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A study on hybrid learning approach to predict solar energy level

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Abstract
The generation of electricity from the sun's rays may be accomplished in one of three ways: directly, via the use of photovoltaics (PV); indirectly, through the use of concentrated solar power; or all three together. Concentrated solar power systems do this by using lenses, mirrors, and solar tracking devices to concentrate the sunlight from a wide region into a narrow beam. Through the use of the photovoltaic effect, photovoltaic cells are able to convert light into an electric current. In the beginning, photovoltaics were only employed as a source of energy for small and medium-sized applications. This ranged from the calculator that was powered by a single solar cell to off-grid rooftop PV systems that provided power to residences in rural areas. Concentrated solar power, also known as CSP, and photovoltaic power, often known as PV power, are the two primary options for harnessing the energy that the sun provides. In the first scenario, which is often referred to as solar thermal power production, there are already established heat-based systems that are in place to convert heat in the form of steam into electricity. In this body of study, we made use of methodologies that included non linear regression analysis. As a result, this article presents a discussion on the various regression strategies that were used in my study. In the course of my research, I will be processing the data by making use of various meteorological parameters, such as solar irradiation, module temperature, and ambient temperature, amongst others. Additionally, the Effectiveness of the model will be assessed by making use of appropriate and widely utilised performance indicators. In this research paper we discuss concept of solar system and also Study on Hybrid Learning approach to Predict Solar energy level.

Keywords: regression, support, vector, machines

Introduction

The present global warming scenario and the energy problems of the previous few decades are heavily impacted by the excessive use of fossil fuels in global economic policy, climatic conditions, and energy security concerns. In this condition, the development and utilisation of alternative energy sources, such as clean and sustainable ones, have been motivated [1]. As a renewable energy source, solar power is becoming more popular. This source of energy is excellent for the environment since it does not pollute177 GW of in-progress solar power capacity reported in 2014, according to EPIA's statistics, reflecting the technology's rising popularity [2]. Because of the unpredictable and chaotic nature of the weather, the electricity produced by photovoltaic (PV) energy systems is particularly unreliable. Because solar power is intermittent and unpredictable, grid operators and solar electric power providers must be able to estimate when it will be produced properly. To optimise the financial return on a PV system, an algorithm for predicting the system's output power must be devised. Besides temperature and humidity, further variables influencing output power include wind speed and dust deposition. In order to preserve stability, power prediction methods should be implemented, as well as secure future approximation production. It supports power supply organisations in building a controller that can switch between a hybrid power plant's numerous energy streams. By employing photovoltaics (PV) or concentrated solar power, solar energy is transformed directly from sunlight into electricity. Solar tracking devices and lenses are utilised in concentrated solar power facilities. These facilities capture sunlight from a vast region and concentrate it into a narrow beam. Photovoltaic cells may transform the light energy they receive into an electric current by employing a technique known as the photovoltaic effect [1]. Small and medium-sized applications originally employed photovoltaics exclusively as a source of power for other small and medium-sized enterprises. Some examples of these applications vary from a calculator powered by a single solar cell to a modest dwelling powered by an off-grid rooftop PV system. In the 1980s, the first concentrated solar power facilities that could compete effectively on a commercial basis came into being. There are presently millions of photovoltaic (PV) systems that are grid-connected and utility-scale solar power plants with hundreds of megawatts of capacity. The price of solar energy continues to plummet. The technology known as solar photovoltaics (PV) is swiftly growing into a way that is both economical and low in carbon emissions to collect renewable energy from the sun. The Pavagada Solar Park in Karnataka in India is currently the largest photovoltaic power facility in the world. It has a producing capacity of 2050 megawatts and is situated in India. According to the "high renewable" scenario presented in 2014 by the International Energy Agency (IEA), solar photovoltaics and concentrated solar power would account for around 16 percent of the world's energy output by the year 2050. This estimate is based on forecasts of worldwide energy usage. China and India are anticipated to have most of the world's solar power installations [3]. In 2017, solar power contributed for 1.7 percent of worldwide energy output, increasing 35 percent from 2016. Utility-scale solar power will have a levelized unsubsidized cost of roughly $36/MWh by October 2020, according to [4, 5] A photovoltaic cell (PV) exploits the photovoltaic phenomena to convert light energy into electrical current in a solar cell. “In the 1880s, Charles Fritts constructed the first solar cell. The importance of the finding was immediately recognised by a great number of individuals, notably the German business magnate Ernst Werner von Siemens. Silver selenide, rather than copper oxide, was used in the photo cell that was invented in 1931 by the German engineer Bruno Lange. [9] On the other hand, the prototype selenium cells were only able to convert only one percent of the light that hit them into usable energy. Researchers Gerald Pearson, Calvin Fuller, and Daryl Chapin developed the silicon solar cell in 1954, building on the work that Russell Ohl had done in the 1940s. Their invention was based on Ohl's research. In the 1960s and 1970s, the cost of a solar cell was $286 per watt, and its efficiency ranged from 4.5 to 6 percent [11]. Mohamed M. Atalla is credited with developing the thermal oxidation process for silicon surface passivation in 1957 while working at Bell Labs [12]. As a direct consequence of this, surface passivation has emerged as an essential component of solar cell efficiency [14]. The amount of direct current (DC) power produced by the array of a PV system is proportional to the amount of available sunlight. The voltage or current must typically be converted by inverters into the required form, such as AC, before they can be put into practical use. Modules are comprised of a number of solar cells that are coupled to one another. Connected to arrays of modules that have been coupled together to construct such arrays, inverters are responsible for generating electricity at the precise voltage, frequency, and phase that is necessary for AC [6]. In industrialised nations with enormous markets, a significant number of residential photovoltaic (PV) systems are wired into the grid. In any case, the use of energy storage is not essential for these photovoltaic systems that are connected to the grid. As a kind of backup power supply, batteries or auxiliary power generators are often used by satellites, lighthouses, and nations that are still in the process of achieving economic progress. With the help of independent power systems like this one, it is feasible to go on with business as usual even when there is very little or no sunshine at all. By concentrating the sun's rays with the use of lenses, mirrors, and tracking systems, a technique known as "concentrated solar thermal power" (CSP) has the potential to generate more electricity than traditional steam-driven turbines.

Proposed System

Solar power is widely recognised as one of the most cost-effective and environmentally friendly forms of renewable energy. If one is interested in maximising the quantity of solar energy captured during the daytime hours and improving the performance of solar power systems, then one must have access to reliable solar energy forecasts. This need cannot be avoided. In order to accomplish this objective, the research project employs a hybrid SVM classifier in addition to KNN classification and LSTM in order to make a prediction about the daily total energy output of a solar system that has been installed. During the process of making predictions, a dataset with historical data spanning a single year is used as the foundation for categorical-valued characteristics. The daily average temperature, the daily total sunlight duration, the daily total global solar radiation, and the daily total photovoltaic energy production are all included in this dataset. Figure 4.1 depicts the proposed block diagram for the system. The classification application is used to increase the sensitivity and accuracy measures for the photovoltaic energy prediction, and it is also used to examine the impacts of various solar qualities on the production of photovoltaic energy. Both of these purposes are accomplished through the utilisation of the word "classification."

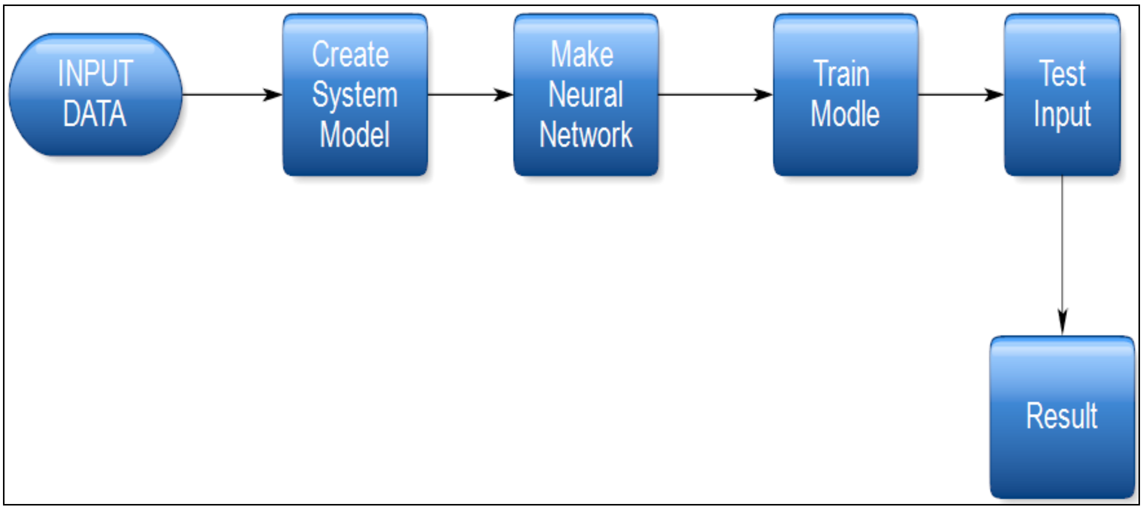

Fig 1

Input Data: The whole dataset that was used in this investigation was obtained from the Kaggle machine learning website as part of this particular piece of work. The parameters "daily average temperature (DAT)," "daily total sunlight duration (DTSD)," "daily total global solar radiation (DTGSR)," and "daily total photovoltaic energy generation (DTPEG)" are included in this dataset. These factors have been given the following unit designations: "°C (Celsius), h (hour), kWh/m2 (kilowatt-hours per square metre), and kWh (kilowatt-hours)"[6], "kWh (kilowatt-hours)." Data Processing: The process of "data preparation" encompasses a wide range of activities, such as "data purification," "the inclusion of features," "the replacement of missing information," and others. The first thing that needs to be done is to check and see whether the reading from the sensor is correct. Negative readings of the GHI, DHI, or humidity might result in incorrect conclusions being drawn from the information. Eliminating readings that are incorrect and replacing them with an interpolation of the points that come before and after them is a straightforward approach to cleaning up the data. The dimensions of the weather are dependent on the daily conditions as well as the annual seasonal circumstances. As a result, it can be beneficial to include variables that the model can use to assess the daily and annual values. Constructing a few variables, such as the date, time, and minute, is the way that is easiest to understand.

Proposed Model (SVM AND KNN HYBRID (Decision Tree))

KNN is a technique that is used in machine learning and is considered to be one of the most basic and widespread methods. The KNN classification approach has become an increasingly popular way of categorization [50] due to the fact that it is very easy to understand. Pattern recognition is accomplished with the use of an instance-based learning technique known as the KNN classifier. It does this by classifying each part of a study case according to the training instances in the feature space to which it is most comparable. This is how it works. In order to properly categorise a sample, such as Si, the algorithm does a search for its K closest neighbours in the feature space. This search is conducted with the aid of the feature vectors and the distance between each pair of feature vectors. After then, the computer will process the votes that have been submitted by these neighbours in line with the labels that have been assigned to them. The item being sampled will be organised into the category that corresponds to the group that contains the greatest number of other items with the same label. This will be done by sorting the item into the category that corresponds to the group. There is a direct relationship between the number of people who vote and the reliability of the results.

Simulation Result

Simulation results on Hybrid based prediction

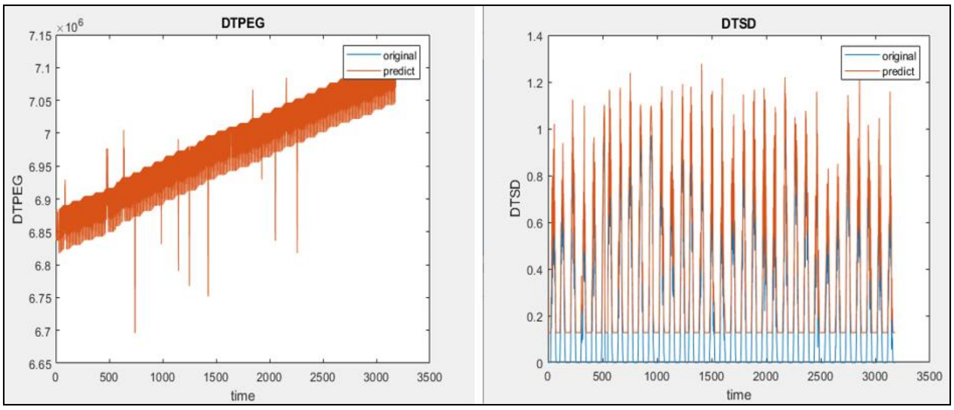

Fig 2: DTPEG and DTSD prediction for original and predict energy

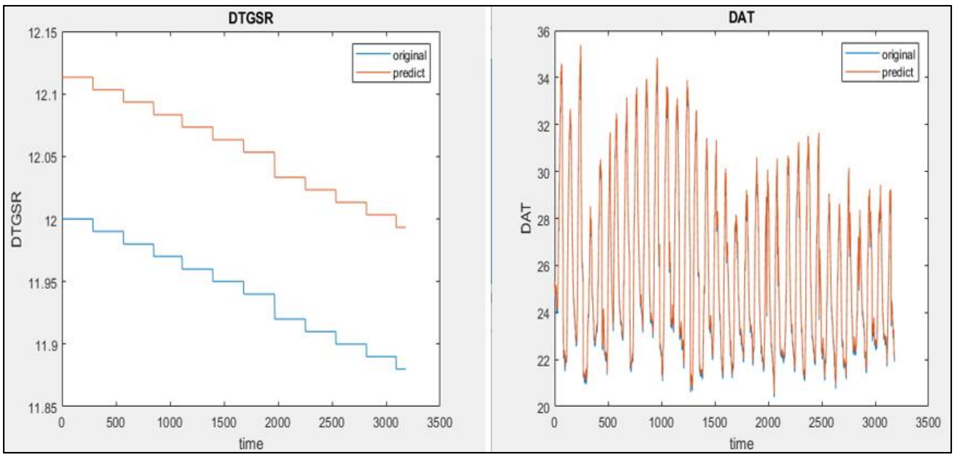

Fig 3: DTGSR and DAT prediction for original and predict energy

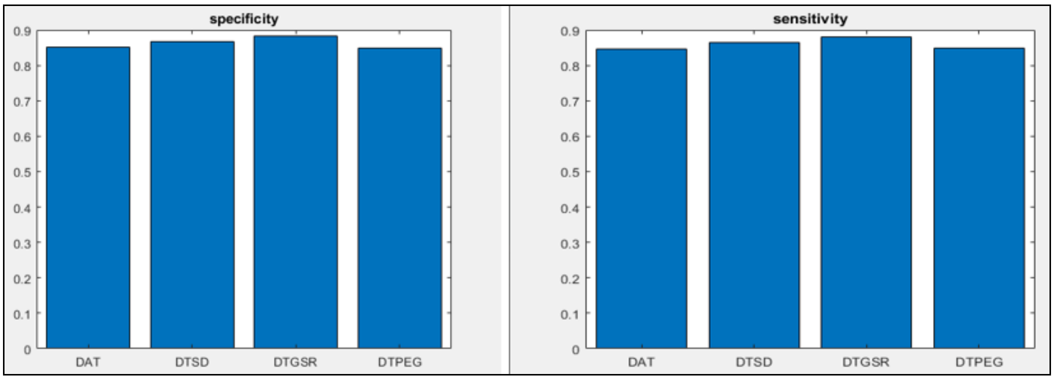

Fig 4: Sensitivity and specificity for DAT,DTSD,DTGSR,DTPEG

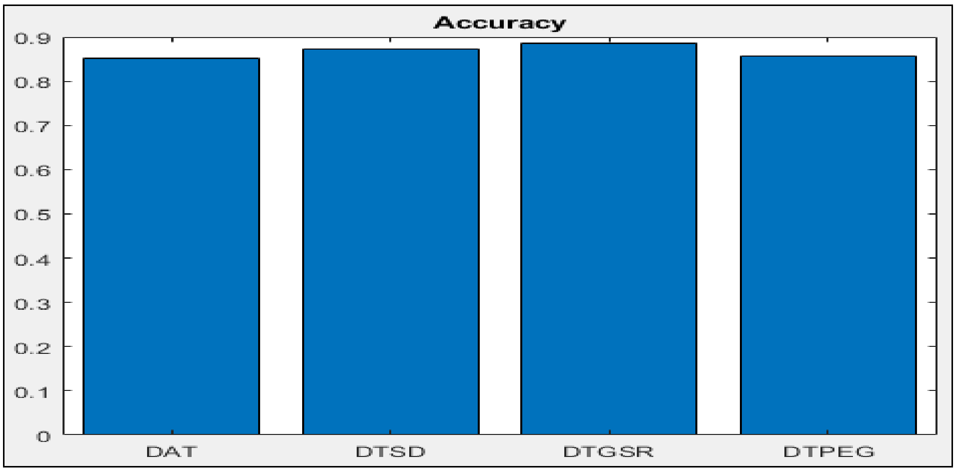

Fig 5: accuracy for DAT, DTSD, DTGSR, DTPEG

The results of a simulation of a hybrid classification are shown in Figure 1 to Figure 4. Multiple solar panels could be tasked with locating the same singularity; these panels could work together in a collection, with each solar panel being tasked with condensing the sensor consequence from all of the other panels in the collection in order to produce a "collective view" of the circumstance. This "collective view" would then be used to determine how to proceed with the investigation. Following that, a conclusion would be drawn based on this so-called "collective perspective."

Table 1: Comparison Graph energy prediction parameters

Machine Learning Classification	DAT(°C)		DTSD (h)		DTGSR(kWh/m²)		DTPEG(kWh)	
	Original	Predicted	Original	Predicted	Original	Predicted	Original	Predicted
KNN+SVM(Hybrid)	24	34	0.5	1	12.3	12	6.89	6.9
LSTM	24	25	0.12	0.9	12	12.08	6.9	6.85

The performance characteristics that were acquired using the Comparison Graph energy prediction parameters are shown in Table 1. KNN+SVM(Hybrid) and LSTM both represent comparisons with various parameters, and the results of these comparisons reveal that hybrid classification produces superior results in terms of energy prediction parameters.

Table 2: Comparison with classification parameter

Techniques	Machine Learning Classification	Attributes	Accuracy	Sensitivity	Specificity
Proposed Techniques	LSTM	DAT (°C)	95%	97.90%	99.99%
		DTSD (h)	96%	97%	99.97%
		DTGSR (kWh/m²)	93%	92%	91%
		DTPEG (kWh)	97%	95%	95%
	SVM+KNN	DAT(°C)	84%	86%	85%
		DTSD(h)	85%	84%	89%
		DTGSR(kWh/m²)	89.99%	89.90%	89.99%
		DTPEG (kWh)	860%	86%	83%

The performance characteristics that were derived utilising a comparison with the categorization parameters are shown in Table 2. The KNN+SVM (Hybrid) and LSTM models examine a variety of parameters and demonstrate that hybrid classification produces superior results.

Table 3: Comparison with existing machine learning classifier

Techniques	Machine Learning Algorithm	Accuracy (%)	Sensitivity (%)	Specificity (%)
Proposed Techniques	LSTM	96 %	97%	99.97%
	SVM+KNN	89.99%	89.90%	89.99%
Existing Classification Ramazan Bayindir [1]	Naive Byes Classifier	82.17%	98.30%	

The performance parameters that were determined via a comparison with the currently implemented machine learning classifier are shown in Table 3. KNN+SVM(Hybrid) and LSTM both provide comparisons with various parameters and indicate that hybrid classification represents superior outcomes in terms of energy prediction parameters compared to the machine learning classifier that is currently in use.

Conclusion

In the beginning, we are going to figure out the parameters of the project by analysing the amount of energy produced by the solar systems as well as their characteristics. Next, we will construct the training set by arranging the labels in accordance with the different intensities of the workout. After that, the processing will be done based on the average temperature (DAT), the total sunshine duration, the daily total global solar radiation, and the total photovoltaic energy production using the values that were supplied in the foundation paper. This will be carried out in the specified sequence. After that, the procedure of classification will be finished in order to maximise the effectiveness of the regulating process regarding the energy levels at the level of the solar system. Following this, the categorization or prediction of the levels of energy will be carried out with the aid of a classifier. After that, the performance will be assessed based on how sensitive it is, how particular it is, and how accurate it is overall. The performance that was stated above has to be at a high level in order to achieve both a high true positive rate and a high true negative rate. For the purpose of carrying out the study work that has to be done, simulations will be used. These simulations will break the system down into its many stages of growth. In order to get reduced bit error rates and improved accuracy rates, we are going to make use of the optimization tactics.

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