# AI-Powered Optimization of Solar Absorbers: Enhancing Industrial Thermal Energy Harvesting Through Deep Learning

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***Abstract:*** Thermal energy harvesting is a recent attention due to the possibility of harnessing the sun to generate sustainable energy. The solar collector is essential components of this process because it turns the sun's rays into heat. A solar deep learning model (SDLM) is used to improve the efficiency of solar absorber in current industrial settings for collecting thermal energy. Several devices in this model gather information over time about things like moisture, speed of the wind, temperature, pressure of air as well as sun energy. This information is utilized for ML program that can predict the energy of a certain panel. For the proposed SDLM, the thresholds were 75.05 percent for absorption prevalence, 69.89 percent for absorption discovery, 81.41 percent for absorption omission, 90.82 percent for crucial success index, and 73.20 percent for threshold. To estimate the amount of thermal energy that may be gathered more precisely, the system includes other parameters like motion as well as insulation. In order to turn sunlight into heat, solar filters are employed in manufacturing. This thermal energy is crucial for many electrical systems, including heating and cooling systems, and industrial activities. Before investing in solar absorbers, companies may use the SDLM to calculate their prospective thermal energy production.

Keywords: Deep Learning Model, Solar Absorber, Thermal Energy Harvesting, Solar Radiation.

## 1. Introduction

The approach to generate power is thermal energy harvesting, which involves drawing heat from the ground and storing it [1]. The way the environment is powered may be altered by this

kind of energy collecting. A wide variety of objects may be powered by thermal energy harvesting, including buildings, vehicles, aircraft, and even spacecraft. Thermal energy harvesting, in its simplest form, is a means of generating electricity by means of thermal energy that is naturally present in the environment [2-5]. Heat may be produced by a variety of sources, including solar radiation, industrial processes that humans have developed, and the burning of fossil fuels. There are a number of ways to collect the heat, such as using thermoelectric generators or heat exchangers. In order to put the gathered thermal toward a storage device such as a battery, it must first be converted into useful electricity via a generator [6-9]. The collection of thermal energy has several benefits. This sustainable form of energy won't have any adverse effects on the environment. This energy is then available for use by people and organizations, providing a cost-effective and sustainable substitute for traditional power sources [10]. The thermal energy that the receiver generates may be used to heat water to the proper temperature. There are several uses for this hot water, such as providing hot water for bathing or heating a swimming pool.

Modern factories often use solar filters to convert heat energy into electricity, which in turn drives various equipment and tools [11–15]. Solar thermal collectors convert solar radiation into usable heat, which in turn fuels various forms of mechanical energy production, such as steam engines. Houses may also be heated using this heat for business reasons. Using less expensive fossil fuels is another way that solar thermal energy may be beneficial.

The most important new thing about this study is that it finds the most effective solutions to the problems listed above. They're,

- Solar thermoelectric absorbers must have regular maintenance in order to function as efficiently as possible. Cleaning the generator on a regular basis can help to get rid of dust which is obstructing the beam of the sun. It's also important to inspect the solar absorber for wear and tear or damage that might lower its effectiveness.
- A solar thermoelectric absorber has become an effective means to get energy from the sun that doesn't cost much. It is possible to get the most sun energy provided that the right materials, plan & setting while maintaining up with regular maintenance.
- It is recommended to place the solar absorber in a position that receives enough of direct sunlight for optimal energy collecting. In addition, the region should not have any big trees or structures that can shade the sun's light.

To improve the reliability of solar absorbers, a new model that uses a DNN approach combines empirical data with solar performance and heat utilization. Compared to traditional solar energy gathering systems, the model is more dependable and effective. During the thermoelectric conversion process, the model may also look at environmental and economical trade-offs.

## 2. Methodology

Sun thermoelectric generators are the example for the renewable energy source which is getting more and more attention. Solar panels take in energy from the sun and turn it into electricity that can be used. In this way, the device's usefulness rests a lot on how much it can take. How much energy a substance can take in is called its absorbance. When solar thermoelectric emitters are used, the absorption depends on the material, how much of the material can be exposed to the warmth of the sun, and how thick the material is. In general, the absorber will work better if it has a higher absorption. Photovoltaic effect turns the sun's rays into electricity, which is how solar thermoelectric generators work. For a STG to work well, the solar absorption of its parts must be high. This refers to how much sunlight the material can take in and turn into electricity. Solar thermal generators (STGs) have to be formed of materials that can receive a lot of sunlight.

The use of many solar absorbers on a network to enhance the system's output is known as interconnection of diverse absorbers. A series of linked absorbers, often arranged in a way that makes the most of the sun's rays, and a reflecting coating to boost the absorbers' radioactive efficiency may do this. The basic idea is that this method may increase solar thermal energy harvesting while decreasing thermal convection, radiation, and conduction losses. In addition, the sun's ideal exposure may be fine-tuned all day long by adjusting the connecting absorbers. Maximizing the amount of surface area that is exposed to sunlight may greatly enhance the system's overall effectiveness.

2.1. Improved Absorption

Materials used to construct solar thermoelectric absorbers had a diverse array of absorption capacities. As an example, some things can take in greater amounts of energy than others. Another thing that will change the absorption is the surface size of the filter. More energy can be collected and turned into power if the surface area is bigger. How much something absorbs is also affected by how thick it is. More energy will be absorbed by something thicker than something thin. Solar thermoelectric receivers are great for green energy because they can take in a lot of energy. The effectiveness for the device will go up as the absorption goes up. Let's say that a group of sun absorbers (a) are linked together and continuously make power. The heat absorption can be calculated using the following equation (1):

$$R^{*}_{TH} = S_S M_a N_i [0 = \theta]. R_R \quad (1)$$

$R^{*}_{TH}$ represents the thermal heat received, whereas 'Ss' represents the direct heat emission of the sun and 'Ma' represents the minor absorption zone. Absorber radiation is shown by '$R_R$'. Finally, '$N_i$' represents the collector's normal incidence. Now equation (2) shows the absorber current flowing using Kirchhoff's criteria to determine the output current.

$$I_a = I_P - I_s[\exp(A[V_a + I_a R_S] - 1)] - \frac{V_a + R_s I_a}{R_s} \quad (2)$$

Changes in the light-generated current Is are determined by the standard and measured irradiation level factors that are used to solve the equation. As shown in equation (3), the source for the absorber synthesis power Ia is connected parallelly with absorber resistance Rs, which is linked in series to Ia. Is indicates shunt resistance.

$$I_a = \left(I_S + A_i[b - b_r]\frac{\varphi}{\varphi_r}\right) \quad (3)$$

Using equation (4), determine the saturation current at,

$$I_S = I_r \left[\frac{b}{b_r}\right]^3 \exp\left[\frac{qE_G}{k\gamma}\left(\frac{1}{b} - \frac{1}{b_r}\right)\right] \quad (4)$$

The choice of parallel or series modules in solar absorbers depends on the required power and voltage. The fundamental purpose of an absorber of mathematical analysis is to provide accurate current or voltage outputs for displaying I-V and P-V characteristics. This renders them a cheaper and more effective renewable energy source.

2.2. Optimization of Performance

Thermal harvesting is an essential way to harness solar energy, but solar absorber efficiency limits it. Optimizing solar absorbers maximizes energy harvesting. Energy efficiency will be the focus of this article on improving solar absorber performance. Solar absorbers' effectiveness depends on the quantity of sunlight absorbed and thermal energy stored. Standard absorber materials absorb less sunlight than multi-layered black carbon. This increases solar energy collection and efficiency. Eq. (7) shows the absorber charging process.

$$P_c = \left([P_{ao} \times \propto_{CR}] - \left[\frac{P_L}{\propto_{ie}}\right]\right) \times \propto_{BAh} \quad (5)$$

## 3. Suggested Model

The maximum quantity of energy that solar panels can produce can be predicted using solar deep learning algorithms. The dataset is publicly available. To precisely anticipate energy production, these models combine information from several sensors with weather projections. To improve accuracy, these models may be evaluated and trained using both recent and historical data. After training, the model may be used to calculate the best inclination angle, optimal position for solar panels, and optimum efficiency with respect to climate, place & additional variables. The working process of the suggested system is illustrated in figure 1.

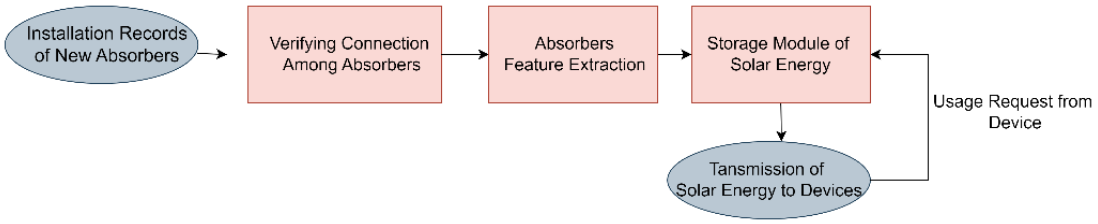


Figure 1 Block Diagram of Suggested System.

For ideal energy gathering from solar energy, a CNN could be one way to solve this problem. Deep learning algorithms like CNNs are great at recognizing and classifying images. Finding the best places to collect solar energy is possible by teaching a CNN with a set of pictures of the sun. In addition, CNN can be taught to spot the best ways to set up solar panels and where they should be placed in a given area. Once this data is collected, the CNN can instantly suggest the best ways to collect solar energy for the most energy output. Multiple factors affect the output for solar absorbers used in the harvesting of thermal energy. These include the absorber's material makeup, its surface area, the wavelengths of light it absorbs, and the temperature of the surrounding environment. Under normal conditions, these absorbers can turn up to 61% of the solar energy that hits them into thermal energy. At lower temperatures, they can work more efficiently and at higher temperatures, they can work at higher temperatures. Figure 2 displays the proposed model's Layering Configuration.

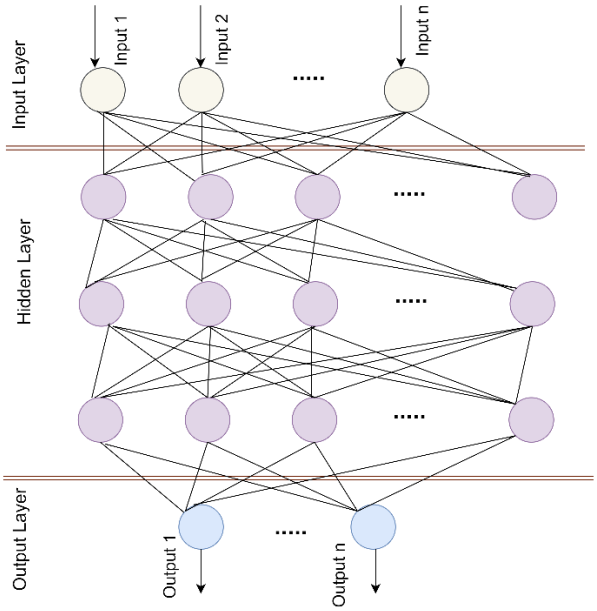


Figure 2 Suggested Model’s Layering Configuration.

3.1. Input Layer

The information that will be utilized to train the solar deep learning algorithm must be received by the input layer. The optimum solar absorber in manufacturing heating & freezing applications in contemporary manufacturing contexts may be found using this data, which may include photographs or actual measurements. After pre-processing the data, the input from this layer will send the pertinent information to a layer of neurons, also known as nodes. An apparatus known as a solar absorber uses solar radiation to generate thermal energy to industrial uses by absorbing and storing it. This layer chooses the optimal absorber based on the local weather conditions. The model will learn how the absorber's dimensions, form, and position affect its solar energy collection from this input layer. This information helps select the most suitable solution for the given scenario.

3.2. Output Layer

Output layer functions within the SDLM are which inform the solar model what it needs to perform. For these tasks, the solar screens' settings need to be changed so that the model works better. This is done so that the energy gathering works as well as possible and over the smallest amount of money. To extract the most energy from sunshine absorption, the form of absorber exterior and the brightness & absorptance of absorbers are often changed as a part for the output layer processes. As little energy as possible is used by the system, and procedures at the output layer make sure that the temperature reaction is secure and works well.

3.3. Hidden Layer

Solar absorbers use a SDLM with hidden layer operations between input and output layers. Hidden layers generate complex models with many parameters and linkages. The model builds a neural network during DL training. SDLM use hidden layers to capture and store environmental data which include absorbed energy, temperature, sunlight incidence angle, and more. It helps the model precisely estimate absorber thermal energy of environment. Hidden layer activities determine the chance of an absorber capturing solar energy & changing to thermal energy. This leads to effective energy harvesting systems for industrial sites, maintaining optimum performance of solar absorbers and the overall system.

3.4. SDLM Features

Predictive analytics methods such as SDLM are used to predict solar performance and evaluate solar energy data. The DNN used in the model is made up of many interconnected layers. The SDLM predicts future solar performance by training the layers using previous solar data, including irradiance measurements. This approach has been utilized for performance trend analysis, site engineering reliability, and solar system optimization.

To identify intensity at each 224 by 224 pixel of solar absorbers, convolution-1 generates a 64-dimensional vector for every picture. A convolution layer combines CNN and pooling layer to extract features from input photos. Convolution blocks with several layers are used in this model for acquiring complex characteristics of input photos. Moreover, this layer as well as model enable precise thermal energy harvesting through locating and isolating concentrated solar energy absorption zones. Convolution-2 uses numerous filters and convolutional layers to provide a more robust representation of absorber performance measures. The convolutional layers are optimized using characteristics like as dimensions, stride & padding to learn spatial correlations between absorber measurements. DL models may recognize trends in input data and build features to predict energy-efficient absorber performance in various industrial settings. Convolution-3, which detects intensity at 56 × 56 pixels, generates 256-dimensional vectors for each picture of energy-efficient solar absorbers. The convolution-3 system identifies pattern in solar radiation collected by absorbers, including materials, surface area & spectrum range. The model learns to identify solar radiation patterns across conditions and temperatures. The model distinguishes between high and low efficiency solar absorbers. This model can predict solar absorber efficiency and advise stakeholders on optimal thermal energy harvest.

The convolution-4 procedure is the most progressive. In order to identify absorbers based on pixels, this CNN method employs a novel 28 per 28 pixel-by-pixel strategy. SDLM has a layer called max pooling that helps it learn more complicated traits. Inputs or traits like gradient values, temperature of the surface, surface size, etc. are used to teach it the highest values. Limiting the number of dimensions in the inputs & helping the system acquire more complex feature pairs are two ways that max pooling improves model performance. The model can handle more data with fewer factors when this layer is used, which makes training more effective and faster. Because of the substantial quantity of data required to be processed, this layer is particularly helpful in manufacturing settings. It can help devices that receive energy from the sun work better by making them more efficient. Researcher can quickly and correctly find out what a thermal energy collecting system's highest potential is with the fully connected layer. The main purpose of this layer is to allow the model to collect pertinent data from the absorbers, including the material type, the absorbers' position and angle, surface roughness, as well as additional factors. The model optimizes system parameters to maximize thermal energy harvesting. The SDLM examines sun exposure patterns to predict the most effective absorber arrangement for maximum energy harvesting in a given region. Minimizing energy expenses by identifying energy-efficient patterns helps minimize losses from design flaws.

## 4. Analytical discourse

An essential part of thermal energy harvesting is the effective usage of sun absorbers. These absorbers are made especially to take in solar radiation & transform to heat energy. Materials with a high thermal emissivity and high reflectivity are used to make solar absorbers. As a result, they can absorb solar energy and transform it into heat energy. Through the use of a heat exchanger, solar absorbers may produce energy or be utilized to directly heat a structure.

### 4.1. Evaporation Waste Heat Management

An innovative advancement in energy generation, solar thermal energy collecting might completely alter the energy landscape. Solar thermal energy collecting converts the sun's heat into usable electrical power by evaporating a thermoelectric absorber. Efficient collection and management of solar heat is necessary for the evaporation process of the thermoelectric absorber. Efficient management of this heat is essential to keep waste heat to a minimum. Several methods need to be used to accomplish this. Utilizing a heat exchanger is among the frequent methods for controlling the temperature. Air heated by the sun is recirculated via a cooling system after passing through a heat exchanger. As a result, the heat is dissipated and less energy is lost. The air may also be preheated in a heat exchanger before entering the evaporator. The evaporator's performance is improved as a result.

### 4.2. Solar Multistage Application

Residential and business solar electricity is growing. Multistage usage of solar energy is an efficient method. The process includes capturing solar energy via an effective absorber and utilizing it to power diverse applications. Solar energy use begins with effective solar absorbers absorbing the sun's thermal energy. This absorber efficiently achieves maximum heat absorption with little energy. Typically, the absorber is constructed of copper or aluminium, which have excellent heat conductivity. It maximizes heat absorption and energy conversion. Step two in solar energy usage involves converting acquired thermal energy into usable energy. It is done by the thermoelectricity process. This method transforms thermal energy to electricity using a semi-conductor substance. This electrical energy may power applications like air conditioning, lighting & warmth. Solar energy storage is the third & final step of multistage use. The process usually involves using battery or additional power storage gadgets. The energy may be utilized when required, not simply during sunny conditions. Multistage solar energy consumption is cost-effective and efficient. Most energy is captured by the efficient solar

absorber, and thermoelectricity converts it into usable energy. Energy storage devices help store energy for later use. Solar energy offers a cost-effective and environmentally friendly solution.

4.3. Latent Heat Utilization

A portion of the sun's rays may be converted into heat by use of the solar absorbers that make up a system. This energy may then be used to move heat from one location to another. When a material changes its phase from liquid to gas or back again, it absorbs or releases heat; this is called latent heat. Every time a material changes state, some of its latent heat is either released or absorbed. A part of the sun's rays can be turned into thermal energy through the application of solar filters. Through latent heat transfer, this energy is able to be utilized to heat the working fluid of the machine. In the past few years, there has been more and more research to thermal energy gathering by using the residual heat of efficient solar filters. The method demonstrates promise as a long-lasting, eco-friendly & profitable energy source.

## 5. Comparative Assessment

The proposed SDLM was tested against AUTO-Encoder Based Neural-Network (AUTO-NN) & GATEO, two algorithms that use GA for techno-economic optimization. Python was used as the simulation tool for implementing the outcomes in this instance. Particle swarm optimization is suggested for hybrid power plants. According to studies, genetic algorithm-based hybrid electrical systems is a fast-emerging field.

According to new research, AUTOEncoder-based models can be used successfully for both predicting PV and creating combined prediction and supervision methods for daily manufacture. For example, production predictions for markets tied to projections have been suggested as other ways to get the most out of units. The planning and optimization for PV plants have also benefited from the use of AUTO-Encoder-based models, which aid in identifying the best plant designs for a range of circumstances, including as location and weather. In order to provide a real-time estimate of energy generating capabilities, other research have also concentrated on creating controlled simulations of big PV systems. Additionally, rather of depending on analytical models, DL breakthroughs have produced strong models that can learn intricate nonlinear interactions. There are a number of encouraging developments in the state-of-the-art for AUTO-Encoder based neural networks that anticipate the energy output level in big PV facilities. PV plants may become more profitable and efficient by optimizing plant performance via the use of such models.

It is the amount of energy that is taken by a solar collector that is energy efficient and doesn't get turned into useful heat energy. This is called the fake positive absorption rate. A proportion for the total energy received is often used to show it. It is usually a sign that the absorber may not be as good at turning received energy into useful heat energy if the fake positive absorption rate is high. The rate of false positives absorbed in the suggested model is shown in Figure 3. There were 83.23 percent of false positives in the testing results and 91.73 percent of false positives in the training results for the suggested SDLM. There were 76.97% of testing results and 41.65 % of training results in the same range for the present GATEO and 66.69% of testing results and 69.30 % of training results for AUTO-NN in terms of false positive absorption rate. SVM as well as tree-based random forest methods work together in this suggested model to better identify data and find more minor trends in it. The precision goes up because this method is better at finding incorrect positives.

5.1. Estimating the Absorption Rate of Incorrect Positive ($AR_{IP}$)

An effective solar absorber's incorrect positive rate of absorption is the amount of energy that is absorbed but does not get transformed into usable thermal energy during thermal energy harvesting. As a proportion for the total energy absorbed, it is usually stated in that way. If the incorrect positive rate of absorption is high, it usually means the absorber isn't doing a good job of turning the energy it takes in into usable heat. The incorrect positive absorption rate

comparing the current and suggested models is shown in Figure 3. The suggested SDLM achieved an absorption rate of false positives of 91.73% in training and 83.23% in testing, both in terms of computational range. In the same lineup, AUTO-NN had an incorrect absorption rate of 66.69% during testing and 69.60% during training, whereas the current GATEO achieved 74.97% during testing and 41.65% while training. In order to better categorize data and identify more complex patterns, the suggested model combines tree-based RF techniques with SVM machines. The accuracy is improved since this approach is better at detecting incorrect positives.

$$AR_{IP} = \frac{P_f}{P_f + N_t} = 1 - NR_t \qquad (6)$$

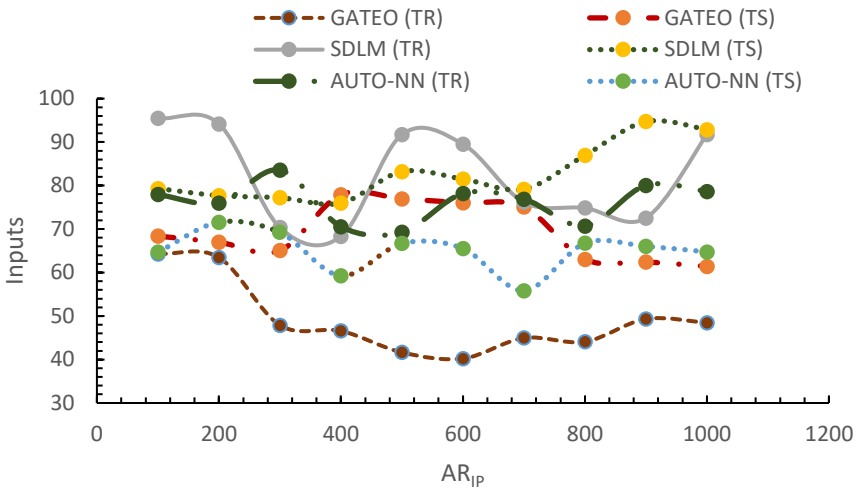


Figure 3 Absorption Rate of Incorrect Positive.

5.2. Estimating the Rate of Incorrect Discovery Absorption ($DR_{IA}$)

A thermal energy harvesting energy-efficient solar absorber's incorrect absorption discovery rate is the rate at which it fails to absorb incoming solar energy. Absorber efficiency is determined in W/m2. The rate of incorrect absorption depends upon the absorber material & ambient circumstances. Fake absorption detection rate is compared between current and suggested models in Figure 4. The SDLM achieved 69.89% during testing and 81.49% during training in incorrect absorption detection rate. GATEO achieved 42.31 % of testing & 61.73% for training outcomes of $DR_{IA}$, whereas AUTO-NN achieved 65.54% & 82.15%. With more judgments to make when detecting incorrect absorption events, this method detects more. Additionally, the suggested model incorporates discriminating capacity to enhance incorrect absorption event detection accuracy in decision-making. Better incorrect absorption event detection increases the model's incorrect absorption discovery rate.

$$DR_{FA} = \frac{P_f}{P_f + P_t} = 1 - PPV \qquad (7)$$

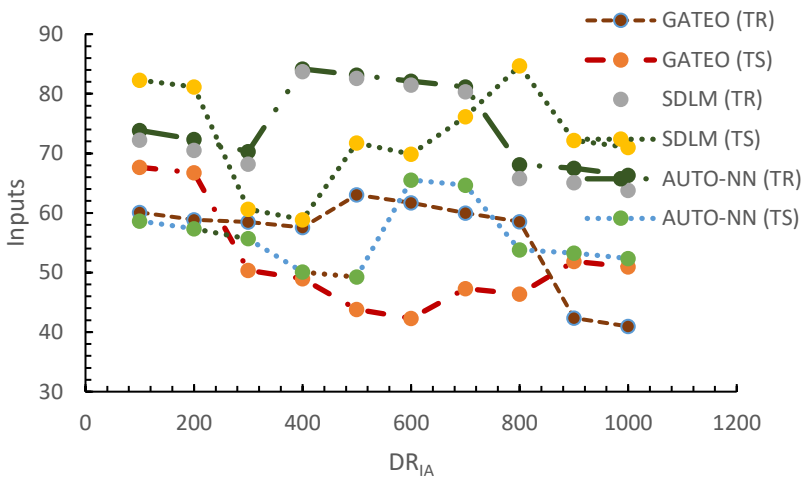


Figure 4 Rate of Incorrect Discovery Absorption.

5.3. Estimating the Rate of Incorrect Absorption Omission ($OR_{IA}$)

A method to evaluate the precision of an investment strategy is by looking at its incorrect absorption omission rate. It is a way to quantify the discrepancy between a portfolio's actual return and its predicted total return. It is determined by dividing the actual return with the predicted return, which is the difference among the two. In other words, the portfolio has hit its target return target with an incorrect absorption omission rate that is zero. Examine how the current and new models stack up against each other in terms of the incorrect absorption omission rate in Figure 5. The suggested SDLM achieved an accuracy rate of incorrect absorption omission of 72.09 percent during training (TR) and 81.41% during testing (TS) within the computational range. Similarly, AUTO-NN achieved an incorrect absorption omission rate of 44.92% in training and 46.78% in testing, whereas the current GATEO attained 46.78% in testing and 41.67% in training. Adding a 2$^{nd}$ layer of capture and setting a secondary capture threshold has raised the predicted incorrect absorption omission rate. To improve the accuracy of the current models, this 2$^{nd}$ layer demands that the likelihood for incorrect absorption be larger that of the chance of genuine absorption. This increases the likelihood that the proper signal will be recognized, leading to better results. To top it all off, the suggested model makes use of a dynamic threshold, that improves the model's accuracy even more by adjusting the capture threshold in response to outside variables like signal intensity.

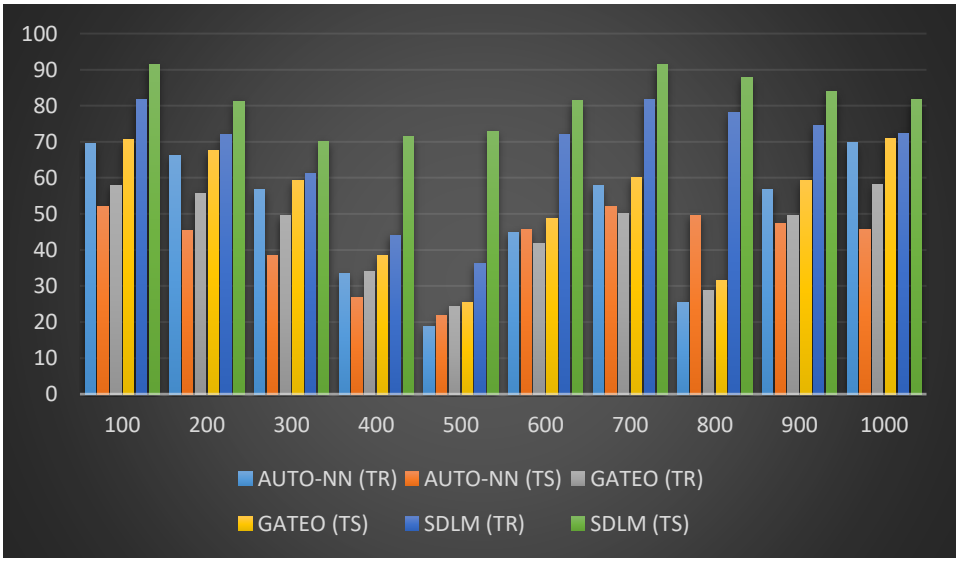


Figure 5 Rate of Incorrect Absorption Omission.

5.4. Absorbance Prevalence Threshold Calculation ($P_{th}$)

Different types of materials have different absorption occurrence thresholds that can be used for thermal energy gathering. For thermal energy gathering, materials that are better at transferring heat and absorbing heat are usually the first choice. Heat energy can usually be collected from materials that have an absorption level of more than 0.8. Seventy-five percent of the testing results and seventy-three percent of the training results for the suggested SDLM were satisfied. It got 23.19 percent of the testing results and 26.41 percent of the training results in the same range as the current GATEO. It also got 31.58% of the testing results and 21.12% of the training results for the absorption frequency level with AUTO-NN. By looking at more factors, like the quantity for absorbance per incident photon, the amount for incident photons, the light source, the sample's distance from the detector, and other sample- & environment-specific factors, the proposed model's $P_{th}$ is higher than existing models. For more accurate and reliable readings, and to be able to compare absorbance readings from different optical devices, this is an excellent approach.

$$P_{th} = \frac{\sqrt{IPR}}{\sqrt{CPR} + \sqrt{IPR}} \tag{8}$$

5.5. Critical Success Index Computation (CSI)

The Critical Success Index (CSI) to thermal energy extracting shows how well a specific process works of how much heat it produces. It's basically a way to measure how well the heat energy gathering process works. The total amount of thermal energy put in can be divided by the overall amount of thermal energy put out. The process of collecting heat energy works better when the CSI number is bigger. To make thermal energy harvesting more effective, different methods can be used, such as improving the thermal insulation, choosing materials that conduct heat better, and making the structure of the harvesting system better.

$$CSI = \frac{P_t}{P_t + N_t + P_t}$$

Consider Figure 6 for the key success index comparison of current and suggested models. The suggested SDLM achieved 90.82 % testing and 78.10 % training CSI in computational range. In the similar range, GATEO achieved 47.31% TS and 59.98% TR outcomes, whereas AUTO-NN achieved 64.69% testing and 81.14% training results for CSI. The suggested model's CSI is higher than current models since it considers more elements. The approach takes into consideration company size, action effect, and initiative strategic alignment. The model can better assess project performance with this extra data. The suggested methodology may assess efforts throughout a company, not just specific departments or teams. It gives a more complete picture of the company's performance. The suggested model's data-driven methodology enables for providing more precise CSI by gathering a wider variety of data and accounting for more initiative factors.

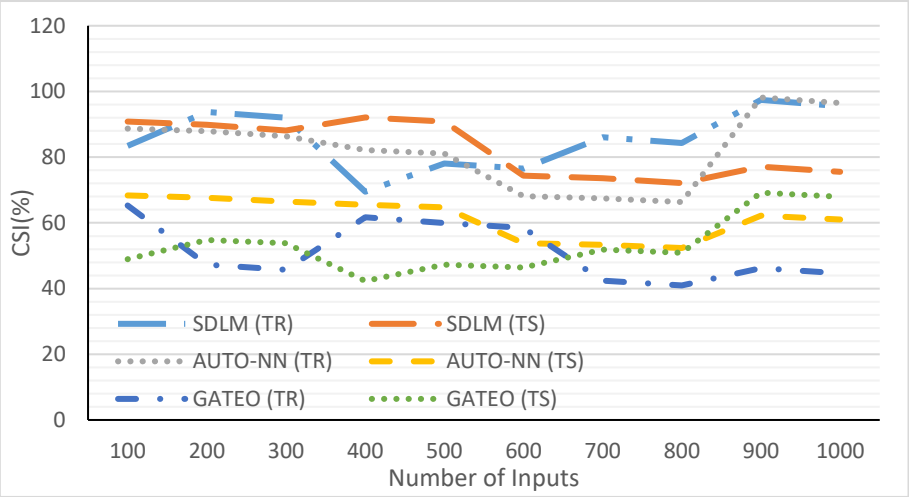


Figure 6 Critical Success Index.

Figure 7, shows how the current and new models compare overall. The proposed SDLM achieved the following results in a computational range: an absorption rate of incorrect positives of 83.23% and a training rate of 91.73%; an absorption incorrect absorption discovery rate of 69.59% and a training rate of 81.49%; an absorption incorrect absorption omission rate of 81.41% and a training range of 72.09%; an absorbance prevalence threshold of 75.05% and a training range of 73.20%; and a critical success index of 90.82% and 78.10%.

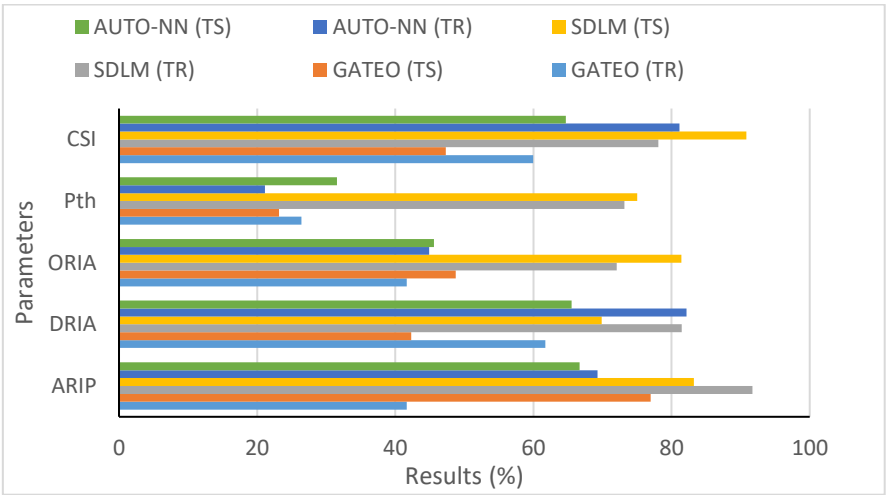


Figure 7 Overall Comparison.

## 6. Conclusion

The significant renewable energy source that has grown in popularity recently is solar thermal energy collecting. It entails harnessing, storing, and utilizing solar energy for a range of applications, including the generation of electricity, heating, and cooling. The highest power density of an effective solar absorber is one of the most crucial factors in solar thermal energy harvesting. The greatest energy that may be collected per unit area is known as the highest power density of effective solar absorber. The capacity that a solar absorber to absorb and transform solar energy to electricity determines its efficiency. A solar absorber's efficiency is influenced by a number of elements, including the material's surface area, reflectivity, emissivity, and composition. The SDLM achieved 83.23% incorrect positive absorption rates, 69.89% incorrect absorption discovery rates, 81.41% incorrect absorption omission rates, 75.05% absorbance prevalence threshold. To enhance solar absorber efficiency, appropriate

material selection and design optimization are crucial. The most effective solar absorber material is black carbon, with an elevated absorption coefficient and low reflectance. The absorber's surface area impacts energy absorption. Overall, larger surfaces increase efficiency. Multi-object deep learning algorithms may soon enhance absorber efficiency and performance based on many factors, such as temperature, surface, and weather. Furthermore, models for financial analysis powered by AI might be created to assess the viability of using such technology economically. Long-term incorporation of the solar absorbers with different manufacturing procedures that enhance as well as regulate energy use throughout manufacturing procedures may potentially be made possible by the creation of increasingly sophisticated DL models. To guarantee the highest possible amounts of energy extraction, further study might be focused on creating sophisticated, automated controls using SDLM.

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