An Integrated System for Monitoring & Control of Solar Panel using IoT & Machine Learning

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ABSTRACT

The proper monitoring and control of solar panels using IoT and machine learning are discussed in this paper. The use of green energy sources like solar power is expanding due to rising electricity costs and worries about the impact of fossil fuels on the environment. But the static position of the solar panel, improper cleaning system & undetected faults may widely affect the total output generated from the solar panel. The efficiency of an array's energy generation is greatly diminished by the buildup of dust and debris on even an individual panel, emphasizing the necessity of keeping the panel's surface as clean as possible. The intention of our project is to create an extensive structure for performance evaluation, automated cleaning, tracking, and fault detection. The dual-axis trackers can give 40% more electricity than a non-moving solar panel. Automated water jet cleaning keeps panels always clean with regularly scheduled cleanings and requires no human labor after installation. The faults that occur on the solar panel are identified by using image detection techniques, in image detection techniques machine learning algorithms are used. Using machine learning algorithms can detect the presence of faults and causes of faults like micro-cracks, hotspots, dust accumulation, snow covering, shading, and so on. The proposed system can enhance customer satisfaction and will help to improve operational efficiency and more economical and easier to analyze performance.

Keywords: Internet of Things, Dual-axis rotation, Machine Learning

1 Introduction

Since the inevitable future scarcity of fossil fuel supplies, renewable energy sources have caught the attention of academics, legislators, shareholders, and developers worldwide. Some of the new energy sources receiving attention encompass tidal, wave energy, hydroelectric energy, geothermal energy, wind, solar, and bioenergy. They are deemed to be acceptable substitutes for fossil fuels simply because they are renewable. One of the most offered sources of various types of energy is solar photovoltaic (PV) energy.

Solar cells are being utilized more frequently in homes as a result of studies and developments meant to boost their performance and turn down their cost. According to data gathered by the International Energy Agency (IEA), the PV systems capacity has increased by 49% annually on average since the early 2000s. Future power sources are anticipated to include solar photovoltaic energy more frequently. Despite the advantages, replacing current conventional sources with solar PV energy will take a long time. Enhancing the electric power output of PV systems with an emphasis on little solar radiation is still a difficult task. This project was carried out with the objective in mind to aid in the advancement of such a promising technology. One of the easiest and most vital strategies to increase excellence is to spend as much time in the sun as possible. The objective of this endeavor is to establish a modeled-down prototype of a sun-tracking gadget, but any solar power system in the real world could benefit from the concept. This research effort will aim to serve as an economic evaluation of the tracking system's performance in contrast with a system that relies on a fixed mounting approach in comparison to keeping the solar panel stationary and

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clean, tracking it can cause an efficiency loss of up to 50%. Large-scale power plants lose more megawatts as a result of the deposits of dust on their solar roofs. The output of small-scale solar plants, in contrast, could not be greatly impacted by low-level dust deposition. Solar panel performance is constantly tracked by means of data acquisition systems, and the system's efficacy has been assessed in realistic circumstances. To maximize the cleaning process, real-time monitoring and assessment of the dirt that has been collected on the solar panels are necessary. Typically, there are two ways to monitor dirt build-up on solar panels: online or offline. To boost the effectiveness of autonomous cleaning techniques, smart technologies strengthened by an internet connection are incorporated into the cleaning of solar panels. This will enable the system to monitor the distant solar panel intelligently. It may initiate its removal from the solar panel surface without human supervision when it detects filthy circumstances. In this work, infrared thermography has been used to capture images of the solar PV module. The impact of faults that form on the direct current side of solar panels, such as open circuits, short circuits, partial shading, and hotspots, was investigated using real-time data. Faults like open circuits, short circuits, and partial shading cause the solar system's output power to decrease. The output voltage and current present at maximum power point are used as the primary criteria for fault detection, along with snow-covering faults and microcracks.

The inclement weather that photovoltaic systems are subjected to severely reduces the panel's lifespan and lowers the system's effectiveness. The solar system's output power is decreased by flaws like open circuits, short circuits, and partial shading. The current flow (I) and electrical voltage (v) at maximum power point (MPP) are used as the typical characteristics in this fault detection process.

2 Literature Review

A transition from static solar panels to dual-axis solar panels increases the entire output power prediction of solar panels. Given it, an integrated system for monitoring and control of solar panels based on machine learning and IoT is present here. The creation and execution of a dual-axis solar panel tracking system, an automatic cleaning system, and machine learning-based fault detection are discussed in this paper.

Solar panels switch solar energy into electrical current to produce electricity. The primary obstacle is to increase the volume of sunlight those panels can absorb, which will boost their capacity to generate electricity. There are two approaches to increasing the output power of systems using solar energy. A solar tracker or an efficient material can be used to create photovoltaic cells, depending on the situation [1]– [2]. A tetrahedron-based dual-axis sun tracker sensor was newly developed by Indonesian scientists Yuwaldi Away and M. Ikhsan in 2016. Three sides of a tetrahedron have three LDRs each. Based on the analysis of the outputs of the three LDRs, the system spins to generate equal outputs from each of the LDRs. Both point-light source and multi-light source configurations are used for additional testing of this technology. It has the perk of being less complicated as there are fewer LDRs and a wider range of Factors of View (FOV) [3]. Sensor-based daylight spot measurement systems must be carefully installed and periodically calibrated because they cannot accurately determine the solar position on a cloudy or intermittent day. In contrast, sun position algorithms use astronomical data or mathematical equations to determine the exact position of the sun at an exact time and place [4]. Bifacial panels may use both sides to increase their collection area in contrast to mono-facial panels, which only collect incident light from the front side. The association of rear-dispersed and surface-reflected radiation may substantially boost energy production, depending on the surrounding conditions and system setup [5]– [8]. Because of an upsurge of sand, dust, water, and other debris on the surface of solar rooftop panels, light is unable to reach the solar cells. Since the materials that block light have external resistances that reduce solar photovoltaic performance, this is a major issue [9]. Additionally, the fixed solar panel's output power losses at a tilt angle of (35) are around 25% of the stated yield and may even be greater depending on the type of dust present. A hot spot is created in the panel by the dirt and bird droppings, and it might appear suddenly in panels through[10]. By eliminating most of the dirt that has accumulated on the panel, cleaning solar panels with water improves cleaning effectiveness [11]. In Thuwal, Saudi Arabia, Brian Parrott, and Pablo Carrasco Zanini were putting into practice a solar Panel Dry-Cleaning Robotic Process using Silicone Rubber Brush in 2018 [12]. When manual cleaning expenses are compared to automatic cleaning costs, automatic cleaning comes out to be much less expensive and time-consuming, especially in systems with several solar panels.

Additionally, routine periodic cleaning guarantees that the solar panel constantly operates with good transmittance [13]– [16]. The PV energy system's power output exhibits substantial complexities concerning its intermittency, fluctuations, and unpredictability due to weather systems being erratic and unreliable. This has the potential to have a detrimental effect on the governance and operation of the source of energy and energy framework, as well as the continuous monitoring of effectiveness and system economics. For optimal utilization of a PV power plant's monetary benefits, power efficiency forecasts are essential. It is well known that solar radiation on solar PV panels possesses an effect on their output energy. However, it has also been noted that other climatic factors, such as ambient temperature, wind speed, relative humidity, and dust collection, can influence the efficiency of solar panels [17]– [21].

A few methods, including historical information, quantitative meteorological information, cloud satellite imagery, etc., are available to predict solar radiation. Based on the non-parametric strategy, improbable irradiation anticipating was developed, and prediction ranges have been determined using a k-nearest neighbors regression model. The forecasting of solar radiation used a probabilistic ensemble approach. Since empirical biassing, a proposal for the spatial and temporal ensemble forecasting of total daily radiation was made. Lasso was used to waiting five minutes before radiation. Data on solar radiation has been investigated in connection with the implications of climate categorization by means of K-nearest neighbor and assistance vector algorithms. In [22]– [24], signal breakdown and a Volterra-least squares support vector neural network model have been applied to predict daily solar radiation. A six-month UTSA Sky Imager database was utilized for foreseeing cosmic rays [25]. A deep learning model called long short-term memory (LSTM) serves for microgrids to anticipate solar radiation for the following day [26]. The prediction over the sun's radiation is made via gated recurrent units (GRUs) [27].

An IoT-based solar energy monitoring system was created in 2017 by Suprita M. Patil, Vijayalakshmi M., and Rakesh Tapaskar to detect potential issues with the system, such as hot spot conditions, shadowing, and dusting, which may limit its production by over 40%. These flaws might be discovered by keeping an eye on the system and its values. The adoption of IoT will make things simpler for improving renewable energy systems' productivity. The Internet of Things (IoT) is a network of tangible things equipped with detectors and interaction software. The system monitoring the system's power flow will provide real-time data as well as historical data so that faults may be reduced before they can cause any harm [28]. As a result of innovations in technology bringing apart the expenses of renewable energy machinery, substantial photovoltaic (solar) deployments are being encouraged internationally. Since most plants are in hard-to-monitor spots and are unable to be tracked from an isolated site, elegant methods for streamlining distant plant surveillance via internet-based interfaces have to be used [29].

3 Components

3.1 Solar Panel

The photovoltaic effect, an ordinary chemical and physical phenomenon, is utilized through a solar cell, commonly called a photovoltaic cell, in order to convert luminous energy directly into electricity. A specific type of photoelectric cell is a device whose electrical aspects, such as current, voltage, or resistance, alter while faced with light. Many solar cells are arranged in an integrated group and are all pointed in the same direction to make up a photovoltaic module or panel.

In solar power systems, the semiconductor silicon wafers are shielded by a transparent panel with a light-facing side which enables light to pass through. Solar cells are typically wired in series to add surplus voltage. If cells are connected in parallel, then the current increases. Because of the contrary bias that their lit rivals employ to the darkened cells, issues with correlated cells, especially shade implications, may trigger a dimly lit (less illuminated) parallel string (a set of attributed cells) to cease functioning lowered, leading to substantial loss of power and potential harm. Even though it can be done to connect modules to generate an array with the intended peak. DC electrical voltage and loading capacity for current might be accomplished either via the addition of distinct MPPTs (maximum power point trackers), or, more ideally, with or without unit-level power electronic (MLPE) units involving microinverters or DC to DC enhancers relying upon each section. Shunt diodes contribute to lower the power loss caused by shadowing in parallel/series arrays. In general, solar cells are wired in series to deliver an additive voltage.

3.2 ATmega328P Microcontroller

Featuring an 8-bit RISC CPU core, the ATmega328P is a single-chip microcontroller. ATMEGA328P is a deep-performance, minimal power consumption controller. AVR RISC architecture is the foundation of the 8-bit microprocessor ATMEGA328P. Because ARDUINO boards use it, it is perhaps the most renowned AVR controller. The necessary program file must be written to the ATmega328P FLASH memory in order to accomplish this. After it has been dumped, the controller runs this program code, which causes the app to have an opiate reaction. The ATMEGA328P has a wide range of applications, including embedded systems like coffee makers and vending machines, SMPS and Power Enforcement systems, Digital media Processing, analog Signal Measuring and Trickery, Motor Management Systems, Display Units, and Periphery Interface Systems. Numerous initiatives and autonomous technologies requiring for an uncomplicated, cost-effective microcontroller occasionally use the ATmega328.

3.3 LDR Sensors

As the term implies, the Light Dependent Resistor (LDR) is comprised of semiconductor substances, such as cadmium sulphide, whose electrical conductivity in gloom differs from a few thousand Ohms to only a few hundred Ohms while bombarded by sunlight. The result is a lighter, more conductive system with reduced resistance. In addition, it takes several seconds for photo-resistive cells to respond to a change in light intensity.

3.4 Dust Sensor

A Sharp GP2Y1010AU0F is integrated into the Dust Sensor, a basic air quality monitoring device. With a diameter larger than 0.8 m, even tiny particles like cigarette smoke can be detected. Dust density has an inverse relationship with the analog voltage output of the sensor. The module has a voltage boost circuit that can work with different power sources.

3.5 Stepper Motor

In applications that demand accurate positioning control, stepper motors are frequently used. A microcontroller called ATMega328P serves as the foundation of the solar tracker's control circuit. This is programmed to activate the stepper motor to position the solar panel where it will receive the most sunlight soon after identifying the existence of sunlight via the LDRs. The stepper motor has excellent response characteristics, is brushless, load independent, able to perform positioning in an open loop, and has a good holding torque.

3.6 DC-DC boost converter

In response to a load's request, the boost converter boosts the input voltage. This special feature is made possible by the energy storage in an inductor and the higher voltage delivery of the energy to the load. The fundamental idea beneath a boost converter lies in an inductor's inclination to withstand fluctuations in current by retaining energy in its magnetic field or both. A boost converter always produces more voltage than it takes in.

3.7 Battery

A battery is a device that transforms chemical energy retained in it into electrical energy. Batteries are by far the most typical method for consumers to safeguard their solar energy. The energy that the battery receives from the sun is stored by chemical reactions between its component parts. The reaction is reversible, and the current can leave the battery when the battery is empty.

4 System description

The system being presented seeks to create a productive solar energy harvesting system. The project has five goals such as:

i. Dual-axis solar panel tracking
ii. Automatic water jet cleaning
iii. Fault detection using a Machine learning
iv. Online/Remote supervision of the panel

A significant rise in solar photovoltaic installations is being driven by the falling cost of renewable energy gadgets as technological developments occur. A great deal of these structures functions as power savings. A rooftop to the middle of a desert—the majority of these reside in daunting-to-reach destinations. They, therefore, need intricate mechanisms for remotely monitoring these setups via broad area networks. A low-cost encased IoT-based Solar PV surveillance system (fig.1) and a relatively inexpensive microcontroller in this study communicate the fabrication-end data via the web for accessibility from all over the entire globe. This will offer us the ability to view current details about the setup that will aid in finding issues and maintenance, and it will likewise provide us with an audit trail of all data collected at recurring times.

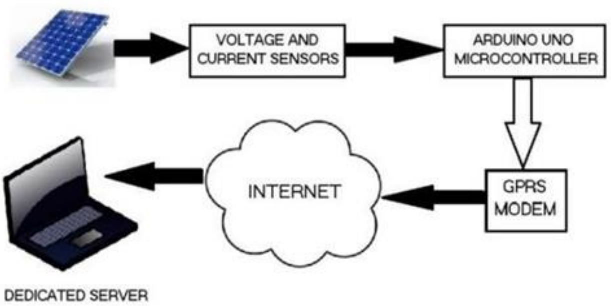


Figure 1: *Schematic diagram of IoT-based solar photovoltaic remote monitoring system*

The sun does not always face the solar panel because it depends upon the rotation of the earth. To utilize solar energy effectively, solar panels should have the greatest absorption capacity. The solar panel can be continuously rotated in the direction of the sun by using a solar tracker to achieve this.

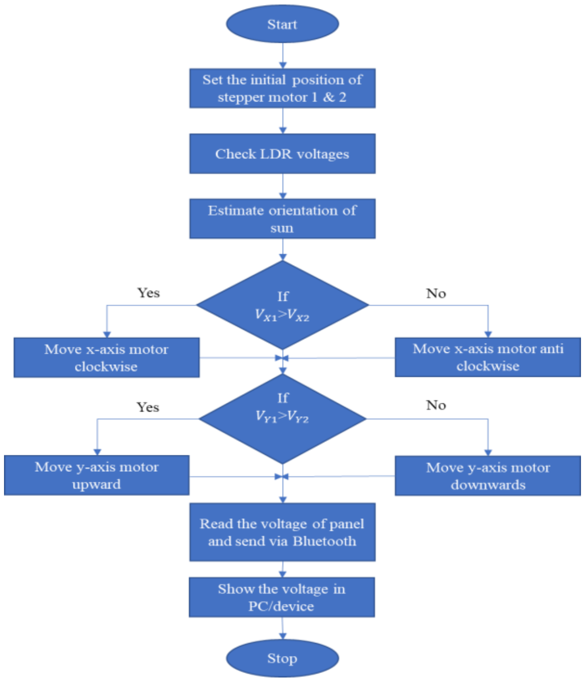


Figure 2: *Flowchat of dual-axis solar panel tracking system.*

The above flow chart (Fig.2) outlines the steps that were taken when developing and designing the solar tracking system. The system is built to react to sunlight striking the solar panel, which determines how the solar panel is moved. An Arduino microcontroller regulates the operational system.

In supervised machine learning decision tree algorithms are used to predict the solar PV modules' output power generation & also helps to detect and classify the faults that occur in solar PV system.

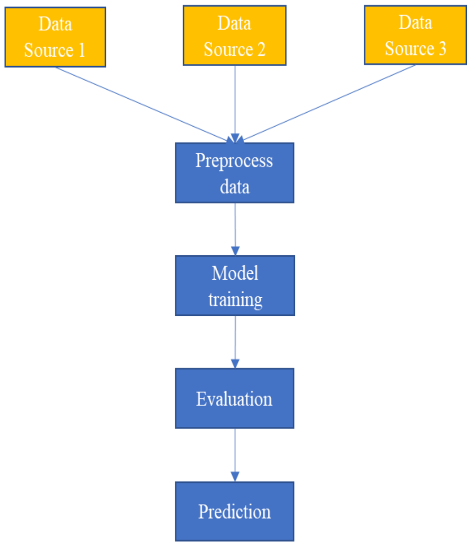


Figure 3: *Machine learning pipeline for classification of solar photovoltaic status*

Machine Learning Process Algorithm (fig.3)

- Step 1: Send the data to the system for detecting corrupted data after retrieving it from the logger.
- Step 2: If invalid information is discovered, proceed to step 3; otherwise, move on to fourth step.
- Step 3: Go to the fifth step since integrating detected info into the collection.
- Step 4: Place the data in the database, then move on to the first step.
- Step 5: Explore all previously recorded inoperative data. Go to step 6 when it is higher than 10.
- Step 6: The user is alerted.

- Step 7: EXIT

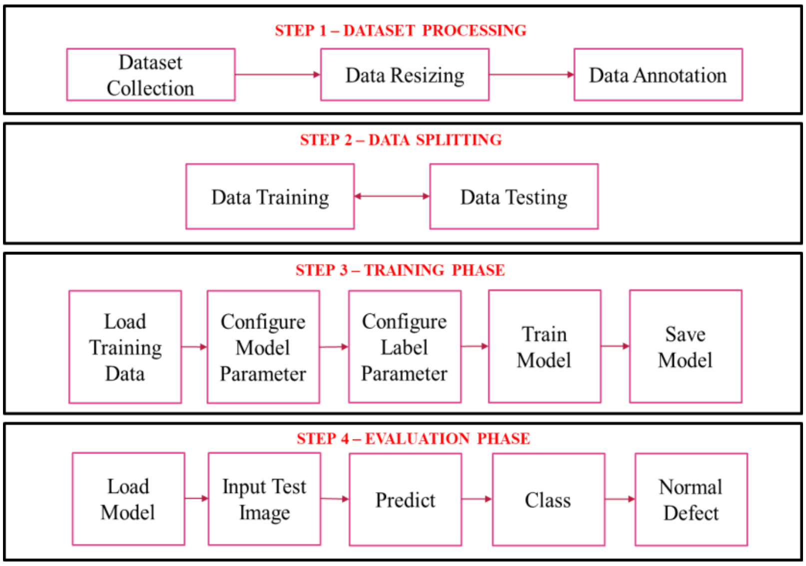


Figure 4: *Steps involved in the ML process*

The main steps involved in the machine learning process are (fig.4);

a. Dataset processing

b. Data splitting

c. Training phase

d. Evaluation phase

The process of getting raw data ready for analysis or machine learning is known as dataset processing. It entails preparing data for analysis by cleaning, transforming, and pre-processing it. The primary procedures in dataset processing are data cleaning, data transformation, data pre-processing, data integration, and data visualization. The first step is to clean the data, which entails getting rid of any extraneous information or outliers. Data normalization, variable transformation, and data format conversion are some examples of this. It might be necessary to pre-process the data after it has been transformed in order to get it ready for analysis or machine learning. Overall, dataset processing is a vital phase in the procedure for data analysis because it makes sure that the information remains precise, relevant, and presented in a manner that can be easily evaluated.

To divide a dataset into two or more subsets for training and testing purposes, data splitting is a technique used in machine learning and data analysis. The objective is to train a machine learning model on one subset, and then assess the model's performance on the other subset. By testing the model's effectiveness on a different dataset, data splitting ensures the model's accuracy. In machine learning, the training phase is the process of creating a model while using a dataset to discover trends and connections between input features and output targets. while performing the training phase, the parameters of the model must be optimized to mitigate the disparity between the predicted output and the real result. Testing a trained model's performance on a different dataset that was not used during the training phase is referred to as the evaluation phase in machine learning.

By employing a dust sensor, the automatic water jet cleaning is operated(fig.5). In the dust sensor, a threshold value can be set. When the threshold value falls below the real value, the dust sensor sends signals to the microcontroller, which then sends signals to the control valve. The overall process will be monitored via IoT.

4.1 Block Diagram

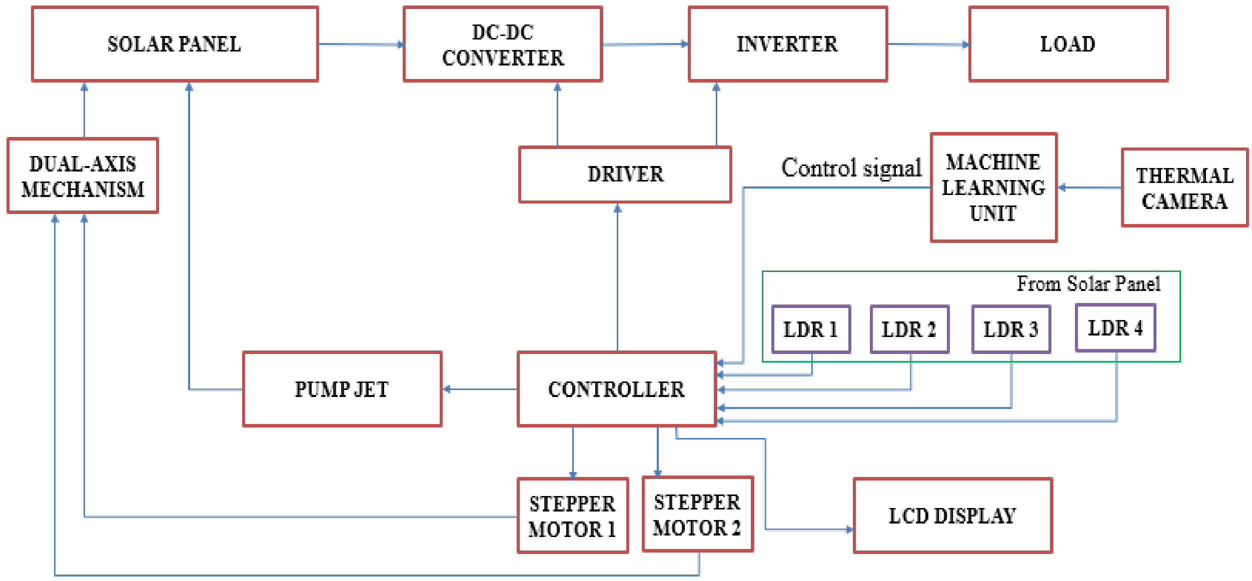


Figure 5: *Block diagram of the proposed system*

4.2 Circuit Diagram

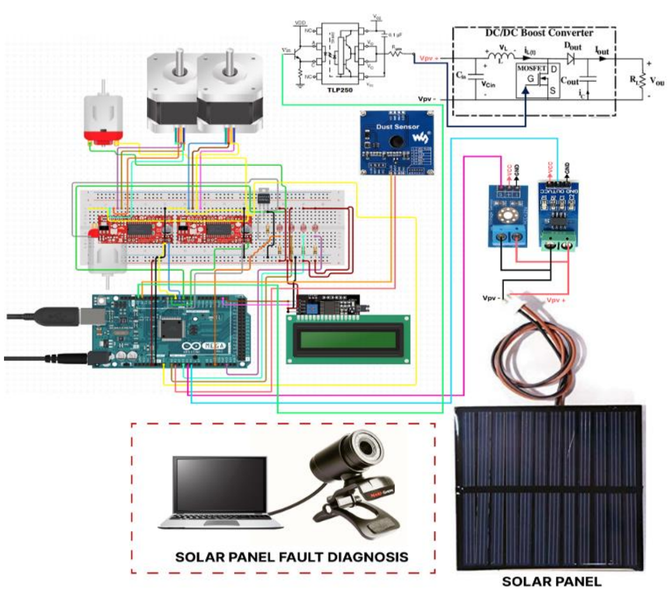


Figure 6: *Circuit diagram of the proposed system*

In the prototype stepper motors, dust sensor & converter (DC/DC boost converter) are wired to the ATmega328P microcontroller(fig.6). 50W 12V Solar panel is linked to the microcontroller via a voltage sensor, current sensor & converter. The voltage sensor senses output from the solar panel and when the microcontroller understands that no sufficient power is reaching from the solar panel. The V_{in} pin of the microcontroller is connected to the V_{DD} of motor driver a4988. Pin 13 & A_1 are connected to the dust sensor. Pin 14 is linked to the gate of the TLP250 driver.

The dust sensor's V_{cc} pin is wired to the Arduino's 5V pin. Additionally, V_{-LED} is connected to 5V using 150 resistors. The Arduino's GND pin should receive signals from the sensor's LED_{GND} and S_{GND}. The Arduino's Analogue pin A2 should be connected to the sensor's LED pin. The digital output pin in this case is analog pin A_2. Since the dust sensor generates analog voltage, the module's Vo pin is linked to Arduino's A6 analog input pin. A pulse driver circuit is also necessary, and it is built around a 150-ohm resistor and a 220-uF capacitor. An I^2C LCD is also incorporated to see the dust concentration. An I^2C LCD is also incorporated to see the dust concentration. SDA and SCL pins of LCD are linked to pins A_4 and A_5, respectively, while GND and V_{CC} of LCD are connected to GND and +5V of Arduino.

The negative power rail is connected to the LCD screen's pins 1 and 16. The backlight and LCD will be powered by this. To power the LCD and backlight, pins 2 and 15 of the LCD are also connected to the positive power rail. Connecting pin 3 to the potentiometer's middle pin will allow you to adjust the contrast. The top and bottom potentiometer pins are connected to 5-volt and GND rails, respectively. Pin 4 of the LCD is connected via cable to pin 12 of the Arduino. A ground connection is made to pin 5 of the LCD. For activating the data, pin 6 of the LCD must be linked to pin 10 of the Arduino.

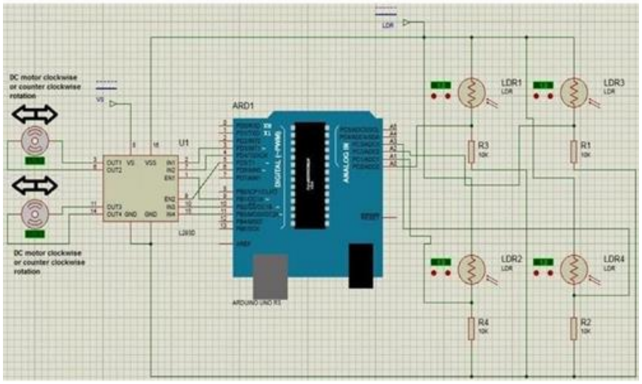


Figure 7: *Circuit diagram of dual-axis tracking system*

The lower horizontal row of the breadboard is wired with the Arduino's 5-volt pin for the dual-axis automatic sun-tracking system(fig.7). Similar links are made regarding the second lower horizontal paddle of the breadboard to the Arduino's GND pin. The breadboard's upper horizontal rows should be used to extend the 5-volt and GND rows, respectively. The stepper motor drive' power pins are hooked up to 5 volts on both their vertical and horizontal axes. Specifically, the horizontal and vertical stepper motor drive' GND pins are thus electrically connected to the ground. An extension cord is employed for attaching the Signal pin of the Vertical Stepper Motor to the Digital Pin No. 10 of the Arduino. One of the two ports on each potentiometer is wired to the ground, and the other two exterior ports have been linked to VCC 5 volts. The right top has two LDR sensors, the right bottom has one, and the left top and bottom have two each. Through the addition of 10k-ohm resistors, a single terminal of each LDR gets linked to the 5-volt supply whereas each of the other ports is anchored. The wiper pins of the potentiometers 1 and 2 belong to pins A4 and A5, accordingly, on the analog signal bus. A1 pin on the Arduino is wired to the bottom left LDR voltage Divider point. The top left LDR voltage Divider Point is linked to Arduino pin A0 by means of a wire. The LDR Voltage Divider Point in the upper right-hand corner as well as the A2 pin ought to be associated the same way. The A3 pin on the Arduino interacts with the LDR's bottom right voltage divider point.

5 Experimental Setup

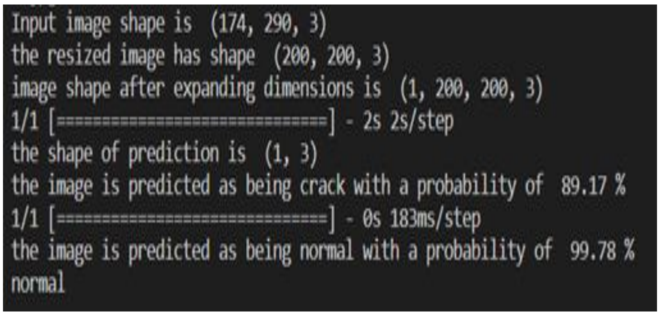
Figure 8 illustrates the experimental configuration of the system, which comprises both software and hardware components. The data collected from the sensors follows a path from the sensors to the microcontrollers and subsequently to the IoT platform for thorough analysis. Inside this system, machine learning models work incessantly to process the data, offering predictive insights into the solar panel's conditions and delivering control commands when necessary. Section 4 provides a comprehensive breakdown of both the hardware and software components. In essence, this integrated system enables effective monitoring, control, and enhancement of solar panel performance, leading to increased durability and energy output. Additionally, it streamlines remote management and contributes to cost savings in maintenance.

Figure 8: *Experimental setup of the proposed system*

6 Experimental Results

6.1 Under normal conditions

Figure 10(a): *Result obtained from the ML model (Normal case-Hardware result)*



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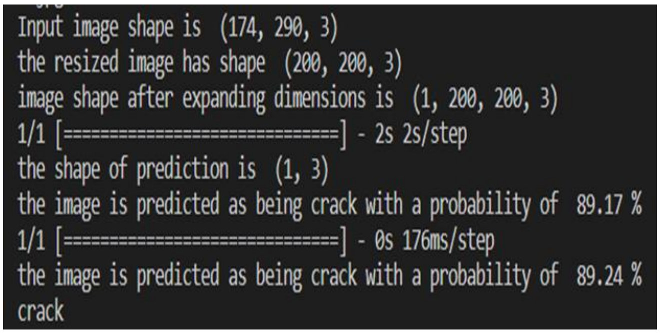
Input image shape is  (174, 290, 3)
the resized image has shape  (200, 200, 3)
image shape after expanding dimensions is  (1, 200, 200, 3)
1/1 [==============================] - 2s 2s/step
the shape of prediction is  (1, 3)
the image is predicted as being crack with a probability of  89.17 %
1/1 [==============================] - 0s 183ms/step
the image is predicted as being normal with a probability of  99.78 %
normal
```

Figure 10(b): *Result obtained from the ML model (Normal Case-Software result)*

Fig.(10a) and Fig.(10b) are providing a comprehensive depiction of the results obtained from solar panel operating under standard conditions. In Fig. 10(a), shows an image of the solar panel functioning under typical circumstances. Meanwhile, Fig. 10(b) presents the software-derived outcomes of this solar panel's performance through the application of a machine learning algorithm.

6.2 Under Fault conditions

Figure 11(a): *Result obtained from ML model (Fault (Cracks)- Hardware result)*



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Input image shape is  (174, 290, 3)
the resized image has shape  (200, 200, 3)
image shape after expanding dimensions is  (1, 200, 200, 3)
1/1 [==============================] - 2s 2s/step
the shape of prediction is  (1, 3)
the image is predicted as being crack with a probability of  89.17 %
1/1 [==============================] - 0s 176ms/step
the image is predicted as being crack with a probability of  89.24 %
crack
```
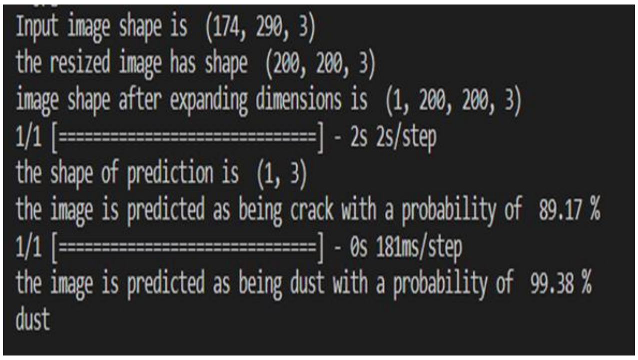

Figure 11(b): *Result obtained from ML model (Fault (Cracks)- Software result)*

Fig.(11a) and Fig.(11b) are providing a comprehensive depiction of the results obtained from a solar panel operating under cracked conditions. In Fig. 11(a), shows an image of the solar panel displaying cracks and damage. Meanwhile, Fig. 11(b) presents the software-derived outcomes of this solar panel's performance using a machine learning algorithm in response to the observed cracks.

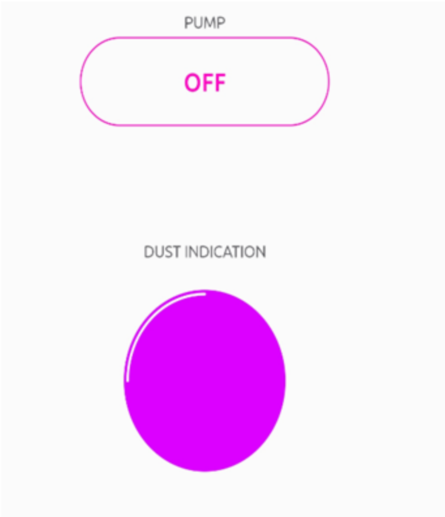
Figure 12(a): *Result obtained from ML model (Fault (Dust accumulation)- Hardware result)*



```
Input image shape is  (174, 290, 3)
the resized image has shape  (200, 200, 3)
image shape after expanding dimensions is  (1, 200, 200, 3)
1/1 [==============================] - 2s 2s/step
the shape of prediction is  (1, 3)
the image is predicted as being crack with a probability of  89.17 %
1/1 [==============================] - 0s 181ms/step
the image is predicted as being dust with a probability of  99.38 %
dust
```

Figure 12(b): *Result obtained from ML model (Fault (Dust accumulation)- Software result)*

Fig. 12(a) and Fig. 12(b) provides a comprehensive illustration of the results obtained from a solar panel operating under conditions of dust accumulation. In Fig. 12(a), displays an image of the solar panel covered in dust and debris. Meanwhile, Fig. 12(b) presents the software-generated results depicting the performance of this solar panel, achieved through a machine learning algorithm, in response to the dust accumulation



observed in Fig. 12(a).

Figure 13: *Dust indication & water jet valve operation via IoT platform*

Figure 13 displays the outcomes derived from a web application implemented through an IoT platform. It provides information regarding the amount of dust accumulated on the panels, as well as the operational status of a pump.

7 Limitations

The Decision Tree algorithms are used to detect the faults and also used to predict total output power generation from solar panels. But Decision Tree model should have some disadvantages, such as

(1) High training costs. The experimental data are produced from actual world data. People may be concerned about the expense and safety of this.

(2) The DT model may not function well when presented with unknown data that is significantly different from the training set.

Since external factors have a significant impact on how well the PV array's function is and since the PV array itself may experience a huge variety of fault circumstances, it may be challenging to gather a training and test dataset large enough to account for every conceivable scenario of malfunction.

8 Conclusion

In this paper, a dual-axis automatic solar-tracking system and associated supervisory and control systems were discussed. It is precise, dependable, and effective. According to the experimental configuration, the suggested automatic solar tracking system generates an overall amount of energy that is between 30% and 45% higher than the fix-angle PV system on bright days and between 8% and 11% higher on overcast days. Effectively sensing the system parameters, a smart control system is developed to boost the system's competitiveness. Additionally, decision-tree (DT) model-based fault detection and classification in solar photovoltaic (PV) systems have been proposed. It is simple to implement the model training process. The trained model has strong classification accuracy and detection accuracy, which may have intriguing real-world applications. By doing this, the prediction accuracy would undoubtedly increase. Implementing this suggested prototype will help with monitoring and regulating the solar system.

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9 Future Scope

Due to the belief that single-axis tracking/fixed-angle tracking is sufficient, dual-axis solar tracking is still uncommon commercially, even in nations where solar energy accounts for a significant portion of the nation's electricity production. Dual-axis tracking, however, will significantly boost the effectiveness. We used a PV panel with intermittent power to conduct this approach for our investigation. On a business level, cost-effectiveness and system potency can be found. In this study, a mono-crystalline PV panel was used.

But the proposed design can also use a PV panel made of polycrystalline materials. For this claimed model, we opted LDR, although LDR is not an acceptable sensor choice because it is impacted by dust. So, in the future, we can also utilize a more effective sensor. Adding solar panels to the system is far more cost-effective than investing in a stable structure because the price of a dependable structure is substantially more than the price of solar panels.

10 Publisher's Note

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