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Hybrid Machine Learning Approach for Day-Ahead Solar Power Prediction Using SVM and KNN

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ABSTRACT

Renewable energy sources are becoming more popular as a means of combating climate change and global warming. Many constraints have limited our ability to predict the future of renewable energy, but lately, many home forecasting models have been created.Solar energy is one of the most economical and clean renewable energy sources in the world. Solar forecasts are an inevitable requirement to achieve the maximum solar energy during the day and increase the efficiency of the solar system. For this purpose, this article work uses a classifier to predict the total daily energy production of installed photovoltaic systems. In the forecasting process, one year of historical data sets including daily average temperature, total daily hours of sunshine, global daily total solar radiation and total daily photovoltaic parameters are used as attributes for classification value. Improve the sensitivity and accuracy of predictable measurements of photovoltaic systems and assess the impact of other solar properties on photovoltaic energy. The core of solar energy forecasts is a weather forecast problem.By means of the hybrid SVM and KNN machine learningclassification technique used to predict the solar energy. It first simulates the position of the sun relative to a given position on the earth's surface and then simulates the transmission of solar radiation through

the earth's atmosphere. Finally, by accurately estimating the availability of solar radiation, power modelling software is used to predict power generation of a given photovoltaic system.

Keywords: Artificial Intelligence, Machine Learning, SVM and KNN

Introduction

Overuse of fossil fuels has had a significant impact on global economic policy, the environment, and energy security. It has also contributed to global warming and the energy crises of the last several decades. As a result, there has been an attempt to develop and deploy environmentally friendly renewable energy sources [1]. Solar power is rapidly expanding due to its merits as a sustainable and environmentally friendly energy source. This energy is safe for the environment since it produces no pollution. In 2014, the European Photovoltaic Industry Association (EPIA) found that 177 GW of solar generating capacity was under construction, proving the technology's increasing popularity [2]. Photovoltaic (PV) energy systems provide a danger to power generation because of the erratic and unpredictable nature of the weather. Considering solar energy's intermittent nature and inability to be reliably forecasted, grid operators and solar electric power supply companies place a premium on reliable projections of solar power production. It is necessary to develop an algorithm to forecast the output power of a PV system in order to maximise the system's potential return on investment. Environmental variables such as temperature, humidity, wind speed, and dust buildup all have an effect on power production [3]. A simple use of power prediction algorithms and the accompanying assurance of roughly future production is all that is needed to maintain peace and order. This knowledge might be used by electricity suppliers to create a controller for a hybrid power plant that can make seamless transitions between its various energy sources. Solar power, very simply, is the process of turning solar energy into usable electricity. Numerous methods, such as directly using photovoltaics (PV), indirectly using concentrated solar power (CSP), etc., may be used to achieve this. Lenses, mirrors, and solar tracking technologies are used in focused solar power systems to concentrate sunlight from a wide area of the sky into a beam. Solar cells may convert light into electricity owing to the photovoltaic effect. From a solar-powered calculator to rooftop PV systems for homes in remote areas, photovoltaics were first used for very small and medium-sized projects. Concentrated solar power plants were initially built for commercial use in the 1980s. Millions of solar PV systems are already linked to the grid, and utility-scale photovoltaic power plants that can generate hundreds of megawatts are now being built. One low-cost and low-carbon solution is solar photovoltaics (PV), which convert sunlight directly into power. Due to its 2050 MW production capacity, the Pavagada Solar Park in Karnataka, India, is the biggest photovoltaic power plant in the world. Solar photovoltaics will account for around 16% and concentrated solar power for about 11% of global electricity output in 2050, according to a report published by the International Energy Agency in 2014. Across the near future, solar energy installations will proliferate in China and India. With a 35 percent increase over 2016, solar energy accounted for 1.7% of worldwide power output in 2017 [4]. The levelized cost of energy for utility-scale solar generation is around $36/MWh without subsidies as of October 2020 [5].

Proposed Methodology

Hybrid (SVM AND KNN) Method

K-Nearest Neighbours (KNN)

The K-Nearest Neighbours (KNN) algorithm is one of the most often used and available choices in machine learning. The KNN approach has been popular in the classification industry because to its ease of use [50]. The KNN classifier, a technique for instance-based learning used in pattern recognition, rates the value of study case components based on how close they are to one another in the feature space. The method identifies K closest neighbours in the feature space to categorise a sample Si, for instance, using the feature vectors and distance threshold. The software then casts a vote based on the labels of the neighbours. The same cluster will include those objects if there is a significant number of items with the same label. A more precise categorization often arises from a larger number of votes. More votes and larger training sets often lead to better KNN outcomes. An easy way to explain the KNN algorithm. The set of triangles with dots was the most popular choice for K = 3. The resultant forms are solid triangles when K = 11, but the target object (the centre circle) is more akin to a square.

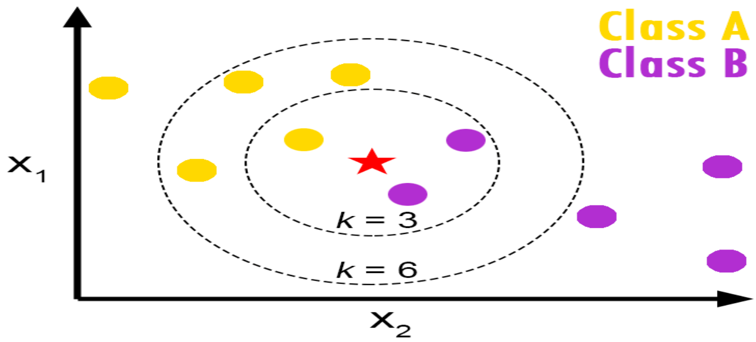


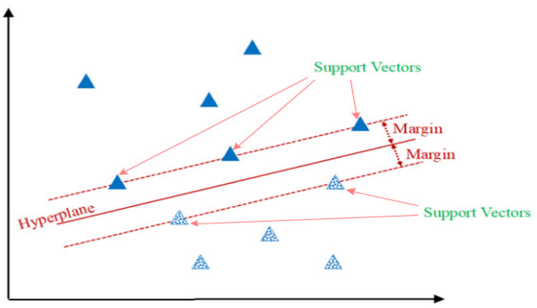
Figure 1:A Presentation of the K-Nearest Neighbours (KNN) Algorithm

Choosing the optimal value for the K parameter is a significant challenge for KNN [53] since the method heavily depends on statistics and is sensitive to small changes in the parameter. Multiple experiments are required to investigate various choices for the parameter K and identify an optimal value. how many trials are needed depends on the categorization issue at hand. The most common, although time-consuming, approach to finding a good value of K has been trial and error.

Support Vector Machines

For the purpose of identifying and labelling patterns, Vapnik suggested using a support vector machine (SVM). The SVM technique is created to build numerous hyperplanes in high or infinite dimensions using the inductive structural risk reduction approach from statistical learning theory [55,56]. Finding a hyperplane that divides the space into n distinct classes is the main goal of SVM. The functional margin, which measures the level of confidence in the classification outcomes, is the separation between the hyperplane and the related training data point. The best data separation is achieved by using the hyperplane that the SVM acquired with the largest functional margin to the nearest training data point. Support Vectors depict the closest training data points. The decision function for a problem with linear partitions is:

x2



x1

Figure 2: Separate the Data Points Linearly or on a Hyperplane

$$F(x)= \left(\sum_{i=1}^{n} a_i y_i x_i\right)^{T} x+b=\sum_{i=1}^{n} a_i y_i (x_i x)+b$$

To categorise a data collection, apply the formula yi = 1 or 1. Whether the training sample belongs to class 1 or class 2, xi is its feature vector. I is the Lagrange multiplier, and I x is an n-dimensional vector. We may examine the sign to see if the function f(x) of interest has a positive or negative sign value. Although the real differences in the sample data are not linear and need more complex separation techniques in this constrained space, practical classification issues are still limited to finite dimensions. Due to the non-linear separability of these samples, Figure 2 depicts a data dimension mapping into a higher dimensional space where separation may be feasible.

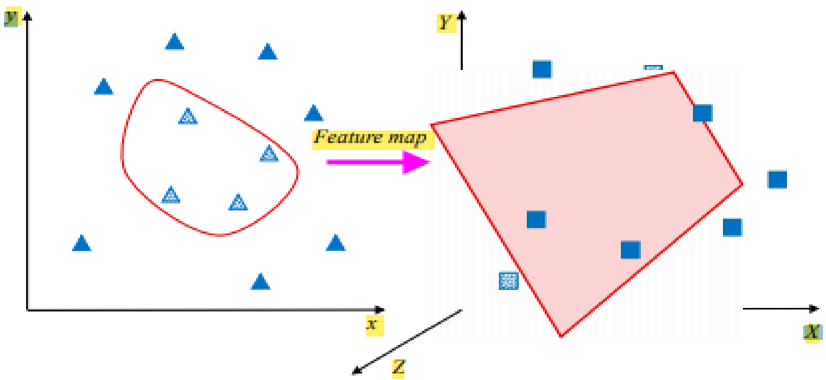


Figure 3: High-Dimensional Mapping of Low-Dimensional Feature Vectors (Depicted as Triangles) (Shown as Squares)

Following that, the decision function might be recast as

$$F(x)=\sum_{i=1}^{n} a_i y_i(\varphi(x_i),\varphi(x))+b$$

The mapping from the original, smaller dimension to the larger one is shown by. A set of points with a constant dot product denotes a hyperplane in the new higher-dimensional space when a vector is supplied. Hyperplanes are vectors that are linearly independent. The kernel function is designed because computing the dot product in larger dimensional spaces may be challenging.

The following conditions define a kernel function:

$$K(x,z)=(\varphi(x).\ \varphi(z))$$

As a result, using K (xi, x), the high-dimensional inner product (xi) may be calculated successfully in low dimensions (x). The linear kernel, polynomial kernel, radial basis function (RBF) kernel, sigmoid kernel, and many more are common kernel functions.

As a result, the functional margin and kernel parameter definition are related to SVM accuracy. Support Vectors may be used to accurately partition the data if the data sample size is small enough, but larger datasets may need more intricate mappings.

Simulation Results

Simulation Results on Hybrid (SVM and KNN) Based Prediction

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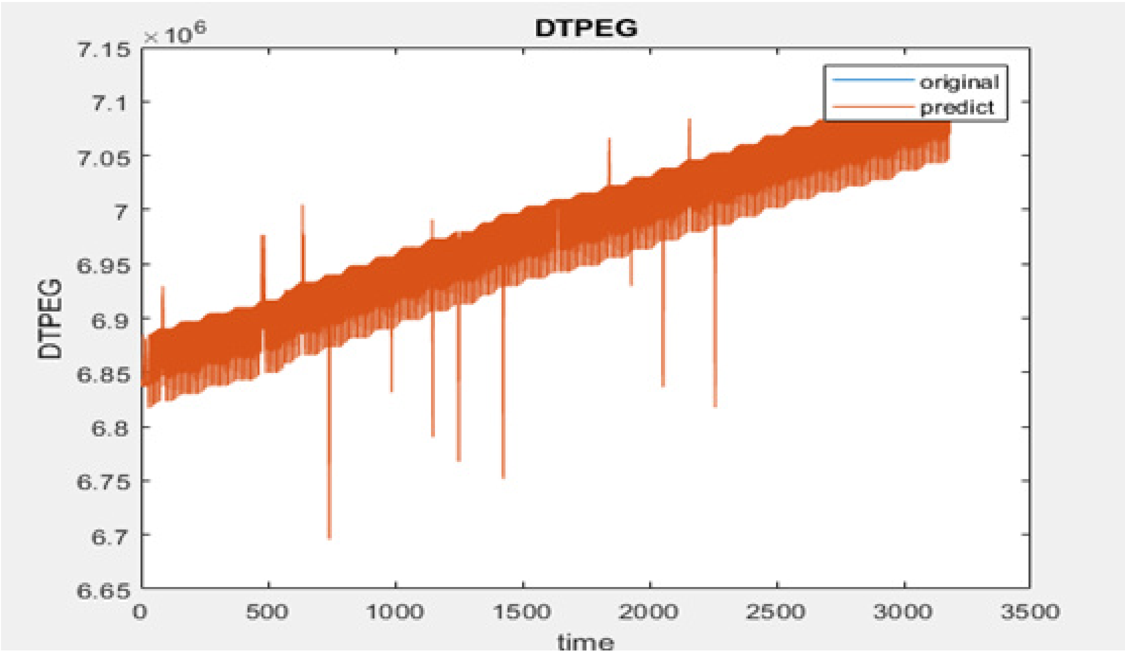

Figure 4: DTPEGPrediction for Original and Predicted Energy Using Hybrid (SVM and KNN)

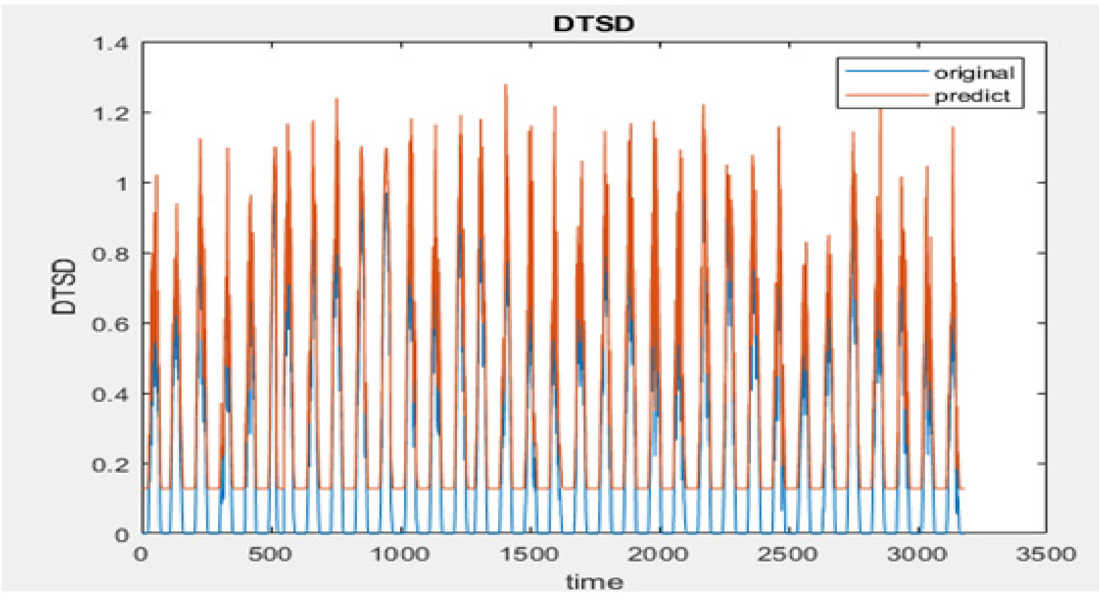

Figure 5: DTSDPrediction for Original and Predicted Energy Using Hybrid (SVM and KNN)

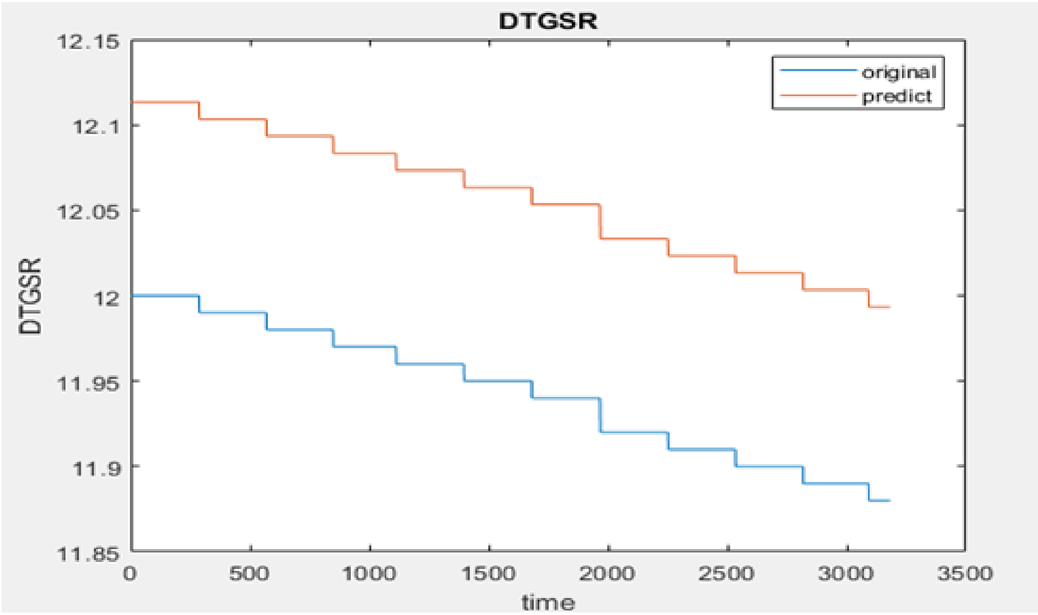

Figure6: DTGSR Prediction for Original and Predicted Energy Using Hybrid (SVM and KNN)

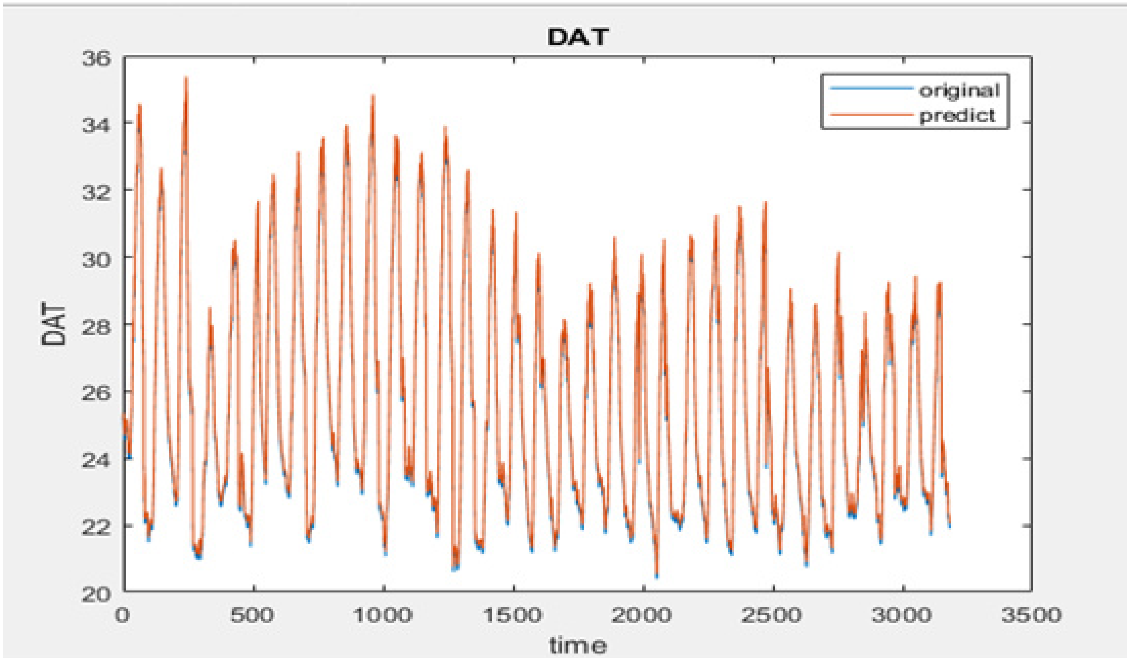

Figure7: DATPrediction for Original and Predicted Energy Using Hybrid (SVM and KNN)

Figure 5 to 7 shows the original and predicted values for DAT, DTSD, DTGSR, and DTPEG using Hybrid (SVM and KNN)

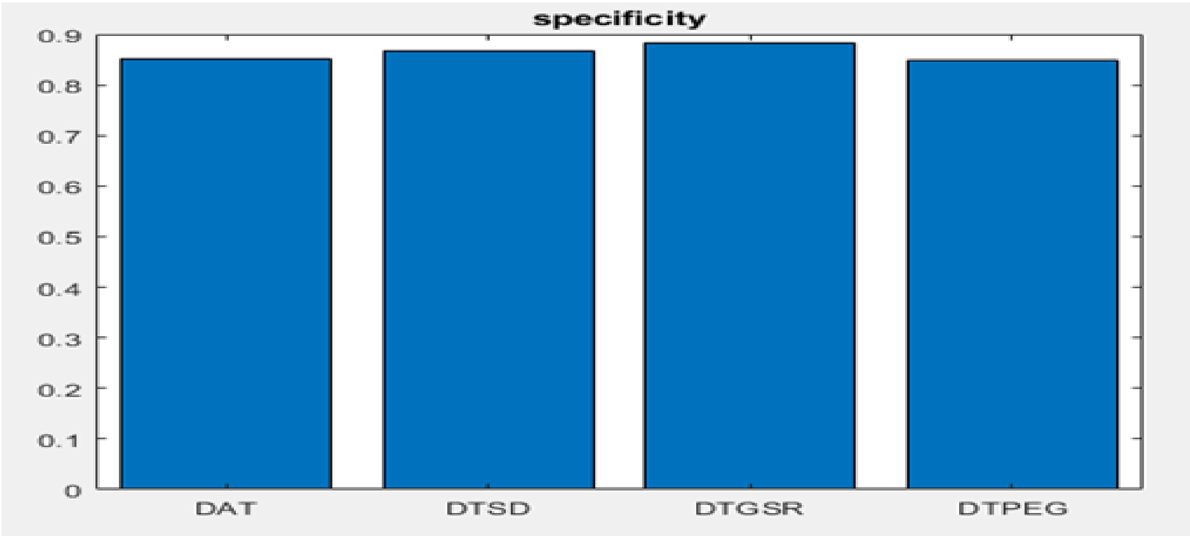

Figure8: Specificity for DAT,DTSD,DTGSR,DTPEG Using Hybrid (SVM and KNN)

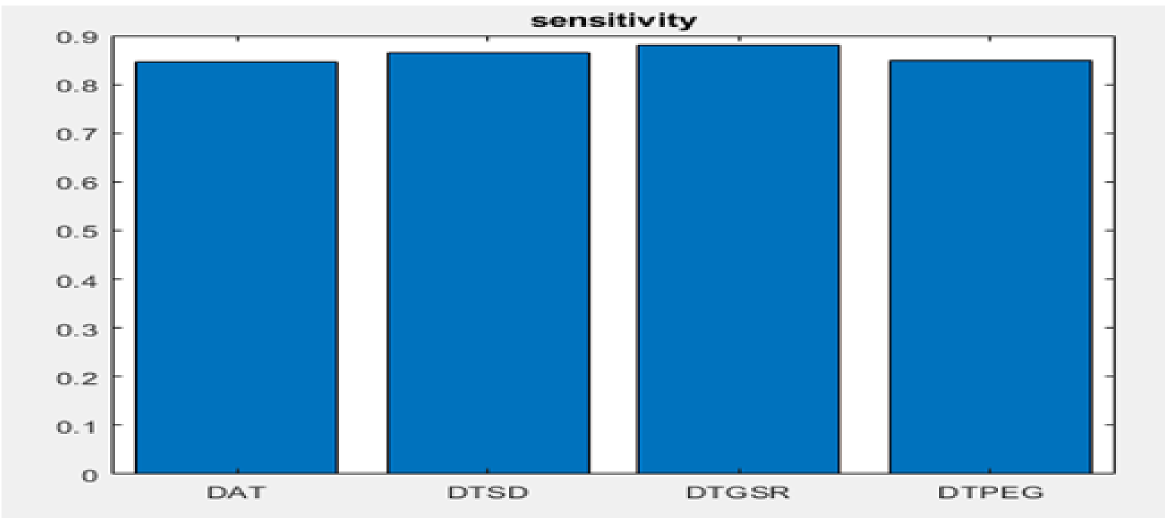

Figure9: Sensitivity for DAT,DTSD,DTGSR,DTPEG Using Hybrid (SVM and KNN)

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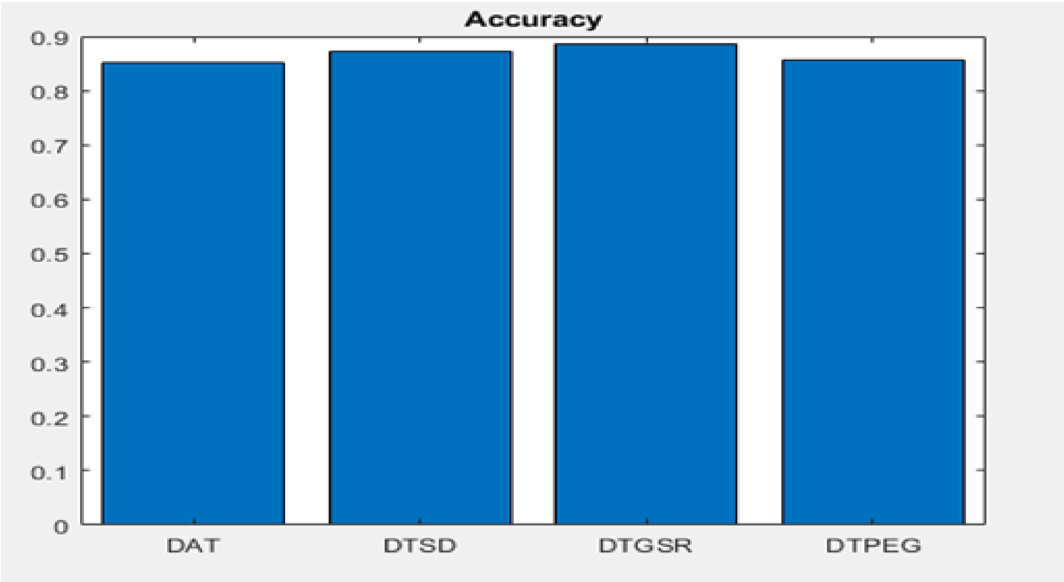

Figure10: Accuracy for DAT,DTSD,DTGSR,DTPEG Using Hybrid (SVM and KNN)

Figure 8 Specificity, figure 9 Sensitivity and figure 10 Accuracy values for DAT, DTSD, DTGSR, DTPEG using using Hybrid (SVM and KNN) Model

Conclusion

This study transforms the continuous value data gathered from the solar system at 1-day intervals into discrete categories. Here, we employ daily values for inputs into a neural network training process, including average temperature, sunlight hours, global solar radiation, and solar cell characteristics. Accuracy, Sensitivity, and Specificity have been determined for this. The suggested model also allows users to assess how various sun conditions affect solar cell power output.

This study employed a number of input parameters to fine-tune the sensitivity and accuracy of the proposed SVM- KNN. The hybrid classifier (SVM and KNN), which achieves an accuracy of 89.98%).

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