DETECTION OF SOLAR PANEL DEFECTS IN ELECTROLUMINESCENCE IMAGES USING DEEP LEARNING

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Bahaa Salih MANDEEL

ABSTRACT

M. Sc. Thesis

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Extreme temperature swings and other environmental stresses are typical causes of breakdowns in the photovoltaic (PV) cell production industry. Manual inspections were formerly the go-to method for finding these defects. Nevertheless, there is a chance of making errors, and the process might be lengthy when utilising this approach. The expense might add up quickly as well. Our study makes use of deep learning methods to address these difficulties. Problems with PV modules may be detected automatically using these methods. During our assessment, we used many models, including an internally developed convolutional neural network (CNN). The InceptionV3 and ResNet-50 models, which were pre-trained, were also used. Moreover, we created a hybrid model that integrates characteristics from the InceptionV3 and ResNet-50 models.

We used a binary classification algorithm on a dataset of 2,624 electroluminescence (EL) pictures to distinguish between PV cells with and without faults. With a 91% accuracy rate, the ResNet-50 model outperformed the others. This is marginally more accurate than the 90.88% accuracy of the InceptionV3 model. At 89.47%, the custom CNN models were the least accurate. We employed a modified model, and it outperformed all of the others. Its 98.43% accuracy percentage is quite remarkable. It has been shown that both pre-trained and custom-designed deep learning models are capable of identifying problems in PV modules. As a result, variables like processing power and available resources may be adjusted to make these models work for a particular purpose. Researchers have shown that machine learning significantly improves renewable energy systems, according to this study. The solar business stands to gain a great deal by automating crucial quality control operations.

Keywords : CNN, Photovoltaic (PV), InceptionV3, Electroluminescence (EL), Defect detection

Science Code : 92431

ÖZET

Yüksek Lisans Tezi

DERİN ÖĞRENME KULLANILARAK ELEKTROLÜMİNESANS GÖRÜNTÜLERİNDE GÜNEŞ PANELİ HATALARININ TESPİTİ

Karabük Üniversitesi
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Aşırı sıcaklık dalgalanmaları ve diğer çevresel stresler, fotovoltaik (PV) hücre üretim endüstrisindeki arızaların tipik nedenleridir. Manuel incelemeler eskiden bu kusurları bulmak için başvurulan yöntemdi. Ancak bu yaklaşımı kullanırken hata yapma ihtimali vardır ve süreç uzun olabilir. Masraf da hızla artabilir. Çalışmamızda bu zorlukların üstesinden gelmek için derin öğrenme yöntemlerinden yararlanılmaktadır. Bu yöntemler kullanılarak PV modüllerindeki sorunlar otomatik olarak tespit edilebilir. Bu çalışmada kendi inşa ettiğimiz evrişimsel sinir ağı (CNN) dahil olmak üzere birkaç model kullandık. Ayrıca önceden eğitilmiş olan InceptionV3 ve ResNet-50 modelleri de kullanıldı. Son olarak InceptionV3 ve ResNet-50 modellerinin özelliklerini birleştiren hibrit bir model oluşturduk.

Arızalı ve arızasız PV hücrelerini ayırt etmek için 2.624 elektrolüminesans (EL) resminden oluşan bir veri kümesi üzerinde ikili sınıflandırma algoritması kullandık. ResNet-50 modeli %91 doğruluk oranıyla diğerlerinden üstün performans gösterdi. Bu, InceptionV3 modelinin %90,88 doğruluğundan biraz daha doğrudur. Özel CNN

modelleri %89,47 ile en az doğruluğa sahip modeller oldu. Değiştirilmiş bir model kullandık ve diğerlerinden daha iyi performans gösterdi. %98,43'lük doğruluk yüzdesi oldukça dikkat çekicidir. Hem önceden eğitilmiş hem de özel olarak tasarlanmış derin öğrenme modellerinin, PV modüllerindeki sorunları tespit edebildiği gösterilmiştir. Sonuç olarak, işlem gücü ve mevcut kaynaklar gibi değişkenler, bu modellerin belirli bir amaç için çalışmasını sağlayacak şekilde ayarlanabilir. Bu çalışmaya göre araştırmacılar, makine öğreniminin yenilenebilir enerji sistemlerini önemli ölçüde iyileştirdiğini gösterdi. Güneş enerjisi sektörü, kritik kalite kontrol operasyonlarını otomatikleştirerek büyük kazanç elde edecek gibi görünüyor.

Anahtar Kelimeler : CNN, Fotovoltaik (PV), InceptionV3, Elektrolüminesans (EL), Kusur tespiti

Bilim Kodu **:** 92431

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Thank you for believing in me and encouraging me to move forward after all the chaos I have been through. I dedicate this success to all of you, from heart to heart.

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PART 1

INTRODUCTION

Fundamental to the solar power sector, photovoltaic (PV) cell manufacture encounters formidable obstacles owing to external forces and very high temperature differentials. Several problems with PV cells may develop under these circumstances [1]. Detecting defects in PV modules has traditionally relied on labour-intensive, error-prone, and expensive human examinations [2]. We have moved our research emphasis to the use of deep learning algorithms for the automatic identification of flaws in PV modules after realizing the limits of conventional manual techniques.

Back in the day, manual inspections were the way to spot these flaws. The basic way is still a thing, but it has some downsides, like taking forever, being very worky, and maybe being off because of human error [3]. An ever-increasing demand for solar power has heightened the need to find better, more automated ways to identify defects. Recent technical developments have accelerated the creation of automated methods for PV cell defect identification in response to this demand [4]. Electroluminescence (EL) imaging is one of these super-promising methods that has recently come to light. [6,7,8]. It might smell flaws that are not obvious to the human eye. More progress is required, nevertheless, before EL imaging and related technologies may reach their full potential in defect detection.

This is an area where deep learning, and CNNs in particular, have remarkable potential [9, 10, 11]. Four different models are used in this study: a custom convolutional neural network (CNN) that was built from scratch, the pre-trained InceptionV3 model, the well-known ResNet-50 model for deep learning, and a model that combines features from the first two models. This method can be used to fully check how well each model can find flaws in a set of 2,624 electroluminescence (EL) pictures that show both polycrystalline and monocrystalline PV modules [6].

Although this study mainly aims to identify defects, it also delves into the wider consequences of using deep learning in solar energy. Part of this process is looking at how these technologies might improve solar energy systems' efficiency and ease of maintenance. The goal of this project is to make a big splash in the renewable energy sector by improving solar power solutions in terms of efficiency, reliability, and sustainability via the use of cutting-edge deep learning models in PV module quality control.

1.1. MOTIVATIONS

When thinking about the tremendous, transformational power of solar power and other types of clean energy in successfully addressing the urgent climate catastrophe, many people feel a profound sense of optimism. These environmentally friendly alternatives have the potential to revolutionize our energy use and ultimately reduce our dependence on fossil fuels. Research like the one he describes is crucial in this regard. Microscopic cracks and other defects in solar cells can cause a significant decrease in solar panel performance. Exposure to stress during the production process is a common cause of these defects. Traditional methods of error detection need to be fixed. Be prepared to face the many difficulties associated with this effort, such as long wait times, high labour costs, and the potential for bias. Automatic detection systems in solar cell manufacturing need to be developed to be more efficient, reliable, and time-saving, as current systems rely heavily on human inspection, which can lead to these shortcomings.

1.2. THESIS PROBLEM

- These characteristics must be developed in order to guarantee the best possible performance and quality of solar panels.
- This helps in identifying problems effectively and accurately.
- To overcome this challenge, advanced computer vision and imaging techniques must be explored.
- Advanced methods such as machine learning and artificial intelligence must also be considered.

- These technological advances ultimately aim to improve and expand solar energy systems, and our goal is to achieve this through accurate, elegant and reliable methods for detecting defects in solar cells.

1.3. DATA PREPARATION

The database used for this study includes 2624 high-res electroluminescence (EL) pics of PV modules, a mix of mono and poly varieties [6]. With its extensive collection of actual PV cell failures, this dataset is ideal for training and testing the proposed deep-learning models.

1.4. AIMS OF THE STUDY

The main goal of this study is to create, test, and rate four different deep-learning models for spotting PV module defects. Custom CNN, namely the well-known InceptionV3 and ResNet-50 models, and a hybrid model that's like a mix of both.

Our method is based on a full comparison of the custom CNN's performance with that of the InceptionV3 and ResNet-50 models that have already been trained. We evaluate them using a wide variety of critical parameters, such as computation efficiency, recall, accuracy in fault detection, and precision.

By comparing several methods, this research aims to establish a new benchmark for automated defect detection in the solar industry. We aim to enhance quality control measures in order to ensure the robustness and dependability of solar panels.

Furthermore, the project intends to examine the broader effects of applying advanced deep learning techniques to the solar energy sector. We want to see if we can use these technologies to level up solar power systems, make them very good at spotting problems, and make them more efficient and, discreetly, easier to keep in check. With these models, solar panel quality management might be a thing of the past, which bodes well for the future of renewable energy. More reliable and environmentally friendly energy solutions for the sector could emerge from this.

PART 2

RELATED WORKS

It is important to read up on the topic and understand how important this job is before using deep learning to find problems in solar PV panels. This section focuses on deep learning models, namely convolutional neural networks (CNNs). We are going to review and make sense of all the previous work on this topic.

Finding tiny cracks in photovoltaic modules is becoming more important for keeping large-scale solar power plants working well, as clear solar panels have become more popular because they are cheaper. Gabor et al. [19] used UV fluorescence with a UV flash camera system placed on a pole to effectively detect cracks in solar panels of varying ages and designs.

Deep learning has made some progress recently, which has helped the field of finding faults in PV modules. In their deep learning approach, Han et al. [20] used a UAV with a thermal camera and GPS to obtain a defect detection accuracy of 96.45%. A YOLOv3-tiny update was applied to the model. Espinosa et al. [21] flexed that CNNs can straight-up classify problems in PV plants by peeping RGB pictures, with an average accuracy of 75% for two classes and 70% for four.

EL images of PV cells are getting more and more analyzed using convolutional neural networks (CNNs). Acharya et al. [13] used a deep Siamese CNN to categorize solar cell flaws; it attained a 90% AUC on benchmark EL image datasets. Rahman et al. [22] did very good work finding small cracks in EL photos of PV modules. They used fancy models like Inception-v3 and ResNet50 and obtained accuracy rates of over 96%.

After collecting EL images of PV modules, Karimi et al. [24] used SVM, RF, and CNN to classify the images. The scientists classified the cells as either good, corroded, or broken using data augmentation approaches. Despite its high level of accuracy, the dataset had 3.5% of cells that were fragmented.

Bartler et al. [25] used the CNN-generated dataset to classify images of polycrystalline PV cells. Using a 2-class classification technique, the researchers modified the VGG-16 deep network to classify solar cells as either functional or malfunctioning. Additionally, data augmentation was used.

Buerhop et al. [6] state that the only publicly accessible collection of PV cell EL images is the "ELPV" seen in published works. Deitsch et al. [7] divided the initial dataset's PV cells into four groups: non-faulty, possibly normal, defective, and perhaps defective. For cell classification, they turned to this dataset. Compare CNN's accuracy of 88.42% with that of SVM, which we discovered to be 82.44% in the classification test.

Akram et al. [9] divided the EL images into working and broken categories using the same ELPV dataset. While training the DNN, they began with nothing and employed many data augmentation techniques to get an accuracy of 93.02%.

Tang et al. [10] used the ELPV dataset to sort EL images of PV cells by the type of defect they showed, and generative adversarial networks (GANs) were used to make fake data. By training CNNs from scratch, we were able to achieve classification accuracy levels between 81% and 84% as an alternate, GAN-based approach.

Luo et al. [12] provide an interface for incorporating synthetic samples into the existing monocrystalline EL image library. Their use of SqueezeNet, ResNet, and AlexNet pre-trained models led to a 14% improvement in classification accuracy. Common practice dictates using pre-trained DNNs using transfer learning rather than developing a DNN from scratch.

In their study, Demirci et al. [14]. Applying transfer learning with several pre-trained DNNs on the previously described ELPV dataset achieves a remarkable maximum accuracy of 78.96%. The use of transfer learning has significantly reduced training time and computational weight, but performance has remained modest.

Xue et al. [27] used AlexNet CNN and fuzzy c-means clustering to identify hidden fractures, and they got 94.4% accuracy.

These studies show how deep learning has changed solar energy, especially in detecting problems with photovoltaic modules. They do more than meet current needs in the solar industry; they pave the way for future advancements in automated defective diagnosis.

The literature review sheds light on how fault finding in PV modules is always changing and clearly points to a move toward automatic methods based on deep learning. Overall, these improvements make solar power systems work better and be more reliable, which is important for finding problems faster.

2.1. PHOTOVOLTAIC SOLAR PANEL SYSTEM

These studies show how deep learning has changed solar energy, especially in detecting problems with photovoltaic modules. They do more than meet current needs in the solar industry; they pave the way for future advancements in automated defective diagnosis.

PV solar panel systems are the latest thing in green energy. They use sunlight to make power. Solar cells, typically composed of semiconducting materials such as silicon, enable this transformation to transpire. The photovoltaic effect, which happens when an electron receives sunlight and excites it, is how these cells generate power.

The PV system is made up of panels that are manufactured from individual solar cells. To increase power generation, these panels are stacked into arrays. To convert the DC output of the panels to AC, a form that is compatible with most modern electrical systems and appliances, the inverter is a vital component.

You can set up photovoltaics in many different ways. People who have systems that are linked to the grid can sell the utility company any extra power they make. In contrast, devices that operate off-grid often use battery storage to maintain power availability rather than depending on the power grid. The integration of solar electricity with other energy sources in hybrid systems might provide more power-generating flexibility.

Using PV systems has economic advantages in addition to benefiting the environment by reducing greenhouse gas emissions. Investing in a PV system now will result in significant savings on energy expenses in the future. As the need for environmentally friendly options grows around the world, solar energy is also getting cheaper because many countries offer funding or other benefits to encourage people to use it.

Two other obstacles that need to be addressed are the efficiency restrictions and the intermittent nature of solar electricity. However, new solutions are on the way as a result of persistent study and technological advancements. The PV solar panel system is an essential component of the transition to a greener energy paradigm because of its endless possibilities and many advantages.

2.2. STAGES OF A PHOTOVOLTAIC SOLAR PANEL SYSTEM

A photovoltaic (PV) solar panel system includes a loop of activities that start with collecting sunshine and end with using and managing power. This process is made up of a number of separate but linked steps:

- Collecting sunlight: This step is really important for PV systems [39] and solar cell efficiency tables [38]. Solar panels are made of cells that flex sunlight into energy.
-

- 2. Making energy: The photovoltaic effect is what makes solar power work. It involves the movement of electrons inside solar cells to change light energy into direct current (DC) [43,39].
- 3. Power Conversion: Inverters are crucial for enabling the majority of home appliances to connect to the grid since they transform DC power into AC energy. Both the book on solar energy production by Goetzberger and Hoffmann [47] and the review of solar power by Razykov et al. [41] focus on this procedure.
- 4. Distributing the converted AC power throughout a property is an important part of renewable energy predictions, according to sources like the International Energy Agency [44] and the debate on scaling up photovoltaics by Haegel et al. [42].
- 5. Connectivity to the Grid (for systems that are part of the grid): The second research by Zweibel et al. [45] and the first by Pearce on photovoltaic for sustainable futures [46] both highlight the importance of connecting solar systems to the electrical grid, which permits a two-way flow of electricity.
- 6. Management and Monitoring: Monitoring efficiency and performance in real-time is a common feature of modern PV systems. It has been studied in scientific papers and reports from the green energy business.
- 7. Upkeep and Maintenance: Professional and technical journals, such as Goetzberger and Hoffmann [47] and others [44], have reported that solar panels should be repaired often to guarantee optimal performance.

2.3. CHARACTERISTICS OF THE PHOTOVOLTAIC

Parameters have a significant impact on the efficiency, efficacy, and performance of photovoltaic (PV) solar panel systems. These criteria provide a framework for evaluating and selecting the most suitable PV systems based on specific needs and geographical limitations. Here are a few key points from the literature [38,39]:

- Efficiency: The efficiency of the PV system, expressed as a percentage, reveals its ability to convert sunlight into electricity. The efficiency of residential solar panels has a significant impact on the system's overall output, which typically ranges from fifteen per cent to twenty-two per cent.

- Capacity/electricity Rating: This metric shows the maximum amount of electricity that a solar system or panel can generate under ideal circumstances. Kilowatts (kW) or watts (W) are the units of measurement. It is an important indicator of the system's total size and power generation capabilities.
- Temperature Coefficient: This coefficient quantifies the impact of temperature on the electrical output produced by solar panels. Keeping in mind that most panels' efficiency drops with increasing temperature will help you understand and manage the effects of temperature swings.
- Degradation Rate: The efficiency of solar panels will naturally decrease over time. Modern solar panels typically degrade at a rate of half a per cent to one per cent each year, meaning that they may still maintain a significant portion of their original output even after twenty or thirty years.
- Longevity: Solar panels typically have a lifetime of 25 to 30 years, but they may continue to function for much longer. However, with time, their efficiency tends to decrease gradually.
- Physical Dimensions and Weight: The weight and dimensions of the solar panels must be considered in conjunction with the installation requirements and the structural requirements of the mounting location.
- The angle of inclination and the direction facing are called the tilt and azimuth of the solar panels, respectively. The ideal values for azimuth and tilt, which are critical for maximizing solar energy collection, vary with latitude and longitude.
- Solar Cell Varieties: There are several types of solar cells, including monocrystalline, polycrystalline, and thin-film solar cells. Aesthetics, price range, and benefits are only a few of the factors that differentiate the many types of solar cells.
- One common metric for assessing solar power systems is the cost per watt, which provides a return on investment (ROI) comparison.
- Solar Panels with Versatile Mounting Options: These panels provide unparalleled versatility in terms of mounting, allowing for installation on

curved surfaces or in unique combinations. This holds true for solar panels made of thin film.

- Warranty and Durability: When discussing the durability of a panel, we are referring to its capacity to endure various weather elements such as wind, snow, and hail. In numerous instances, the manufacturer shall furnish a warranty that ensures the product shall perform as advertised.
- The compatibility and interconnection of solar panels with other system components, including mounting structures, inverters, and the grid, is a guarantee of their ease of use.
- There are, like, so many tolerances for panels and systems to lessen the impact of partially shaded areas on the finished result; some are better equipped to handle this kind of shading.

2.4. SOLAR PANEL DETECTION SYSTEMS

The successful implementation of solar panel detection systems necessitates the advancement and application of diverse technologies and methodologies to proficiently identify, monitor, and assess solar panel installations. These devices are crucial for tracking the popularity of solar energy, ensuring compliance with rules, and identifying malfunctions in solar panel arrays. Here are a few examples of popular solar panel detection systems:

- Photography with remote sensing: Remote sensing using satellite photography has been a topic of interest in recent studies. For instance, Malof et al. [31] and Zhang et al. [32] have delved into the subject and provided insights on how satellite photography and machine learning algorithms can be utilized to identify solar panels automatically.
- Drone surveillance: There have been studies conducted by researchers like Ma et al. [33] and Nguyen et al. [34] that explore the use of drones for monitoring solar panels, particularly in large-scale installations.
- Infrared Imaging: Infrared imaging techniques for solar panel identification and problem diagnostics are described in Buerhop-Lutz et al.'s work [6].

- In their study, Meola and Toscano [36] delve deeper into the topic of using acoustic emission testing to detect faults in solar panels. They offer additional insights and information that can be valuable in understanding this potential application.
- Thermography and Electroluminescence: In works like Luo et al. [12] and Breitenstein et al. [37], Many researchers have dedicated a significant amount of time and effort to discussing the potential of thermography and electroluminescence as effective techniques for detecting defects in solar panels.
- Systems of Monitoring: Real-time monitoring systems influence performance tracking in solar Implementations, as shown by Stein's study [35].
- AI and machine learning: Tang et al. [10] and Akram et al. [9] examined the increasing usage of AI and ML in domains such as photo shooting and solar panel installation.

All solar panel installations rely on these systems, which are backed by research and technological breakthroughs, to run efficiently and need little maintenance. They showcase the integration of cutting-edge sensing and monitoring technology with renewable energy sources.

2.5. MACHINE LEARNING

As an important subfield of AI, machine learning (ML) includes a wide range of techniques that teach computers new skills by analyzing existing data and drawing conclusions or making choices without human intervention. This subfield of computer science is similar to medical methodology in that it makes use of trained algorithms and statistical approaches to carry out activities like classification and prediction [48, 49]. Different types of learning algorithms are used to categorize machine learning approaches [50, 51]:

- **Supervised Learning:** Algorithms utilize labelled training data to acquire new skills in this method. Algorithms generalize what they know about how to transfer input data to labels in order to create predictions for new, unseen samples. There are essentially two primary functions of supervised learning:

- Classification: Here, we need a way to tell which input samples go into which categories. Through analysis of a training set of labelled samples, the algorithm is taught to classify incoming events into predefined groupings.

- **Regression**: A continuous value is the outcome of a regression analysis. The algorithm is able to anticipate values for future data points by learning the link between input variables and a continuous output variable.

- **Unsupervised Learning:** Without labelling individual occurrences, unsupervised learning algorithms may find underlying patterns, connections, and structures in the training set. Finding previously unknown connections in data is a typical use case for models. The more difficult kind of machine learning, known as unsupervised learning, requires learning sample distributions without labelling them.
- **Reinforcement Learning (RL):** In this method, models acquire understanding by communicating with the outside world and adapting their behaviour based on the input they receive, all with the aim of achieving specific objectives. The creation of methods that maximize the cumulative reward is driven by the learning process, which is influenced by the rewards or penalties obtained for activities committed. The complexity in assessing long-term impacts and repercussions of algorithm decisions makes RL implementation difficult, especially in sensitive fields like medicine [52].
- Classification and regression are two main categories of machine learning tasks [53, 54] that are defined by the kind of output variable:

- **Classification**: This process entails building models that anticipate particular classifications or labels using unique characteristics in a dataset.

- **Regression**: In this method, the dependent and independent variables are learned, and models are created to predict a continuous variable.

- Many industries, such as healthcare, banking, and technology, rely on machine learning due to its adaptability and its capacity to derive valuable insights from data. When used in PV systems and solar energy, machine learning may greatly improve renewable energy solutions in areas such as problem detection, performance improvement, and predictive maintenance.

2.6. DEEP LEARNING

Deep Learning is a sophisticated branch of Machine Learning that uses multi-layered Neural Networks to simulate human intellect by processing massive amounts of data. This fresh technique of learning and decision-making stands out since it breaks away from the conventional wisdom of Machine Learning. Deep Learning systems use their intricate network architectures to autonomously find essential features rather than depending on attributes that are deliberately picked. Weighting various data elements enables the network to gradually hone in on its focus and enhance the Accuracy of its outputs, enabling it to learn autonomously [55, 56, 53].

Deep Learning excels at handling complex and massive datasets, which is one of its main strengths. In data-rich settings, it may greatly enhance classification accuracy and reduce regression analysis mistakes. Deep Learning models' adaptability is boosted by their numerous activation functions, pooling layers, convolutional layers, and other network designs. These properties allow these models to excel in situations where complicated or large amounts of data pose challenges for typical machine-learning methodologies [57].

With its more complex and independent method of data extraction, Deep Learning is a huge step forward in the field of artificial intelligence. Its flexibility to various data formats and mastery of large datasets make it a priceless tool in many AI domains. Deep Learning's capacity to improve and diagnose systems is particularly noticeable in sectors like solar energy management, highlighting its revolutionary influence in high-tech fields.

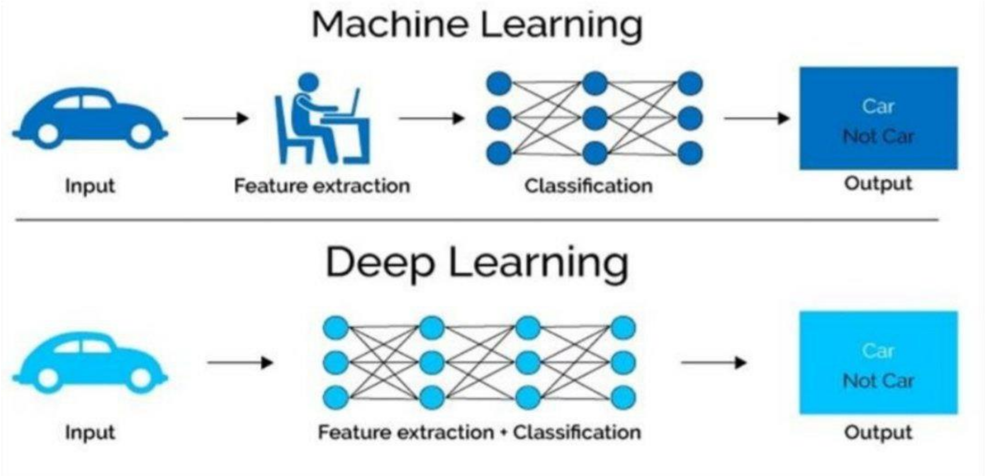
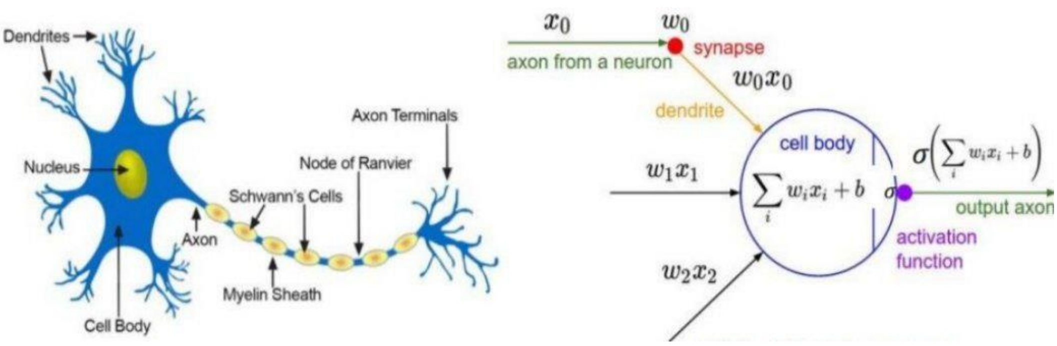


Figure 2.1. Comparison between Deep Learning and Machine Learning [58].

2.6.1. Artificial Neural Networks and MLP Overview

ANNs Draw Inspiration from Biological Neural Networks: The human brain's own neural networks serve as an inspiration for ANNs. An ANN is a network of artificial neurons or nodes that simulate the way real neurons transfer electrical impulses and activate outputs through synapses depending on a predetermined threshold [59]. To further grasp this parallel, Figure (2.2) provides a visual representation of the similarities and differences between artificial neurons and human neurons [60].



(a) Human neuron (b) Artificial neuron

Figure 2.2. A Relative Analysis of Real and Artificial Neurons [60].

Multi-Layer Perceptron (MLP)—The Building Block of Contemporary ANNs: One popular type of artificial neural network (ANN) is the multi-layer perceptron (MLP) [61, 62]. The following components make up this structure, as shown in Figure (2.2):

Neurons in the input layer are a direct reflection of the characteristics that are input into the layer. The input data is sent to the hidden layers via it.

- In order to analyze incoming data, neurons in the hidden layers—which are located between the input and output layers—use weighted connections. Different models have different amounts of hidden layers and different types of neurons in each layer. You may change the weights of these connections while you work out.
- The Output Layer: In classification tasks, this layer generates the final output that represents the anticipated feature or class. Data processed by the hidden layers is used to create the output.

MLP Network Depth and breadth: In an MLP setting, the network's depth is the total number of layers, and the network's breadth is the total number of neurons per layer. The network's complexity and capacity are determined by its depth and breadth, which are critical parameters [63, 64].

2.6.2. Deep Learning Architectures

Vector graphic models based on artificial neural networks (ANNs) have become common in deep learning (DL), and each ANN has its own distinct architecture derived from the building blocks of a neuron.

In these DL designs, you can see a lot of recurrent, fully connected, and convolutional neural networks; each of these networks is great at what it does [49].

- Text, time series, and speech are examples of sequentially organized tasks that recurrent neural networks excel at.
- Classification layers and other activities where all incoming data is equally relevant often employ fully linked networks.
- To take advantage of the local connectivity, such as in the pictures, convolutional neural networks are employed.

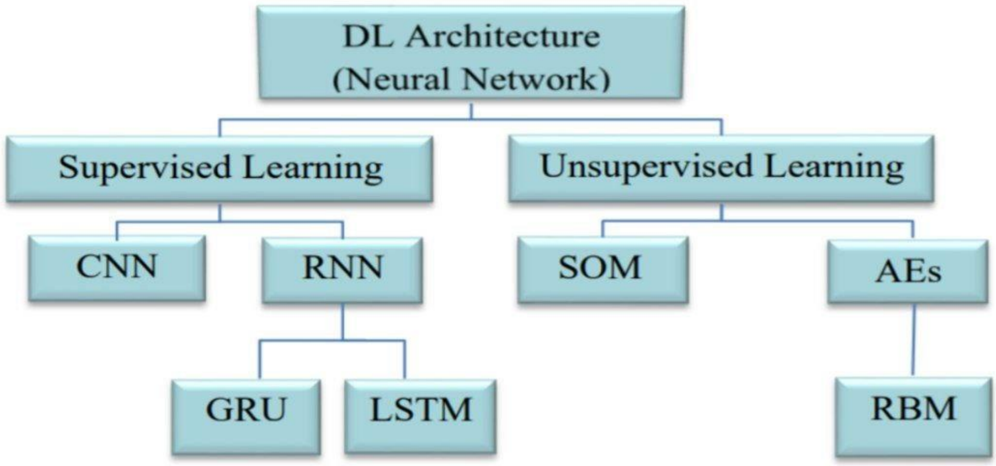


Figure 2.3. A Variety of Neural Network-Based DL Architectures Categorized as Supervised and Unsupervised Learning [65].

Among the most common supervised and unsupervised learning architectures, as shown in Figure (2.3), are the following: CNN, Restricted Boltzmann Machine (RBM), Recurrent Neural Networks (RNNs), Long Short Term Memory (LSTM), Autoencoders (AEs), and Self-Organizing Map (SOM) [65].

With widespread use and success in many applications, CNNs are considered the computer vision powerhouse. One of the most notable uses is medical image analysis [50], [51], and [66]. When it came time to classify solar panels, we opted for CNN as the supervised DL model.

2.7. CONVOLUTIONAL NEURAL NETWORKS

Among the most popular Deep Learning techniques, Convolutional Neural Networks (CNNs) are known for their robust multi-layer training. It stood a good chance of succeeding and is now the de facto standard in many computer vision applications. Figure (2.2)[67] shows the general layout of the (CNN) system.

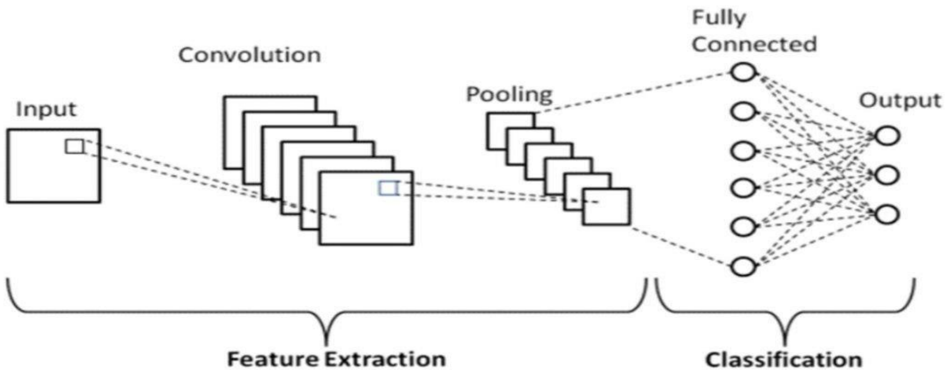


Figure 2.4. Is the Common Structure of the (CNN) System [67].

The four essential neural layers of a convolutional neural network (CNN) are the flattening layer, the density layer, the max pooling layer, and the convolutional layer. Various kinds of layers serve multiple purposes. Image categorization is achieved layer by layer in Figure (2.4) using a convolutional neural network (CNN).

2.7.1. Convolutional Layer

A CNN would only be complete with convolutional layers. The building blocks of a convolutional layer are a set of width- and height-distributed learnable kernels. A two-dimensional kernel motivation map is generated by the input characteristics during the forward permit. As seen in Figure (2.5), the operation of convolution requires a kernel that incorporates a layer of assembly weights with relative weights. The input is the size of minor 2D cover, and the output is a single unit.

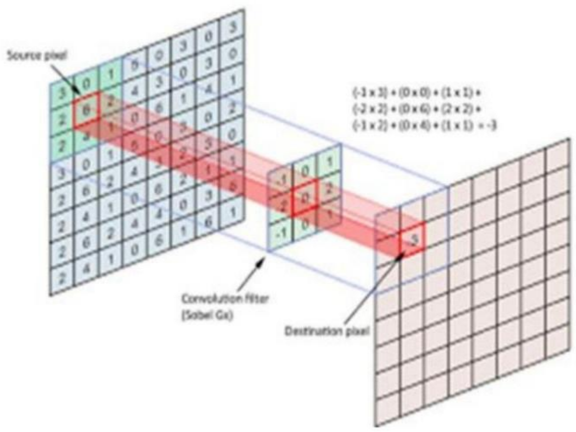


Figure 2.5. Convolution Operates.

2.7.2. Pooling Layer

A CNN's pooling layer, sometimes called the subsampling layer, is another essential component. It follows the activation function and the Conv layer in a typical application. Minimizing input dimensions is the main goal of pooling, which, in turn, reduces CNN parameters and computation time [63]. When it comes to specifying the stride value and filter size, the pooling kernel in the pooling layer is quite similar to the kernels in the Conv layers.

But this is only a preview; the kernel does not have any parameters or weights to be learned [49], [68]. The most common kinds of pooling functions are illustrated in Figure (2.6), and they are:

- Max pooling: This method uses a filter that moves over the feature map to extract the highest value in each region while disregarding the lower values [68].
- Average pooling: It takes into account all steps and finds the average value in the pooling window [68].

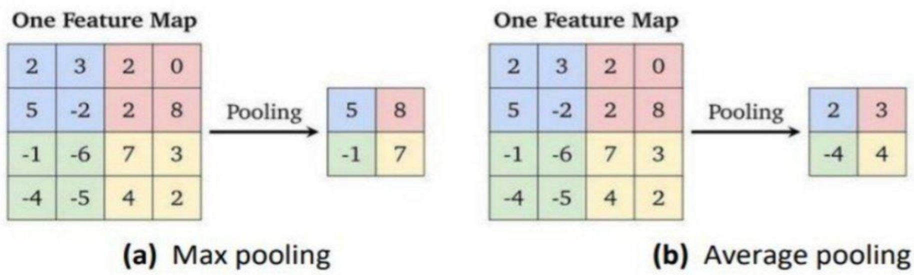


Figure 2.6. A (2 x 2) Pooling Window with Stride (2) Example of the Two Predominant Pooling Layer Types [68].

2.7.3. Flatten Layer

One of the first steps in convolutional neural networks (CNNs) for image classification is the flattening layer, which involves modifying data in order to recover results. Make it seem like a link to the 1-dimensional array's next level. To make one long function direction, the output of the Convolution Layer has been flattened. In addition, it is a part of the most recent kind of classification model, the dense layer [67].

2.7.4. Dense Layer

A fully connected layer is also its proper name. A weighted linear process is one in which each input is related to each output. Its weights are m x n since it takes in m inputs and produces n outputs [67].

2.7.5. Soft-Max Function

This idea is expanded into a set of several classes by soft-max. Put, when faced with a situation involving several classes, Soft-max assigns decimal likelihoods to each class. Up to 1.0.0, these decimal possibilities must be improved. Because of this new limitation, brand training is now completed more quickly than before. Previously, a Neural Network Layer found Soft-max beneficial as an output layer. As shown in Figure (2.7) [69], the number of nodes in the Soft-max essential layer is identical to that of the output layer.

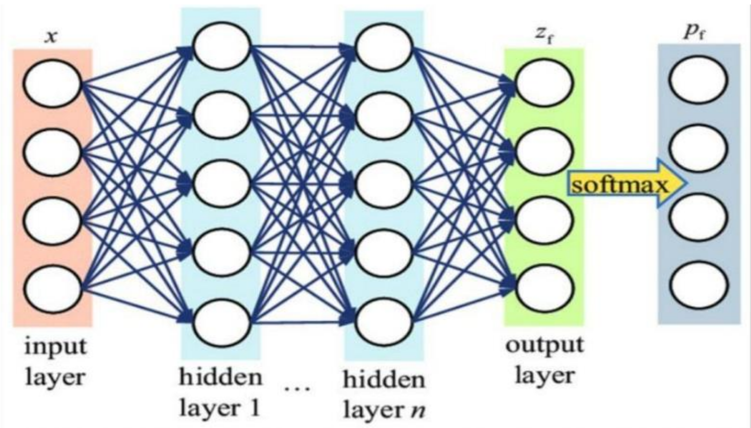


Figure 2.7. Soft-Max Function [69].

2.8. TRAINING OF CNN

Supervised learning involves training deep neural networks using data input and labels for output. In order to minimize prediction errors, the objective of training is to finetune the network's parameters (weights and biases) such that it correctly assigns a class label to each input [65]. At startup, the network's weights are allocated at random. During training, the difference between the actual and anticipated outputs is measured using a loss function, which is used to compute the error. Gradient descent, which iteratively modifies the weights, is then used to minimize this mistake. The weights are further fine-tuned via back-propagation in an effort to identify the best configuration that minimizes the network's total prediction error.

2.8.1. Gradient Descent Optimization Algorithms

One optimization method, known as gradient descent, involves adjusting the neural network's internal weights in order to lower the cost function values [70], [71]. After each iteration, the weights are adjusted using the gradient descent approach to minimize the cost function value. The process continues until further adjustments have little to no effect on the loss value, which is called convergence [72]. The following are only a few examples of the numerous forms of optimization:

- Batch Gradient Descent (BCD): Before updating weights, or the epoch, in BCD, all training data is assessed to compute the gradient. Although this helps get the weights precisely right, training is sluggish due to how long it takes to make modifications.
- SGD with Momentum: SGD's delayed convergence is caused by its oscillation towards the smallest error, which in turn requires a slow learning rate. With momentum's little contribution to the preceding change, the SGD may be guided towards quicker convergence and away from oscillations.
- Momentum is a variant of SGD that considers the prior gradient steps to mitigate the update's harshness. Boosts convergence and dampens oscillations. Implements a momentum term that takes the gradients and uses them as a moving average.
- Mini-Batch Gradient Descent is a middle ground between batch and stochastic gradient descent. It updates the Model's parameters by utilizing a mini-batch, which is a subset of the training data. Outperforms stochastic gradient descent and batch processing in terms of computing efficiency, particularly when

optimized for GPUs.The standard range for mini-batch sizes is tens to hundreds.

- Adam, or Adaptive Moment Estimation, is an optimization approach that only requires one step and works with stochastic objective functions. The neural network weights may be repeatedly updated based on training data using adaptive low-order moment estimation [63]. Not only is this method easy to implement, but it also uses very little memory and is highly efficient in calculating [73]. The Adam method works well with large data sets or parameter values because its diagonal gradient scaling is invariant.
- Adagrad, an Adaptive Gradient Algorithm, changes the learning rate of each parameter according to the gradient data used in the past. Works well with scarce data. During training, the learning rate might be reduced too drastically, leading to the Model ceasing to learn.
- Adam with Nesterov acceleration (Nadam): Adam with Nesterov momentum integrated. Gives a little faster convergence than Adam.
- Adadelta: an update to Adagrad that aims to soften the program's harsh, monotonically declining accuracy rate. Instead of adding up all the squared gradients from the past, Adadelta limits the size of the window in which all the prior gradients are added up.
- Follow The Regularised Leader (FTRL): Works well with sparse datasets that have a high number of dimensions. Combinations of L1 and L2 regularisation are common when using this method.

2.8.2. Algorithm for Back-Propagation

The backpropagation algorithm is one of the most popular supervised learning methods to help neural networks learn their parameters because of its effectiveness and simple construction. The gradient descent technique is employed to reduce network error, and both forward and backward propagation training paths are used to update weights, as explained below [65]:

- Forward Propagation: During the forward voyage, the input data is sent from the input layer to each subsequent layer in the network, until it reaches the output layer. The output is calculated using the previously mentioned equations in accordance with the Conv layer, pooling layer, and FC layer of the CNN architecture. Before backward propagation occurs, the activation functions and output values for each layer must be determined [74].

- Backward Propagation: The backward route feeds the error back from the output layer to the input layer by calculating the error derivative for each layer and then adjusting the weights to lower the error in the network by repeating steps [59,70].

2.9. SPARSE AUTOENCODER (SAE)

Autoencoders are a type of unsupervised learning, and a sparse auto-encoder's architecture is comparable to a three-layer conventional neural network. The two stages of the auto-encoder's processing are encoding and decoding. All three layers—layers 1 through 3—are involved in the encoding and decoding process [40]. It is only emphasized in the first layer of evolution to make the structure of every layer in the suggested SAE clear. Every layer that comes after it has the same architecture, as seen in Figure (2.8).

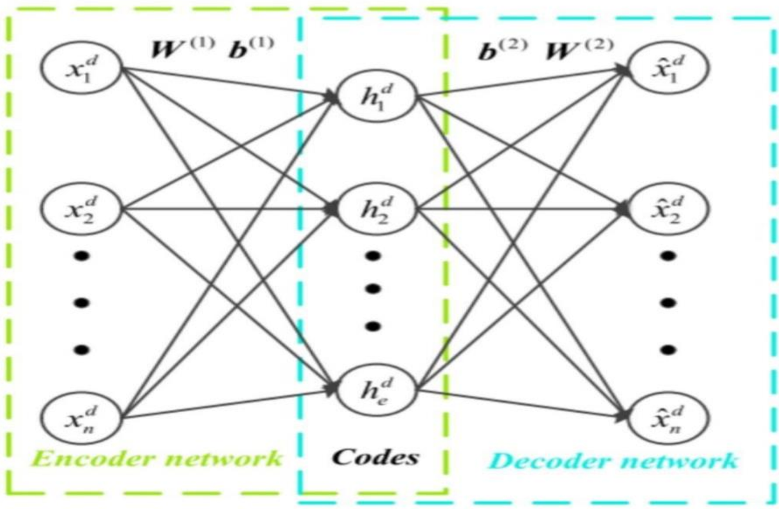


Figure 2.8: Structure of auto encoder [75].

The output layer's decoder vector is x n, and the hidden encoder vector, hn, is derived from the unlabeled input dataset {xn} N n=1, where xn ∈ R m×1. Thus, the following is the encoding procedure:

$$h_n = f\,(W_1 x_n + b_1) \qquad (2.1)$$

Where W1 is the encoder's weight matrix, b1 is the bias vector, and f is the encoding function.

This is the definition of the decoder process:

$$x_n = g\,(W_2 h_n + b_2) \qquad (2.2)$$

Where b2 is the bias vector, W2 is the decoder's weight matrix, and g is the decoding function[40].

2.10. CHALLENGES IN THE TRAINING

It can be difficult to train deep neural networks, particularly Convolutional Neural Networks (CNNs). These difficulties result from the delicate interactions between several hyperparameters, big datasets, and deep architectures. The following are some typical difficulties encountered during training [49]:

2.10.1. Vanishing Gradient

Any deep neural network with sigmoid or tanh activation functions will exhibit derivative fading since deep neural networks are trained via backpropagation techniques. This makes training particularly challenging because it might be challenging to modify the parameters in the initial layers. Due to the derivative dependence of backpropagation, this problem gets worse with increasing network depth. Consequently, utilizing the ReLU activation function is more successful with deep networks and less prone to derived fading because the derivative is always 1 [53].

2.10.2. Underfitting and Overfitting

A suitably generalizable model is what deep learning model training aims to achieve. A model's ability to function well on data that it hasn't been trained on before is referred to as generalizability [76].

- Underfitting is the result of the Model not receiving a little amount of error during training and not learning correctly from the training set of data.
- The term "overfitting" refers to a model's ability to learn well even in the face of failure to generalize or a significant discrepancy between errors made during training and testing. It is one of the most prevalent problems with deep learning training because of the sheer amount of parameters that need to be learned. Regularisation techniques like dropout and early pausing may be used to address overfitting problems.

2.11. TRAINING REGULARIZATION TECHNIQUE

In particular, deep neural networks need the use of training regularisation approaches to avoid overfitting in machine learning models. When a model learns the training data too closely—including its noise and outliers—and performs badly on unknown data, this is known as overfitting. Regularisation techniques ensure that the Model stays basic and improves in generalization by adding certain restrictions to the learning procedure. Here are a few popular methods of regularization.

2.11.1. L1 & L2 Regularization

Known as "weight decay" methods, these approaches impose a penalty on the loss function according to the weights' magnitudes.

- L1 Regularisation (Lasso): Increases the penalty in accordance with the weights' absolute values. It may result in sparsity, which would make some weights absolutely zero.

- L2 Regularisation (Ridge): This method adds a penalty based on the square of the weights' magnitude. Weights tend to decrease, but they don't always get zero.

2.11.2. Dropout

Dropout's basic idea is to randomly disable a certain input after every training cycle, as Figure (2.9) illustrates. Training CNN with dropout may be compared to a collection of other networks with fewer units, but the total number of parameters remains constant due to the uniform distribution of weights[63]. This constraint forces the network to develop more resilient features instead of relying solely on the ability of a small subset of neurons to predict the future. A single, dropout-free network is employed for testing. This significantly reduces overfitting and outperforms others.

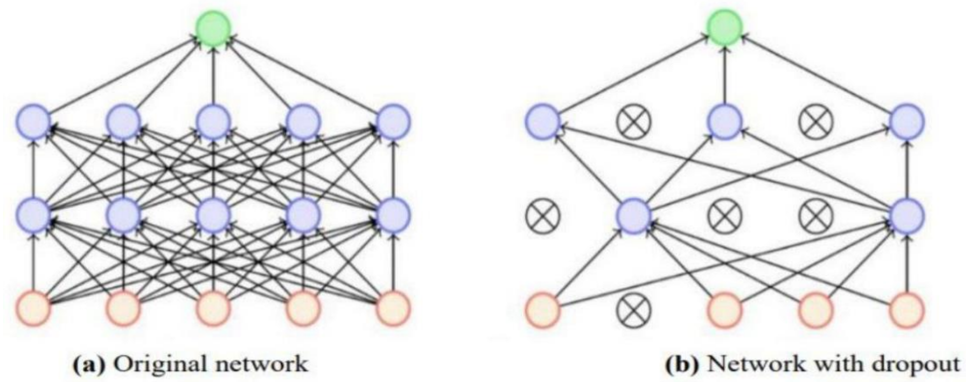


Figure 2.9. Shows the network both before and after the dropout technique is used. Dropout deactivates the crossed nodes.

2.11.3. Batch Normalization (BN)

Two parameters are used in a training technique called batch normalization (BN) to decrease the variability of distributions in the input layer: shifting, which subtracts the mean, and scaling, which divides the batch standard deviation.

BN speeds up training convergence and may lead to better results. After normalizing each feature during training at the batch level (scaling inputs to zero mean and unit variance), the entire training dataset is rescaled in order to achieve this. The batch-level data are replaced with the recently found mean and variance. This reduces overfitting, speeds up learning, and accelerates training [77][78].

2.11.4. Early Stopping

Monitoring the network's performance on training samples and stopping training early if the network's performance declines or if it runs into the overfitting issue is one of the most often used methods for training neural networks [79].

2.12. MEASURES OF PERFORMANCE

To assess a system and extract data for Accuracy, Recall, Precision, and F1-Score, system performance should be calculated for each system in use[80]. The following acronyms are utilized in the equation:

2.12.1. Precision

The number of true positives, which is divided by the number of true positive states, is displayed together with the number of false positives, or cases that the Model accurately classifies as positive but are actually negative, such as individuals who are labelled as terrorists but are not. The ratio of (true positive) to all forecasts is the definition of precision. This may be expressed in numbers as

$$\text{Precision}= \frac{TP}{TP+FP} \tag{2.3}$$

2.12.2. Recall

The Accuracy of a model is the percentage of data points that it considers to be relevant out of the total number of relevant examples it can identify in a dataset. The percentage of all correct observations to correct predictions within the given sample.In terms of math:

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \tag{2.4}$$

2.12.3. F1-score (F1)

is weighted recall and accuracy harmonic mean. When the dataset is unbalanced, this assessment measure is frequently used. The Fmeasure is used to evaluate the Model's performance when the class distribution is unbalanced. More importantly, the results improve with increasing Fmeasure.

$$\text{F1-score} = \frac{2*(\text{Precision}*\text{Recall})}{\text{Precision}+\text{Recall}}. \tag{2.5}$$

2.12.4. Accuracy

is defined as the ratio of all observations to (correct forecasts). A model is said to have the highest Accuracy for the two-class problem if and only if we have a symmetric dataset with values for FP and FN that are almost identical. In diverse and uneven data sets, alternate assessment measures, such as the F1-score, may be evaluated rather than Accuracy.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2.6}$$

PART 3

METHODOLOGY

Our approach examines and contrasts four separate models by testing their performance: a Custom CNN Model fine-tuned for PV module fault detection, an InceptionV3 model enhanced to extract complex features, the deep learning ResNet-50 model, and a Hybrid Model that harmoniously merges elements of the previous two models. Solar power system quality assurance and maintenance will be substantially aided by the results of this comprehensive study, which aims to improve the reliability and precision of defect diagnosis in photovoltaic panels.

3.1. THE PROPOSED WORK

We aim to develop and evaluate computational models capable of accurately and swiftly identifying and characterizing faults in photovoltaic cells. Our models are constructed with a focus on efficiency and accuracy, considering the diverse range of PV cells used in practical settings. The sequential approach of our technique begins with the collection of raw EL photos and ends with a thorough evaluation of the constructed models. The approach is based on contemporary best practices and cutting-edge research in deep learning and image analysis. Figure 3.1 shows the overall flow diagram of the recommended models, which includes the Custom CNN, InceptionV3, ResNet-50, and the Hybrid Model.

- Approach: the Custom CNN Model.
- Approach: adapted InceptionV3 model.
- Approach: ResNet-50 Model.
- Approach: Hybrid Model.

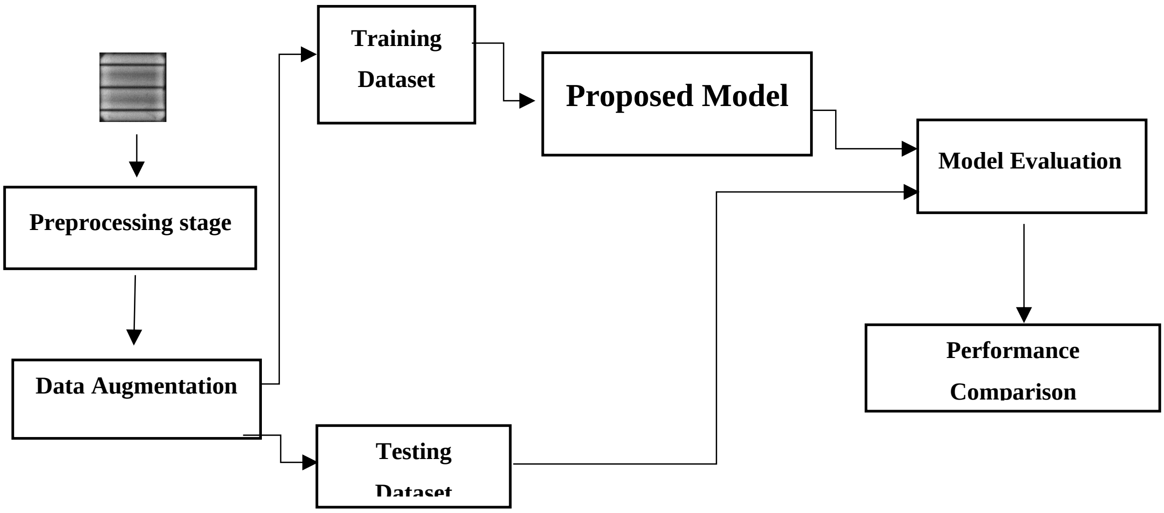


Figure 3.1. General flow chart of the proposed models.

3.2. TECHNICAL REQUIREMENTS

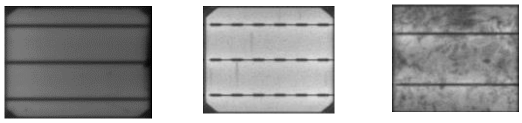
We will use the following to implement the suggested system:

Computer central processing unit (CPU) and related hardware: Intel(R) Core(TM) i7-10750H, running at 2.60 GHz. 16 GB of RAM and an NVIDIA GeForce GTX 1660 Ti. The preferred programming language is MATLAB, and the operating system is Windows 10 (64-bit).

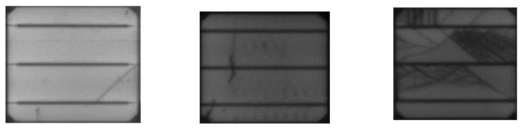
3.3. DATASET

2624 high-resolution electroluminescence (EL) pictures of monocrystalline or polycrystalline solar modules were taken from a large database for this investigation. The precise features of one of 44 distinct PV module types are shown in each 300-pixel picture, giving a thorough overview of the varieties most often used in the industry. The dataset's diversity allows for a thorough analysis that may be used with a range of PV systems.

The dataset of Buerhop-Lutz et al. [6] is clearly separated into two sections: photographs of solar systems with different flaws classified as "defective" (715 images) and images of photovoltaic systems with no abnormalities, designated "without defects" (1508 images). The investigation is characterized as a binary classification problem due to the significance of discerning between PV cells that are healthy and those that are diseased. The longevity and efficiency of PV modules rely heavily on the presence of effective fault detection and classification technology. Figure 3.2 illustrates the surfaces of a typical photovoltaic (PV) cell (A) and a deficient PV cell (B).



(A)



(B)

Figure 3.2. Surfaces of normal (A) and damaged (B) photovoltaic cells.

3.4. PREPROCESSING

To make it easier to analyze pictures of solar panels using AI, it is necessary to do pre-processing for this study. A multi-stage image preparation pipeline was conceived to diminish noise and enhance relevant features. The actions that went down were as follows: The pre-processing step's flowchart is shown in Figure 3.3.

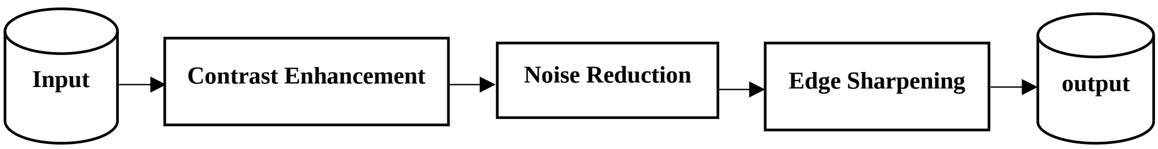


Figure 3.3. Flowchart of the Preprocessing Stage.

Contrast Enhancement Using CLAHE: To make pictures pop in any lighting and texture situation, we used contrast-limited adaptive histogram equalization (CLAHE). By implementing this methodology, distinguished for its superior retention of edge intricacies, the legit spotting of flaws in photovoltaic (PV) modules is very important.

Noise Reduction: Applying a Gaussian blur filter with dimensions of 5x5 pixels totally made the image pop, like it got very clear. In order to enhance the perception of challenging features and facilitate the process of recognizing patterns, it is crucial at this particular stage to eliminate any random noise present in the images.

Edge Sharpening: A 3x3 sharpening filter was used to flex those high-frequency edge elements and make the image edges. This serves as a crucial step in highlighting minuscule yet perceptible abnormalities in the images of PV modules.

Expansion of Flawed Photo Dataset:

The database was expanded from 715 to 1668 instances of defect images. Now, we have a way bigger and way more diverse training set. This upgrade has the potential to level up the models' skills for flexing and spotting errors in all sorts of situations.

By implementing those calibrated preprocessing techniques, the features become very visible, and the noise gets deleted, making it easier for machine learning algorithms to spot errors with greater precision. The accurate preparation of data through these procedures is crucial for the successful identification and categorization of PV module defects by deep learning models. Figure 3.4 shows the image pre-processing stage.

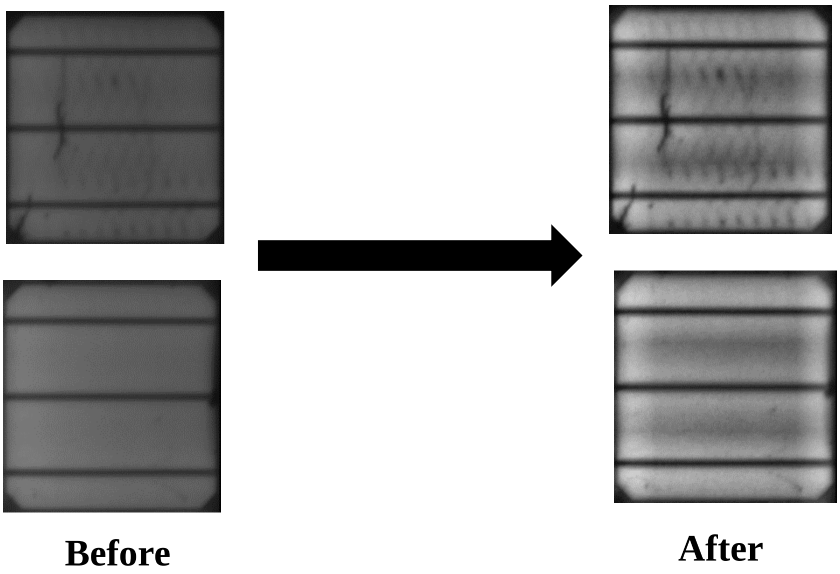


Figure 3.4. The impact of enhancement.

Advantages of process adaptation [81]:

- Pre-processing techniques such as adaptive histogram equalization and morphological methods significantly improve image quality. They improve readability by increasing contrast, reducing noise, and highlighting previously invisible elements.
- Increased Accuracy. By improving image quality, these methods improve the Accuracy of automatic analysis and classification. Accurate detection of features and structures is of paramount importance in medical imaging, aiding in the diagnosis and treatment of diseases.
- Functional improvement: Structures such as blood vessels and lesions become clearer in preprocessed fundus photographs. This makes it easier for clinicians and machine learning methods to detect and analyze these features.
- Standardizing the images produced by preprocessing techniques makes it easier to compare patients and data sets, which brings us to the first point: consistency.

Disadvantages of preprocessing methods [82]:

- Overtreatment. If the preprocessing is too extensive, the enhanced images will create unwanted artefacts or lose some of their original features.
- The use of preprocessing methods should be approached with caution due to the potential for failure or bias. These artefacts may influence future research.
- Computational complexity. Some tuning operations can be computationally intensive, which can slow down the analysis process when processing large data sets.
- Data set characteristics play an important role in determining appropriate preprocessing settings, which can be a subjective process. Therefore, results may vary slightly.
- Troubleshooting [83]:
- Careful optimization of parameters is necessary to avoid overprocessing and distortion. Different types of images require different parameter settings to achieve the best results.

- Preprocessing quality control procedures can help identify and correct problems such as distortion and distortion.
- The advantages and disadvantages of different pretreatment methods can be reduced by combining them. For example, morphological methods and adaptive graph alignment can complement each other rather than compete with each other.
- Careful review and evaluation of preprocessing procedures are required to ensure that they do not compromise the reliability of subsequent studies. To do this, we compare the results either with a specific standard or with expert comments.
- One way to make the process less subjective and the results more reliable is to use adaptive methods. These methods change the preprocessing settings according to the characteristics of the image.

Thus, the methods described above for processing fundus images have a number of advantages. Their potential to improve the Accuracy and quality of future tests is impressive, but extensive research and validation are still needed to overcome their limitations and demonstrate their value.

3.5. DATA AUGMENTATION

Optimizing the training data set is an important part of deep learning-based fault detection of PV modules. One such method is data augmentation. We can increase the diversity of training data used by our method by changing the format of the original EL images. The generator is used to dynamically modify each image before sending it to the network for training. Typical scaling techniques include scaling, rotation, flipping, and adding Gaussian noise [30]. When working with a small training data set, as in this case, these strategies become critical. When it comes to photoelectric anomaly detection, where the goal is to identify small, unnoticeable problems, data augmentation helps reduce overfitting. Using this approach significantly improves the performance and reliability of the model. Machine learning algorithms vary greatly in their use of data augmentation, which is especially evident in highly specialized applications such as detecting problems with photovoltaic modules. Fig. 3.5 shows the extended data.

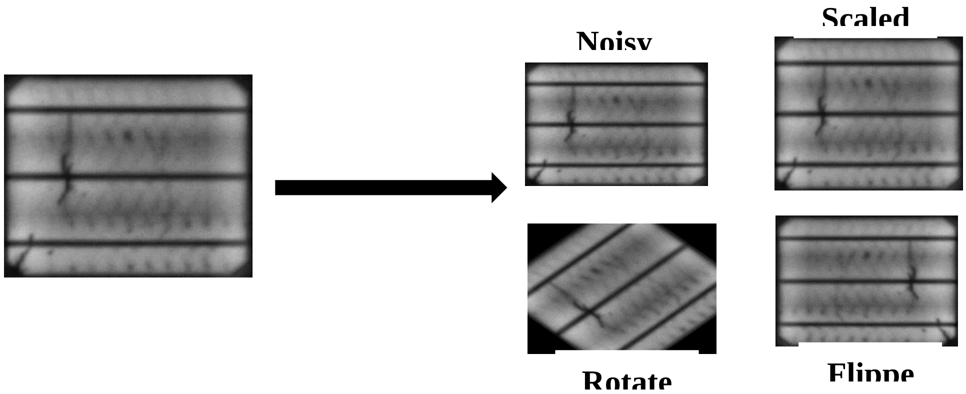


Figure 3.5. Data Augmentation.

3.6. SYSTEM MODELING

In this section, we detail our methods by investigating four separate deep-learning models that have been trained to identify flaws in PV modules. To show how each model overcomes the obstacles to automated solar panel flaw detection, this section highlights their technological features and advancements. With the initial model, we set out on our journey:

3.6.1. Custom CNN Model

The Convolutional Neural Network (CNN) model that we created for our research is used to get high-resolution electroluminescence (EL) pictures of photovoltaic (PV) cells. This model is designed to process 300x300x3 photos in an effective manner using convolution layers and 3x3 filters that have sizes 32, 64, and 128. To level up feature extraction and flex some nonlinearity, we slap on batch normalization and ReLU activation after every convolution layer.

A 2×2 pooling size and a max pooling level step size of 2 are used to flex computational performance and memory use. A layer is slapped on top of the structure to detect any flaws in the solar cells. The classifying layer, which totally relies on the probs from the softmax layer for each class, makes the ultimate decision. There are some major factors, including the learning rate, batch size, and number of epochs, that are adjusted to improve the performance of a CNN model. These things are to make the model good at detecting defects. The choice of layers, filters, and the sequence in which they are applied have a significant impact on the model's capacity to extract features. Activation functions such as ReLU may be used to recognize intricate patterns in images that point to PV module problems automatically.

Picking an optimizer, like Adam or SGD, is very important for optimizing the model and slaying that loss function while boosting accuracy. These adjustments, which include a trade-off between prediction accuracy and training efficiency, determine the model's resilience and efficacy in identifying certain PV defects. The Custom CNN model is very well-suited to handle the challenging job of flaw identification in solar cells because of its unique combination of complexity and efficiency. Table 3.1 flexes a list of parameters we use when training and building our CNN models. These characteristics were specifically selected with the intention of improving the models' performance by accurately classifying PV module flaws.

Table 3.1. Settings for Training and Compilation of CNN Models.

Parameter	**Value**
Optimizer	sgdm
Loss Function	Categorical Cross-Entropy
Learning Rate	0.001
Batch Size	64
Number of Epochs	100
Validation Split	0.2 (20% for validation)

3.6.2. InceptionV3 Model

To spot the flaws in the photovoltaic (PV) modules, our research was all about using Google's InceptionV3 model, a super-dope deep convolutional neural network (CNN) setup. This specific model, like its part in the powerful Deep Inception squad, is designed to function admirably with complex learning networks. We totally recommend using it in our study because it has unique architectural elements designed for high-quality picture processing.

Within the context of the InceptionV3 paradigm, "starter modules" are quite important. These modules enable the integration of filters of various sizes into a single layer. The model may take into consideration a very broad variety of geographic scales and different characteristics, thanks to this multidimensional approach. A big part of finding flaws in photovoltaics is finding the right balance between how quickly the computer can do things and how well it can describe complicated features [84]. Using convolutions (1x1, 3x3, and 5x5), fully linked layers, and convolutions of different sizes in pooling, the InceptionV3 architecture effectively lowers the number of dimensions. Considering the intricacy of EL pictures processed by PV modules, this is significant.

The inclusion of global mean pooling, which significantly reduces the number of parameters and helps to reduce the likelihood of overfitting, is one of InceptionV3's most significant features. This is really important because of how specialized our dataset is. The only ones that are taken into account are solar module failures. The model performed very well in photo recognition and classification tests since it was trained on the massive ImageNet dataset.

Table 3.2 lists every parameter that was utilized throughout the training and model compilation procedures for InceptionV3 for this query. Considerations such as multiple epochs, learning rate, batch size, optimizer type, and loss function are crucial.

Table 3.2. Training and Compilation Parameters of InceptionV3 Model.

Parameter	**Value**
Optimizer	sgdm
Loss Function	Categorical Cross-Entropy
Learning Rate	0.001
Batch Size	64
Number of Epochs	100
Validation Split	0.2 (20% for validation)

The InceptionV3 model's structure and configuration provide depth and precision in image analysis, allowing it to perform very well in the complex job of PV module defect identification.

3.6.3. ResNet-50 Model

One of the most popular pre-trained CNNs that revolutionized deep learning architecture was ResNet-50, which is short for Residual Network. The issue of degradation, wherein deep networks paradoxically result in worse training errors as the number of layers increases and fail to learn useful new properties, served as the driving force behind this choice. To solve this problem, ResNet-50 uses residual connections, also known as skip connections or identity maps. These paths facilitate the improvement and learning of more complex features, which allow the network to learn the remaining features relative to the layer's inputs. Object detection, image segmentation, and image classification are just some of the computer vision applications that have benefited from ResNet-50, a new standard for deep learning models for visual tasks, thanks to its 50 different layers [71, 72].

3.6.4. Hybrid Model

It is critical to develop specific machine learning models that can handle the complexity of electrical imaging (EL) and accurately identify defects in PV modules. We improved the model to improve detection accuracy since traditional architectures may miss unique error patterns in these types of images.

First, we use the InceptionV3 architecture, pre-trained on a huge ImageNet dataset, to extract valuable features from EL images of PV modules. This is the first step in our best model. By putting these images into the InceptionV3 model and using the output of the avg_pool layer, we get a compressed version of the visual properties. Capturing small parts at this stage is critical for accurate defect detection.

After feature extraction, we use the ResNet-50 model fitted to our dataset. In response to the processed InceptionV3 output, the input layer was compressed to 300x300x3 pixel images, which represents a significant shift. Our goal is to identify defective and healthy cells, which corresponds to a binary classification. To better reflect this, we modified the output layer of ResNet-50.

The combination of these models occurs in two stages. We first use InceptionV3 to extract features from our dataset. Classification is then performed using our custom ResNet-50 model, which takes these features as input. To achieve the optimal tradeoff between speed and accuracy, training parameters such as the learning rate and batch size are carefully calibrated.

The tuning parameters used to train and build the extended deep learning model are listed in Table 3.3. The performance of the model in detecting defects in PV modules is improved by the careful selection of parameters.

Table 3.3. Training and Compilation Parameters of Modified Model.

Parameter	**Value**
Optimizer	Sgdm
Loss Function	Categorical Cross-Entropy
Learning Rate	0.001
Batch Size	64
Number of Epochs	100
Validation Split	0.2 (20% for validation)

PART 4

RESULTS

In this study, deep learning models—Custom CNN, InceptionV3, ResNet-50, and a Hybrid model—were employed and trained with electroluminescence (EL) images of photovoltaic (PV) modules. After 100 training epochs, varying performance metrics such as Accuracy, precision, Recall, and F1-score were observed. These results are summarized in Table 4.1. To assess the models' ability to identify and classify defects in PV modules accurately, we conducted thorough testing using metrics like True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). Key performance indicators, including Area under the Curve (AUC), F1 Score, Accuracy, Precision, and Recall, were calculated using standard formulas:

$$Acc = \frac{correct\ predictions\ result\ in\ the}{whole\ number\ of\ results} * 100\% \tag{4.1}$$

$$\text{Precision} = \frac{TP}{FP+TP} \tag{4.2}$$

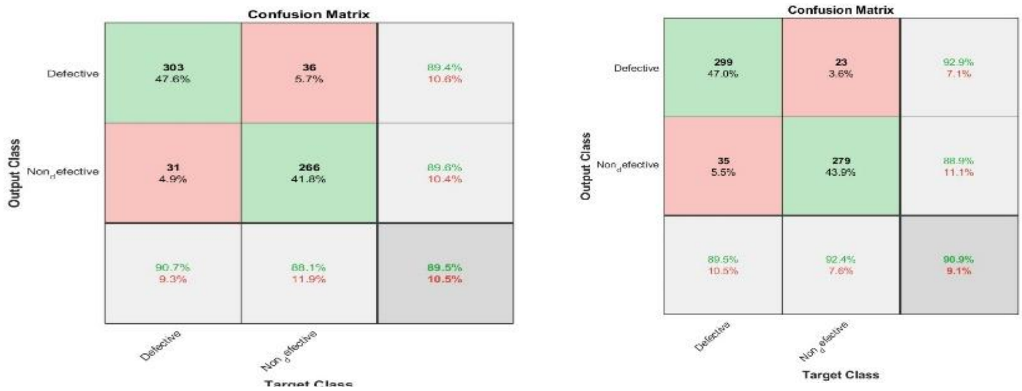
$$\text{recall} = \frac{TP}{TP+FN} \tag{4.3}$$

$$\text{F1} = \frac{2(\text{Precision}*\text{recall})}{\text{Precision} + recall} \tag{4.4}$$

Table 4.1. Summarized are Results.

Techniques	AUC	Accuracy	precision	recall	F1- score
Custom CNN	94.38%	89.47%	90.72%	89.38%	90.04%
Inceptionv3	97.37%	90.88%	88.85%	92.38%	90.58%
ResNet50	97.27%	91%	87.93%	94%	90.88%
Hybrid Model	99.85%	98.43%	98%	98.68%	98.35%

One useful technique for evaluating classification models, including pre-trained ones, is the confusion matrix. Detailed explanations of the Model's predictions for different classes are provided. Both figures 4.1 and 4.2 compare the suggested models' confusion matrices.



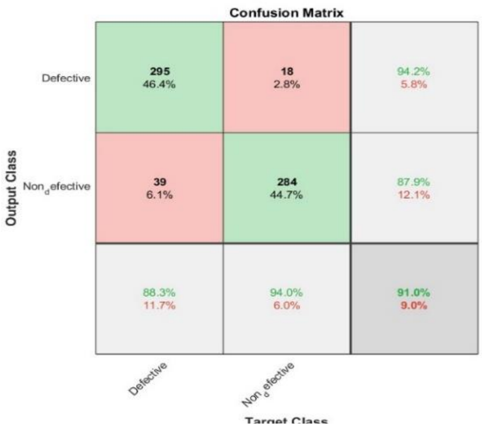
(A) Custom (B) InceptionV3

Figure 4.1. (A) Custom CNN and (B) InceptionV3 classification confusion matrices.

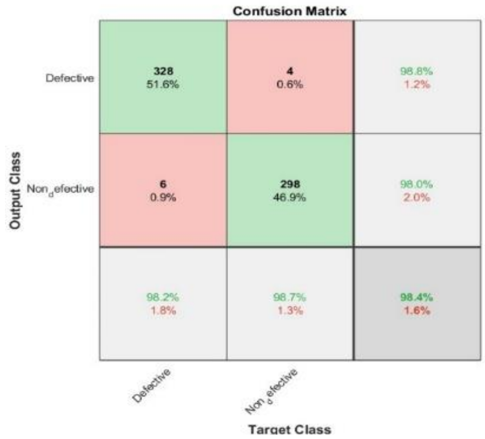
Using recall, precision, F1 score, and precision of 89.5%, the custom CNN model produced balanced results. This indicates a high level of accuracy, especially for optimistic forecasts. Figure 4.1(a) shows a confusion matrix that highlights the importance of identifying damaged cells for quality control.

In contrast, the InceptionV3 model achieved excellent results, with F1 and precision reaching over 90% and a recall rate of 92.38%. The improved ability to accurately identify and summarize data in Inception V3 is the reason for the higher recall rate. These functions are critical to preventing improper cell destruction. Figure 4.1 (b) shows the confusion matrix.

Both models do their job perfectly. But InceptionV3 offers a slight advantage, especially in recall, making it a better choice when avoiding false negatives is critical. The results show that state-of-the-art models such as InceptionV3 can significantly improve the detection of PV cell defects, a critical aspect of solar module quality management.



(A) Resnet50



(B) Hybrid

Figure 4.2. (A) Resnet50 and (B) Hybrid classification confusion matrices.

ResNet50 AUC, 97.27% strong, suggests the cell distinction F1 score is so high, recall and precision are strong, and accuracy shines. These metrics reveal that the model can effectively detect faulty cells, which is a crucial feature of quality control. It shows a balanced performance with a particularly high hit rate. Confusion matrix, ResNet50 model displayed, Figure 4.2(a). The model detects harm to solar panels' strength-preserved cells.

Near-perfect AUC, the hybrid model excelled brightly, 99.85%. The model's success shines in accuracy, precision, recall, and F1 score. The hybrid model finds Defective cells, true and clear Accurate, less false The error matrix shows the model's high memorability. Figure 4.2(b) recognizes, synthesizes, and prevents damaged cells' entry.

Models performed well; the hybrid model excelled with bright, efficient control. Results show progress in solar panel learning. The hybrid model shines.

PART 5

DISCUSSION

This study looked at four deep learning models that use electroluminescence (EL) images to find problems in photovoltaic (PV) modules. The models were Custom CNN, InceptionV3, ResNet50, and a hybrid model. As a consequence of each model's unique benefits, the findings demonstrated that the models are useful tools for precisely detecting mistakes.

The bespoke CNN model performed well, retaining excellent levels of accuracy, precision, and recall while attaining an F1 score of about 89.5%. This balance supports the hypothesis that the model can precisely detect damaged cells. Slightly better accuracy in identifying faulty cells is the model's strongest suit since it greatly reduces false positives in quality control.

The InceptionV3 model outperformed the custom CNN, which had an efficiency of 92.38%, in the categories of recall, F1 score, and overall accuracy. This improved recall reduces the likelihood that flaws would go unnoticed during quality control, which is crucial to ensuring PV module dependability.

The ResNet50 model has significantly improved performance because it has shown to be able to accurately generalize new data and reliably identify errors with 91% accuracy. It is excellent at identifying the majority of real-world mistake instances, with a recall rate of 94%.

The hybrid model produced near-perfect data correctness and completeness, outperforming all other models with an astounding accuracy of 98.43%. By using several architectural elements, this model demonstrates how to enhance the defect detection performance of PV modules.

Table 5.1 shows that our models are much better than previous studies:

Table 5.1. Comparison with Previous Works.

References	Method	Dataset	ACC
[7]	SVM	solar cell	82.44%
[7]	CNN	solar cell	88.42%
[13]	CNN	solar cell	74.75%
[14]	L-CNN	solar cell	89.33%
[14]	DFB-SVM	solar cell	94.52%
This study	Custom CNN model	same as used	89.47%
This study	InceptionV3 model	same as used	90.88%
This study	ResNet50 Model	same as used	91%
This study	**Hybrid Model**	**same as used**	**98.43%**

5.1. STUDY ANALYSIS

By flexing on those EL pictures of PV modules, this study straight up evaluated how Custom CNN, InceptionV3, ResNet50, and Hybrid Model performed in spotting defects. Accurate and efficient fault detection is very crucial to the solar energy industry. In this study, they were all about checking out how models and their impact in this specific area were being investigated.

With its superior performance, the custom CNN model has established a strong foundation. As a consequence, recall improved for the InceptionV3 model, a critical metric for minimizing the probability of undetected errors. As an indication of its prowess in defect detection, the ResNet50 model consistently improved its precision and recall.

In contrast, the hybrid model won first place with superb performance in every category. This model's increased recall and precision, among other metrics, were outcomes of its redesign, which ResNet50 and InceptionV3 informed.

In addition to conducting direct comparisons, we also assessed the comparative efficacy of the models using historical data. We have achieved significant advancements in this field due to the increased accuracy of our models in comparison to prior research. The hybrid model piqued our interest in innovative techniques in particular.

The results could lead to more research on useful ways to process electroluminescent images captured from different angles and in different lighting conditions, use them in real-life manufacturing settings, and make them better at finding multiple types of defects at once for classification.

PART 6

CONCLUSION

In this study, we looked at how artificial intelligence can be applied to renewable energy, with a particular focus on identifying problems with photovoltaic power. Our goal is to overcome the shortcomings of traditional manual screening methods since the efficient operation of photovoltaic cells is critical. Our approach involves creating and comparing four different deep learning models: a native CNN, a modified InceptionV3 model, ResNet50, and a hybrid model.

The training goal of all models was to achieve binary classification using a dataset of electrofluorescence images of photovoltaic cells. There is a difference between normal and damaged cells. The results were optimistic: with an accuracy of 89.47%, the custom CNN model was quite proficient in detecting errors. The accuracy of the InceptionV3 model was 90.88%, which was slightly higher, demonstrating its superior feature extraction capabilities. A further improvement of up to 91% was achieved using the ResNet50 model, demonstrating its flexibility in fault detection. With an impressive 98.43% accuracy, the hybrid model has set a new standard for error detection accuracy.

These results show that both custom-designed and pre-trained deep learning models are effective in improving the photovoltaic control process. The models improve both the accuracy of fault detection and the potential for significant reductions in operating costs.

The renewable energy industry will greatly benefit from the findings of this study. In our ideal world, artificial intelligence will one day greatly improve the efficiency and reliability of renewable energy sources. Our results show that the use of advanced artificial intelligence techniques in renewable energy systems improves their reliability and efficiency, which in turn encourages greater use of artificial intelligence in the industry.

6.1. FUTURE WORK

The encouraging results of the study pave the way for further research in the fields of renewable energy and artificial intelligence in the future. Improving Models Through Optimization Although deep learning models, especially the hybrid model, have performed well, they can always be improved. Improving these models to account for different PV module technologies and a wider range of defects may be a topic for future research. Increasing accuracy and reducing false positives requires exploring different topologies, adding more layers, and using sophisticated training techniques.
Future research could examine how well these models perform in multi-category classification tasks that identify and classify different types of errors. Quality control and maintenance can benefit from the increased insight this method can provide.

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RESUME

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