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DEVELOPMENT OF SOLAR IRRADIANCE WEATHER CLASSIFICATION SYSTEM

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Abstract

Solar energy is a promising renewable source, but the performance of photovoltaic (PV) systems depends on local weather conditions, particularly solar irradiance, which fluctuates with cloud cover, humidity, and atmospheric changes. Advanced forecasting tools like satellite imaging and machine learning models are often too complex and costly for small-scale applications. This project develops a low-cost, standalone solar irradiance-based weather classification system using an Arduino Uno, BH1750 light sensor, DHT22 humidity sensor, and DS3231 RTC. The system calculates solar irradiance, estimates the clear sky index using the Haurwitz model, and classifies weather conditions (clear, partly cloudy, mostly cloudy, cloudy, or overcast) based on simple logical rules. Designed for solar tracking, microgrid energy management, and off-grid power systems, the system provides an accuracy approaching 60% without relying on complex machine learning. It offers a practical solution for tropical regions with limited resources and serves as an educational tool for understanding solar energy and environmental sensing.

Keywords: Clear sky index, Humidity, Ruled based classification, Solar irradiance, Weather classification.

1. Introduction

Solar energy has become one of the leading renewable energy sources globally. Climate change became a growing concern, decreasing the number in fossil fuel and increasing in energy demand. Solar energy is considered as a clean, sustainable and environmentally friendly alternative energy source. Solar photovoltaic (PV) systems have become the most accepted due to their adaptable, cheap operational expenses and ability to reduce the amount of greenhouse gas. According to the International Energy Agency (IEA), solar PV is expected to generate over 50% of global renewable electricity generation by 2050, which will become a crucial role in the future energy supply [1]. Research also shows that there is rising power generation from solar energy in recent past and future years (2000-2050) [2]. Not only that, but solar PV also installed globally will exceed 1000 GW by 2022 and the number is still increasing over the years [3].

However, the performance of solar photovoltaic (PV) systems is heavily influenced by weather conditions, particularly solar irradiance. Solar irradiance is the measurement of solar power received per unit area; solar irradiance can be affected by cloud, humidity, air mass and time. This may lead to fluctuations in power output, affecting grid reliability and energy planning [4]. Therefore, accurately classifying weather states based on solar irradiance can improve forecasting, energy management, and overall solar system efficiency. Accurate forecasting can help operators to make changes in solar generation and adjust load shifting, backup generation and battery usage [5, 6].

The current solar irradiance forecasting methods are divided into three groups: physical models, statistical models and hybrid models. Common physical models such as numerical weather prediction (NWP), NWP model predict weather based on current atmospheric conditions and ground based meteorological data to predict irradiance. While these models can provide spatial and temporal prediction, they are computationally demanding and may cause issues of decreased resolution for short-term prediction. Statistical models such as machine learning algorithms and time series forecasting using historical data to forecast future irradiance value. These are some methods that are suitable for real time or short terms forecasts, but when it comes to non-linear conditions or chaotic effects of cloud motion will affect the performance [7]. For complex conditions hybrid models tend to perform better and provide higher accuracy results [8].

Some research proposed a classification method using ground based solar radiation measurements [9], clearness and brightness were used to identify clear, cloudy and overcast conditions. These approach shows that irradiance derived index can effectively represent cloud condition without relying on visual sky images. Similarly, combination of weather research and forecasting (WRF) model with machine learning techniques [10] tend to improve irradiance forecasting in tropical climates. Hybrid methods can achieve higher accuracy but requires large datasets, strong computation power and model training, which limits the use in low-cost systems. The literature review carried out have shown impressive performance in solar irradiance forecasting. For example, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied to sky image classification, significantly improving the accuracy of solar forecasting, particularly under highly variable conditions. Similarly, forecasting-driven solar weather clustering techniques, such as those using Long Short-Term Memory (LSTM) networks, have shown promising results in predicting solar irradiance with high precision. These methods, while highly accurate, often require large datasets, intensive model training, and high computational power, which makes them less suitable for low-cost or resource-constrained applications. In contrast, the proposed rule-based classification system offers a computationally efficient and cost-effective alternative.

Other than that, there are still needs for accessible, real time and low-cost solutions for solar irradiance-based weather classification systems, especially for small scale solar deployments. For higher computing ability and conventional weather classification systems often require expensive sensors and complex infrastructure which is not suitable and limiting educational, community and energy projects. Therefore, this project proposes the development of solar irradiance-based weather classification systems using Arduino microcontroller, light sensor, humidity sensor and real time clock module.

Rule based classification system is proposed due to its cost-effective ability for forecasting techniques. It suits well for people who need a real time classification system even though the forecast is low-detailed, for example solar tracking equipment, smart microgrids and academic research projects. The project contributes to the existing literature in the subject area of solar energy monitoring and integrated weather systems by showing the low-cost sensor networks and empirical model in real environmental conditions. Furthermore, it assists in the worldwide movement towards smart and sustainable energy solutions by localized decision making and improving energy yield estimation regardless of external forecasting systems [11].

The theoretical contribution of this study lies in the novel application of a rule-based classification system for solar irradiance weather classification, which offers a significant advantage over more complex forecasting methods such as machine learning or numerical weather prediction (NWP) models. While these advanced models can achieve higher accuracy, they often require large datasets, high computational power, and extensive model training, making them less practical for small-scale, low-cost applications. In contrast, the proposed rule-based approach integrates empirical models (such as clear sky index) with real-time sensor data, offering a computationally efficient, easily deployable, and cost-effective solution. This approach advances theoretical understanding by demonstrating that simplified, low-cost methods can still provide reliable and real-time classification for solar energy systems, especially in educational, research, and off-grid settings where access to high-end technology is limited.

2. Research Methodology

The research methodology focuses on data collection, processing, and analysis using a prototype embedded system. The system measures real-time illuminance and relative humidity (RH), converts these measurements into solar irradiance and clear sky index (CSI), the system classifies the weather based on fixed threshold value.

2.1. Overview

The main goal of this research paper is to develop a solar irradiance-based weather classification system using Arduino microcontroller and sensors.

As shown in Fig. 1, the research will focus on data collecting and analysing. Sensor calibration and testing will be carried out before every single use. The prototype will be deployed at Taylor's University for data collection. Data such as lux and humidity level will be collected using the BH1750 light intensity sensor and DHT22 sensor, clear sky index will be calculated at the same time. If nothing goes wrong, it will proceed to store the data into the SD card module otherwise recalibration of the sensor will be needed and redo the process. The stored clear sky index and humidity level will be used as the classification input for the rule-based classification system. The result will be compared to the actual weather forecast to evaluate the accuracy of the system.

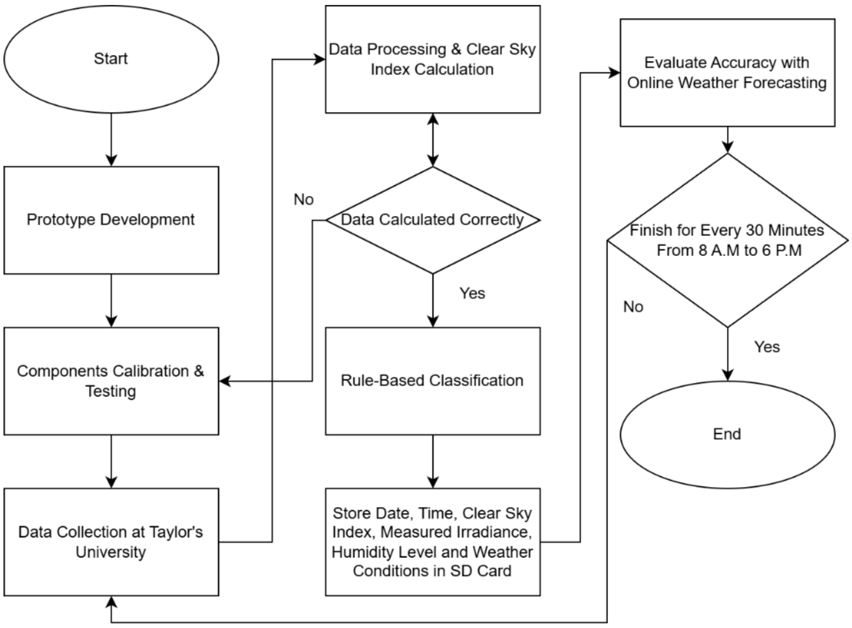

Fig. 1. Flowchart of methodology.

Figure 2 shows the online forecast website AccuWeather, this website is chosen for comparison due to the detailed parameters provided such as sky condition, humidity level and cloud cover. Not only that the website also provides other parameters such as wind speed, pressure point and temperature which can be used to predict the weather even more accurate for future use.

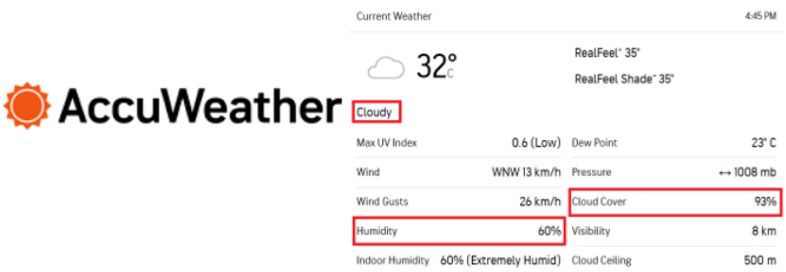

Fig. 2. AccuWeather online forecast.

2.2. Data conversion

BH1750 light intensity sensor only able to measure lux, the conversion is shown in Eq. (1), an approximate conversion of lux into solar irradiance value [12].

$$Solar\ Irradiance\ Value = \left(\frac{1000}{120000}\right)(Lux\ Value)\ W/m^2 \tag{1}$$

Other than solar irradiance, global horizontal index is also required to convert before analysing the clear sky index in Eq. (2), the theoretical clear sky irradiance is estimated based on Haurwitz model [13].

$$GHI_{clear} = 1098 * \cos(\theta_z) * e^{-0.059/\cos(\theta_z)} \tag{2}$$

To find $\boldsymbol{\theta}$z, solar zenith angles the angle between sun and vertical, latitude, time and date were required. This is why a RTC clock module is needed to capture the current time for calculation.

2.3. Clear sky index

Clear sky index will be calculated in Arduino coding using Eq. (3), by dividing the measured irradiance and theoretical clear sky irradiance [14].

$$CSI = \frac{Measured\ Irradiance}{GHI_{clear}} \tag{3}$$

The system will operate from 8.00 A.M to 6.00 P.M and record data for every 30 minutes. The sky condition will we classify as clear sky, partly cloudy, mostly cloudy, cloudy and overcast. The weather classification of this system uses clear sky index which is the ratio of measured irradiance to theoretical clear sky irradiance. Studies have shown clear sky index ranges to show different sky conditions, from 0.4 to 1.0 to show overcast, mixed and clear sky [15]. But due to the limitation of the BH1750 light intensity sensor the maximum measured irradiance value is limited and causing clear sky index to not reach 1.0 during peak hours, therefore the clear sky index for clear sky is lowered to 0.8. Humidity level threshold of 60% and 90% were selected based on previous findings [16]. Clear sky index and humidity level will be used in the ruled based classification system to classify the weather conditions based on the threshold value shown in Table 1.

Table 1. Threshold value for all weather conditions.

Clear Sky Index, CSI [15]	Humidity Level, RH [16]	Weather Conditions
CSI>=0.8	>=60%	Partly Cloudy
CSI>=0.8	<60%	Clear Sky
0.4=<CSI<0.8	>=60%	Mostly Cloudy
0.4=<CSI<0.8	<60%	Cloudy
CSI<0.4	>=90%	Overcast
CSI<0.4	<90%	Cloudy

2.4. Prototype setup

The prototype is built using Arduino Uno with all components connected. All of the Vcc pins are connected to the 5V terminal and GND is connected to the GND terminal The BH1750 light intensity sensor and DS3231 real time clock module are both connected to the Arduino via the I²C interface A4 and

A5. DHT22 temperature and humidity sensor is connected to digital pin D2 for data transmission. For storing data, an SD card module with connections to pins D10 (CS), D11 (MOSI), D12 (MISO), and D13 (SCK). A 5 V regulated battery, or laptop can be used as a power source for the Arduino board. The prototype is deployed near the solar panel area at Taylors University to get the same sunlight exposure area. BH1750 light sensor is pointing upwards to the sky to get clear light exposure, DHT22 sensor and rtc module are fixed on a breadboard as shown in Fig. 3. A laptop is used as a power source and serial monitor for easier monitoring and calibrating.

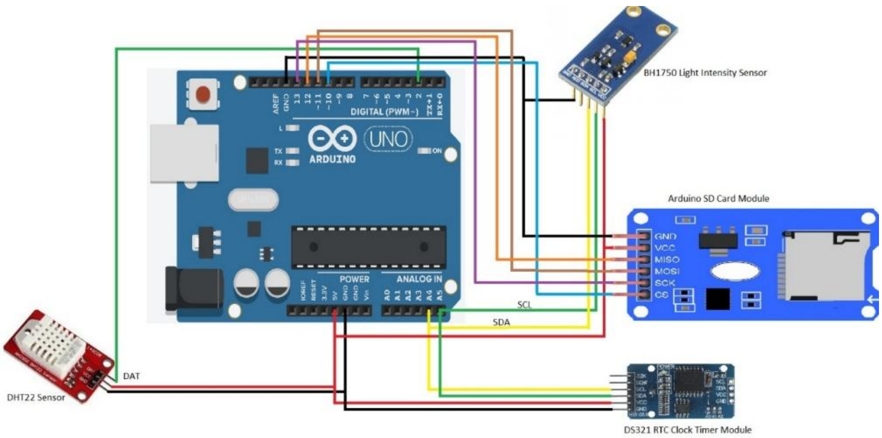

Fig. 3. AccuWeather online forecast.

2.5. Arduino coding

Figure 4 shows the declaration of library using, sensor objects, constant and parameters used. Several libraries is used such as Wire for I2C communication, BH1750 for light intensity measurement, DHT for humidity measurement, RTClib for real time clock, SPI and SD for SD card data logging. Several constants are defined such as Pi, SD card chip select pin, lux to irradiance conversion factor and latitude of Taylor's University and sampling interval. In Fig. 5, the first function is used to determine Julian day for solar position calculations, the second functions calculate the zenith angle, θ_z based on time, latitude and solar declination. The final function will use the zenith angle, θ_z to estimate the theoretical clear sky global horizontal irradiance, but if the zenith angle is >=90° the model will output zero since the sun is below the horizon. Figure 6 presents the function of rule based classification using the threshold mentioned in 2.4. During the initial startup shown in Fig. 7, SD card SPI chip select pin need to be temporarily disable to avoid conflicts with the sensors that connected to I2C. RTC will also checks for power loss and if occurs it will reset to Arduino's compile time. If the SD card initializes successfully, a CSV file is created if not presented to store all the data.

```
#include <Wire.h>
#include <BH1750.h>
#include <DHT.h>
#include <RTClib.h>
#include <SPI.h>
#include <SD.h>

BH1750 lightMeter;
DHT dht(2, DHT22);
RTC_DS3231 rtc;
File dataFile;

#define MY_PI 3.14159265
const int chipSelect = 10;
const float LUX_TO_WM2 = 0.0079;
const float LATITUDE = 3.07;

unsigned long lastLogTime = 0;
const unsigned long logInterval = 5UL * 1000UL; //
```

Fig. 4. Setup.

```
int getDayOfYear(DateTime now) {
  static const int daysInMonth[] = {31,28,31,30,31,30,31,31,30,31,30,31};
  int day = now.day();
  for (int i = 1; i < now.month(); i++) day += daysInMonth[i-1];
  if ((now.year()%4==0 && now.year()%100!=0) || (now.year()%400==0))
    if (now.month()>2) day++;
  return day;
}

float calcSolarZenith(DateTime now) {
  int day = getDayOfYear(now);
  float hour = now.hour() + now.minute()/60.0;
  float dec = 23.45 * sin(2 * MY_PI * (284 + day) / 365.0);
  float ha = 15.0 * (hour - 12.0);
  float z = acos(
    sin(LATITUDE*MY_PI/180.0)*sin(dec*MY_PI/180.0) +
    cos(LATITUDE*MY_PI/180.0)*cos(dec*MY_PI/180.0)*cos(ha*MY_PI/180.0)
  );
  return z * 180.0 / MY_PI;
}

float calcClearSkyIrradiance(float zDeg) {
  if (zDeg >= 90) return 0;
  float zRad = zDeg * MY_PI / 180.0;
  return 1098 * cos(zRad) * exp(-0.059 / cos(zRad));
}
```

Fig. 5. GHI calculation.

```
String classifyWeather(float CSI, float RH) {
  if (CSI >= 0.8 && RH < 60) return "Clear";
  else if (CSI >= 0.8 && RH >= 60) return "Partly Cloudy";
  else if (CSI >= 0.4 && CSI < 0.8 && RH >= 60 ) return "Mostly Cloudy";
  else if (CSI < 0.4 && RH < 90) return "Cloudy";
  else if (CSI < 0.4 && RH >= 90) return "Overcast";
  else return "Cloudy";
}
```

Fig. 6. Weather classification.

```
void setup() {
  Serial.begin(9600);
  delay(300);
  Serial.println(F("System starting..."));

  pinMode(chipSelect, OUTPUT);
  digitalWrite(chipSelect, HIGH);
  delay(100);

  Wire.begin();
  lightMeter.begin();
  dht.begin();

  if (!rtc.begin()) {
    Serial.println(F("RTC not found!"));
  } else if (rtc.lostPower()) {
    rtc.adjust(DateTime(F(__DATE__), F(__TIME__)));
  }
  if (!SD.begin(chipSelect)) {
    Serial.println(F("SD init failed! Running without SD."));
  } else {
    Serial.println(F("SD ready."));
    if (!SD.exists("weather.csv")) {
      File f = SD.open("weather.csv", FILE_WRITE);
      if (f) {
        f.println(F("Weather Data Log (timestamped)"));
        f.close();
      }
    }
  }
  Serial.println(F("System initialized."));
}
```

Fig. 7. Initial startup.

3. Results and Discussion

The results obtained from the developed solar irradiance weather classification system and discusses the observed performance under real outdoor conditions. Solar irradiance and humidity level were collected over a period of 13 days using low-cost sensor as shown in Table 2. The system recorded illuminance and convert it to irradiance value, relative humidity and time information from RTC module. The measure irradiance value is compared with theoretical clear sky irradiance using Haurwitz clear sky-model to find clear sky index (CSI) and use it as threshold along with humidity to evaluate weather conditions. Measurements were recorded at fixed time intervals throughout the daytime period, covering morning, noon, and late afternoon conditions. This ensured that the dataset captured both daily solar variation and short-term atmospheric fluctuations.

Table 2. Summary of table parameters.

Total number of days	**13 Days**
Measurement interval	30 Minutes
Sensor used	BH1750, DHT22, RTC DS3231
Location	Taylor's University
Time window	8 A.M – 6 P.M

3.1. Measured and calculated irradiance

The measured solar irradiance was compared against theoretical clear-sky irradiance computed using Haurwitz model, which estimate the clear-sky global horizontal irradiance based on solar geometry and assumes minimal atmospheric attenuation. Therefore, it provides the upper bound reference for expected irradiance under ideal clear-sky conditions.

The clear-sky irradiance shows a smooth and symmetrical graph, which peaking around 12 P.M-2 P.M and starts decreasing gradually. While the measure irradiance demonstrates deviations from the theoretical curve due to cloud cover, wind speed and humidity effects. During clear weather the measured closely follows the clear-sky curve, where significant reductions occurs when cloudy or overcast conditions. This can be shown in Figs. 8 and 9, where during sunny day the measured irradiance increase overtime until 2 P.M and start to decrease overtime, while during cloudy day the measured irradiance is significantly lower especially during peak hours.

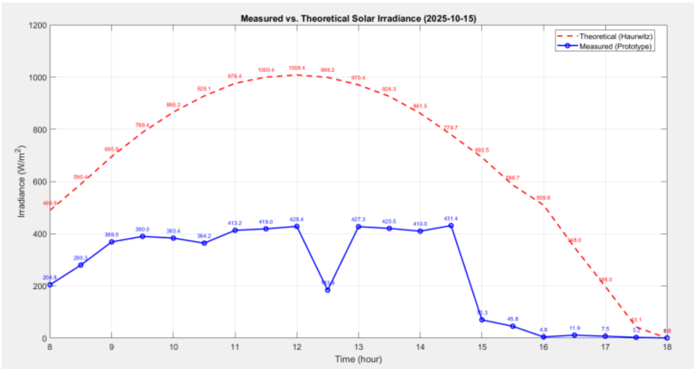

Fig. 8. Measured and theoretical irradiance graph under sunny day.

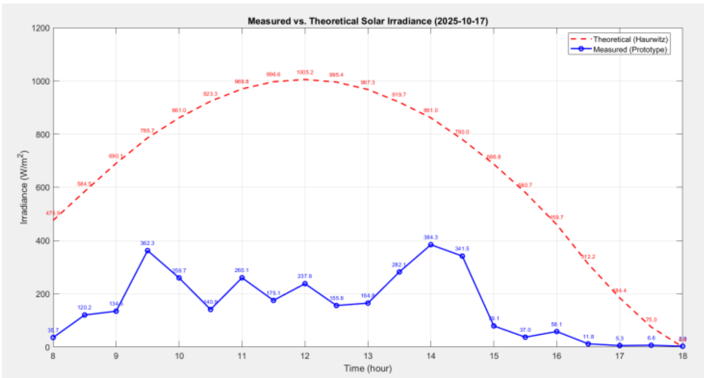

Fig. 9. Measured and theoretical irradiance graph under cloudy day.

3.2. Clear sky index (CSI) behaviour and weather classification

To normalize the effect of solar position and enable consistent comparison across different times of day, Clear Sky Index (CSI) was calculated as the ratio of measured irradiance to clear-sky irradiance. CSI provides a dimensionless indicator of weather conditions as shown in Fig. 10, where values close to 1 indicate clear sky conditions and lower values represent increasing in cloudiness.

```
2025-10-30 08:02:59, Lux: 8367.50, Irradiance: 66.10, Clear Sky Irradiance: 462.25, RH: 76.60, CSI: 0.14, Weather: Cloudy         Online: Cloudy
2025-10-30 08:31:12, Lux: 6400.00, Irradiance: 50.56, Clear Sky Irradiance: 572.60, RH: 77.60, CSI: 0.09, Weather: Cloudy         Online: Cloudy
2025-10-30 09:01:40, Lux: 5205.83, Irradiance: 41.13, Clear Sky Irradiance: 676.04, RH: 78.30, CSI: 0.06, Weather: Cloudy         Online: Cloudy
2025-10-30 09:31:48, Lux: 4995.00, Irradiance: 39.46, Clear Sky Irradiance: 766.73, RH: 78.00, CSI: 0.05, Weather: Cloudy         Online: Cloudy
2025-10-30 10:03:14, Lux: 34600.83, Irradiance: 273.35, Clear Sky Irradiance: 847.63, RH: 71.40, CSI: 0.32, Weather: Cloudy       Online: Cloudy
2025-10-30 10:31:30, Lux: 20765.83, Irradiance: 164.05, Clear Sky Irradiance: 903.74, RH: 70.10, CSI: 0.18, Weather: Cloudy       Online: Cloudy
2025-10-30 11:01:04, Lux: 31359.17, Irradiance: 247.74, Clear Sky Irradiance: 947.66, RH: 66.90, CSI: 0.26, Weather: Cloudy       Online: Cloudy
2025-10-30 11:31:08, Lux: 10975.83, Irradiance: 86.71, Clear Sky Irradiance: 974.08, RH: 62.70, CSI: 0.09, Weather: Cloudy        Online: Cloudy
2025-10-29 12:01:33, Lux: 26782.33, Irradiance: 211.58, Clear Sky Irradiance: 986.33, RH: 63.80, CSI: 0.21, Weather: Cloudy       Online: Cloudy
2025-10-30 12:39:25, Lux: 54612.50, Irradiance: 431.44, Clear Sky Irradiance: 967.25, RH: 61.40, CSI: 0.45, Weather: Mostly Cloudy  Online: Mostly Cloudy
2025-10-30 12:59:41, Lux: 54612.50, Irradiance: 431.44, Clear Sky Irradiance: 947.66, RH: 60.60, CSI: 0.46, Weather: Mostly Cloudy  Online: Mostly Cloudy
2025-10-30 13:34:58, Lux: 48203.33, Irradiance: 380.81, Clear Sky Irradiance: 894.77, RH: 59.50, CSI: 0.43, Weather: Cloudy       Online: Partly Cloudy
2025-10-30 14:05:28, Lux: 44630.83, Irradiance: 352.58, Clear Sky Irradiance: 829.03, RH: 58.10, CSI: 0.43, Weather: Cloudy       Online: Partly Cloudy
2025-10-30 14:32:08, Lux: 13068.33, Irradiance: 103.24, Clear Sky Irradiance: 758.29, RH: 61.30, CSI: 0.14, Weather: Cloudy       Online: Partly Cloudy
2025-10-30 15:12:18, Lux: 40748.33, Irradiance: 321.91, Clear Sky Irradiance: 632.67, RH: 61.20, CSI: 0.51, Weather: Mostly Cloudy  Online: Mostly Cloudy
2025-10-30 15:35:53, Lux: 11567.50, Irradiance: 91.38, Clear Sky Irradiance: 550.54, RH: 60.80, CSI: 0.17, Weather: Cloudy        Online: Mostly Cloudy
2025-10-30 16:01:11, Lux: 45905.83, Irradiance: 362.66, Clear Sky Irradiance: 450.34, RH: 61.30, CSI: 0.81, Weather: Partly Cloudy  Online: Partly Cloudy
2025-10-30 16:31:18, Lux: 35509.16, Irradiance: 280.52, Clear Sky Irradiance: 326.88, RH: 60.40, CSI: 0.86, Weather: Partly Cloudy  Online: Partly Cloudy
2025-10-30 17:03:29, Lux: 8445.00, Irradiance: 66.72, Clear Sky Irradiance: 189.08, RH: 61.10, CSI: 0.35, Weather: Cloudy         Online: Partly Cloudy
2025-10-30 17:31:08, Lux: 21942.50, Irradiance: 173.35, Clear Sky Irradiance: 68.90, RH: 64.10, CSI: 2.52, Weather: Partly Cloudy  Online: Partly Cloudy
2025-10-30 17:57:40, Lux: 14963.33, Irradiance: 118.21, Clear Sky Irradiance: 0.00, RH: 64.30, CSI: 0.00, Weather: Cloudy         Online: Mostly Cloudy
```

Fig. 10. Data of different weather conditions.

Across the 13-day dataset, CSI values showed differences between different sky conditions. High CSI values were observed during periods of strong solar irradiance, while low CSI values equal to cloudy and overcast periods. Transitional CSI values were commonly observed during partly cloudy conditions, where intermittent cloud cover caused rapid fluctuations in measured irradiance.

3.3. Integration of relative humidity in weather classification.

Relative humidity (RH) was used as an additional environmental parameter to improve classification accuracy, particularly in tropical climates where high humidity may affect even during visually bright conditions. High humidity levels increase atmospheric scattering and are often associated with cloud formation and haze.

The combined use of CSI and RH enabled better differentiation between clear, partly cloudy, and overcast conditions. As shown in Fig. 11, instances where CSI values were moderately high but relative humidity exceeded fixed thresholds were classified as partly cloudy rather than clear. This integration reduces misclassification caused by relying solely on irradiance-based classification.

```
2025-10-29 16:31:36, Lux: 33880.83, Irradiance: 267.66, Clear Sky Irradiance: 327.76, RH: 60.60, CSI: 0.82, Weather: Partly Cloudy  Online: Partly Cloudy
2025-10-29 17:03:02, Lux: 19641.67, Irradiance: 155.17, Clear Sky Irradiance: 189.75, RH: 64.10, CSI: 0.82, Weather: Partly Cloudy  Online: Partly Cloudy
```

Fig. 11. Humidity as second threshold.

3.4. System performance and validation

The prototype is deployed for 13 days, 21 data every day from 8 A.M to 6 P.M for every 30 minutes. To validate the performance of the proposed solar irradiance classification system, the results were compared with real-time weather data obtained from AccuWeather's API over a 14-day period. The online dataset provided key weather parameters, including solar irradiance, humidity, and sky conditions, which were used to assess the system's accuracy in classifying weather states. The comparison showed that the system's classifications were consistent with the forecasted weather conditions, with a classification accuracy of 57.87%. Minor discrepancies were observed during transitional weather states, such as partly cloudy conditions, indicating the potential areas for further refinement in handling dynamic weather fluctuations. This validation confirms the viability of the system for real-time weather classification in low-cost solar applications. This accuracy is calculated by using Eq. (4)

$$Average\ accuracy = \frac{Total\ number\ of\ data\ in\ same\ sky\ condition}{Total\ number\ of\ data\ in\ sky\ condition} \quad (4)$$

To evaluate the sensitivity of the system to different input features, a sensitivity analysis was conducted to determine how variations in solar irradiance (lux), humidity, and clear sky index (CSI) affected the classification accuracy. The analysis revealed that humidity was the most significant feature affecting the system's performance, particularly during transitional weather conditions such as partly cloudy periods. Additionally, the system's classification accuracy was compared against experimental data obtained from previous studies on solar irradiance classification systems, such as the work by [10, 17], who used a hybrid forecasting method in tropical environments. This comparison showed that the proposed rule-based system achieved a comparable classification accuracy, despite being more computationally efficient and cost-effective than the experimental systems used in those studies. Overall, the developed system demonstrates reliable performance in monitoring solar irradiance and classifying weather conditions using low-cost sensors and simplified models. The CSI and relative humidity together offer meaningful indicators of weather conditions.

The accuracy of the system is limited by the highly stochastic and intermittent nature of solar irradiance, particularly under partly cloudy conditions. These conditions lead to rapid fluctuations in irradiance, causing larger prediction errors when using a single, unified forecasting model. To address this, future work will explore hybrid models, combining the rule-based classification system with machine learning or ensemble forecasting techniques to enhance accuracy, especially during transitional weather conditions. Additionally, data smoothing techniques and multi-model approaches could be implemented to minimize prediction errors caused by the rapid changes in cloud cover. The use of sensor fusion, which combines data from multiple environmental sensors, could also improve the system's ability to handle variable weather conditions and enhance the overall accuracy of the system.

4. Conclusion

This research developed a low-cost, standalone solar irradiance-based weather classification system using the BH1750 light intensity sensor and the Haurwitz clear sky model. The system successfully classified weather conditions such as clear, partly cloudy, and overcast with an overall accuracy of 57.87% compared to AccuWeather's forecast over 13 days. The system performed well under stable weather conditions but encountered increased classification errors during transitional weather and high humidity periods. Key challenges included sensor overheating, SPI/I2C communication issues, and lux range limitations of the BH1750 sensor. Future improvements include ventilated housing to manage heat, a frosted cover for the sensor, and thermal management to reduce sensor drift. Additionally, the high humidity near the lakeside location at Taylor's University caused misclassifications, highlighting the need for active thresholding to account for local environmental variations. Future work will focus on enhancing accuracy by implementing active ventilation, UV filtering, and improved thermal stability, making the system more suitable for real-world tropical climates.

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Abbreviations

CSI	Clear Sky Index
GHI	Global Horizontal Irradiance
IEA	International Energy Agency
ML	Machine Learning
NWP	Numerical Weather Prediction
PV	Photovoltaic
RH	Relative Humidity
RTC	Real Time Clock
SD	Secure Digital

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