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Performance Prediction of Dual Working Medium Solar Drying System Using Machine Learning Approaches

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Abstract: Research into solar-assisted drying systems has been stepped up in response to the growing need for environmentally friendly drying technologies. These systems provide an alternative to traditional drying processes that is both cost-effective and beneficial to the environment. The utilization of solar energy, on the other hand, frequently faces challenges in the form of intermittent power and uncertain operating circumstances. The purpose of this research is to design a solar drying system that utilizes a dual working medium in order to increase the efficiency with which energy is utilized while simultaneously maintaining appropriate drying temperatures. Machine learning algorithms such as Bayesian Ridge, Linear Regression, Elastic Net, Support Vector Regression (SVR), and Gradient Boosting Regression Trees (GBRT) were utilized in order to forecast outlet air temperature depending on environmental parameters. This was done in order to improve performance prediction. According to the findings of the comparison, the GBRT model attained the highest accuracy, with an R2 value of 0.98 during training and 0.94 during testing. This model outperformed other models, despite the fact that it required more time for training. The results of this study reveal that machine learning is a powerful tool that can accurately forecast the performance of solar drying systems, which in turn supports improved operational control and design optimization.

Keywords: *Dual Working; Solar Drying System; Machine Learning*

INTRODUCTION

As a measure to combat climate change, several nations have adopted and are working toward the carbon neutral goal. At the same time, the world's energy consumption has been seeing a dramatic uptick due to both population growth and the expansion of industrialization. The majority of the world's energy comes from fossil fuels [1]. For that reason, we must do all in our power to upsurge the practice of non-coventional energy sources.

Power generation, heating and cooling of buildings, drying, and household hot water are only a few of the many diverse uses for solar energy. However, solar energy's dispersion, instability, and low radiation intensity contribute to its relatively low utilization rate [2,3]. In addition, many academics have been worried with agricultural product drying technologies for storage and transportation as a means to address the paradox of rising populations and food insecurity. The drying of agricultural crops by solar radiation is becoming increasingly frequent. Opening sun drying, direct sun drying, indirect sun drying, and hybrid sun drying are the four main types of solar drying [4]. In solar drying, there are two main areas of research: studying the drying properties of agricultural products and analyzing drying systems' effectiveness.

The thin-layer drying evaporation kinetics and the corresponding convective heat–mass transfer coefficients were assessed for various biomass systems, and drying materials in relation to the drying properties of agricultural products. A study conducted by Mewa et al. (2019) [5] examined the rate of drying of beef using a solar tunnel dryer. After Stegou-sagia et al. (2018) [6] established the isothermal drying kinetics of Granny Smith apples with TGA, they offered a new model for predicting their drying curve. The Midilli and Kucuk model was determined to be the most effective in describing the drying curve of sludge in an indirect forced convection solar dryer when Ameri et al. (2020) [7] investigated the kinetics of sludge drying at three different temperatures. Furthermore, the impact variables of convective heat and mass transfer coefficient on Oryza sativa L. were investigated by Golpour et al. (2021) [8] under various solar drying conditions.

There has also been a lot of performance evaluation of drying systems done, which is great news for the drying industry's bottom line and solar energy's efficiency in use. Solar drying also has the primary challenge of transforming solar radiation into thermal energy suitable for drying agricultural products. The sun drying sector has seen extensive use of air-based solar thermal collector as a means of capturing solar energy. As a result, studying the thermal efficiency for drying is highly important.

Most of the recent research on solar air collector thermal performance has relied on traditional thermodynamic analysis and AI prediction techniques, but there has also been substantial exploration of experimental approaches. However, using thermodynamic analysis to forecast solar air collector performance is a very involved process. The general forms allow one to present an overview of the thermodynamic governing equations, despite the fact that solar air collectors have varied structures and characters. [9].

Conversely, solar air collector performance predictions have made use of clever computing prediction approaches. Intelligent computer prediction methods do not necessitate the detailed character characteristics of the air-based solar thermal collector, in contrast to conventional thermodynamic analysis. Solar dryers, solar aided heat pumps, solar stills, and other solar energy systems were optimized and predicted using artificial neural networks (ANNs), as reviewed by Elsheikh et al. (2019) [10]. The article by Ghritlahre and Prasad (2018) [11] provided a synopsis of the use of artificial neural networks (ANNs) to model, simulate, and operate solar collector systems; the authors argued that ANNs are superior at handling complicated, nonlinear situations. Additionally, ML algorithms have been greatly enhanced and utilized in several domains due to the advancements in computer theory and research.

Problem statement

Traditional solar drying systems face significant limitations due to fluctuations in solar radiation, ambient conditions, and drying air flow, leading to unstable outlet air temperatures and reduced efficiency. Conventional thermodynamic models, while useful, are computationally intensive and require detailed system parameters, making them less practical for real-time prediction and control. Therefore, there is a critical need for intelligent, data-driven approaches that can accurately forecast solar drying system performance under varying environmental conditions, ensuring reliability and efficiency in agricultural applications.

Objectives of this study

The major goal of this research is to develop and test a solar drying system with two working mediums that can stabilize drying conditions for agricultural products while increasing solar energy usage. The aim of the study is to find the impact of important environmental factors on the system's heat collecting efficiency and the temperature of the air coming out of the exhaust, including the amount of sunlight, humidity, and the velocity of the supply air. For accurate performance forecasting machine learning models used in the study to accomplish accurate prediction and control. To find the best model, the study compares various methods' prediction accuracy and computing efficiency using statistical measures like MAE, RMSE, and R^3. Improving energy efficiency and sustainability in agricultural drying applications is the ultimate goal of the project, which aims to offer practical insights for real-time monitoring and optimization of solar drying systems.

METHODOLOGY

Hot air convection drying systems usually maintain a tolerable drying temperature by controlling the working capacity of the system. Although this design approach can hinder the process of solar energy usage, it presents a novel technique for multiple working mediums based on the notion of energy storage conversion. A drying system with two working media is illustrated in Figure 1.1, along with the design approach.

The process works like this: a solar heat unit heats the drying air to a high temperature, which is then used to dry the material. After that, the air is discharged into the outdoors. A drying chamber, auxiliary gear, pipelines, and a solar thermal unit are all part of the system. The two-working media—the drying air and the other, such water or refrigerant—form the dual working medium. The system's energy use is prioritized by making maximum use of solar energy, followed by other sources of supplementary energy. The solar heating unit may store and use solar energy to heat auxiliary equipment or dry the air; it is the heat exchange hub of the system. Making efficient use of solar energy while maintaining a manageable drying temperature is the primary advantage of the method. This hybrid sun drying system employs two distinct working media to successfully dry fabrics. It operates in a single mode. The working medium flow can be adjusted to dry the system intermittently or continuously.

To regulate the system, we need to keep an eye on climatic and meteorological parameters in real time, use models to estimate the air temperature coming out of the outlet using the equivalent solar heat units, and compare drying temperatures to figure out which operating mode to use. Operational control strategies vary from system to system.

The direction of the energy and working medium flows may be found by comparing the values of T_{pre} andT_{su} as illustrated in Figure 1.1.

1. The solar heating unit stores some of the energy it absorbs in auxiliary equipment when $T_{pre} > T_{su}$
2. A portion of the energy needed for drying is supplied by auxiliary equipment when $T_{pre} < T_{su}$

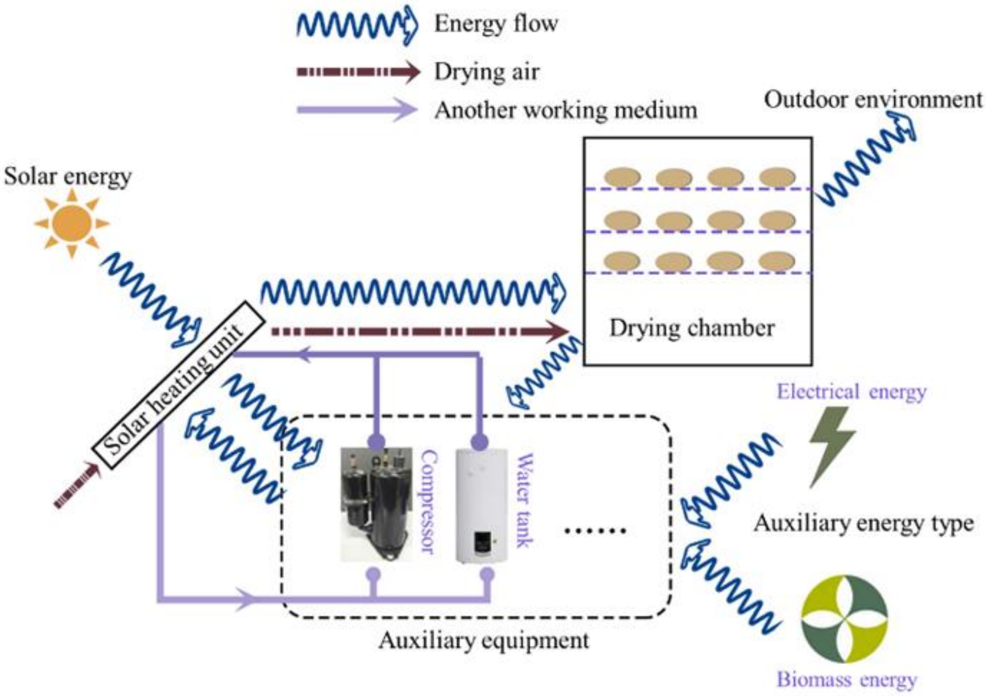

Figure 1. Working procedure.

Determination of operation environment constraints

An integral part of the system for drying two working media at once is the solar heating unit. We can predict the system's operating conditions by applying thermal theory to the solar thermal unit's efficiency. The ideal working conditions are indicated by the effectiveness of heat collection and the temperature of the outflow air. There is just one metric used to determine how well a solar heating device works. Academics in the field have poured a lot of time and energy into studying solar collectors' physical properties and how different climates and environments affect their performance in the hopes of making these devices more efficient thermally. For this experiment, it is necessary to heat the air-drying chamber to a specific temperature using the solar thermal unit. In addition, the solar heating unit's operating environment control system must be supplied. Supply air flow, ambient temperature, and solar radiation intensity are the dependent variables that determine how the simulation operates for this reason.

There is a hybrid solar dryer plant located in Jinan, a city in the Shandong province of China, at 36.67 N and 117.08 E. An example of a hybrid solar dryer may be shown in Figure 1.2. This research takes a look at a dual-purpose flat-plate solar collector as an example of how this idea works. In reference [12], the precise features and thermal mathematical model of a flat-plate solar collector with two functions were discussed.

During the simulation process, the parameters are often adjusted to a range. The range of values for the simulation parameters is shown in Table 1.1. Unless something unexpected happens, the following parameters will be maintained: outside temperature of 10 degrees Celsius, solar radiation strength of 600 watts per square meter, and the heat collecting unit's supply air volume of 500 cubic meters per hour.

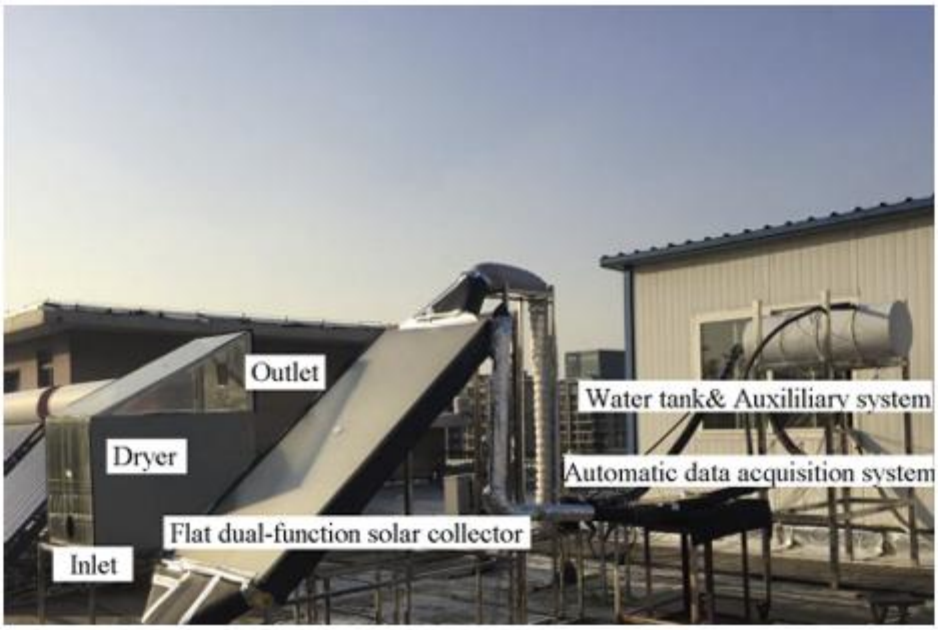

Figure 2. hybrid solar dryer snapshot.

Tab 1. Range of simulated operating conditions.

operating conditions	Range	Unit
Outside temperature	0,10,20,25	°C
Solar radiation intensity	200,400,600,800	W/m^2
Amount of the air supply for the heat collector	100,300,500,700	m^3/h

Sample data

As shown in Figure 1.2, the hybrid solar dryer facility is where the data utilized for training in this study is located. To enhance the model's accuracy for real-world engineering, testing periods were randomly planned from September 2017 to June 2018. The major goal of the study was to evaluate the temperature of the outflow air from the dual-function flat plate solar collector, and the air cycle was the only tool employed for this purpose. Outdoor relative humidity, temperature, wind speed and direction, solar radiation intensity, and air temperature as it was evacuated from a dual-purpose flat plate solar collector were sampled as experimental data types. Machine learning input variables are defined using types of experimental monitoring data. The air temperature as it leaves the collector is yet another output variable.

Approximately 3,800 data samples are deemed valid after mistakes and missing values have been handled. The training set received 80% while the testing set received 20%. Since system variables such as structural parameters, absorptivity, transmittance, etc. were utilized to predict the same operational characteristics of the system, machine learning models did not use them as inputs [13]. Table 1.2 displays the output and input variables in a number of formats. Despite extensive investigation, no obvious correlation between the input and output variables has been identified. The goal, then, is to use machine learning to predict the air temperature at the collector's exit.

Tab 2. The variety of possible inputs and outputs.

Parameters	Range (Min-Max)	Mean Value
Solar irradiance(W/m^2)	0-699	278
Ambient air temperature (°C)	14-39	24
Atmospheric relative humidity (%)	43-65	54
Airflow Velocity (m/s)	0-2.7	1.2
Airflow direction	-	-

Estimate Evaluation Metrics

The three indices can be expressed in this fashion

$$R^2 = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{\sum_{i=1}^{N} (y_i - \bar{y})^2} \ldots\ldots (1.1)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - y_i)^2} \qquad \ldots\ldots (1.2)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N} |x_i - y_i| \ldots\ldots\ldots (1.3)$$

Findings

Characterizing the parameters of the operational environment

An increase in the supply air flow causes the heat collecting unit to become less efficient and causes the air to depart the unit at a higher temperature. Both the efficiency of heat collection and the temperature of the output air tend to remain rather constant until the supply air reaches a particular point in the flow. The absorber plate temperature will rise with an increase in the collector's supply air flow, but the heat gain per unit volume of air will fall, leading to cooler output air and better heat collecting efficiency.

When the air temperature decreases, the absorber plate's temperature difference increases, which causes the air temperature to fall at a slower rate until the supply air flow reaches a certain quantity. Convective heat transfer between the two surfaces is therefore improved. Since a result of a slowing of the rise rate of both the quantity of heat carried out by the air and, ultimately, the rate of change in heat collecting efficiency, reduced outlet air temperatures reduce heat transfer per unit air volume.

Since the outflow air is both more efficient and hotter, the heat collection unit's heat loss will decrease as the ambient temperature increases. Therefore, the first priority for achieving maximum thermal efficiency should be to improve the heat collection unit's thermal insulation performance.

The ejected air temperature and the effectiveness of the heat collector both rise almost linearly as the sun's rays get stronger. By increasing the temperature of the absorber plate, the space between it and the air becomes wider, enhancing its heat transmission capability, as the sun's rays get more intense.

The characteristics and operation of a dual work medium drying system are investigated in this study, along with the effects of solar radiation intensity, ambient temperature, supply air flow on output air temperature, and the heat collection unit's efficiency. Finding the operation settings according to the materials' ideal drying temperatures might provide light on the technological uses of the system. If the ambient temperature is less than 25°C and the dry air temperature is 45°C, for example, and the flow rate is 100 cubic meters per hour, then the operating parameters of solar radiation intensity may be reached. This part is used at the beginning of the system design process to determine if the system can function in the given local climate and environment.

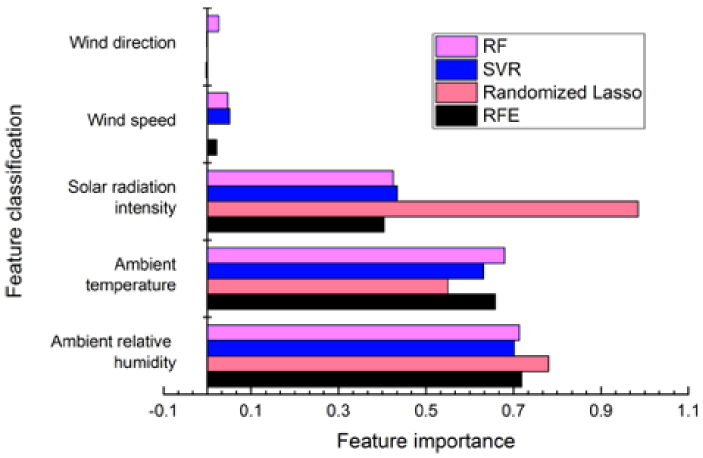

Figure 3. Performance of feature set selection with four methods.

AS given in figure 1.3 the Bayesian Ridge model, which was tuned with $\alpha_1 = 0.01$ and $\alpha_2 = 10$, had an R^2 of 0.98. Linear Regression with intercept enabled and one job having a recorded R^2 of 0.92. The Elastic Net, with $\alpha = 1$ and L1 ratio = 0.5, had an R^2 of 0.93. The R^2 value of 0.98 was achieved by the SVR model, which is optimized using $C = 0.005$, $\varepsilon = 0.01$, and a linear kernel. The GBRT model, with $\alpha = 0.01$, learning rate = 0.01, max depth = 1, and 300 estimators, came up with an R^2 value of 0.95.

Predictive performance assessment

The selection of features is a critical first step in enhancing the predictive power of machine learning models. Model interpretability, training time reduction, and generalizability are all enhanced by feature selection. A few examples of the feature selection approaches are LASSO, random forest, additional trees, and Pearson correlation analysis. We use recursive feature elimination (RFE), randomized lasso, stochastic volatility retrieval (SVR), and random forest (RF) to pick features in this investigation. As illustrated in Figure 1.3, four different strategies were used to choose the feature sets. When analyzing the impact on collector outlet temperatures, the average feature importance value ranks ambient relative humidity as the most relevant element. The randomized lasso technique, on the other hand, estimates solar radiation intensity to be the most critical variable.

Evaluation of hyper-parameters

One optimization method for making machine learning more accurate is to assess its hyper-parameters. Here we show how to optimize the hyperparameters of the aforementioned algorithms using k-fold cross-validation. The value of k is set to 5 in this work. outcomes of optimizing various model hyperparameters given above

Prediction accuracy analysis

How well the generated models can foretell the future is demonstrated by the evaluation indices on the prediction results. Table 1.4 displays the results of comparing several models' training and testing datasets. With GBRT, we get R2 values of 0.98 and 0.94 on the training data and testing data, respectively, which means that our predictions are spot on. Elastic Net's R2 scores of 0.86 on training data and 0.84 on testing data made it the model with the weakest prediction performance among the five. If we compare GBRT to other ML algorithms using the training time index, we see that it trains the slowest and produces the slowest predictions. When looking at Figure 1.4, which compares the two datasets, it becomes clear that the experimental results were typically lower than the anticipated findings. Hence, more frequent data collection on the strength of sun radiation trials is necessary to help eliminate the results' random character. Values for the projected results, correlation coefficient, and root mean square error are all quite similar when comparing Bayesian Ridge with Linear Regression. On the other hand, training Bayesian Ridge takes more time than Linear Regression. Despite potential differences in processing speed, these examples demonstrate that several machine learning methods may produce comparable prediction results.

Tab 4. The outcomes of comparing several models' training and testing datasets.

Algorithm	Training metrics (MAE / R^2 / RMSE)	Testing metrics (MAE / R^2 / RMSE)	Time (ms)
Bayesian Ridge	0.62 / 0.93 / 0.86	0.76 / 0.90 / 0.83	11.03
Linear Regression	0.62 / 0.93 / 0.86	0.76 / 0.90 / 0.83	5.92
Elastic Net	0.91 / 0.86 / 1.03	1.06 / 0.84 / 1.36	8.00
SVR	0.82 / 0.89 / 0.91	0.85 / 0.88 / 1.04	50.9
GBRT	0.30 / 0.98 / 0.55	0.58 / 0.94 / 0.71	205.45

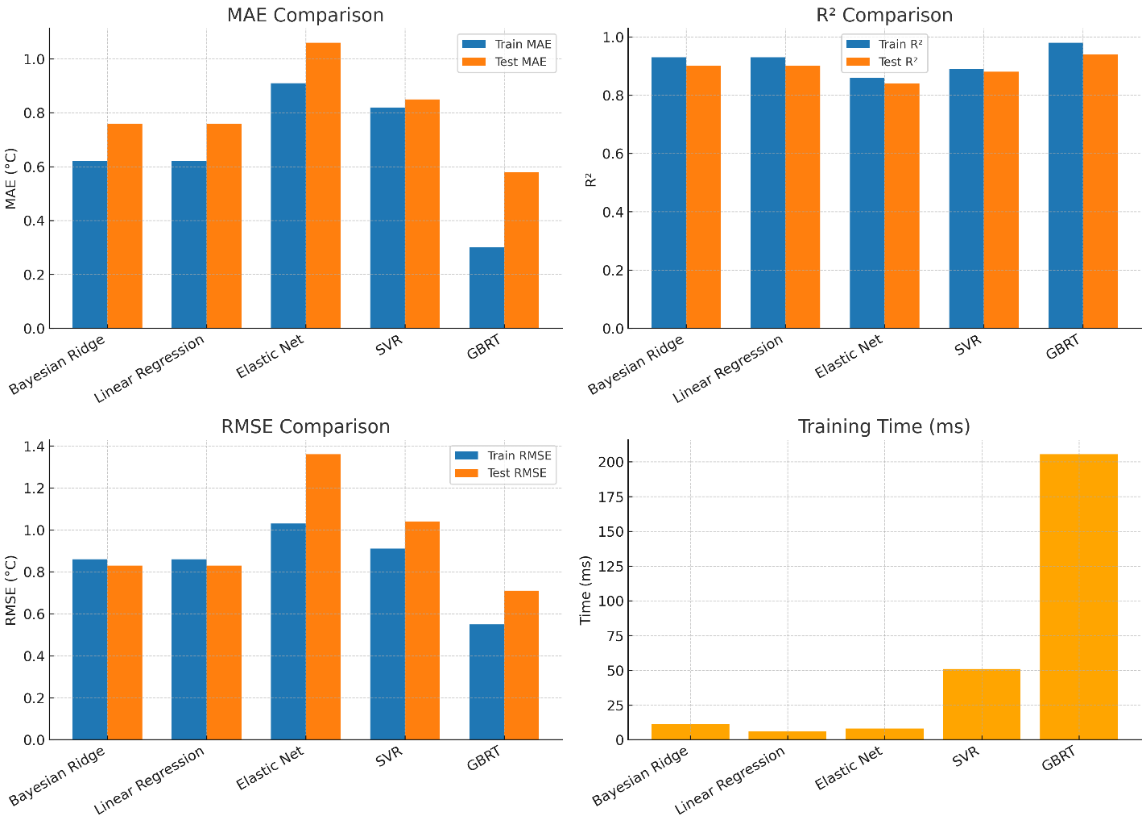

Figure 4. The outcomes of comparing several models' training and testing datasets.

DISCUSSION OF RESULTS

The comparative evaluation of ML models revealed that Gradient Boosting Regression Trees (GBRT) exhibited the highest predictive accuracy, with an R^2 of 0.98 for training and 0.94 for testing, demonstrating its strong capability to capture nonlinear relationships in solar drying performance. Bayesian Ridge and Linear Regression produced nearly identical results with moderate accuracy and lower computational time, while Elastic Net performed the weakest, particularly in testing scenarios. Support Vector Regression (SVR) provided balanced accuracy but required considerably more training time. These findings highlight that although GBRT offers superior accuracy, its computational demand may limit real-time applications.

CONCLUSIONS

Traditional solar drying has its limits; this research proposes a dual working medium drying system to overcome these issues. We use classical thermodynamics and machine learning to study the heat collecting unit of this two-working-medium drying system. Here are some potential results:

(1) To ensure that solar energy is utilized to its fullest potential while simultaneously satisfying the temperature requirements for drying materials, a system with two working mediums is introduced. It also includes the method for managing the system's activities. In contrast to the conventional approach to drying system design, this system meets drying demands by adjusting the working medium cycle switch rather than the system's working power.

(2) In this case study, we look at how various environmental factors affect the heat collector's performance in the drying system. An increase in the supply air flow rate of the heat collector lowers the temperature of the output air and increases the efficiency of the collector in collecting heat. Heat collecting efficiency and output air temperature are quite stable beyond a certain point in the supply air flow range. The efficiency of heat collection and the temperature of the emitted air both rise practically linearly with increasing solar radiation. Depending on the drying needs, the operation atmosphere may be adjusted to fit the situation.

(3) Five machine learning approaches, implemented in Python, are used to forecast the thermal performance of the heat collecting device. Although other feature set selection approaches place solar radiation intensity ahead of external relative humidity in terms of importance impacting the heat collecting unit's output air temperature, the randomized lasso strategy rates it higher. Gradient Boosting Regression is the most accurate approach for forecasting the temperature of the air flowing out of the heat collecting device, even if other methods have faster prediction rates and require less time. Both the tests and the training confirmed this.

(4) The study compares and contrasts the methods of classical thermodynamics with machine learning when it comes to

design and prediction. Future research goals are also detailed in the study, along with potential applications, pros, and cons of each approach.

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