0.172	0.414	0.173
L6464	0.890	0.169	0.411	0.153
G6464	0.893	0.164	0.405	0.161
C6464	0.904	0.147	0.383	0.168
L128128	0.888	0.181	0.426	0.156
G128128	0.894	0.163	0.404	0.151
C128128	0.877	0.190	0.435	0.174
L256256	0.880	0.184	0.429	0.165
G256256	0.886	0.175	0.418	0.162
C256256	0.878	0.187	0.432	0.168
C88888	0.891	0.167	0.408	0.206
C1616161616	0.891	0.168	0.410	0.207

In this study, 22 multilayer models were created after single-layer models. The predictive errors of these models were quantified utilizing various metrics, namely RMSE, MSE, MAE, and R-squared values. The values obtained after the error calculations of the predictions made on the test set are given in Table 4. In this table, models are created with two or more layers for the same number of neurons and the same deep learning method. In the table, the four highest R-squared values and the four lowest MSE, RMSE, and MAE values are indicated in bold. Although all hyperparameter variables are kept constant except the number of neurons, the models with the least prediction errors are those created with 4, 8, and 16 neurons. However, it can be seen that the error metrics of the L88, G88, and C88 models, which consist of two layers with 8 neurons each, are very close to each other.

Table 5: Hybrid Model Results

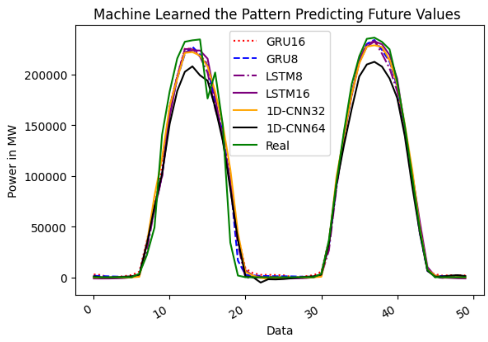
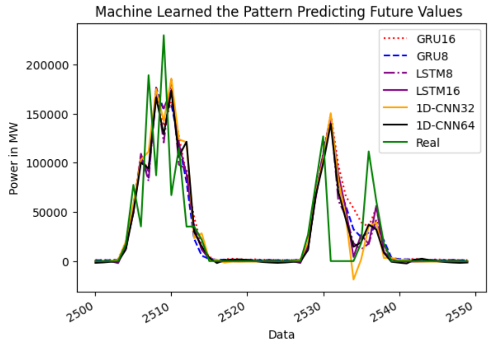
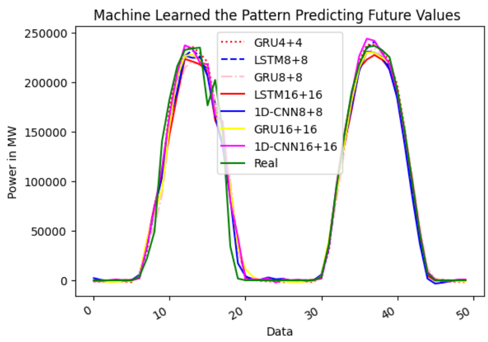
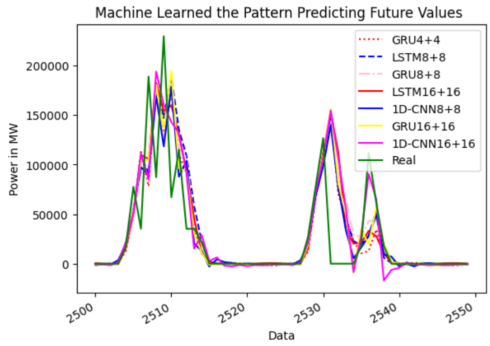
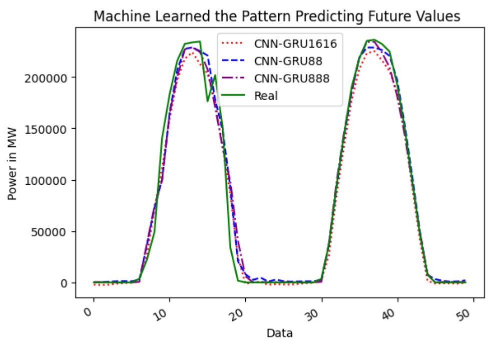
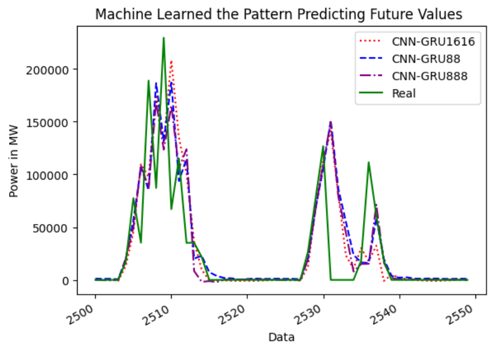
Model	R-squared	MSE	RMSE	MAE
L1616C1616	0.888	0.172	0.415	0.275
L16C64	0.888	0.171	0.414	0.166
G16C64	0.889	0.171	0.414	0.169
G1616C1616	**0.901**	**0.151**	**0.389**	**0.186**
C16161616L1616	0.889	0.171	0.413	0.266
G88C88	**0.903**	**0.149**	**0.387**	**0.172**
C16161616L881616	0.893	0.164	0.405	0.220
L88C88888	0.867	0.205	0.452	0.246
G888C888	**0.907**	**0.143**	**0.378**	**0.166**
C161616161L8888	0.856	0.221	0.470	0.278
C88888G88	0.862	0.212	0.460	0.260

Finally, 11 different hybrid models were created. These models were developed by combining different numbers of layers with different numbers of neurons in the LSTM-1D-CNN and GRU-1D-CNN types, based on single-layer methods with high prediction success. The aim here is to observe whether a more consistent prediction can be achieved by combining two different methods with higher success. The three models with the best prediction rates among the models whose R-squared, RMSE, MSE, and MAE error metrics are given in Table 5 are indicated in bold.

Especially when the structures of the models are examined, it has been seen that models with the GRU layer can make more effective predictions in hybrid models created with 1D-CNN layers compared to models with the LSTM layer. The L16C64 and G16C64 hybrid models, which were created considering the success rates of the single-layer L16, G16, and C64 models, did not show the expected performance. However, the G88C88 and G888C888 hybrid models, which were created by considering the success rates of the two-layer L88, G88, and C88 models, managed to be the two models with the best prediction rates among the 11 hybrid models examined in the study. This success was followed by the G1616C1616 model, which has two layers of 16 neurons.

In the study where 51 models were examined, the predictions on the test set, which included cloudless and sunny summer days and cloudy and rainy autumn days, are visualized in Table 6. Two randomly selected days representing cloudless summer days are given in the first column of the table, and two randomly selected days representing cloudy autumn days are given in the last column of the table. Comparisons of the models examined in the three parts of the study are given among themselves, with the predictions made for these days, with single-layers in the first line, multi-layers in the second line, and hybrids in the third line. When the forecast images made especially on cloudy days are examined, it can be seen that the 1D-CNN model with 64 neurons in single layers, the LSTM8+8, GRU8+8, and 1D-CNN8+8 models in multilayers, and the CNN-GRU888 model in hybrid models stand out in their groups. In this study, previously unused production data from a solar energy field in İzmir was utilized. Different deep learning models were examined for one hour ahead forecasting using only the univariate time series production data. In particular, models created with only a few hidden layers were observed to exhibit significant performance despite being trained with a limited amount of data. If a comparison is made with the performances of similar models used in the literature, even if they were created with different hyperparameter variables; Özbek et al. stated that an LSTM model created with 700 hidden layers and 700 epochs, using the production data of a solar field established in Mersin province for 2018 and 2019, gave the best prediction result Özbek et al. (2021). In another study by Özbek, the researcher found the MAE value of his prediction for İzmir province to be 0.555 and the RMSE value to be 0.753, using the LSTM model he created for an hour-ahead forecast using the atmospheric temperature data of more than one province, including the city of İzmir mentioned in this study Özbek (2023). This result falls far behind the MAE value of 0.137 and RMSE value of 0.372 of the L16 model, which has the highest performance among the LSTM models examined in the present study. In the study conducted by Suresh et al., the researchers found RMSE 0.466 and MAE 0.451 for CNN in their predictions for one hour ahead (RMSE value was 0.370 and MAE value was 0.139 for the CNN model, C64, examined in this study): 0.297 RMSE for CNN-LSTM, They reached MAE values of 0.295 Suresh et al. (2020). The RMSE value for the LSTM model created by Yalçın and Herdem for the prediction of global horizontal solar irradiance with meteorological data is 4.62, the RMSE value for the LSTM-GRU hybrid model is 3.14, and finally, it was created with an LSTM layer of 64 neurons and a CNN layer of 32 neurons, which were presented with the best performance in the study. The RMSE value for the hybrid LSTM-CNN model was found to be 0.61 Yalçın & Herdem (2022). In this study, the RMSE value of the L16C64 model, which is the hybrid model with the closest structure to the model proposed in the researchers' study, was 0.414. Although it does not have the highest performance among the models examined, it can make a more successful prediction than the RMSE value of 0.61. The biggest reason for this 0.196 performance difference may be that the model proposed by the researchers conducts a more complex multivariate study. Li et al., in their study proposing a hybrid deep learning model combining Wavelet Packet Decomposition (WPD) and LSTM networks, made predictions for one hour ahead using production data of the Alice Springs facility in Australia recorded at five-minute intervals. The performance of the hybrid model compared with the individual LSTM,

Table 6: Forecasting visualizing on test set of proposed models

	Forecasting on clear days	Forecasting on cloudy days
Single Layer		
Multiple Layer		
Hybrid		

RNN, GRU, and MLP models was calculated separately for four seasons. For the LSTM and GRU models compared in the study, the summer period predictions were calculated as 1.250 and 1.238, respectively, and the autumn period predictions were calculated as 1.071 and 1.074 RMSE error metrics, respectively Li et al. (2019). In another study using Alice Springs PV system data, Wang et al. presented a hybrid model consisting of two LSTM and two CNN hidden layers consisting of 64 and 128 pieces, with an MAE value of 0.221 and an RMSE value of 0.621, without specifying the prediction distance Wang et al. (2019). Especially considering the RMSE values and MAE values of the one hour ahead predictions of the LSTM and GRU models mentioned in Table 3 and Table 4 and that the test set consists of summer and autumn days, the model performances in the tables be much more efficient than the models compared by the researchers. Using the PV power output dataset and meteorological datasets recorded for 39 months (from June 1, 2013 to August 31, 2016) from a PV operator in Gumi, South Korea, Lee and Kim made predictions for one hour ahead using the LSTM models they used. They found the MAE value to be between 0.239 and 0.468 for the summer and autumn seasons, and the RMSE value to be 0.563 for summer and 0.698 for autumn Lee & Kim (2019).

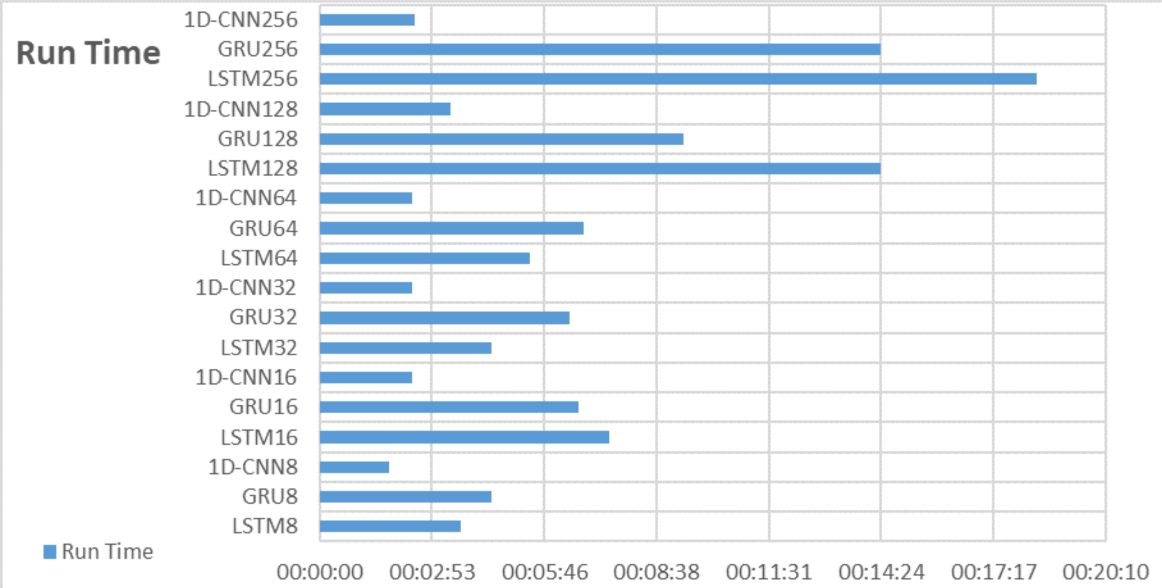


Figure 11: Run time of Single Layer models

When the performances of the different models examined in this article are examined in general, especially the 1D-CNN model named C64 in Table 3, with statistical error calculations of R-squared 0.911, MSE 0.137, RMSE 0.370, and MAE 0.139, it is obvious that it is the most successful model in predicting the next hour using the past 8 h of data on the test set.

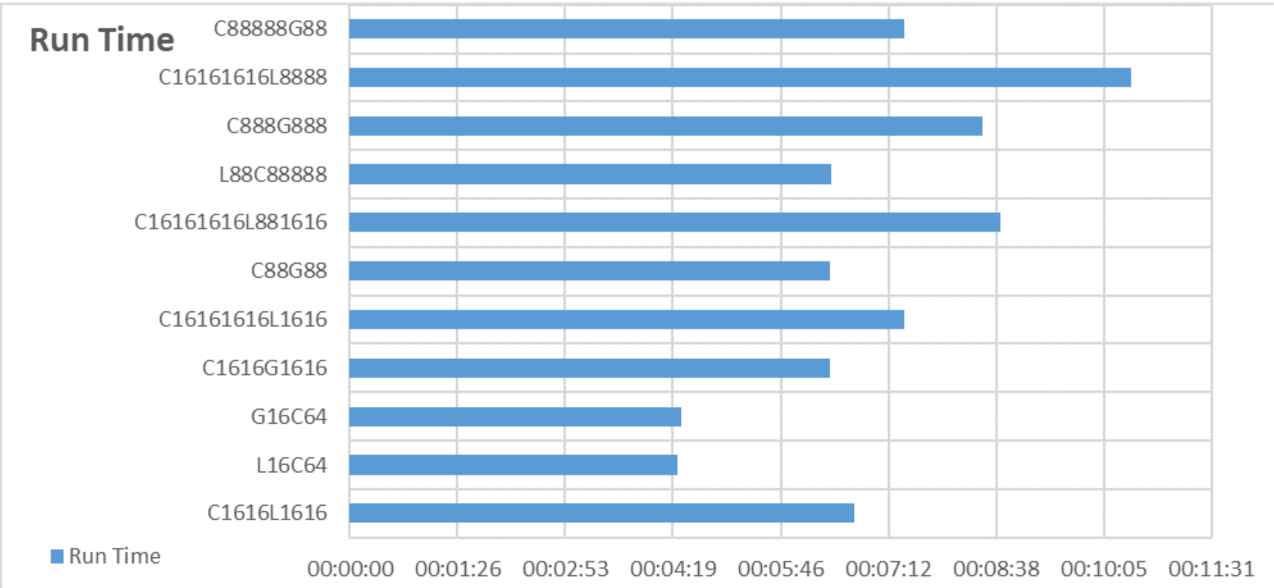


Figure 12: Run time of Hybrit models

On the other hand, when the run times of the models in Table 3 are compared, as can be seen in detail in Figure 11, 1D-CNN models exhibit an economical operating performance on approximately 16000 data. This is supported by the fact that training of 1D-CNN models on univariate nonlinear time series could be completed in less than 3 min. In addition to all these, in Figure 12, where the running times of the hybrid models given in Table 5 are compiled, it can be observed that the addition of 1D-CNN layers reduces the running times of the models. However, the estimate that a single-layer 1D-CNN alone can complete in 2minutes and 23 seconds can only be achieved by hybrid models in over 4 minutes.

4 Conclusion

The primary resource for deep learning algorithms to achieve optimal performance is the gathered data. The efficiency of the algorithms increases when data, which are meaningful, relevant, and accurate, are collected under appropriate conditions. The process of recording and collecting these data is both cost-intensive and time-consuming. Therefore, data repositories are commonly utilized in researches Suri et al. (2008), Marion et al. (2014). While utilizing publicly accessible datasets offers an economic advantage in the process of data collection, it detrimentally influences the originality of the research Meer et al. (2018). To overcome this disadvantage, data must be accumulated for long periods of time using the necessary sensors and hardware, as was done in previous studies Essam et al. (2022), Akhter et al. (2022), Yılmaz & Şahin (2023). This method will not be economical in terms of both the hardware requirements to be used to obtain and accumulate data and the time spent. In order to make a significant and original contribution to the existing body of literature, despite various inherent limitations, it is essential to utilize a dataset that has been appropriately gathered and has not been previously used in any research study. The data set used in this research was obtained after an agreement with a company that installs solar power plants and has not been used in any previous study.

As can be seen in many studies such as Toğrul & Toğrul (2002)-Jebli et al. (2021), Gao et al. (2020), Neshat et al. (2023) using the amount of solar radiation to estimate the amount of electrical production from solar energy, although it is very common, the panel features located outdoors are used for the most effective estimation indicates that output is required. All PV panel types have some disadvantages, such as the module temperature. An increase in panel surface temperature results in a decrease in production voltage. The negative impact of reducing the generation voltage predominates, and as a result, this reduces the power of the PV panel compared to standard test conditions Sornek et al. (2022). Researchers often overlook this negative effect when estimating PV output through solar radiation, which reduces the reliability and consistency of the prediction.

In this research, with the inverter data received from the contracted company, the data collection phase, which is the most important phase of the research, was able to proceed regardless of time constraints, and the use of real PV power production data contributed to the study obtaining reliable results.

As applied in this study, in many studies, researchers develop hybrid models by combining more than one algorithm in different ways, especially to increase accuracy. However, this process has a disadvantage. In particular, as Alcañiz et al. mentioned, the use of hybrid models increases complexity and therefore reduces interpretability Alcaniz et al. (2023). In fact, the hybrid models examined in this study could reach values below the performance of the 1D-CNN model. One of the most effective reasons for this may be that the solar energy system dataset, which is a variable renewable energy source used in training the models, is data recorded hourly for only two years. That is, for the complex operating structure of hybrid models, a univariate two-year data set must not have been an efficient choice in terms of both running time and prediction accuracy. As Cordeiro et al. stated in their study, 1D-CNN models are more advantageous to use compared to other deep learning architectures, because they have low computational complexity and good performance on time series with a limited number of data, and can complete this in fast training times Cordeiro et al. (2021).

Studies make short, medium and long-term predictions, and each prediction is beneficial to a different field of study. This study provides the most accurate forecast for one hour ahead, which is considered a short-term forecast. The concept of time horizon is typically examined under three main categories: very short-term forecasts for instantaneous response or up to one-hour predictions; short-term forecasts for periods ranging from one hour to one week; and long-term forecasts for durations exceeding one week. Although variations exist in its classification, this structure is generally followed. Very short-term forecasts are utilized to enhance the quality of operational programming in power plants, such as photovoltaic (PV) maintenance and emergency response, thereby ensuring the stable and reliable operation of the system. Short-term forecasts are integral in programming PV energy production and in economically distributing the yielded energy to the grid. Additionally, long-term forecasts play a crucial role in the installation and planning phases of PV power plants. Konstantinou et. al., especially short-term predictions made in studies; researchers stated that it has a critical importance in network operation, designing new management systems, controlling stored energy reserves, and evaluating contracts between energy buying and selling companies, and that it serves as a keystone in increasing reliability Konstantinou et al. (2021).

In this research, production data of a solar energy system integrated on the roof of a factory located in İzmir, Türkiye's third largest city, were studied. The robustness of this study could be enhanced by incorporating data from a greater number of established facilities, spanning both within the same province and across different provinces. According to Bakay and Ağbulut, it is expected that the tendency to use wind and solar energy as renewable energy sources in Türkiye recently and the concrete steps taken to reduce the use of nuclear power plants are expected to lead to a further reduction in the amount of greenhouse gas emissions per unit of electricity production in the future years Bakay & Ağbulut (2021).

This article provides an opportunity to compare the performance of the models by selecting hyperparameter values for some deep learning models under the same conditions, using only the time series of univariate PV power production data. However, in order to eliminate the disadvantages of using a single variable, making a single-step prediction, and testing models on only one dataset, future studies are planned to use PV system data from more than one location, work with multivariate data that will be created by adding meteorological data of the locations, and make multi-step forecasts.

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