RjNet: Convolutional Neural Network for Detecting Dust on Solar Panel

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NATIONAL UNIVERSITY OF MODERN LANGUAGES

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AUTHOR'S DECLARATION

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Candidate of Master of Science in Mathematics at the National University of Modern Languages do with this declare that the thesis RjNet: Convolutional Neural Network for Detecting Dust on Solar Panel Submitted by me in partial fulfillment of my MSMA degree, is my original work and has not been submitted or published earlier. I also solemnly declare that it shall not, in the future, be submitted by me for obtaining any other degree from this or any other university or institution. I also understand that if evidence of plagiarism is found in my thesis/dissertation at any stage, even after the award of a degree, the work may be canceled and the degree revoked.

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ABSTRACT

Title: RjNet: Convolutional Neural Network for Detecting Dust on Solar Panel

Electricity production from fossil fuels causes increasing greenhouse gas emissions in the environment. This climate impact can be considerably reduced by utilizing power with renewable resources, particularly solar energy. Due to this, electricity production from photovoltaic (PV) systems has increased during the recent few decades. However, several factors, most notably the accumulation of dust on the panels, have resulted in a significant reduction in PV energy output. To detect dust and minimize power loss, many techniques are being researched, including thermal imaging, image processing, Internet of Things sensors, machine learning, and deep learning, highlighting various downsides, including high maintenance costs and inconsistent accuracy. In this study, we used a dataset from Kaggle and built another dataset of solar panels from Pakistan. We carefully incorporated a variety of lighting conditions to make the dataset more comprehensive, allowing the model to perform well in a variety of real-world scenarios. These two merged datasets were then tested using the current state-of-the-art classification methods (SOTA). Afterward, a new convolutional neural network (CNN) architecture, RjNet, is presented exclusively for detecting dust on solar panels. The suggested RjNet model outperforms other SOTA algorithms, achieving 99.218% accuracy with only 2.14 million trainable parameters. Hence, future research should concentrate on diversifying the dataset for multi-class classification by including images from various global regions and climates, using automated data collection methods such as drones, and incorporating environmental factors while addressing class imbalances to improve model robustness.

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LIST OF ABBREVIATIONS

RjNet	-	Rasheed Jokhio Network (Proposed CNN Model)
AI	-	Artificial Intelligence
ML	-	Machine Learning
DL	-	Deep Learning
SOTA	-	State-of-the-Art
ANN	-	Artificial Neural Network
CNN	-	Convolutional Neural Network
CNN-BC	-	CNN-Based Classifier
CNN-		Convolutional Neural Network-Based Dust Detection
DSP	-	on Solar Panels
CNN-SS	-	CNN-Based Solar Surface
PV	-	Photovoltaic
AC	-	Alternative Current
DC	-	Direct Current
DSP	-	Dust Detection on Solar Panels
ACC	-	Accuracy
AUC	-	Area Under the Curve
F1-Score	-	F1-Score (Combines Precision and Recall)
ROC		Receiver Operating Characteristic
IoU		Intersection over Union (used in image segmentation)
MAE	-	Mean Absolute Error
MSE	-	Mean Squared Error
TP	-	True Positive
TN	-	True Negative
FP	-	False Positive
FN	-	False Negative
RGB	-	Red, Green, Blue (color channels in image processing)
IoT	-	Internet of Things
TNDT		Thermographic Non-Destructive Tests

LIST OF SYMBOLS

N	-	Total number of images in the dataset
C	-	Number of clean images
D	-	Number of dusty images
X	-	Input data (image)
Y	-	Output label (clean or dusty)
$\hat{Y}$	-	Predicted output
$F(x)$	-	Convolutional neural network function
$\sigma(x)$	-	Activation function
θ	-	Model parameters (weights and biases)
$\mathscr{L}$	-	Loss function

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DEDICATION

Every challenging task requires self-endeavor and the guidance of elders, especially those very close to our hearts.

My little effort I dedicate to my beloved

Parents

"All that I am, or hope to be, I owe to my mother and father."

- Abraham Lincoln

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

1.1 Overview

This chapter contains a complete introduction and literature review focusing on environmental and technological barriers to solar energy efficiency, particularly dust collection on photovoltaic systems. First, it discusses the global problem of climate change. It elaborates on how vital it is to use renewable energy sources, with special emphasis on solar power, to reduce the effects of climate change. It underlines the significance of photovoltaic systems in electricity generation around the world and how dust settling affects the performance and efficiency of a solar panel. The chapter further discusses Artificial Intelligence (AI)-based techniques, defining their goals and guiding principles, and how they might be used in automated dust detection and overcome this challenge. In addition to emphasizing the importance of Convolutional Neural Networks (CNNs) in image classification tasks such as dust detection on solar panels, the chapter explores more deeply into important subfields of artificial intelligence (AI), with a focus on Machine Learning (ML) and Deep Learning. Finally, an evaluation of current approaches for dust detection on solar panels with a focus on CNN-based techniques concludes the literature analysis and builds the foundation for the study that is described in the coming chapters.

1.2 Global Warming

Global energy consumption and greenhouse gas (GHG) emissions have increased dramatically, as has human well-being, due to the increasing prevalence of technology in modern life. Fossil fuels, the primary source of carbon emissions, currently account for approximately 80% of global energy use [1].

Human activity, particularly the increased use of fossil fuels since the 20th century, is one of the leading causes of global warming due to energy consumption. Burning fossil fuels (coal, oil, and gas) has significantly increased CO_2 emissions, which currently represent more than 80% of all anthropogenic greenhouse gas emissions globally. In 2016, the energy sector alone accounted for 73.2% of emissions of greenhouse gases measured in CO_2 equivalents, with transportation utilizing fossil fuels substantially (96.7%). Furthermore, as a result of factors such as financial growth and institutional quality, global energy consumption has increased, resulting in higher energy consumption per person and output while limiting the quantity of energy available from renewable sources. Among the strategies used to mitigate global warming are investing in renewable energy technology, boosting energy efficiency, and imposing carbon emission levies [1].

The production of energy from fossil fuels is a primary contributor to both air pollution and global warming. Fossil fuel combustion releases harmful substances into the atmosphere, endangering both human health and the ecosystem [2]. These emissions include particulate matter and ozone-forming precursors, which are both hazardous to human health, as well as carbon dioxide, the main contributor to global warming [3].

The results from 2023 and 2024 are particularly concerning, with 2023 exhibiting continuously elevated anomalies, frequently exceeding 1.5°C, and 2024 approaching 2.0°C early in the year. This rising trend underlines the significant impact of human activities on global climate, emphasizing the importance of immediate and decisive climate action. The growing anomalies not only demonstrate a persistent warming trend but also indicate an acceleration, emphasizing the vital urgency of addressing climate change to avert significant environmental and social implications [4].

Figure 1.1 [5] displays the expected worldwide energy mix for 2030. At 34%, oil will lead the way, followed by gas at 25%, coal at 22%, renewable energy at 14%, and nuclear energy at 5%.

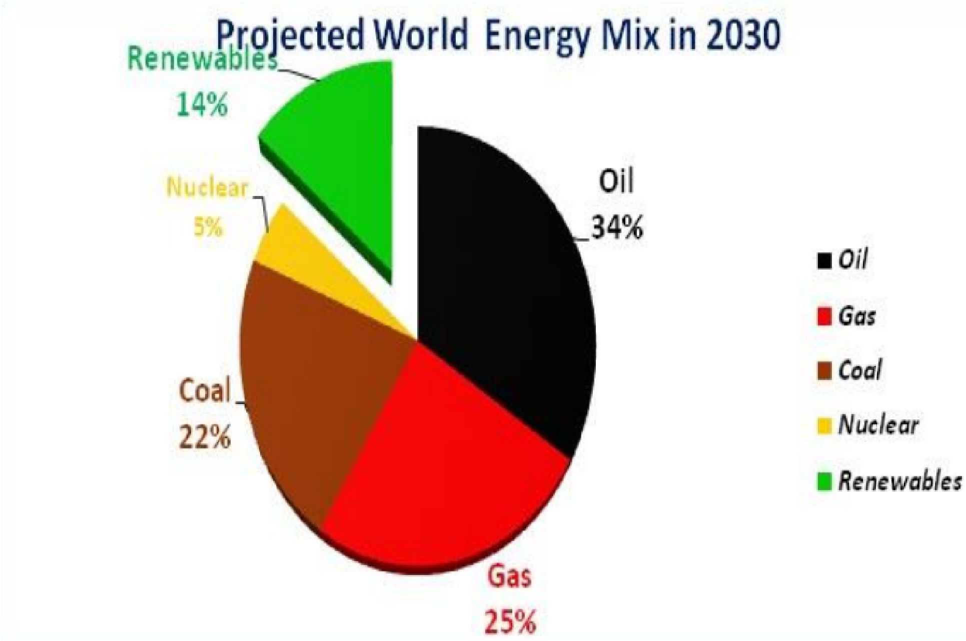


Figure 1.1: Projected World Energy Mix in 2030.

According to research, a worldwide phaseout of the use of fossil fuels may drastically lower excess mortality rates and avert millions of preventable deaths caused by outdoor air pollution each year [6]. The greenhouse effect and global warming are exacerbated by the pollution caused by burning fossil fuels, especially in metropolitan areas where carbon monoxide and carbon dioxide are released. Switching to cleaner energy sources is essential to lowering health risks, enhancing air quality, and lessening the effects of climate change [7]. A global study on the production of renewable energy sources indicates a trend toward decarbonization and a rise in the use of clean energy technologies. Studies underscore the noteworthy advancements in sustainable energy, encompassing solar, wind, bioenergy, and hybrid systems, intending to mitigate greenhouse gas emissions and enhance energy accessibility, particularly in isolated regions [8, 9]. Since the production of traditional energy leads to pollution and resource depletion, the switch to renewable energy is essential for economic growth, environmental preservation, and sustainable development [10]. The expansion of renewable energy sources is crucial for reducing global warming, guaranteeing energy security, and fostering social and economic progress, despite obstacles including market barriers and public ignorance [11].

Based on more than 21,000 interviews conducted between January and June in 21 countries, the survey was carried out by Glocalities opens a new tab in association with advocacy groups Global Citizen and The Fossil Fuel Non-Proliferation Treaty Initiative. The countries present were the United States, Turkey, South Africa, South Korea, Brazil, China, India, Italy, Mexico, and Australia. According to the survey, 68% of respondents favored solar energy, followed by wind (54%), hydropower (35%), and nuclear (24%). Only 14% of respondents choose fossil fuels for electricity generation [12].

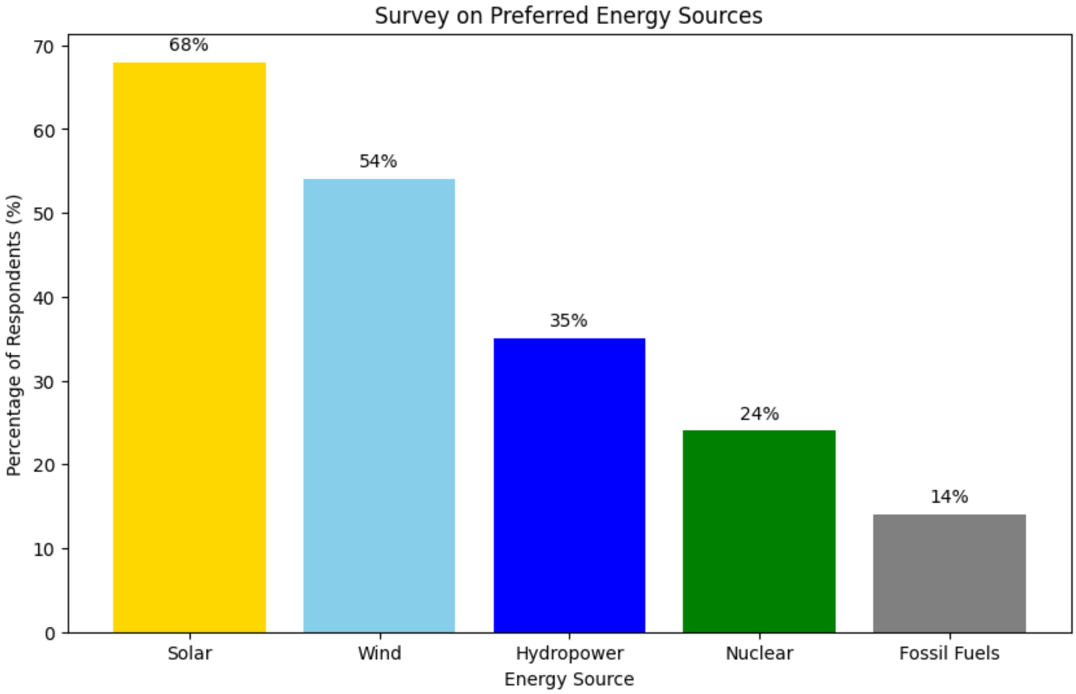


Figure 1.2: Solar Energy has a global Acceptance Rate of 68%.

1.3 Photovoltaic System

The photovoltaic effect, in which light is absorbed by the solar cells and produces an electric current, is how solar panels turn sunlight into power. To facilitate internal photon reflection, the procedure uses numerous layers of photovoltaic wafer material aligned with the direction of the incident sun [13]. Solar cells' ability to generate electricity is influenced by variations in temperature and light intensity, with higher temperatures and light intensities producing more electricity. Utilizing light-collecting holes and lenses to maximize energy production in a constrained space, stacked solar panels transform solar energy into electric energy. Selectivity spectrum approaches, including axial confinement of light trapping and fluorescence concentrators, maximize the efficiency of solar cells by lengthening internal paths

and absorbing more light, which increases power production and solar cell efficiency [14]. Moreover, systems with multiple PV panels, energy storage, and power electronic interfaces can convert solar energy into alternating current that can be fed into the electrical grid [15].
Fig 1.3 illustrates a simple solar power system setup, with energy flowing from the solar panel to a controller, battery bank, and an inverter before being converted from DC to AC for consumption at home [16].

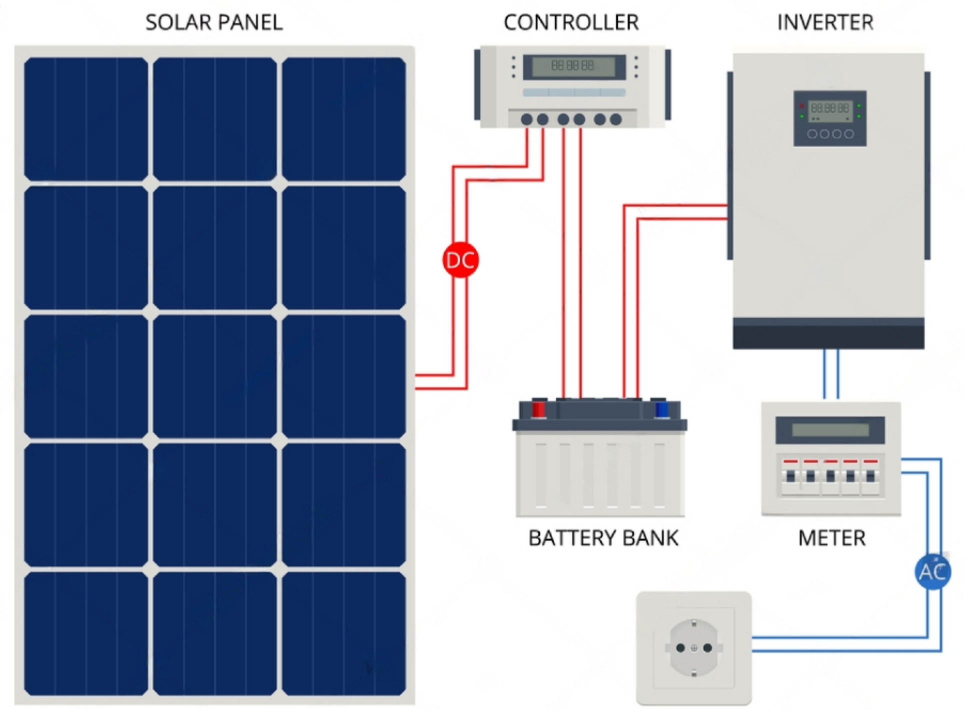


Figure 1.3: Components in a Photovoltaic Solar System.

Around the world, solar energy, particularly specifically photovoltaic (PV) systems, is essential for producing power. PV systems contribute to combating climate change and promote sustainable development by converting solar energy into useful electrical power [17]. A growing number of PV power plants are being installed worldwide, which brings with it both potential and challenges. One of the most important things to do is to use the electricity produced by these plants directly to reduce the load on energy networks. Household PV energy use can lower grid electricity demand, as demonstrated by the tremendous rise in PV technology that has occurred in Europe due to supportive policies and schemes [18]. Due to their low environmental effect and zero fuel expense, solar photovoltaic cells are preferred for the production of electricity, which makes them an essential part of the shift to renewable energy sources [19]. The PV industry is still growing quickly on a global scale, and advances in PV technology are helping to drive down

the cost of producing solar power globally [20].
According to a Gallup and Gilani Pakistan study, 93% of Pakistani solar panel users stated that their electricity expenditures were the driving force behind their decision to install the panels. The question, "What factors encouraged you to install Solar Panels?" was put to a sample of people who were net-metered nationwide. The respondents provided the subsequent justifications for solar panel installation: 93% of respondents cited their power bill as the reason, 42% stated they wanted to live a more sustainable lifestyle (i.e., reduce their carbon footprint), 27% claimed they were reliant on outside sources, 13% said the installer's information inspired them, 8% claimed advice from friends, family, and neighbors, and 6% claimed other factors [21].

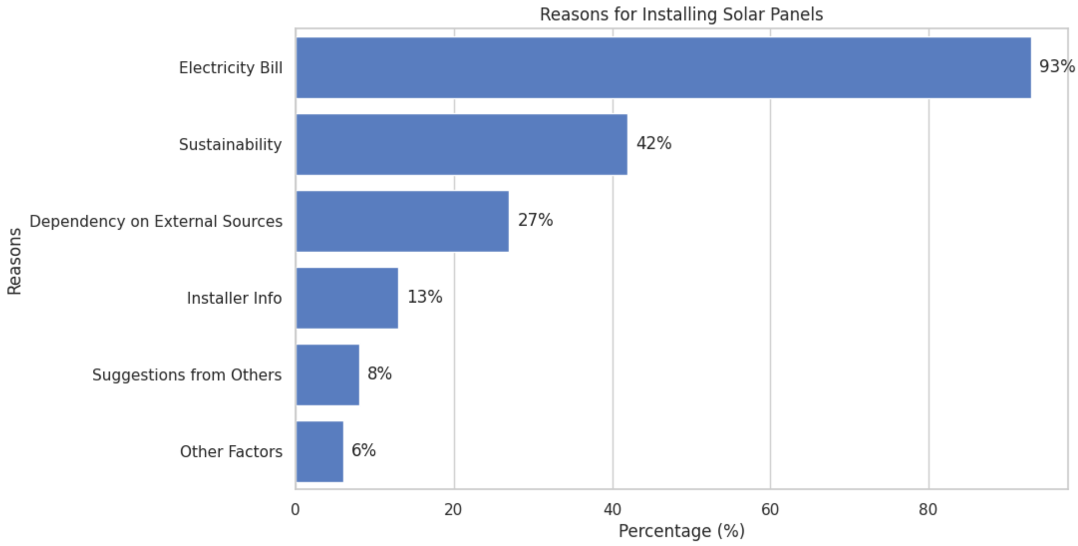


Figure 1.4: The survey, conducted by Gallup and Gilani Pakistan.

1.4 Globally Production of Electricity from Solar Panel

The amount of solar energy produced worldwide has risen significantly each year, with certain countries contributing significantly to this expansion. Globally, China, India, Japan, the USA, Germany, Spain, and Australia have played a key role in increasing solar electricity production. With approximately 60% of this capacity built in just the last two years, the world reached a milestone in 2012 when it produced over 100 gigawatts (GW) of power from solar photovoltaic (PV) sources [22]. The installed photovoltaic capacity worldwide reached 480GW by 2018 a 3.5-fold growth in just five years [23]. Furthermore, China alone recovered to 53GW in 2021 after a fall in 2020, with more than 180GW of new solar photovoltaic energy generation capacity in 2021. These patterns point to a significant and continuous increase in solar production worldwide, which is being fueled by technological developments, government policies that are favorable to the industry, and rising investments in renewable energy sources [24].

The rate at which photovoltaics are growing globally is very dynamic and varies greatly per nation. The capacity of solar electricity worldwide hit 1 TW in April 2022 [25]. China topped the world rankings for solar power in 2022 with an installed solar capacity of about 390 GW, [26, 27] or about two-fifths of all installed solar capacity worldwide. As of 2022, Canada, South Africa, Chile, the United Kingdom, South Korea, Austria, Argentina, and the Philippines are among the more than 40 nations worldwide with a cumulative PV capacity exceeding one gigawatt. China, the US, and India were the leading installers in 2022. [28] Among the top installers of 2022 were also Germany, Brazil, the Netherlands, France, Mexico, Japan, and the Netherlands. While Honduras, Italy, Spain, Germany, and Greece can provide between 9% and 14% of their respective yearly domestic electricity consumption, Australia currently has enough solar PV capacity to satisfy more than 15% of the country's electrical energy needs [29]. In 2007, the deployment of CSP was restarted following an almost two-decade break. Still, several new projects are having their designs altered to use less expensive photovoltaics. The majority of CSP stations that are now in operation are found in the US and Spain, however, massive photovoltaic solar farms are being built in an increasing number of geographical areas. Any percentage of the power consumed by other nations, such as Finland, Denmark, Israel, Ukraine, and Algeria, can likewise be produced domestically [30].

China produced the most energy from solar in 2023, with an estimated 584 terawatt hours. Second place went to the United States, with significantly less than half of China's production. Japan and India ranked third and fourth, respectively, in the rankings [31]. Over the next five years, the amount of capacity added to renewable power sources will rise, with solar PV and wind power accounting for a record 96% of this increase. This is because, in most countries, their generation costs are lower than those of both fossil and non-fossil alternatives, and policies continue to promote them. Research indicates that by 2028, solar PV and wind additions will more than double from 2022 levels, shattering records every step of the way to over 710 GW [32].

The predicted growth of the world's solar capacity from 2016 to 2028 is depicted in Figure 1.5.

It compares historical data with two future possibilities, referred to as the **Main case** and the **Accelerated case**, which represent varying degrees of expansion in gigawatts (GW) in addition to the percentage of total capacity [33].

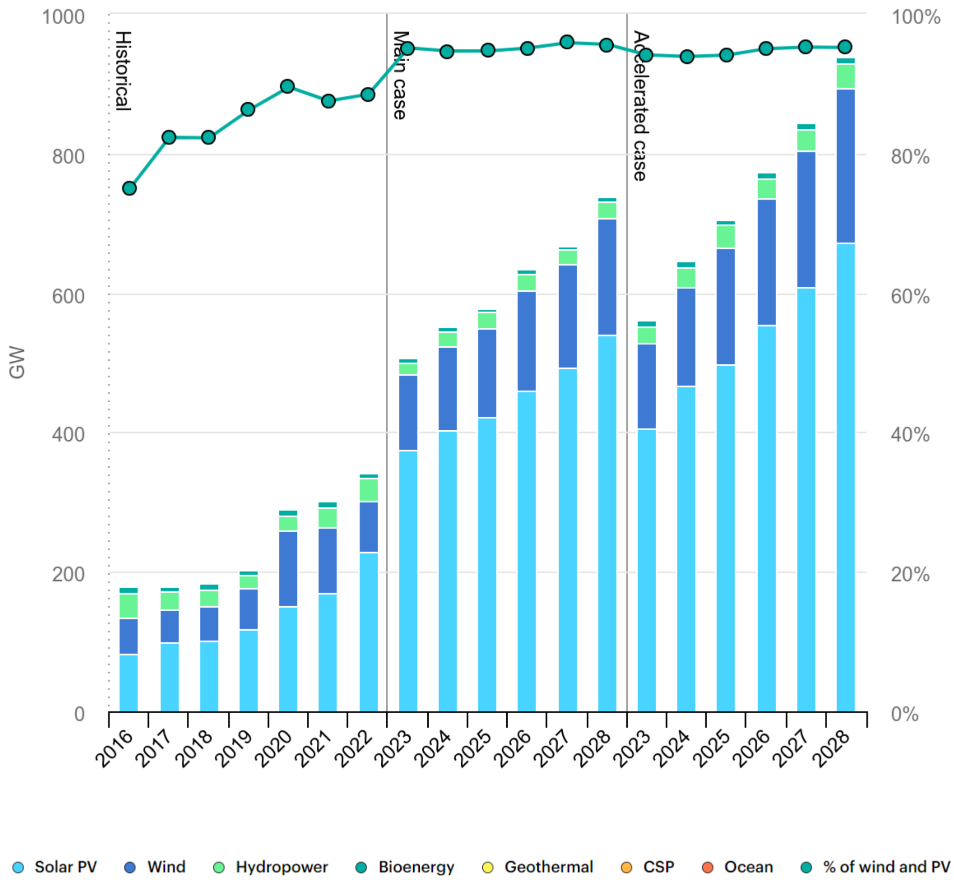


Figure 1.5: Increases in Renewable Power Capacity by Technology from 2016 to 2028.

1.5 Dust Impact on Solar Panel

The collection of dust on solar panels has a substantial effect on their energy output and efficiency. Research has demonstrated that dust accumulation can cause solar panel efficiency to decrease, therefore cleaning intervals are essential to preserving optimal performance [34]. Various dust types, including chalk, brick, and ordinary dust, affect solar energy efficiency differently; the loss in power production caused by thicker dust layers becomes more noticeable [35]. Patil et al. [36] highlighted in 2019 the efficiency of automated cleaning systems but also pointed out that these systems can boost running expenses and demand a thorough cost-benefit analysis. Based on the research results, the use of the well cleaning techniques can potentially increase output energy by 25% or conversion efficiency by 15-20%.

In a simulation comparing dust deposition on clean and dirty panels, Rouway et al. [37] demonstrated in 2020 that dust deposition can minimize power loss by 40% at the maximum operational point (MPP). Their research brought to light the crucial factors influencing PV panel pollution and the significance of determining the most effective cleaning schedules.

Different types of dust have different effects on efficiency. For example, among coal, sand, brick powder, and chalk dust samples, Lakshmi et al. [38] in 2022 discovered that coal dust causes the largest power loss. This finding emphasizes the importance of determining which types of dust are the most damaging so that the cleaning efforts can be focused on them first. Furthermore, in 2022, Brahma et al. [39] investigated that the environmental elements such as wind speed, rainfall, and panel tilt angle all have a significant impact on the pace and extent of dust deposition. Panels can be naturally cleaned by rainwater; however, the effectiveness of the cleaning process depends on the amount and frequency of the rainfall.

In 2023, Ferreira et al. [40] highlighted the substantial detrimental effect of dirt on efficiency in their computational analysis by showing a 4.01% increase in power output following panel cleaning. Ahmed et al. [41] found in 2023 that dust deposition can reduce panel efficiency by up to 7.1% over four weeks, recommending cleaning every three weeks.

Kirpichnikova et al. [42] in 2023 found that dust can reduce solar panel efficiency by up to 47% in dusty locations such as Tajikistan and the Urals. They emphasized that modules must be free of dust to perform properly. Similarly, in 2022, Zhang et al. [43]. examined dust deposition on solar panels in desert trains using CFD-DEM simulations. They discovered that the deposition rate of fine sand particles is higher than clay particles, depending on wind speed and consistency. According to study [44], dust induces temperature variations that lead to a slight difference in open-circuit voltage and a drop in short-circuit current, which are both reduced by 2% to 6% and 15% to 20%, respectively. Another study that examined the impact of dust on various PV modules found that a-Si and CdTe type modules saw a 33% reduction in output power at a dust level of $4.25\,\mathrm{mg/cm^2}$ [45]. Over six months, it was also noted that filthy Si solar cells experienced a 66% decrease in efficiency. However, compared to a clean module, a dusty module produced 8.41% less power [46].

In 2024, Alhajji et al. [47] assessed the consequences of sandstorms in Saudi Arabia and proposed preventative methods to reduce production losses due to environmental debris. Their research demonstrated how vulnerable regions like Al-Ahsa are to recurrent sandstorms, emphasizing the importance of providing proper protection for solar modules.

1.6 Artificial Intelligence

Artificial intelligence (AI) is the human-like intelligence displayed by robots and computers, which enables them to simulate human functions including making decisions, solving problems, and gaining knowledge from data. The automation of intelligence was first proposed by Thomas et al. [48]. These individuals are credited with contributing to the concept of artificial intelligence. Artificial intelligence (AI) has progressed from early approaches to symbol manipulation to the use of machine learning techniques, especially deep learning, which allows systems to address challenging real-world issues in domains like vision and natural language processing [48]. Concerns over robots potentially surpassing human intellect are growing as AI develops, raising concerns about whether people will accept data provided by AI without inquiry and learn from it, erasing the distinction between fiction and reality. In general, artificial intelligence (AI) is a noteworthy technical development that has the potential to completely transform a range of sectors and facets of society, ultimately influencing humankind's destiny [48].

1.6.1 Principles and Objectives of AI

The primary objectives of artificial intelligence (AI) are to solve knowledge-intensive problems, build autonomous learning systems, and imitate human cognitive processes including learning and solving problems [49, 50]. AI seeks to emulate human intelligence and behavior. The multidisciplinary nature and vast breadth of artificial intelligence (AI) are highlighted by the fact that the field spans multiple disciplines, including technology, psychology, neurological sciences, biology, mathematics, social science, and philosophy [49]. The ultimate goal of AI research is to achieve broad intelligence, and it focuses on domains such as knowledge, planning, learning, natural language processing, object manipulation, reasoning, and perception. AI governance is an important topic, and ideas for centralized worldwide governance with human centrism and maintaining world peace as guiding principles are worth considering [51]. AI has the potential to be used in a wide range of healthcare applications, including enhanced medication creation, teletherapy, and picture and voice recognition [52, 50].

1.6.2 AI Subfields

Figure 1.6 displays the relationship between artificial intelligence, machine learning (ML), and deep learning (DL). AI includes machine learning (ML), which allows machines to learn from data, and deep learning (DL), a subset of ML that uses deep neural networks to handle complicated data patterns, driving advances in AI technologies [53].

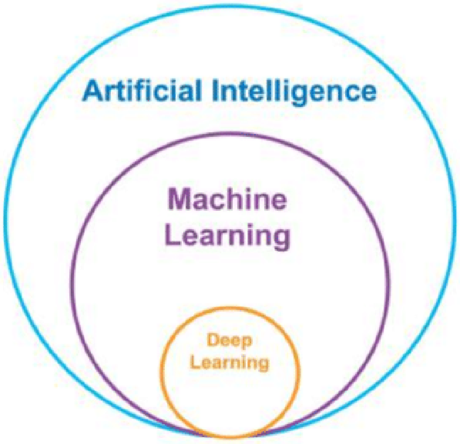


Figure 1.6: Subfields of Artificial Intelligence.

Artificial Intelligence (AI) encompasses several subfields with notable technological advancements. Machine Learning (ML) is the application of algorithms to data so that computers can learn and make judgments. Artificial neural networks are used in Deep Learning (DL), which transforms voice and image detection by simulating the human brain. Deep learning is essential for image identification tasks in Computer Vision, a state-of-the-art technology that replicates human visual processing to analyze and comprehend images [54, 55]. These subfields have altered the healthcare, automotive, and financial industries, improving accuracy and efficiency while bringing up moral issues like prejudice and privacy. Supervised machine learning and deep learning approaches, namely in the field of computer vision, have demonstrated noteworthy progress in highlighting the advantages, constraints, and uses of these advances in technology [56].

1.7 Machine Learning (ML)

The creation of methods that enable computers to learn from data without explicit programming is known as machine learning, and it is a branch of artificial intelligence. It uses training data to build decision-making and prediction models, simulating human learning patterns [57]. A vast array of instruments, including supervised and unsupervised learning strategies, are used in machine learning to extract knowledge from diverse data sources. It is a cornerstone technology in the field of artificial intelligence, influencing many different sectors and day-to-day activities. Its ongoing development gives rise to new approaches [58]. The field of supervised machine learning, which is extensively used in fraud detection, natural language processing, and image recognition, focuses on training models with labeled data to produce precise predictions and judgments [59].

1.7.1 Types of Machine Learning

Multiple methodologies, such as supervised, unsupervised, semi-supervised, and reinforcement learning, are included in machine learning. During training, supervised learning requires the provision of input-output pairings [60], whereas unsupervised learning finds patterns without labeling. When classifying data is expensive, semi-supervised learning is helpful as it integrates labeled and unlabeled data for training [60]. By rewarding preferred behaviors, reinforcement learning concentrates on coaching agents to make successive decisions. With the help of these many techniques, machines can learn from data on their own and become more efficient over time as they receive access to more data. Each of the types is essential to several applications, including natural language processing, picture identification, and predictive analytics, demonstrating the range and importance of machine learning in contemporary technological developments [61].

1.7.2 Important Techniques of ML

Machine learning includes several fundamental methods, each with a specific function, including decision trees, k-means clustering, and linear regression. Because they offer a hierarchical structure to direct decision-making based on particular traits, decision trees are frequently employed for categorization tasks. Although K-means clustering has historically been less interpretable, explainable alternatives such as kernel k-means, which approximate partitions using decision trees and increase interpretability without compromising accuracy, have advanced. A basic tool for predictive modeling is linear regression, which is important for stock price prediction. However, empirical studies have shown that decision tree regression models outperform linear regression models, especially when it comes to predicting stock prices like Apple's [62]. Furthermore, in financial forecasting, tree-based machine learning methods such as random forests, XGBoost, and decision trees have shown to be quite successful in predicting gold prices, beating conventional methods with high accuracy metrics [63].

1.7.3 The Uses of Machine Learning

According to various research, machine learning has a wide range of applications in many industries. Through the analysis of consumer preferences and operational trends, it gives businesses the ability to design new products that give them a competitive advantage. Trends include the automatic selection of learning tools, the integration of learning modules into databases, and the ability for programmers to use techniques from machine learning in system development. These indicate that machine learning has reached a level of maturity that allows it to be integrated into conventional systems and algorithms. Machine learning models are created utilizing offline and online metaheuristics in industrial applications such as health management and prognostics, to supplement conventional statistical methods for supervised and unsupervised learning [64]. Additionally, by enhancing target validation, biomarker identification, decision-making processes, and clinical trial data analysis, machine learning plays a critical role in drug discovery, ultimately accelerating the drug development pipeline and lowering failure rates [65].

1.8 Deep Learning (DL)

Deep artificial neural networks are used in deep learning, a specialized type of machine learning. Deep feedforward networks, backpropagation, regularization, optimization strategies, hyperparameters, loss functions, and parameter initialization techniques are only a few of the basic ideas, techniques, and applications it covers [66]. Deep learning models such as autoencoders, convolutional neural networks (CNNs), recurrent neural network models (RNNs), and deep belief networks are critical for classification, detection, and segmentation. In complicated issues in which shallow architectures suffer from the curse of dimensionality, this learning paradigm is especially successful since it uses numerous layers of non-linear processing to extract robust features. When deep learning concepts are acquired using project-based learning strategies and resources like as TensorFlow, they become more understandable and practical [67].

1.8.1 Applications of Deep Learning

Convolutional neural networks have shown their efficacy in a variety of computer vision applications. Because of their versatility and robustness, CNNs have been applied to a wide range of applications, including digit identification, face recognition, automobile damage recognition [68], intricate analysis of gymnastic movements [69], classification of images, identification of targets, and floristic recognition in ecological and biological products studies [70]. By utilizing cutting-edge methods like as 3D CNNs for temporal and spatial analysis, these networks perform better in tasks involving complex pattern recognition and feature extraction. With CNNs being used in these applications, there has been a dramatic shift in the deployment of deep learning algorithms to improve accuracy and efficiency in computer vision-related activities. Research on ecology, sports science, document processing, and other areas have all advanced significantly as a result of this [71].

Deep learning offers several advantages in several fields, such as economic forecasting, image processing, computational imaging, medicine, and drug discovery. It performs exceptionally well at handling high-dimensional, complex data, picking up detailed patterns, and continuously adjusting to new data [72, 73]. Deep learning uses patterns to analyze and real-time data merging to improve accuracy, lower costs, and assist in early disease diagnosis in medical diagnostics [74]. It streamlines decision-making in the drug discovery process, saves money and time, offers objective insights, and permits virtual screening and medication repurposing [75]. Furthermore, by capturing and maintaining priors and resolving the difficulties of modeling the interaction between light and matter, deep learning in computational imaging also shows effectiveness in non-invasive 3D image reconstruction [76].

1.8.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are computer models that are based on biological neural networks and are made up of linked neurons that process data in layers [77, 78]. Neurons in artificial neural networks (ANNs) usually execute specific tasks, such as integrating inputs and executing non-linear changes, in each layer [79]. ANNs typically have three layers: input, output, and hidden. These networks are capable of learning from data and generating predictions on previously unseen data by employing a training technique that establishes a connection between input and output patterns [78]. Artificial neural networks (ANNs) use learned knowledge about node connections and weights to accomplish tasks like classification and function approximation [80]. Activation functions are another way that ANNs can behave non-linearly, allowing for intricate calculations and pattern detection [78].

1.9 Overview of CNNs

CNNs, a subclass of deep neural networks, are often used for image processing, recognition, and classification in computer vision applications [81, 82]. CNNs are distinguished from other forms of neural networks by the fact that they perform convolution operations inside at least one layer, as opposed to general matrix multiplication. These networks are largely made up of convolutional, pooling, and fully connected layers to assess the input and extract properties from images [81]. CNNs have shown effectiveness in a variety of applications, such as enhancing sports science, assisting nearsighted individuals in identifying objects in their surroundings and utilizing 3D CNNs to evaluate intricate gymnastic routines [82]. More research has focused on compressing and accelerating CNNs to improve their performance for low-power devices like smartphones and Internet of Things devices to overcome processing and storage constraints [83].

1.9.1 CNNs for Image Classification

Convolutional neural networks (CNNs) are a popular multilayer network design used in image recognition and classification applications. It consists of basic layers such as convolutional, pooling, activation, and fully linked layers, each with distinct qualities that impact output generation and data flow [84]. Adaptive filter banks are a unique approach that divides input signals into sub-bands, allowing CNNs to extract properties for each sub-band independently before merging them for classification. This leads to reduced computation costs and structural regularization while maintaining great accuracy [85]. CNNs show their versatility and effectiveness in real-world circumstances across a range of applications, from facial recognition for presence monitoring to complicated pattern identification. CNNs can automatically extract features, which makes it possible to precisely classify images using machine learning techniques [86]. CNNs have also revolutionized computer vision by automating feature extraction, eliminating the need for manual engineering, and offering a neural architecture assessment framework for designing the optimal CNN structures for image classification tasks [87].

Components of CNNs: Essential elements of a Convolutional Neural Network (CNN) include convolutional layers, pools, hidden layers, and fully connected layers. Convolutional layers use kernel filters to extract basic features from input images. The pooling layer downsamples the extracted features by combining successive convolutional layers [88]. CNN hidden layers include convolution, ReLU, pooling, and fully connected layers, each of which identifies features automatically without human intervention. In Convolutional Neural Networks (CNNs), the pooling layer is essential for dimensionality reduction and feature extraction. Several creative strategies have been put out to improve on the conventional pooling techniques, such as average and maximum pooling. In particular, learnable parameters can be added to pooling methods to optimize the selection of essential features during training, consequently enhancing model performance [89]. Fully connected layers help get around restrictions associated with huge pixel images by connecting every neuron in one layer to every other layer's neuron [90]. Together, these elements allow CNNs to automatically recognize and distinguish between characteristics in images, which makes them incredibly useful for a variety of tasks like object identification, image classification, and processing natural language [84, 81]. Figure 1.7 describes the general workflow of the CNN model [91].

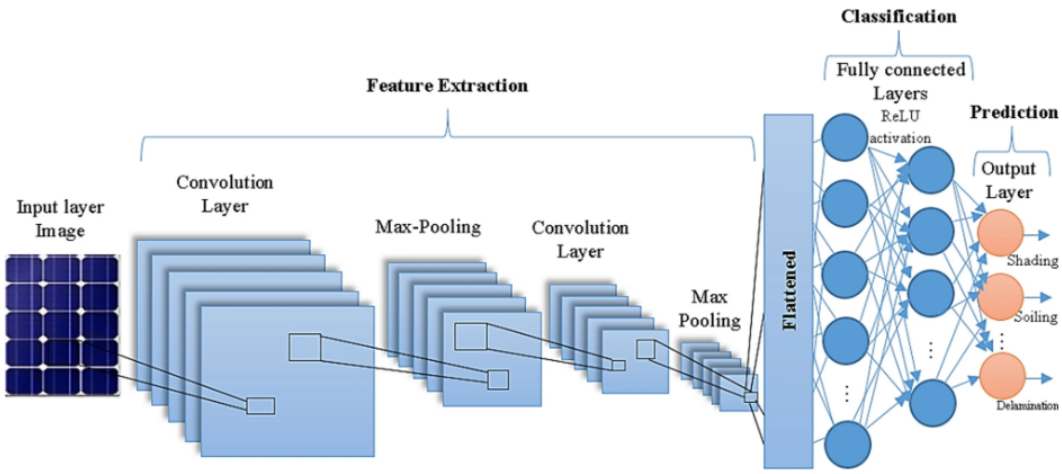


Figure 1.7: General Architecture of CNN Model.

1.9.2 CNN Training and Optimization Techniques

CNN training uses a variety of techniques to enhance model performance. One method involves calculating the deflection angles of face images, extracting shallow-layer characteristics, and updating the parameters of the model based on calculations of error [92]. An alternative technique reduces redundant features and improves classification performance by fusing several shallow features, connecting layers in a full connection mode, and updating parameters using label layers and classification results [93]. Furthermore, convolution layers, an entirely connected stair layer, and a SoftMax layer are included in a CNN model for vein identification, which allows multiple classifications of neural network training to identify vein parameters and calculate picture similarity according to feature cosine distance. Additionally, collecting patches from endoscopic film projects to augment the database and improve automated diagnosis systems greatly enhances CNN performance for medical applications such as colonic polyp classification [93].

Optimizing CNN models for better performance is known as CNN optimization. Several methods can be used to improve accuracy and generalization, including integrating the Spatial Transformer Network (STN) and the stochastic gradient descent (SGD) [94], utilizing high-performance computing (HPC) technologies to speed up training [95], using Bayesian algorithms to optimize hyperparameters to cut down on training time and resource requirements, and using metaheuristic algorithms like Particle Swarm Optimization (PSO) for tuning of hyperparameter. With these techniques, CNN models are expected to perform better in terms of accuracy, loss reduction, generalization, and hardware resource optimization. Through the integration of these methodologies, scientists can make noteworthy progress in the domain of deep learning applications, namely in areas such as image classification and intelligent agriculture. This will open the door for more effective and precise model implementations [96].

Transfer Learning and Fine-Tuning in CNNs: Transfer learning in Convolutional Neural Networks (CNNs) reduces the need for labeled data and processing resources by utilizing information collected from a source task to enhance training for the desired task [97]. This methodology has been applied in several sectors, such as fraud detection [98], cancer prediction [99], and COVID-19 diagnosis. Transfer learning has been shown to improve model performance, reduce training time, and enhance neural network capability when applied to CNNs [100].
Convolutional Neural Networks (CNNs) fine-tune by modifying pre-trained models to adapt to certain tasks effectively. Several methods have been put out to improve the fine-tuning procedures. One technique aims to provide parameter-efficient tuning by modifying filter atoms in pre-trained models to preserve spatially invariant channel combination information [101]. Another method, known as AdaRand, enhances classification performance without the need for additional source data by dynamically updating feature extractors by reducing the difference between feature vectors and random regard vectors [102].

1.10 Fundamentals of Image Classification

Image data representation: A variety of research addresses an important feature of image classification: picture data representation. Convolutional neural networks (CNNs) are one method used for classification based on picture inputs; higher dimensional data is handled by applying techniques including reduction of dimension, feature ranking, and extracting features [103, 104]. Additionally, digital gray-level images can be efficiently classified based on local texture features for images like tree barks according to the Vectorial Image Representation Using Texture Space (VIR-TS) approach, which converts gray-level digital images into textural vectors [105]. Additionally, addressing class imbalances and finding and combining identical or extremely similar data can optimize datasets and improve classification performance, particularly in situations when data volume is constrained or exceeds processing capability. These various methods help to enhance the representation of picture data for precise and effective image classification tasks [106].

Image Data Preprocessing: When it comes to imagery classification, image data preprocessing is the act of enhancing and manipulating images before putting them into a neural network for training. Many methods are frequently employed, including random cropping with rotation, Laplacian equalization, smoothing, unmask sharpening, and grayscale conversion [106]. To create training sets with better features for analysis, data preparation is essential for producing independent features for classification tasks [107]. A wide range of users can easily access the data preparation, assessment, and modeling processes with the help of tools like Orange, which provides an intuitive interface. Furthermore, new metric learning-based preprocessing techniques seek to streamline spatial information in hyperspectral pictures, lowering complexity and enhancing deep learning models' classification accuracy. In general, preparing image data improves picture quality for image classification tasks by improving model accuracy, speeding up training, and conserving resources [108].

Feature Selection and Extraction: In tasks involving machine and deep learning, feature selection and extraction are essential stages. To improve the effectiveness of algorithms and model generation, feature selection entails selecting important features from high-dimensional data. Removing unnecessary data helps to reduce the number of datasets, which enhances learning procedures and the performance of models. Feature extraction, however, aims to extract relevant information from collections of data such as network traffic, photographs, and music. In the domain of music analysis, supervised machine learning is used to automate tasks like recognizing emotions by extracting features from different digital formats [109]. Similarly, feature extraction is crucial for object recognition and picture classification to provide high-quality images that can be further analyzed using CNN and other machine-learning techniques [110]. Furthermore, pre-trained CNN models are used for feature extraction using chest X-rays in healthcare applications including COVID-19 testing to identify pictures with high accuracy utilizing machine learning models [111]. Feature selection plays a critical role in improving the classification accuracy of intrusion detection systems by identifying the most important features while cutting down on the training time and size of the model [112].

Dimensionality Reduction Techniques: Dimensionality reduction approaches convert high-dimensional data into lower-dimensional space while protecting important information, which is critical for improving the performance of the machine and deep learning algorithms. The literature [113, 114, 115] has examined many techniques, including deep dimension reduction approaches, linear discriminant examination (LDA), kernel primary component analysis (KPCA), and principal component analysis (PCA). By using these strategies, algorithm performance is enhanced, the computational burden is decreased, overfitting is avoided, and the interpretability of the model is increased.

Supervised Learning for Image Classification: In image classification, supervised learning is teaching algorithms to identify patterns in data by giving them labeled data. This allows the algorithms to forecast the labels of newly unseen data. In several fields of study, including computer vision and medical image analysis, this procedure is essential [116, 117, 118]. The fundamental ideas of supervised learning include comprehending the input-output relationship, learning from small amounts of data, and generalizing to accurately anticipate unseen datasets. Two crucial techniques for supervised learning in image classification applications are support vector machines (SVM) and instance-based classification [117]. Evaluation metrics like as recalls, accuracy, and precision are important for assessing how effectively models developed via supervised learning function in image classification [116, 117].

1.11 Techniques Used To Detect Dust

Hicham [119] presented an image processing system in 2019. It calculates the power loss rate and tracks how much dust soiled the solar panels. The technique improves measurement accuracy by using unique telltales with grid texture. The study shows that the suggested strategy works, but further research is needed to find out how well it works in other circumstances.

In a 2019 publication, Tribak et al. [119] described an image processing-based approach to estimate the rate of dust accumulation and solar panel power loss. This novel method determines the impact of dust collection by comparing the energy output of clean and dirty panels. The results show how well the image processing system can predict the subsequent power loss and accurately estimate the amount of dust present. However, the study does not address potential execution barriers or the system's operation in different environmental conditions.

The impacts of dust on solar panels were examined by Shaaban et al. [120] in 2020, and they suggested using a regression tree model to estimate dust buildup. The study emphasizes the significance of precise dust measurement for starting cleaning actions and makes use of a variety of machine-learning regression models. Nonetheless, the study notes that additional evaluation of the suggested estimating unit and its functionality in various environmental settings is required.

Using thermal images from UAVs, Díaz et al. [121] compared deep-learning methods with traditional approaches for solar panel detection in 2020. While a region-based CNN is used in the deep learning approach, edge detection, and SVM with an improved texture descriptor are exemplary classical techniques. The study reveals that both approaches work well, but it also emphasizes how conventional image processing suffers when dealing with intricate or low-contrast backgrounds. Future studies ought to concentrate on enhancing detection precision in these demanding settings.

An approach based on computer vision was proposed by Abuqaaud et al. [122] in 2020 to distinguish dirt and dust from solar panels. High identification rates of the system enable more effective cleaning methods. Nonetheless, the study highlights the difficulties brought on by unforgiving environmental factors that may have an impact on the effectiveness of renewable energy systems. To overcome these obstacles and strengthen the suggested method's resilience, more investigation is required.

Using artificial neural networks (ANN) to anticipate power output based on irradiance and dust percentage, Saquib et al. [123] focused on using image processing to detect dust on solar panels in 2020. The study highlights the substantial effect that dust has on PV module performance, especially in the United Arab Emirates. This study recommends more research to enhance the precision of power estimates and improve dust detection techniques.

Dantas et al. [124] investigated a variety of image-processing techniques in 2020 to detect dust on solar panels. The study emphasizes the various advantages of automated dust detection for energy production and maintenance, but it also draws attention to the underdeveloped state of some systems, which makes them difficult to repeat. Moreover, a higher level of validation becomes necessary because not all of the reviewed studies assess the accuracy of their dust detection methods.

To identify dust conditions on solar panels, Cao et al. [125] developed IDS-Net in 2021. It is a residual neural network constructed with a convolutional block considerations module. With over 80% accuracy in tests, the IDS-Net shows promise for efficient dust detection. According to the study's findings, more investigation is required to raise the network's effectiveness and degree of environmental adaptation.

In 2021, Narvios et al. [126] announced an Internet of Things (IoT) system that identified dust on photovoltaic (PV) panels and enabled automatic cleaning. To guarantee optimal solar energy generation, the device continually checks the ambient temperature and the amount of dust. The research is inadequate in addressing certain implementation issues and giving statistics on the system's long-term success, despite the potential benefits of the system.

An Artificial Neural Network (ANN) was used in research by Mokhtar et al. [127] in 2022 to assess dust levels on solar panels and schedule cleaning procedures based on a predetermined dust threshold. The suggested method seeks to lower dust collection energy loss to save maintenance expenses. The research indicates that while the ANN model has the potential for precise dust level estimation, more extensive validation and practical testing are necessary to establish its use and effectiveness.

Anaya et al. [128] presented a system in 2022 to evaluate dust deposition on solar panels that combines neural networks, linear discrimination, principal component analysis, and genetic algorithms. To produce a reliable dust level forecast, the technique integrates statistical feature extraction, optimal feature selection, and dimensionality reduction. The study shows that the suggested approach works, but it also emphasizes the need for future research to enhance and broaden the use of techniques in many settings.

Alfaris [129] presented an artificial intelligence system in 2023 that uses photovoltaic (PV) power data, sun irradiance, and predicted temperature to detect dust on PV panels. Optimizing the efficiency of the cleaning unit is the goal of the MATLAB system. One of the main concerns raised is the limited input capacity of the processing unit since it might have a substantial impact on PV performance. Due to the small quantity of data inputs, the study also highlights how difficult it is to accurately detect dust-related issues. Empirical field data are used to demonstrate the feasibility of the proposed resolution.

Purwono et al. [88] published a comprehensive review of dust detection methods for solar panels in 2023, with a focus on deep learning and image processing. The study examines at a variety of image-processing techniques for dust identification and emphasizes how crucial it is to increase the precision and consistency of these techniques, particularly when addressing shifting environmental circumstances. The study concludes that additional research is required to create more reliable methods that can adjust to changing circumstances and improve detection precision.

Ruiz et al. [130] concentrated on analyzing the amount of soiling on the solar panels in 2023 using machine learning models. Many supervised learning approaches are used in the study, such as Random Forests, Decision Trees, Multilayer Perceptrons, Linear Regression, and Long Short-Term Memory networks. The results imply that machine learning may effectively increase energy output and forecast soiling. Unfortunately, the study only looks at machine learning accuracy, not the practicality of employing such models in real-world scenarios or the challenges of implementation.

Lakshmi et al. [131] revised the DenseNet121 model (an Internet of Things-based system) in 2024 to detect dust on solar panels. By using Internet of Things (IoT) devices with cameras to take and evaluate pictures of the solar panels, the model aims to improve the accuracy of dust detection. Although the study points out drawbacks, such as decreased output and increased maintenance expenses due to dust accumulation, the approach shows potential in terms of accurate identification. The research also emphasizes the necessity for a comparison with other dust detection techniques and a more thorough explanation of the difficulties associated with practical application.

1.12 CNN Based Approaches for Dust Detection

A system that uses spectral breakdown of light and scattered analysis of color pictures was developed in 2016 by Ramos et al. [132] to identify dirt on solar panels. By utilizing statistical classification approaches, they were able to identify dirty panels in their system with an accuracy rate of over 90%. This method effectively keeps solar panels clean, boosting their efficiency and energy generation by distinguishing between clean and dirty surfaces.

In 2020, Unluturk et al. [122] used photovoltaic modules in a laboratory setting to study the effects of varying dust concentrations under artificial lighting. An artificial neural network was utilized to categorize the data, resulting in a 96.86% accuracy rate, after features from the photographs were extracted using the Gray Levels Co-occurrence matrix. This approach demonstrated how neural networks for image processing and machine learning might be utilized to maintain PV efficiency and give a precise assessment of the effect of dust on power generation.

Maity et al. (2020) [133] created a CNN-based method for an RGB image test environment in 2020 that includes dust detection on solar panels and power loss forecasting. Their model has an accuracy rate of 80% and a mean squared error of 0.0122 for training data and 0.0241 for the validation data. The study shows how image processing is crucial for maintaining the performance of solar panels and shows how using bigger datasets and more intricate models may improve accuracy.

Ferrah et al. [134] introduced a computer vision technique for dust and debris identification on photovoltaic (PV) panels in 2020. The method extracts features with 82% accuracy by using Gray Levels Co-occurrence Matrices of data with a linear classifier. To improve accuracy and resilience, future studies should consider a range of PV panel types as well as environmental conditions like as shadows and damp panels. The study emphasizes that diverse datasets are necessary to enhance the system's performance in real-world scenarios.

In 2020, Cipriani et al. [135] proposed using CNN to identify dust and hotspot conditions in PV modules using thermographic non-destructive testing. The technique demonstrated a 98% accuracy rate and the ability to diagnose quickly and accurately. This method rapidly detects issues with performance, such as dirt and hotspots, which reduces maintenance costs and boosts PV system efficiency. It also makes quick decisions possible to maintain maximum energy production.

A method for the identification and categorization of contaminants on solar photovoltaic arrays in industrial settings was introduced by Krishna et al. [136] in 2022. They utilized CNNs for processing picture data and LSTM networks for processing meteorological data. The accuracy rate of the merged CNN-LSTM approach was significantly higher at 96.54% when compared with the accuracy of the CNN technique using only images, which was 50.91%. The study highlights how important it is to integrate different data sources to optimize cleaning schedules and increase the performance of industrial solar cogeneration installations.

A deep belief network model was introduced by Khilar et al. [137] in 2022 to detect dust on solar panels and improve cleaning schedules depending on temperature, dust levels, and solar irradiation. Compared to previous models, the accuracy rate of the new model was 99%, indicating that it was successful in raising power production and lowering maintenance expenses. The study concludes that if solar panel efficiency is to be maintained, timely cleaning and predictive maintenance using machine learning are both achievable.

In 2023, El Ydrissi et al. [138] established the InSMS model. This image processing system looks for dust on solar reflectors using a convolutional neural network. The system is an effective real-time monitoring and maintenance solution for solar concentrators, with a 96% accuracy rate achieved through the use of genetic algorithms to refine cleaning strategies. This technique enhances solar reflector performance and reflectivity through precise dust measurements and efficient cleaning regimens.

In 2023, Saif et al. [139] introduced a unique CNN architecture designed to identify dust accumulation on solar panels. These researchers suggested a unique dataset that has images showing both dusty and clean panels in order to address the issue of class imbalance that commonly occurs in studies with comparable characteristics. Their SolNet CNN-based method beats the state-of-the-art dust recognition algorithms with an accuracy of 98.2%.

Ghosh et al. [140] developed a CNN-based system in 2024 to detect dust on solar energy installations, automate maintenance, and improve efficiency. The efficacy of CNNs in enhancing solar panel maintenance is demonstrated by the system's 85% dirt detection rate. By quickly detecting and eliminating dust accumulation, automated detection may greatly increase the effectiveness of solar panels and lessen the detrimental effects of dust on energy production.

1.13 Preface

In-depth discussions of the methodology, findings, and major ideas that are pertinent to this study will be provided in later chapters of this thesis.

An introduction to solar energy and PV (photovoltaic) panels is provided in Chapter 2. After that, it moves on to fundamental image processing methods that are concentrated on enhancing and representing images. This chapter explores the architecture of neural networks, focusing on convolutional neural networks (CNNs). Notable developments that are analyzed include VGG16, InceptionV3, ResNet50, and MobileNetV2. The chapter concludes with a discussion of advanced approaches, such as data augmentation, transfer learning, and performance assessment metrics, that emphasize the necessity of validation and testing during the model construction process.

In Chapter 03, the SolNet CNN model, which was designed by M. Saif to identify dust on solar panels is discussed. The model has 56 million trainable parameters and is designed to improve processing efficiency. It consists of three fully connected layers, eight convolutional and pooling layers, and three fully connected layers. SolNet outperforms other pre-trained models, such as ResNet50, InceptionV3, AlexNet, and VGG16, with an impressive 98.2% accuracy in dust detection.

Chapter 4 presents the suggested RjNet model for dust detection on solar panels. It makes use of strong machine learning and deep learning techniques. This chapter explains the different stages and research methods with an emphasis on the design and functionality of the RjNet model. Graphs and tables are used to compare the RjNet model to other notable pre-trained models. The RjNet model surpasses the other models in terms of accuracy and computational cost, proving its superior use in dust buildup detection. Additionally, the chapter highlights the primary objective of maximizing environmental impact and improving solar panel efficiency.

In conclusion, Chapter 05 provides an overview of the RjNet model's contributions and performance. It deals with the issues raised, looks at how the model could increase the efficiency of solar panels, and makes suggestions for possible future studies.

CHAPTER 2

PRELIMINARY CONCEPTS

2.1 Overview

This chapter provides an extensive overview of the major ideas behind this study. It begins with an analysis of photovoltaic (PV) systems and solar energy before going into important image-processing strategies including picture enhancement and representation. The chapter examines neural network design and components, with a particular emphasis on convolutional neural networks (CNNs') structural elements. It also discusses the use of popular CNN architectures, such as VGG16, InceptionV3, ResNet50, and MobilNetV2, for image classification applications. The discussion advances to include transfer learning, data augmentation approaches, and performance evaluation metrics, emphasizing the significance of correct validation and testing in model construction.

2.2 Solar Energy

Solar energy is the term for the heat and light emitted from the sun that is captured and used in various ways to support a wide range of industrial and commercial purposes, including heating and power production. It is a vital energy source that helps solve the world's energy problems because it is abundant, clean, and renewable [141]. Photovoltaic cells and concentrating solar power are prominent instances of solar energy systems that provide effective means of converting sunlight into useful energy, hence lowering dependency on fossil fuels and promoting sustainable development. Solar power has seen a notable increase in the production of electricity, considering its cost and efficiency issues in comparison to other renewable sources [142].

2.3 Photovoltaic (PV) Systems

A solar energy system that converts light into voltage through the process of photovoltaic effect is called a photovoltaic (PV) system [143]. The energy source for these systems is usually photovoltaic (PV) modules, which can be connected to the electrical grid to supply electricity. Photovoltaic systems (PV) are made up of various parts, including PV panels, a governing body converter, distributed power converters, and a control system, which manage the forward and backward flow of electricity and allow the system to either supply electrical energy produced to the grid or receive electricity from it [144].

Components of PV Systems: Modules for photovoltaic (PV) solar systems, inverters, and energy storage systems are essential components. PV modules, sometimes called solar panels, are devices that gather solar energy and convert it into direct current (DC) power [145]. The solar inverter is a crucial part of the process that converts the direct current (DC) output of photovoltaic (PV) panels into alternative current (AC) power suitable for grid connection or off-grid consumption [146]. Moreover, the system may be fitted with energy storage components, such as batteries, to store extra energy produced by the PV system for a later time or to supply backup power if the grid goes down or there is insufficient sunshine. It's critical to understand how these components are assembled and function, as well as how environmental variables and maintenance techniques affect the PV systems' lifespan and efficiency [145].

Working Principle of Solar Panels Solar panels, also known as photovoltaic (PV) cells, convert sunlight into energy by utilizing the photovoltaic effect, which is a substance's capacity to produce voltage and electrical power when struck by light. Electric current is produced and electrons are triggered when photons from sunlight are absorbed by semiconductor materials [147]. This is the fundamental mechanism by which solar cells function. Utilizing solar energy for a variety of purposes, such as producing electricity for residences, companies, and even whole power plants, requires this procedure [148]. Solar photovoltaic (PV) systems, of which solar panels are a fundamental component, have made enormous advancements in recent years, enabling them to become economically competitive with other electricity-generating methods and an essential component of many nations' future energy policies [149].

2.4 Dust on Solar Panels

Particles less than 0.5mm are considered dust. Except for dolomite and limestone, dust can be extremely combustible and prone to burning when ground into a fine powder. It can exist in a variety of forms, including chemical, mineral, metallic, and natural dust that contains substances like endotoxins and heavy metals [150]. Globally, dust particles come from a variety of sources, including anthropogenic activities like metallurgical processes, industrial emissions, and urban pollution, as well as natural sources including soil, desert resources, volcanic debris, and biogenic residues. [151, 152]. About 5 billion tons of dust are produced each year by drylands alone; the majority of these sources are found in areas that are close to large deserts in the northern hemisphere, which stretch from North Africa to central & eastern Asia. The Tarim Basin/Taklamakan Desert, the Sahara Desert, the USA's Great Basin, the mid-latitude deserts of Asia and Mongolia, and parts of South America, Africa, and Australia are notable sources. Urban areas close to industrial facilities experience poorer air quality due to emissions of particulate matter from industrial activities such as port operations, steel production, and coal burning [152, 153].

2.5 Image Processing

Image processing is the technique of enhancing the graphical content of digital images for both autonomous machine perception and human interpretation by modifying or analyzing them [154]. Using complex mathematical techniques, this field includes the process of segmentation morphological operators, noise reduction, and tagging, among several other methods to extract information from photos without changing their pixel composition. When a user submits a request for processing, image processing equipment can use previously processed image data and parameters to determine how often to use them and to optimize subsequent processing activities. More methods for processing photos include extracting feature points from them, defining geometric surfaces by evaluating control parameters, and producing corrected images by cropping these surfaces [155]. In addition, systems for processing images can graphically depict differences in parameter configurations and processing results, allowing users to spot anomalies and make inferences from the data [156].

2.5.1 Image Representation (Pixels, Color Spaces)

In image processing, color spaces and pixel representation are two basic concepts. Pixels, the fundamental units of digital images, are utilized for image analysis and the storing of physical attributes such as scene brightness [154]. Digital pictures are represented using colorimetry, which is produced by processing images and rendering using several color spaces. Innovative color spaces that mimic human vision and enable color modification and segmentation are crucial for capturing picture pixels for further evaluation [157]. Techniques for processing images, such as sampling, quantization, and scanning, enhance how digital images are represented and altered [158]. These fundamental ideas of image processing contribute to improving the graphical content for both machine and human interpretation [154].

2.5.2 Image Enhancement Techniques (Contrast Adjustment, Filtering)

Image enhancement techniques, which raise the quality of the pictures by adjusting contrast and filtering, are key concepts in image processing. Convolutional neural networks are utilized in conjunction with a variety of approaches, including contrast enhancement, median filtration, bicubic interpolating, and deep learning, to improve images [159]. Enhancing content recognition requires contrast augmentation, which brightens and clarifies images [160]. Filtering techniques aid in the overall preparation of images by being utilized for tasks like edge improvement, sharpening and smoothing [161]. The requirement for image improvement and restoration technologies is evidenced by the wide range of businesses that rely on them, including medical imaging, industrial automation control, and astrophotography [162].

2.6 Artificial Neural Networks

The structure and operations of the brain serve as an inspiration for artificial neural networks (ANNs), also known as neural networks, a subclass of machine learning models. These networks are made up of interlinked nodes, or artificial neurons, which process data and provide predictions [163].

Artificial Neural Networks are made up of artificial neurons known as nodes. The Artificial Neural Network of a system comprises these neurons grouped in a sequence of layers. Depending on how many complicated neural networks are needed to discover the dataset's underlying patterns, a layer may consist of a few dozen or millions of nodes. An artificial neural network typically consists of input, hidden, and output layers. The input layer is where external data is fed into the neural network for analysis or learning. After that, the data goes via one or more hidden layers, which convert the input into useful data for the output layer [164].

2.6.1 Weights

Weights are real-valued coefficients assigned to each input object that controls the strength of the connection between neurons. During training, they efficiently learn the correlations between input features and target outputs by modulating the amount of influence an input has on the neuron's output. The following is the mathematical expression for a neuron's output [165].

$$z = \sum_{j=1}^{n} w_j x_j + b \tag{2.1}$$

where w_j denotes the weights, x_j is the input features, and b is the bias term.

2.6.2 Biases

Contrarily, biases are constant values that are added to neurons' outputs to enable them to activate even in the absence of any input. This adds flexibility to the model so that it can adjust the activation function to better fit the training set of data. When inputs alone are insufficient for learning, the bias acts as an intercept in a linear equation [166].

2.6.3 Activation Function

Artificial neural networks (ANNs) rely heavily on activation functions, which provide non-linearity to the model and allow it to recognize intricate patterns in the data. They essentially enable the network to model complex interactions between inputs and outputs by deciding whether to activate a neuron depending on the weighted sum of its inputs and biases. Without activation functions, a neural network behaves like a linear regression model, whatever the number of layers, because the composition of linear functions is linear. Activation functions that are often used are [167]:

- **Binary Step Function:** When the input crosses a specific threshold, it returns a binary value.

$$f(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{2.2}$$

- **Linear Activation Function:** Directly outputs the input value, limiting the network's ability to learn complicated patterns.

$$f(x) = x \tag{2.3}$$

- **Sigmoid Function:** It converts input values to a range of 0 to 1, which is important for binary classification tasks.

$$f(x) = \frac{1}{1+e^{-x}} \tag{2.4}$$

- **Tanh Function:** Similar to sigmoid, but produces values ranging from -1 to 1, resulting in better gradients during training.

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2.5}$$

- **ReLU (Rectified Linear Unit):** If the input is positive, the output is immediately produced; if not, zero is produced, which helps to alleviate the vanishing gradient issue.

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{2.6}$$

Following is the general architecture of ANN [164].

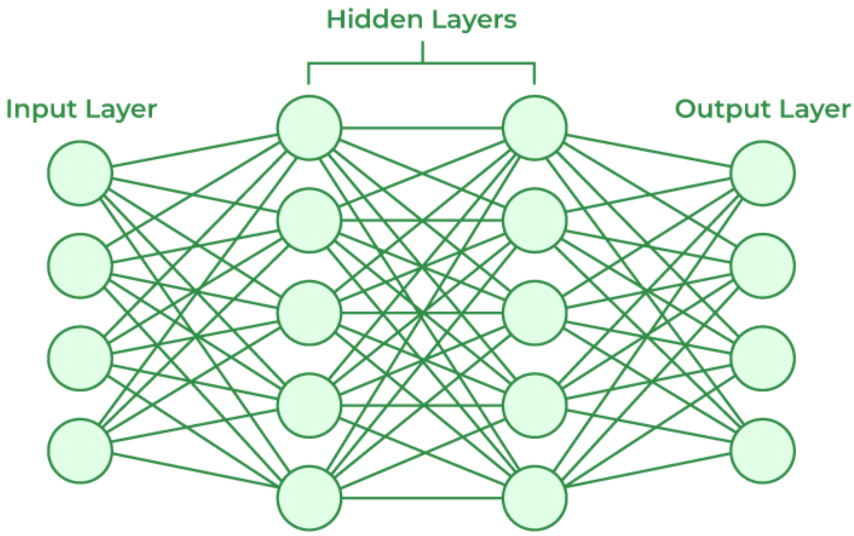


Figure 2.1: A simple Artificial Neural Network

2.7 Deep Learning

Deep learning is a branch of artificial intelligence and machine learning that uses multi-layered neural networks to learn different levels of abstraction for data representations. With the use of backpropagation techniques, this type of approach has enabled models to automatically find complex patterns in enormous datasets, revolutionizing fields like speech recognition, visual object recognition, and natural language processing [168]. The key to deep learning's success is its capacity to handle non-convex optimization problems well, which frequently results in very good predicted accuracy even for complex models [169].

2.8 Convolutional Neural Networks (CNNs)

Convolutional neural networks, or CNNs, are a type of deep learning model that is designed to analyze input such as images and has a specific grid-like architecture. A CNN is built with multiple distinct layers, each with a unique purpose and combining to form an overall hierarchical structure. A typical CNN has the following layers: an input layer, convolutional layers, activation functions (usually ReLU), pooling layers, flattening layers, fully connected layers, and an output layer for classification or regression. Additional features such as dropout and batch normalization are frequently added to improve the network's robustness and training efficiency [170].

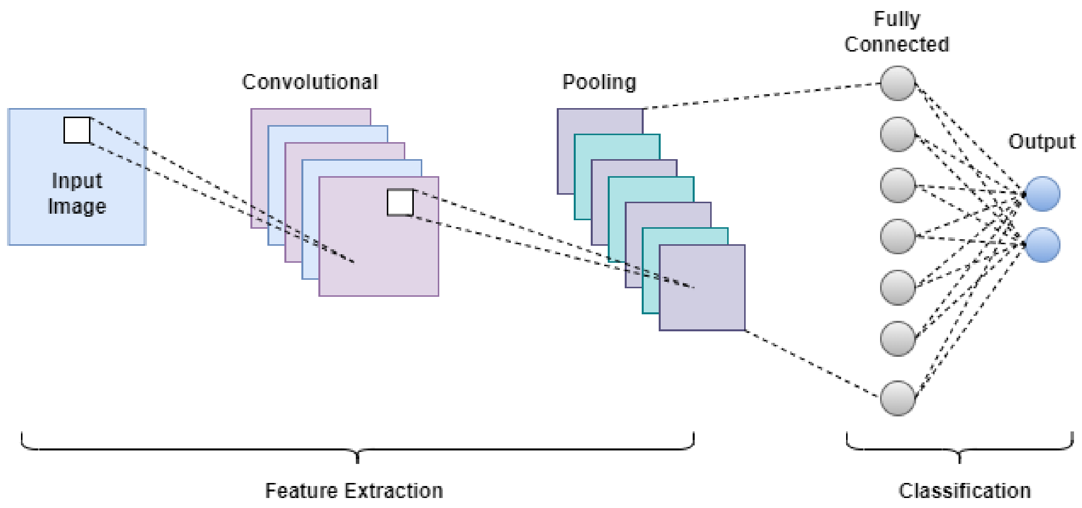


Figure 2.2: Simple CNN Architecture.

2.8.1 Input Layer

According to [171] CNN's input layer is the point at which raw data enters in the network. In image processing, the input is often a three-dimensional tensor having dimensions corresponding to the height T, width W, and number of channels C in the image. Red, Green, and Blue are the three color channels in RGB image $C = 3$. For instance, the input tensor for an image with dimensions of $32 \times 32 \times 3$.

Input Shape: $32 \times 32 \times 3$. This input tensor passes to the next layer, which performs convolution operations.

2.8.2 Convolutional Layer

The core component of a CNN is the convolutional layer. It processes the input data through filters (kernels) to extract local patterns like textures or edges. In terms of mathematics, this is

accomplished by applying a discrete convolution operation between a set of learnable filters and the input tensor. Each filter builds a two-dimensional feature map that emphasizes the presence of specific features by sliding over the input tensor [172].
Convolution is defined by [173] as follows:

$$\mathbf{f(x) = (W * X) + b} \tag{2.7}$$

Where:

$$\begin{aligned} W &: \text{ the filter (kernel)} \\ X &: \text{ the input tensor} \\ b &: \text{ the bias term} \end{aligned}$$

The final feature map is shown by:

$$Z = \sum_{i=1}^{m} \sum_{j=1}^{n} X_{i,j} W_{i,j} + b \tag{2.8}$$

Where:

$$\begin{aligned} m, n &: \text{ dimensions of the filter (kernel)} \\ X_{i,j} &: \text{ input values within the region covered by the filter} \\ W_{i,j} &: \text{ filter weights} \\ b &: \text{ the bias term} \end{aligned}$$

Figure 2.3 demonstrates the convolutional operation between the image and filter (kernel) [174].

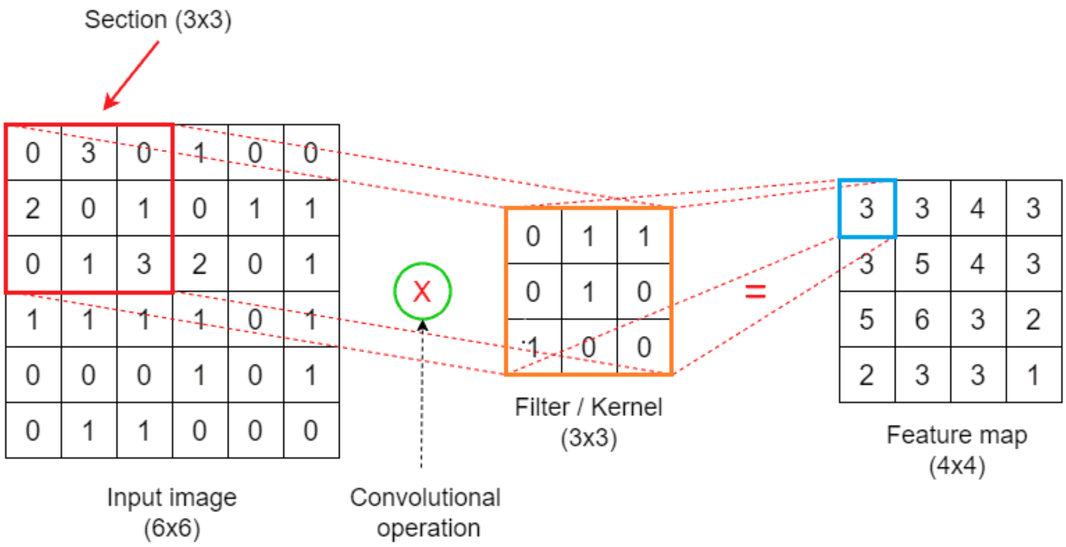


Figure 2.3: Convolutional Operation

2.8.3 Pooling Layer

The pooling layer down-samples the feature maps, lowering their spatial dimensions while keeping important information. Pooling layers lower the model's computational complexity, while also preventing overfitting by abstracting the representation. The most commonly used method is max pooling, which selects the greatest values from all patches of the feature map represented by the pooling windows [89]. The max pooling procedure and mathematical representation are defined as follows for a given patch $X_{i,j}$ [175]:

$$f(x) = \max(X_{i,j}) \tag{2.9}$$

Where:

$X_{i,j}$: values in the pooling window

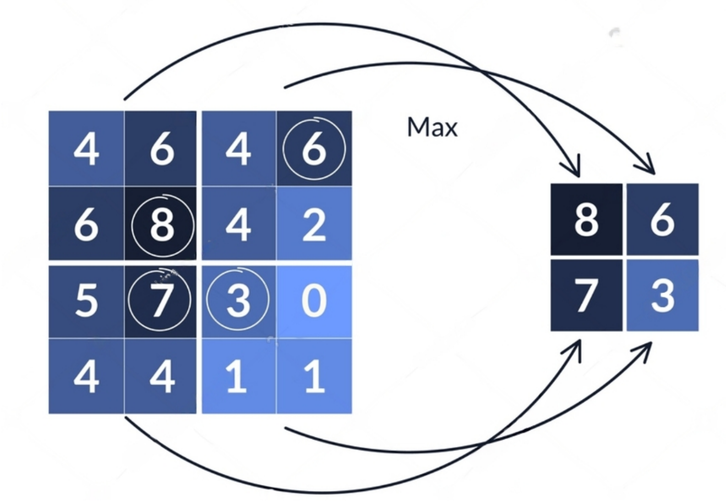


Figure 2.4: Max Pooling.

Stride and Padding

Padding and stride are important components of convolutional neural networks (CNNs) that are used for data processing. To avoid spatial artifacts and guarantee that the output size equals the input size, padding is applied to the input volume by adding extra border pixels [176]. Stride, on the other hand, controls the step size that determines how the filter convolves around the input volume, which has an impact on the feature maps' spatial dimensions and output size. Consequently, improving padding strategies and considering stride settings are crucial for raising CNN accuracy and performance in a variety of applications, including image classification and quantitative susceptibility mapping [177]. Figure 2.5 describes the procedure of stride and padding [178].

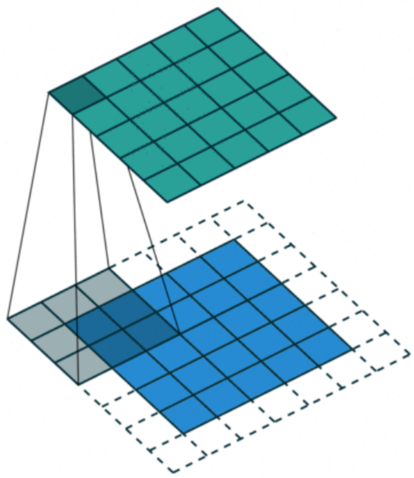


Figure 2.5: Stride and Padding.

The pooling operation has the following mathematical representation: When a pooling layer with filter size f and stride s is applied to an input feature map with dimensions $n_h \times n_w \times n_c$ (height, width, and channels), the output dimensions are as follows [179]:

$$\left(\frac{n_h - f}{s} + 1\right) \times \left(\frac{n_w - f}{s} + 1\right) \times n_c \tag{2.10}$$

2.8.4 Flattening Layer

The flattening layer transforms two-dimensional feature maps into one-dimensional vectors that can be fed into a fully linked (dense) layer. This procedure is necessary because the input to fully linked layers is expected to be in the vector format rather than the matrix or tensor.
For instance, the flattening layer converts the output of previous convolutional and pooling layers into a one-dimensional vector $8 \times 8 \times 32 = 2048$. This feature map has dimensions of $8 \times 8 \times 32$. The flattened vector is then sent to fully connected layers performing classification or regression [180].

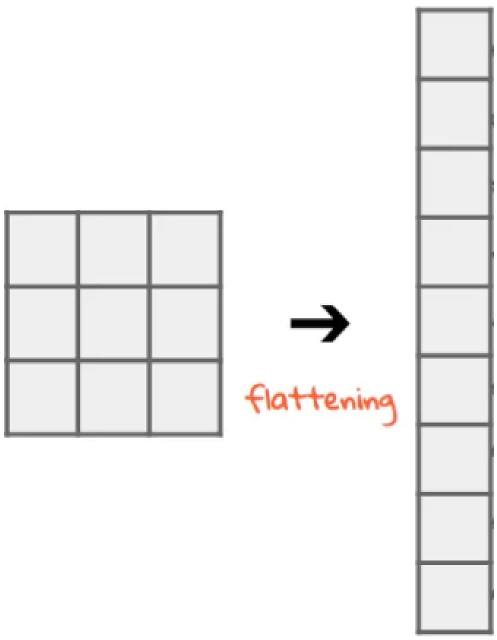


Figure 2.6: Flattening Layer of CNN.

2.8.5 Fully Connected Layers

The fully connected (FC) layer connects each neuron in the previous layer to each of the neurons in this layer. It integrates and summarizes the learned elements to make predictions or classifications. Each neuron in the FC layer calculates a weighted sum of all inputs before applying an activation function (often ReLU or Sigmoid). Fully connected layers make high-level network decisions and produce final outputs [181]. The fully connected layer calculates the weighted sum of the inputs while adding a bias term [181]. The workflow of the fully connected layer is given in Figure 2.7 [182].

$$f(x) = Wx + b \tag{2.11}$$

Where:

$$\begin{aligned} W &: \text{ weight matrix} \\ x &: \text{ input vector} \\ b &: \text{ bias vector} \end{aligned}$$

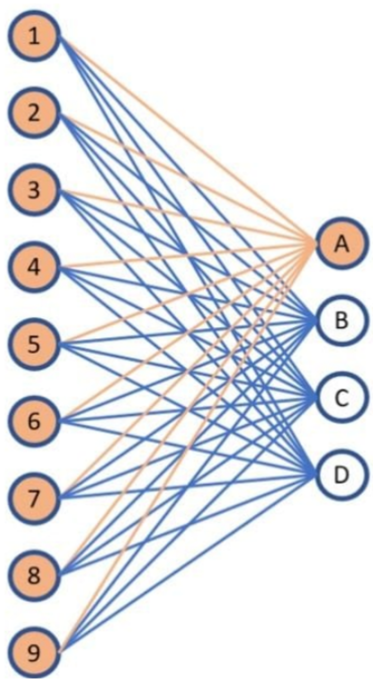


Figure 2.7: Fully Connected Layer.

2.9 Activation Function

Activation functions make the network non-linear, allowing it to learn complicated patterns. In convolutional and fully connected layers, CNNs commonly use the ReLU (Rectified Linear Unit) activation function by default. ReLU processes elements one at a time, producing zero if the input is negative and the input directly if it is positive. This expedites training and helps to mitigate the vanishing gradient problem [183, 184].

$$f(x) = \max(0, x) \tag{2.12}$$

$$x: \text{ is the input}$$

2.9.1 Softmax Function

For multi-class classification, the Softmax function is usually used in the neural network's output layer. It has the following definition [185]:

$$f(x_i) = \frac{e^{x_i}}{\sum_j e^{x_j}} \tag{2.13}$$

Where:

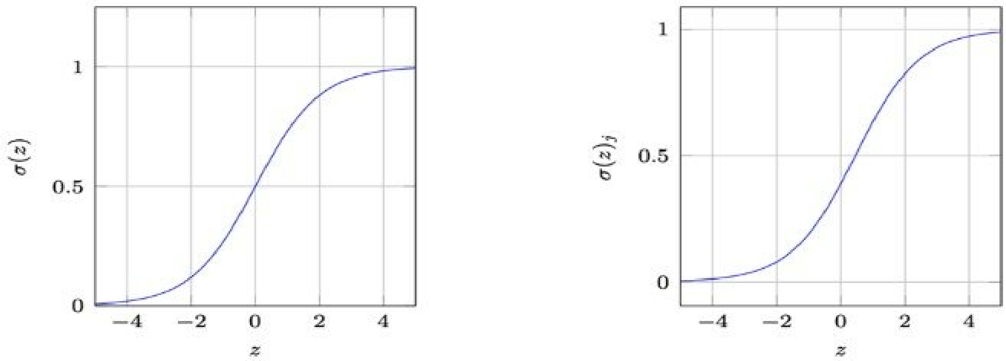
$$x_i: \text{ the input to the } i\text{th unit}$$

2.9.2 Sigmoid Function

The Sigmoid function, which is defined as follows, is frequently used for binary classification [186].

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2.14}$$

Following Figure 2.8 is the graphical representation of Sigmoid and Softmax activation functions [187].



(a) Sigmoid activation function. (b) Softmax activation function.

Figure 2.8: Grph of Activation Functions.

2.10 Dropout Layer

Dropout is a regularization approach to neural networks that disables a fraction of neurons at random during training to prevent overfitting. This promotes more broad feature learning by making the network rely on numerous independent neurons rather than just a small number of activations [188].

During each training iteration, a proportion p of neurons is discarded with a probability p, effectively reducing neuronal co-adaptation and enhancing the model's capacity to generalize to unseen data. Mathematically, the dropout for each neuron is applied as follows [188]:

$$\tilde{h}^{(l)} = h^{(l)} \cdot d^{(l)} \tag{2.15}$$

Where:

$h^{(l)}$: neuron activation in layer l

$d^{(l)}$: random binary mask with probability p

In a CNN model, dropout layers serve to prevent overfitting by randomly "dropping" a certain number of neurons during training, which is shown in Figure 2.9. This enables the network to learn more resilient and broad patterns rather than relying on individual attributes [189].

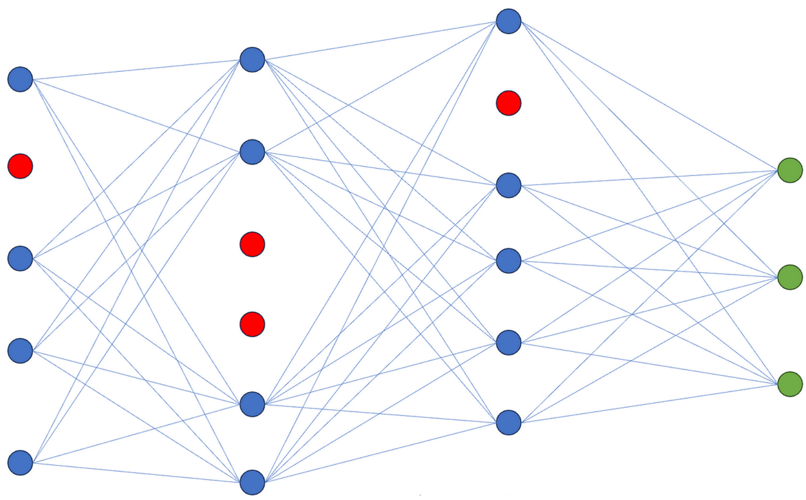


Figure 2.9: Dropout Layers.

2.11 Batch Normalization

Batch normalization is a technique for standardizing layer inputs by normalizing each mini-batch to ensure a mean of zero and a variance of one. By removing internal covariate changes, this technique stabilizes and accelerates the training process, making it easier for the network to learn. For input x, the batch normalization is provided by [190]:

$$\hat{x} = \frac{x - \mu_{\text{batch}}}{\sqrt{\sigma^2_{\text{batch}} + \varepsilon}} \tag{2.16}$$

Where:

$$\begin{aligned} \mu_{\text{batch}} &: \text{ batch mean} \\ \sigma^2_{\text{batch}} &: \text{ batch variance} \\ \varepsilon &: \text{ small constant added for numerical stability} \end{aligned}$$

Batch normalization keeps layer output balanced and constant while improving the learning process of a CNN. The model learns more quickly and accurately when sudden changes are removed from the data [191].

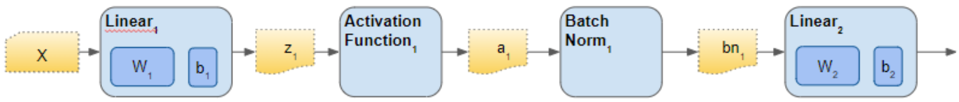


Figure 2.10: Batch Normalization Technique.

2.12 Feature Maps

Feature maps are depictions of the learned features that CNNs' convolutional layers extracted from the input data. Understanding the fundamental workings of CNN models requires an understanding of these maps [192]. Feature maps provide an analytical and visual depiction of hidden representations, providing insights into the intricate characteristics of CNNs [193]. By supporting the understanding and validation of CNN choices, they increase the transparency and dependability of models [194]. Additionally, by altering feature maps, one may increase the network's resilience to alterations such as rotation and scale by adding variances to the retrieved features [195]. Moreover, adversarial assaults may be detected automatically using spatial entropy in hidden layer feature responses by recording perturbations, allowing for detection without altering the network design [196]. Figure 2.11 represents the workflow of feature maps in CNNs [195].

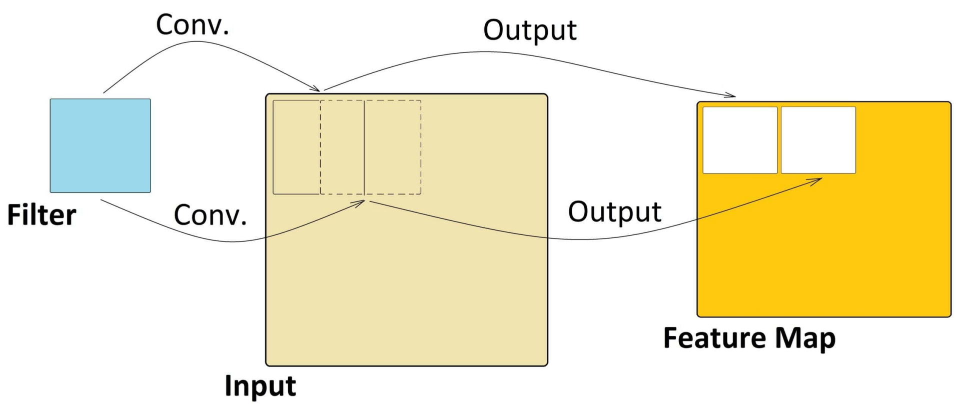


Figure 2.11: Feature Map in CNNs.

2.13 Pre-trained Models

Pre-trained neural networks are deep learning architectures that have already learned generic image characteristics on large datasets like ImageNet, VGG16, InceptionV3, ResNet50, and MobileNetV2. These models are frequently applied in transfer learning, where the parameters are learned and then adjusted for certain tasks. By using pre-trained models, researchers may significantly reduce the amount of time needed for training and improve the prediction power for tasks like image categorization [197].

2.13.1 VGG16

VGG16 model proposed by Simonyan et al. [198], a deep convolutional neural network (CNN) for image classification tasks, is a breakthrough because of its consistent architecture and ease of use. It was developed by the Visual Geometric Group at the University of Oxford. Thirteen convolutional layers and thirteen fully connected layers make up the network's sixteen layers. The layers are arranged into blocks, with max-pooling happening after down-sampling convolutional layers. An image with dimensions of $224 \times 224 \times 3$ is fed into the VGG16 network. Two consecutive convolutional layers, each with 64 filters, make up the first block. The filters are similarly padded and have a 3×3 filter size in order to preserve the spatial dimensions. The following layer is called max-pooling, and it has a stride of two and a pool size of 2×2. The second block consists of two layers of convolution with a filter width of 3×3 and 128 filters, after a max-pooling layer. Complicated convolutional layer blocks follow the architecture even further. The fourth and fifth blocks also have three convolutional layers, each with 512 filters, while the third block has three convolutional layers with 256 filters, using the same 3×3 filter size and padding [198]. Every block ends with a max-pooling layer that has a pool size of 2×2 and a stride of 2. The network then has more convolutional layers with 512 filters and a 3×3 filter size after these blocks. A vector with a size of 25088 is created by flattening the output of the final convolutional layer. After that, three fully connected layers have ReLU activated. The final classification result is created by transforming the feature map through the completely connected layers [198]. With its emphasis on depth and simplicity, the architectural design of VGG16 has proven to be highly effective in picture classification tasks, setting a standard for deep learning [199]. The architecture of the VGG16 model is given in [198] Figure 2.12.

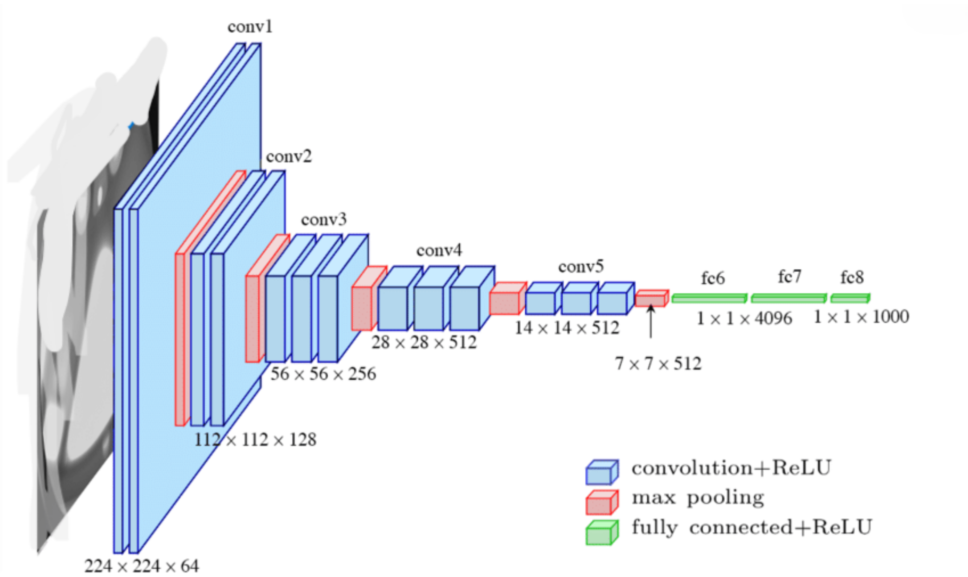


Figure 2.12: Architecture of VGG16 Model.

2.13.2 InceptionV3

Factorized convolutions, which divide more complex convolution operations into smaller ones and hence reduce computational complexity without sacrificing performance, are used in InceptionV3 proposed by Szegedy et al. [200]. In particular, it employs 1×1, 3×3, and 5×5 convolutions, which enable the network to efficiently learn various spatial feature hierarchies. By adapting to different item sizes inside photos, this architecture helps the model perform better in terms of classification [201]. Along with these strategies, InceptionV3 also uses label smoothing, which keeps the model from growing too certain of its predictions and minimizes overfitting. Furthermore, by normalizing the layer outputs, it makes use of batch normalization to stabilize and expedite training. To improve learning in the network's earlier layers, the architecture incorporates auxiliary classifiers that supply more gradients during training [201]. Additionally, Figure 2.13 provides an architecture of the InceptionV3 model [201].

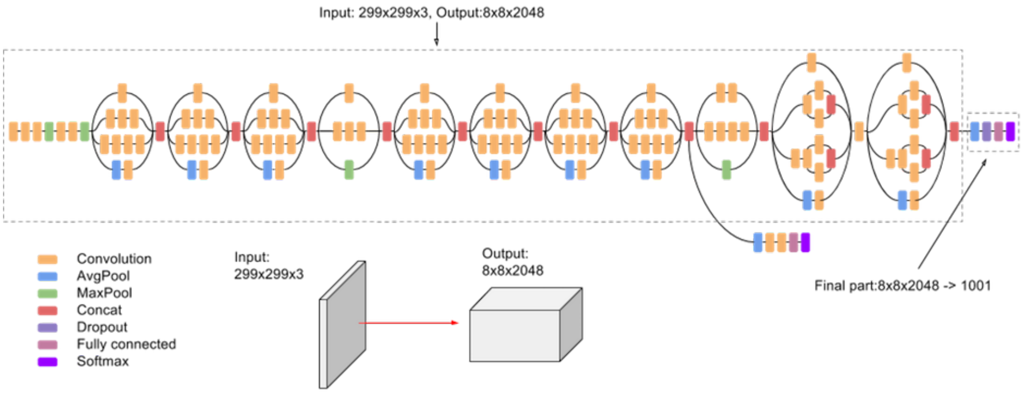


Figure 2.13: Architecture of InceptionV3 Model.

2.13.3 ResNet50

The ResNet50 [202] network, or CNN, architecture proposed by Kaiming et. al is well-known for its exceptional capabilities in image classification tasks, especially when dealing with delicate feature representations and substantial training datasets. By including skip connections for residual learning, ResNet50 solves the vanishing gradient issue and makes deeper network training possible. Using this architecture, manipulation in digital images has been detected with great accuracy in a variety of fields, including the detection of image forgery, dog breed identification, emotional recognition, and plant disease [203]. The architecture of the ResNet50 model is given in Figure 2.14 [202]:

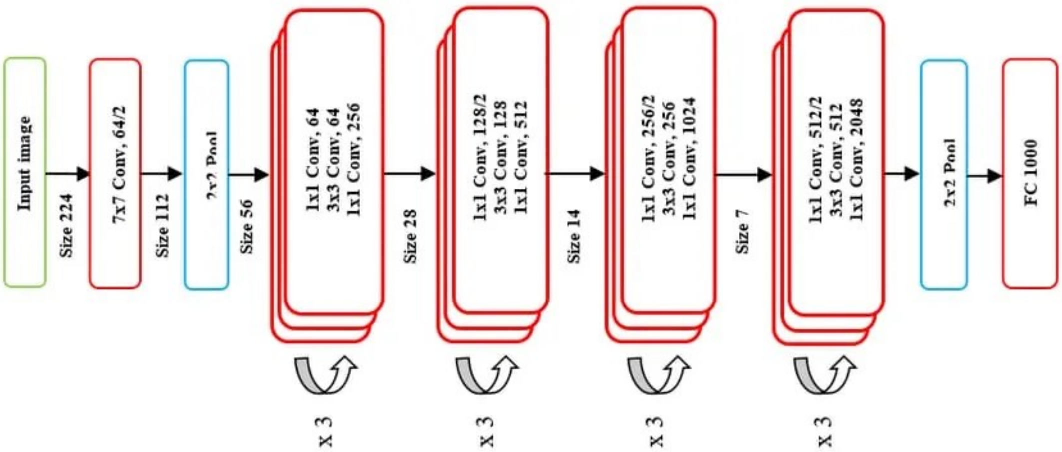


Figure 2.14: Architecture of ResNet50 Model.

2.13.4 MobileNetV2

A convolutional neural network (CNN) architecture called MobileNetV2 was created to retain excellent accuracy in image classification tasks while optimizing performance on mobile and edge devices. It was first presented by Sandler et. al [204] and expanded upon the ideas of its predecessor, MobileNetV1 while introducing several improvements to increase efficacy and efficiency. For effective feature extraction and lower computing costs, MobileNetV2's design makes use of inverted residuals and linear bottlenecks. The network has 19 leftover bottleneck layers after commencing with a conventional convolutional layer. A bottleneck layer consists of three primary components: a linear layer for dimensionality reduction, a lightweight depth-wise separable convolution, and a residual connection for information maintenance between the levels. The model's structure allows it to be used on devices with limited computing power and yet acquire detailed features while maintaining a reasonable size. One of the main benefits of the MobileNetV2 model is its performance when compute limitations are achieved. The output combining layer and the filtering layer are the two distinct stages of the convolution process that are produced by depthwise separable convolutions. There is a significant decrease in computation and parameter costs when this technique is substituted for traditional convolutional layers. This makes MobileNetV2 an excellent choice for embedded and mobile system programs as it can offer real-time classification performance [205].

MobileNetV2 additionally allows for transfer learning, allowing users to enhance the learned model on specific datasets. This feature improves the model's adaptability to a variety of tasks, such as the identification of fruits and vegetables, the categorization of agricultural diseases, and other domain-specific applications. MobileNetV2 has been utilized in several applications because of its versatility, and it has proven to work well in terms of inference speed and accuracy. MobileNetV2 has been shown to perform better in terms of accuracy and latency than its predecessor, MobileNetV1. Because of this, it is the go-to option for developers who want to use deep learning solutions on devices with limited resources [206]. The architecture of the MobileNetV2 model is described in Figure 2.15 [204]:

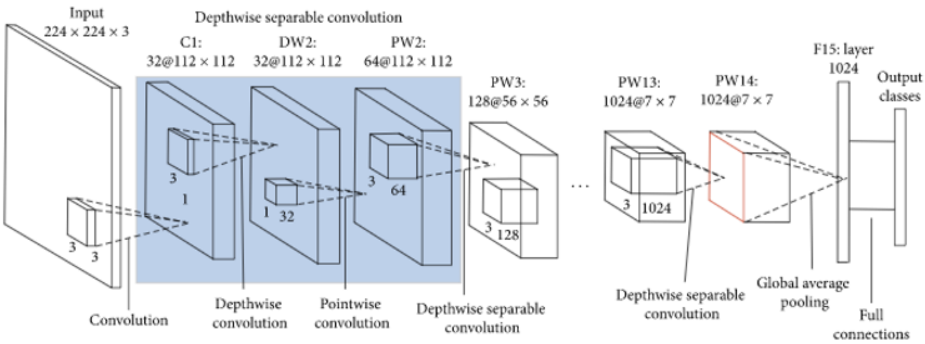


Figure 2.15: Architecture of MobileNetV2 Model.

2.14 Transfer Learning

Transfer learning is a machine learning approach that allows one task's learning to be applied to another task. It is described as a process that applies the knowledge of a trained model created for one task to another similar but distinct task. As a result, the second model, which concentrates on the new task, incorporates the knowledge gained from task one [207]. The weights that in the ML model picks up while solving one problem are applied to another in a process known as transfer learning. The goal is to finish a new task with less data or labels by reprocessing the knowledge learned from a task with labeled training data. Instead of starting from scratch, the learning process might start from a more advanced starting point by leveraging patterns discovered while solving similar problems. Natural language processing and computer vision applications frequently make use of transfer learning. Utilizing the knowledge from previously trained models expedites training, enhances performance, and permits efficient learning even with a small amount of data. If the model is overly optimized for the new task or if the original and new domains are not compatible, overfitting may result [208].

Importance of Transfer Learning in CNNs

In a variety of applications, transfer learning is essential for improving the effectiveness and performance of convolutional neural networks (CNNs). It has a big influence on computer vision since it makes it possible to apply previously trained models to new tasks. Saving time and computational resources during training is one of the main benefits of transfer learning. Large datasets can require time-consuming and computationally expensive training for a CNN that is started from scratch. Transfer learning speeds up the training process by using pre-trained models, which have already picked up helpful features from large datasets like ImageNet [209]. Limited labeled data is another issue that transfer learning tackles. It can be challenging to gather a large labeled dataset in many real-world circumstances. Working with smaller datasets can benefit from the generic features that pre-trained models have learned. Even with insufficient data, practitioners can obtain increased performance by fine-tuning these models on certain tasks. Additionally, transfer learning enhances a model's ability to generalize. Features derived from large datasets are often applicable to other related tasks. This suggests that a model trained on one type of data can perform a different, related task with sufficient effectiveness. For example, a CNN trained for general picture classification can be adapted for specific uses such as object identification, facial recognition, and image segmentation by applying the knowledge learned during the first training [210]. The CNN transfer learning process is shown in Figure 2.16 [211].

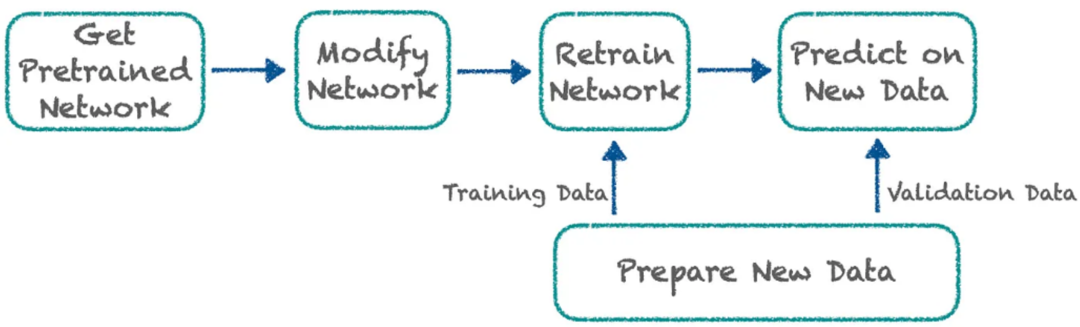


Figure 2.16: Transfer Learning within CNN.

2.14.1 Fine-tuning of Pre-trained Models

Fine-tuning pre-trained models is a key strategy in machine learning, particularly when deep learning and convolutional neural networks (CNNs) are used. This approach retrains a model using a smaller dataset tailored to the tasks at hand from its initial large-scale training. The basic goal of fine-tuning is to get the pre-trained model to work well on a new task while making use of its existing understanding. Typically, the process of fine-tuning begins by selecting a pre-trained model that closely resembles the goal task. The model selection must be followed by the preparation of the task-specific dataset. It needs to be labeled and representative of the upcoming task [212].

During the fine-tuning process, the model's parameters are updated using the new dataset. This is accomplished by training the model for a limited number of epochs, usually at a slower learning rate than in the initial training phase. Because it enables the model to make little weight modifications rather than large ones that might cause overfitting, a lower rate of learning is essential. It is standard procedure to freeze particular training model layers when fine-tuning. Later layers of the model can focus on learning characteristics particular to a given task because early levels are often frozen to preserve learned representations. Additionally, methods such as gradual unfreezing which involves gradually unfreezing layers during training can be utilized to improve fine-tuning performance [213].

Particularly when the task-specific dataset is small, regularization techniques like weight decay or dropout are frequently used to avoid the danger of overfitting during fine-tuning. Data augmentation may be used to increase the diversity of the training data, which will improve the generalization ability of the model [214]. While the model is being adjusted, it is critical to monitor and evaluate its performance using validation datasets. Experts may use this information to make well-informed judgments on additional modifications, such as altering the model architecture or the hyperparameters. When labeled data is limited, fine-tuning allows robust pre-trained models to effectively and successfully adapt to new tasks without requiring a lot of initial training. Using the stability of current models, this method saves time and resources while improving performance across a range of applications, such as image classification and processing of natural languages [214].

2.15 Data Augmentation

Data augmentation is used to artificially expand the quantity and variety of a dataset used for training by making several changes to pre-existing data. Common methods include:

Rotation: Rotation: Orienting images in a new way to aid models in object recognition from various perspectives.

Flipping: This technique of horizontally or vertically mirroring images is helpful for activities when orientation is not crucial.

Scaling: Scaling is the process of resizing images to different dimensions so that models can be trained with a variety of object sizes.

Cropping: Cropping is the process of choosing and resizing a section of an image to assist models in concentrating on specific features.

Color Adjustment : Changing saturation, contrast, or brightness to get models ready for various lighting scenarios.

These techniques boost the model's performance and capacity for generalization, particularly in situations where training data is minimal [215].

2.16 Performance Evaluation Metrics

True Positive (TP): When the model accurately classifies a solar panel as dusty, when it is dusty. For example, if the model detects high dust deposition on a panel and classifies it as such, this is considered a true positive [216].

True Negative (TN): This shows how many times the model predicts the negative class accurately. If a panel is dust-free and the model properly recognizes it, it is classified as a true negative [216].

False Positive (FP): This indicator indicates how many times the model incorrectly categorized a clean solar panel as dusty. When a clean panel has to be cleaned, for instance, the model's recommendation is a false positive [216].

False Negative (FN): This demonstrates how the model mistook a filthy solar panel for a clean one. A false negative occurs when a panel coated in dust is mistakenly identified as clean [216].

2.16.1 Confusion Matrix

A confusion matrix can provide an in-depth analysis of the effectiveness of a classification model. The model's performance across several classes is clearly illustrated visually using a matrix format that counts true positives, false positives, and false negatives [217]. These characteristics are arranged to produce a confusion matrix, which provides a clear visual representation of the categorization results [217].

	Predicted Negative	**Predicted Positive**
Actual Negative	True Negative (TN)	False Positive (FP)
Actual Positive	False Negative (FN)	True Positive (TP)

Table 2.1: Confusion Matrix

A more comprehensive evaluation of the model's efficacy may be achieved by obtaining other metrics from the confusion matrix, such as specificity (actual negative rates) and class majority [218].

2.17 Important Metrics

Performance metrics are measured in numbers used to assess a model's quality, efficacy, and efficiency in a variety of settings. Through the provision of objective standards for evaluating model performance, these metrics enable comparisons and improvements. Measures like as AUC-ROC, accuracy, precision, recall, F1 score, and area under the ROC curve are frequently employed to evaluate the predictive capacity of a model. Because metrics have a direct impact on model construction, optimization, and the interpretation of outcomes in certain circumstances, choosing the right ones is essential [219].

2.17.1 Accuracy

The accuracy of a model determines how accurate its predictions are overall. It is calculated by dividing the sum of true positive (TP), and true negative (TN) predictions by the total number of samples. Although accuracy is a basic statistic, it can be deceptive, especially when there is a significant discrepancy in the number of members between two groups. [220].

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \tag{2.17}$$

2.17.2 Precision

Precision measures how accurate the model's positive predictions are. It is the proportion of true positives to the total of both false positives (FP) and true positives. A high precision means that the model is usually right when it predicts a positive class. This measure is especially crucial in situations when there is a large cost associated with false positives, such as spam detection, where misidentifying a valid email as spam might have negative consequences [220].

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2.18}$$

2.17.3 Recall

Recall determines how well the model recognizes all relevant instances; it is also referred to as sensitivity or true positive rate. It is the ratio of true positives to the total of false negatives (FN) and true positives. When making a diagnosis in medicine, for example, where identifying the wrong disease could have major consequences, high recall is essential because missing a positive instance can be costly. A low-precision, high-recall model may detect the majority of positive cases but may also contain a large number of false positives [220].

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{2.19}$$

2.17.4 F1-Score

The F1-Score is a statistic that provides a balance between precision and recall, calculated as the harmonic mean of the two. It is especially helpful in situations where one metric cannot be given up in favor of another. When dealing with imbalanced datasets, the F1-Score is particularly crucial because it must be used to decrease both false positives and false negatives. A high F1-Score denotes a well-balanced recall and precision [220].

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2.20}$$

2.17.5 Importance of Validation and Test Sets

Validation sets are employed in the training phase to optimize a model's hyperparameters. They offer an objective assessment of a model fit on the training set, enabling modifications to be performed without introducing bias from the data used for training. By doing this, overfitting is prevented, a situation in which a model performs well on training data but badly on untested data. Practitioners can evaluate performance and make appropriate improvements to increase generalization by assessing the model on the validation set following each training epoch [221]. On the other side, test sets are used when the model training is over. They offer an unbiased estimate of the model's potential performance on new, unseen data and for the final check. To ensure that the test set continues to be an accurate reflection of the model's generalization capabilities, it should not be used during the training or validation stages [222].

2.18 Summary

This chapter discussed solar energy, photovoltaic systems, image processing algorithms, CNN architectures, and well-known CNN models such as VGG16, InceptionV3, ResNet50, and MobileNetV2. It covers dust detection techniques, CNN-based approaches, and advanced methods like transfer learning, data augmentation, and performance evaluation, with a focus on the importance of validation and testing in the development of models.

CHAPTER 3

SOLNET: A CONVOLUTIONAL NEURAL NETWORK FOR DETECTING DUST ON SOLAR PANELS

3.1 Overview

This chapter examines the SolNet CNN model by Saif et al. [139] designed for detecting dust on solar panels. SolNet classifies panels as dirty or clean, utilizing eight convolutional and pooling layers and three fully connected layers. With a focus on reducing computational complexity, the model uses 56 million trainable parameters. SolNet achieves an accuracy of 98.2%, outperforming pre-trained models like ResNet50, InceptionV3, AlexNet, and VGG16 in the specific task of dust detection.

3.2 Dataset Description

The dataset of clean and dusty solar images presented in this research includes 2231 images that were taken in different parts of Bangladesh, ensuring varying degrees of dust on the panels. There are two classes in the dataset: 1130 pictures of clean panels, and 1101 pictures of dirty panels.

There are $227 \times 227 \times 3$ When rendered, it will display square-shaped images in the dataset, all of which were meticulously labeled for supervised learning. The dataset is divided into training and testing sets, with 422 clean panel images and 418 dirty panel images in the testing set 708 clean panel images, and 683 dirty panel images in the training set.

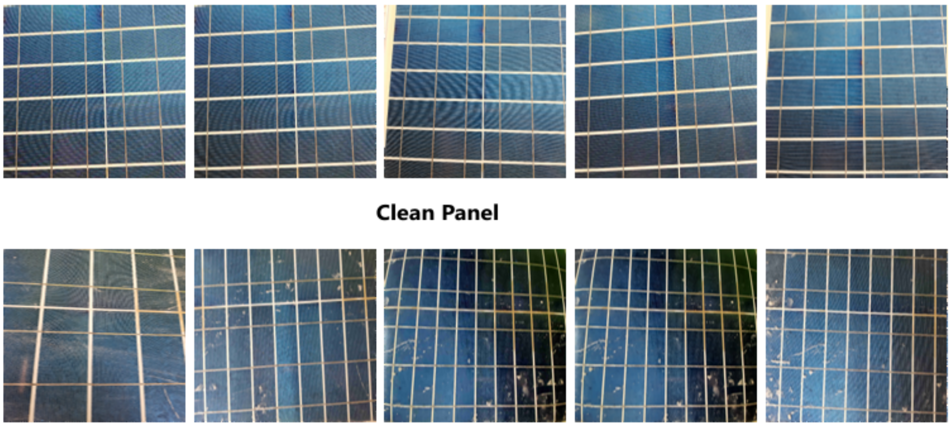


Figure 3.1: Images of Clean and Dusty Solar Panels from the Dataset.

The dataset offers an even distribution of clean and dirty panels, preventing class imbalance and enabling precise model testing and training. The resulting dataset's adaptability and applicability for upcoming research projects are increased by enabling testing on models with different input shapes. The following table explains the dataset in tabular form:

Category	**Clean Panels**	**Dirty Panels**	**Total**
Total Images	1130	1101	2231
Training Set	708	683	1391
Testing Set	422	418	840
Image Dimensions	$227 \times 227 \times 3$ (RGB)		

Table 3.1: Distribution of Clean and Dirty Solar Panel Images in the Dataset

3.3 Overview of SolNet Model

The CNN model SolNet was created specifically to detect dust on solar panels. It is composed of eight convolutional and pooling layers and three dense layers, or fully connected layers. The purpose of developing this model was to guarantee a decrease in computational complexity by using fewer trainable parameters. To lessen the overfitting of the model, max-pooling layers with dropouts were also employed. Following the input layer are two levels of conv-pool pairings. The 64, 128, and 256 filters that make up the convolution layer have kernel sizes of 11×11, 5×5, and 2×2, and strides of 4×4 and 1×1. To improve training efficiency, batch normalization layers are introduced after every conv-pool pair, significantly reducing the parallel processing training epoch. After the flattened layer, the dense layers are applied. There is a sigmoid activation function in the final dense layer or output layer. To maintain a balance of model complexity and performance, the model consists of 56 million trainable parameters in total.

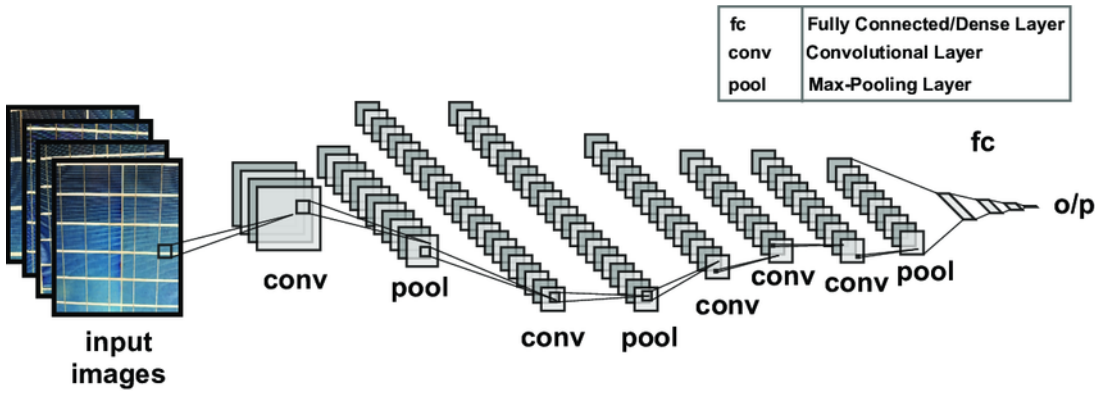


Figure 3.2: Architecture of SolNet Model.

3.4 Comparision of SolNet Model with Pre-trained Models

A customized CNN SolNet model has outperformed other popular pre-defined models in the specific task of dust detection on solar panels. These pre-built models consist of ResNet50, InceptionV3, AlexNet, and VGG16. SolNet used 56 million trainable parameters to obtain a remarkable accuracy rate of 98.2%. Comparatively, VGG16 obtained 97.5% accuracy with 138 million parameters; InceptionV3 obtained 95.2% accuracy with 6.4 million parameters; AlexNet obtained 96.6% accuracy with 62 million parameters; while ResNet50 severely underperformed with 84.0% accuracy and 60 million parameters. One of the key features of SolNet is its ability to strike a balance between accuracy and computational efficiency. SolNet outperformed InceptionV3, which had the fewest parameters, in terms of accuracy with a respectable number of parameters. This demonstrates how SolNet achieves exceptional speed while keeping computational complexity within attainable parameters.

Furthermore, overfitting is a common concern for machine learning models, and SolNet's architecture contains techniques to mitigate it. SolNet uses K-fold cross-validation and early-stopping techniques to deliver dependable model training and generalization. By preventing the model from becoming overly used to the training set, these strategies improve the model's performance with the unknown dataset.

3.5 Training Procedure

During training, SolNet employs both forward and backpropagation, changing weights and biases as needed to reduce error. The hardware specifications, training hyperparameters, and significant image classification models are listed in the following table. The features of the system configuration (CPU, RAM, and GPU), learning rate, optimizer, and backbone are all included.

Parameter	**Value**
Backbone	Custom
Classes	2 (Binary)
Batch size	32
Image size	$227 \times 227 \times 3$
Optimiser	Adam
Learning rate (Lr)	0.0001
Loss	Binary Cross-entropy
Output layer activation	Sigmoid
Epochs	30
Processor	Xeon (2.3 GHz)
RAM	12 GB
GPU	Tesla K80 (12 GB)

Table 3.2: Training Hyperparameters and Hardware Specifications.

3.6 Result Evaluation

This section provides the testing outcomes as a foundation to extensively analyze and evaluate the model's performance metrics.

3.6.1 Average Accuracy

The SolNet model achieved an impressive 98.2% average accuracy. This demonstrates that the model can reasonably effectively discriminate between dusty and clean solar panels, which is important for preserving photovoltaic systems' maximum output.

3.6.2 Loss

The loss value that the model produced was 1.12. Lower values for this statistic show increased prediction accuracy and show how well the model performed during training. The loss suggests that there may still be work to be done in the model's learning process, even with outstanding accuracy.

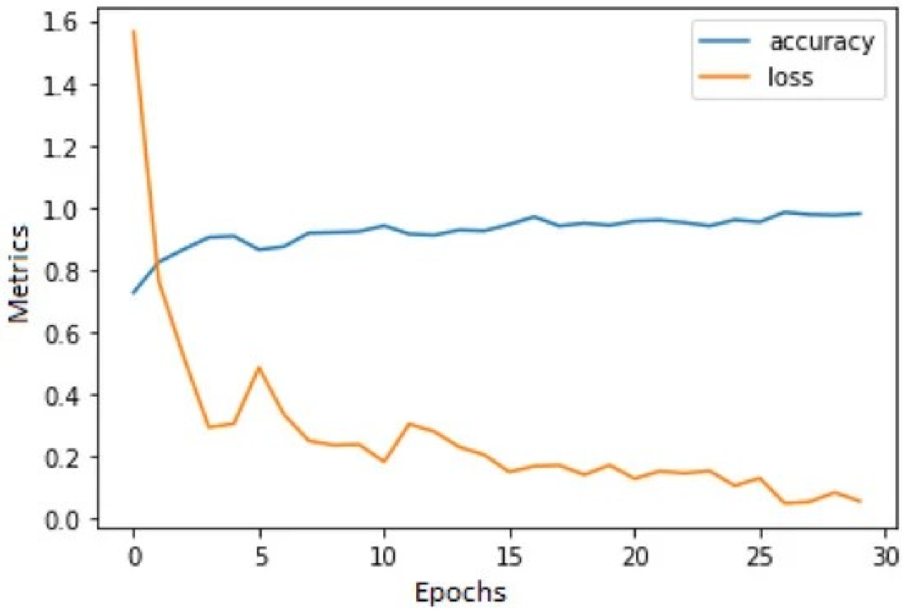


Figure 3.3: Accuracy and Loss VS Epochs During Training.

3.6.3 Five-fold Cross-validation

An essential method for assessing how long-lasting machine learning models are is cross-validation. In this instance, SolNet was trained on the dataset using a five-fold cross-validation method, yielding an accuracy of 99.62% at maximum and 98.2% on average. Table 3.3 summarizes SolNet's performance over each fold by showing the accuracy and loss numbers for each fold and emphasizing the top and lowest performing values.

Fold Sequence	**Avg Accuracy**	**Loss**
Fold-1	99.62% (highest)	0.89
Fold-2	96.46% (lowest)	1.29
Fold-3	98.52%	1.75
Fold-4	97.79%	0.93
Fold-5	98.61%	0.74
Average	**98.2%**	**1.12**

Table 3.3: Performance of SolNet Model for Five-fold Cross-validation

3.6.4 Confusion Metrics

The confusion metrics of the SolNet architecture on test images are displayed in Table 3.4 The performance can be shown with the help of this error matrix. In this matrix, each row indicates the predicted class, whereas each column represents the ground truth. It becomes simple to determine whether and to what extent two classes are confused by the model.

Table 3.4: Confusion Matrix and Precision Scores on Test Images

Ground-Truth Class	**Predicted Clean**	**Predicted Dirty**	**Precision (%)**
Clean	412	18	97.6
Dirty	10	400	95.7

Fig 3.3 Shows confusion metrics in percentage, where columns represent ground truth and rows represent the predicted class.

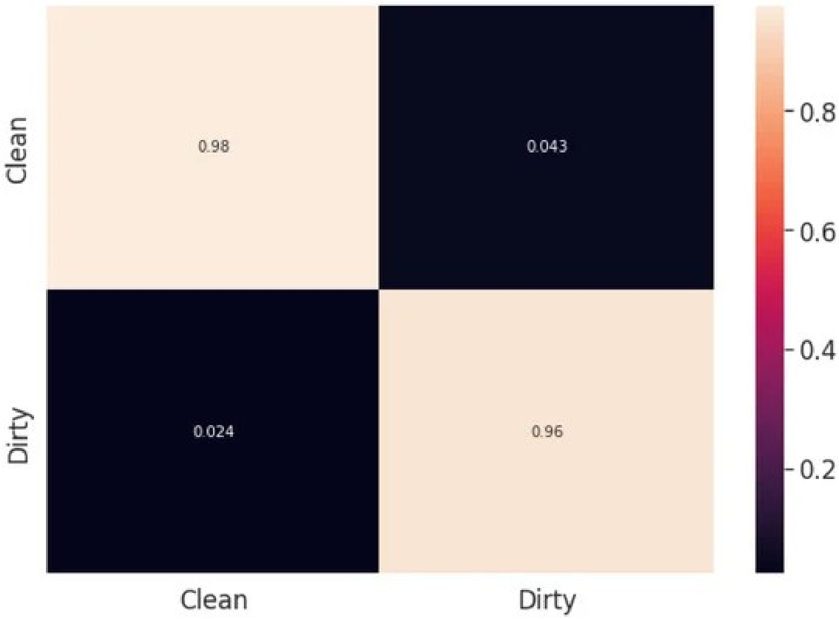


Figure 3.4: Percentage Representation of the Confusion Measures.

3.6.5 Computational Costs

Based on test accuracy and trainable parameters, the given table 3.5 compares some State-of-the-Art (SOTA) models with the SolNet model. It emphasizes that SolNet exceeds most models in terms of accuracy (98.2%) while using fewer parameters (56M). VGG16 requires a lot more parameters (138M), yet has a high accuracy of 97.5%. Other models, such as InceptionV3, ResNet50, and AlexNet, achieve lower accuracies with varied parameter counts.

Authors	Model	Accuracy (%)	Trainable Parameters
Simonyan et al. [198]	VGG16	97.5	138M
Szegedy et al. [201]	InceptionV3	95.2	6.4M
Kaiming et al. [202]	ResNet50	84.0	60M
Krizhevsky et al. [223]	AlexNet	96.6	62M
Saif et al. [139]	SolNet	98.2	56M

Table 3.5: A Comparison of Average Accuracy of Testing and Trainable Parameters for SolNet Model and SOTA Models.

3.6.6 Strengths of the SolNet Model

High Accuracy: SolNet, a comparable approach for dust detection on solar panels, has reached an accuracy of 98.2%. This accuracy level ensures reliable detection of dust deposition on solar panels, which is crucial for practical applications.
Reduced Computational Complexity: It is anticipated that SolNet be computationally efficient and has 56 million trainable parameters. Its decreased complexity allows it to be applied to a variety of scenarios, which facilitates deployment in real-world scenarios and expedites training.
Comparative Analysis of Pre-trained Models: Through performance comparison with other pre-trained models, the study illustrates SolNet's effectiveness with fewer parameters. This implies that modifications have been made to the model specifically for dust detection.

3.6.7 Weaknesses of the SolNet Model

Limited Dataset Variation: The training dataset's exclusive source from Bangladesh was one of the primary problems found. This lack of geographical diversity could make the model less applicable to other places with different dust characteristics and climate conditions.
Requirement for Dataset Variation: To make the method more reliable and applicable, a more varied dataset including images from various locales and climates is needed. This might improve the model's ability to adapt to different levels of dust and weather.
Possibility of Further Trainable Parameter Reduction: Even when there are fewer trainable parameters, the model can still be optimized. The model's efficiency would increase with even fewer parameters, as this would probably lead to even higher accuracy and less processing complexity.

3.7 Consequences of the Study

The findings of the study will have a big influence on the solar energy industry. Power companies may act quickly to reduce energy loss and increase overall system efficiency when dust builds up on solar panels, which are easily identifiable. The SolNet model's exceptional precision makes it an effective means for maintaining solar panels, particularly in regions where dust collection is a significant issue.

3.8 Summary

The SolNet CNN model, created by Saif et al. [139], was examined in this chapter. It is specifically designed for dust detection on solar panels. Panels are classified as clean or dirty using eight convolutional and pooling layers and three fully connected layers in this model. SolNet is designed to achieve 98.2% accuracy with 56 million trainable parameters. It gives superior results than pre-trained models such as ResNet50, InceptionV3, AlexNet, and VGG16 for dust recognition tasks. Moreover, SolNet incorporates techniques to decrease overfitting and improve training efficiency.

3.9 Transition to the Next Chapter

The findings of this study demonstrate how important it is to increase the accuracy and computational efficiency of dust detection on solar panels. In the upcoming chapter, we will introduce our new Custom RjNet model, which is designed to improve accuracy while reducing the number of trainable parameters, our model will focus on enhancing both performance and efficiency for real-world applications.

CHAPTER 4

RJNET: A NEW CNN MODEL FOR DUST DETECTION

4.1 Overview

This chapter introduces a novel RjNet model, which uses machine learning and deep learning techniques to detect dust buildup on solar panels. This study aims to enhance the efficiency of solar panels, develop a cleaner and safer environment, and help to reduce the impact of climate change. As seen in Figure 4.1, the research methodology comprises different stages that are explained under the headings of research methodology. Then the processes are detailed, as well as the proposed RjNet model.

4.2 Research Methodology

As illustrated in Figure 4.1, the research methodology consists of four steps: the first is the selection and definition of the problem, which is completed by moving over the methods that have already been used for gap identification and dust detection on solar panels in Chapters 1 and 3. The second step describes the design and development of the proposed (RjNet) CNN-based model. The third step goes into detail about the analysis of results in the form of tables and graphs, and the comparison of the RjNet model with pre-trained CNN-based models that have already been developed. Step four presents the conclusions of this research and suggestions for future work.

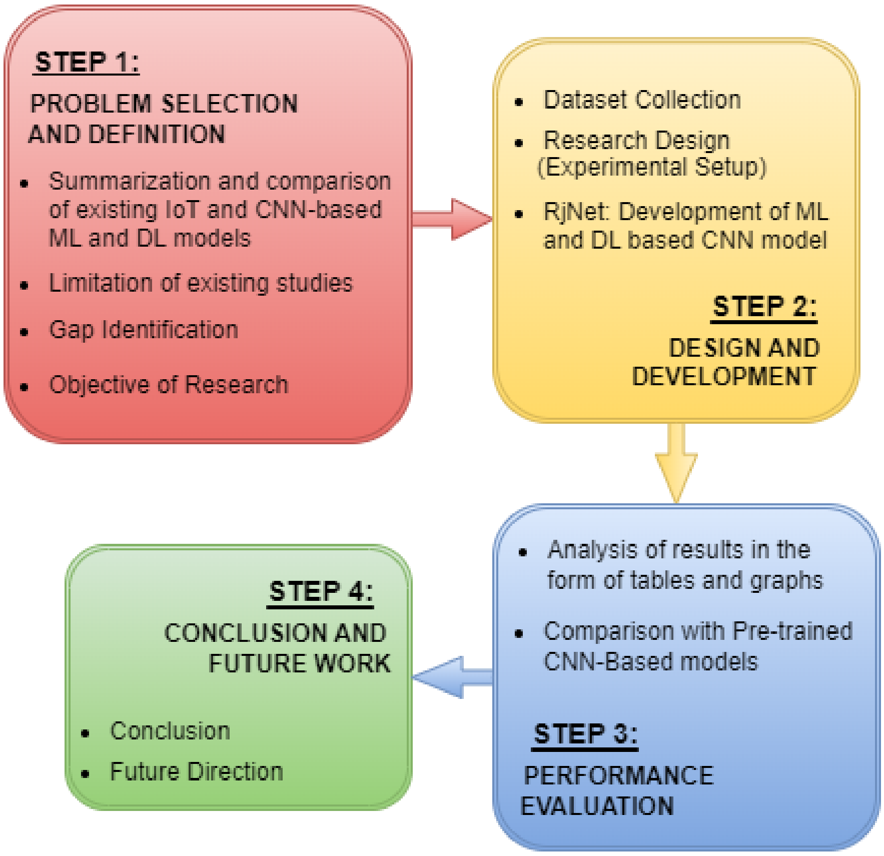


Figure 4.1: Research Methodology

4.3 Background and Motivation

The buildup of dust on solar panels significantly reduces their efficiency, which lowers their power output. This decrease in efficiency has a direct impact on the amount of electricity generated, which minimizes the potential benefits of solar energy. Therefore, to retain maximum performance and offer timely cleaning, it is imperative to create reliable dust-detecting methods. Numerous methods have been put out for detecting dust on solar panels, but many of them are costly, computationally intensive, and offer insufficient precision. These methods include infrared imaging, sensor-based systems, and the most recent developments in artificial intelligence (AI) and deep learning.

This endeavor aims to create a convolutional neural network (CNN) model that maximizes accuracy while using the fewest trainable parameters. This approach is essential to guaranteeing the sustainability of solar energy generation and optimizing the efficiency of solar panels.

4.4 Problem Statement

Dust on solar panels can lower the generation of electricity by up to 50%, especially in areas with heavy air pollution and frequent dust storms. To maintain optimal performance, efficient monitoring is necessary [224].

The advancement of computer vision algorithms recently for solar panel inspection emphasizes the need for automated dust detection to minimize labor costs and human error. These methods provide trustworthy dust detection systems by balancing usability and efficacy [225].

In this work, we present the RjNet model, a low-cost computational technique for detecting dust on solar panels based on convolutional neural networks (CNNs). This idea aims to reduce reliance on fossil fuels, which are expensive and a primary contributor to global warming, while simultaneously increasing the productivity of solar energy systems. The RjNet model's objective is to optimize feature selection and produce useful maintenance data by accounting for significant environmental factors like location and weather. Through the use of this paradigm, we want to make solar systems more resource-efficient and contribute to a more sustainable power future.

4.5 Objectives of Study

I. To increase the model's ability to forecast dust collection in a variety of scenarios, provide an extensive dataset that includes environmental factors like location, humidity, and panel alignment.

II. Create the RjNet model to surpass existing CNN-based pre-trained models for solar panel dust detection in terms of accuracy.

III. To increase RjNet's computational efficiency, reduce the model's complexity (number of trainable parameters). The model will become more scalable and lighter as a result.

4.5.1 Contribution of the Research

This work makes major contributions to the field of solar energy maintenance by tackling the essential issue of dust accumulation on solar panels, which reduces efficiency. This research offers enough groundwork for understanding and predicting dust buildup through the development of a sizable dataset that incorporates environmental factors including location, weather, panel orientation, and maintenance procedures. By adding these variables, the RjNet model's ability to forecast dust is improved, increasing its usefulness in practical situations.

The study specifically optimizes the RjNet model for accuracy and processing efficiency. The study finds a compromise between minimal computational needs and good prediction accuracy by employing complex data preparation techniques, streamlining models, and improving feature selection. It is especially important for deployment in contexts with restricted computing resources since this method paves the way for future machine-learning applications in similar circumstances.

The study also compares the RjNet model to CNN models that have already been trained, concentrating on two key areas: accuracy and computational complexity, namely the number of parameters that can be presented. This comparison sheds light on the advantages and disadvantages of pre-trained and custom models.

Finally, real-world validation of the RjNet model demonstrates its effectiveness and dependability, which helps to better maintenance plans for solar energy systems and ensures increased performance and longevity of solar panels.

4.6 Gap Identification

While good progress has been achieved in the field of image-based dust detection on solar panels utilizing various CNN architectures, numerous gaps remain, which this research intends to address:

Accuracy against Computational Efficiency: While some existing models, such as VGG16, and ResNet50, exhibit great accuracy, they come at a significant computational cost. These models are not as well suited for deployment in real-time applications or situations with limited resources since they need a lot of trainable parameters. On the other hand, models like MobileNetV2 and InceptionV3, which prioritize efficiency, often compromise accuracy.

Environmental Factors: A lot of the research being done now ignores the important environmental factors that have a big impact on dust collection on solar panels, like location, weather, panel orientation, and maintenance procedures. This omission reduces the models' capacity for prediction and their suitability for use in practical situations

Diversity and Quality of Datasets: A large number of currently available datasets, which are used to train and validate dust detection models, are not diverse enough about geographical variability and environmental variables. This may result in models that work effectively in confined or specialized domains but not well in other contexts.

Comparative Analysis and Benchmarking: There is a scarcity of detailed comparative assessments that compare custom models to cutting-edge pre-trained models in terms of accuracy and computing efficiency. These kinds of comparisons are essential for comprehending the trade-offs and determining the most workable solutions for actual applications.

Practical Validation: The effectiveness and dependability of many models are not practically validated since they have not been put through a rigorous trial in real-world settings. Testing in the real world, it is essential to make sure the models can manage a variety of dynamic environmental circumstances.

This study aims to establish a highly accurate and computationally efficient approach to dust detection on solar panels by resolving these limitations. To improve prediction accuracy and generalizability, the suggested RjNet model takes into account important environmental aspects and makes use of a wide dataset. Furthermore, this study conducts a detailed comparative analysis with cutting-edge models, providing vital insights into the optimal balance of accuracy and computing efficiency. Lastly, the RjNet model's efficacy and dependability will be practically validated in real-world scenarios, which will enhance maintenance plans for solar energy installations.

4.7 Research Design and Development

The research design requires proper planning. To Solve the problem of detecting dust on solar panels with high predicting accuracy and with less computational cost by developing a diverse dataset and CNN-based model namely RjNet. Then, data preprocessing is used to eliminate inconsistencies in the data, and categorical data is converted into numerical data by using one hot encoding technique. Moreover, feature selection, data normalization, and training-testing data splitting are also applied. The performance of the proposed model is improved by picking the best hyperparameters using hyperparameter tweaking.

4.8 Experimental Setup

The experimental setup details the processes and resources employed in the research. It delves into dataset collection and preparation, explaining how to obtain and prepare data for statistical analysis. The next section describes the techniques for data augmentation that were used to improve the dataset. The CNN architecture known as RjNet: Proposed Model is introduced in this section. Lastly, it discusses the setups, tools, and training environment used in the model-building and evaluation process. The whole testing and training process for the RjNet model is shown in Figure 4.2.

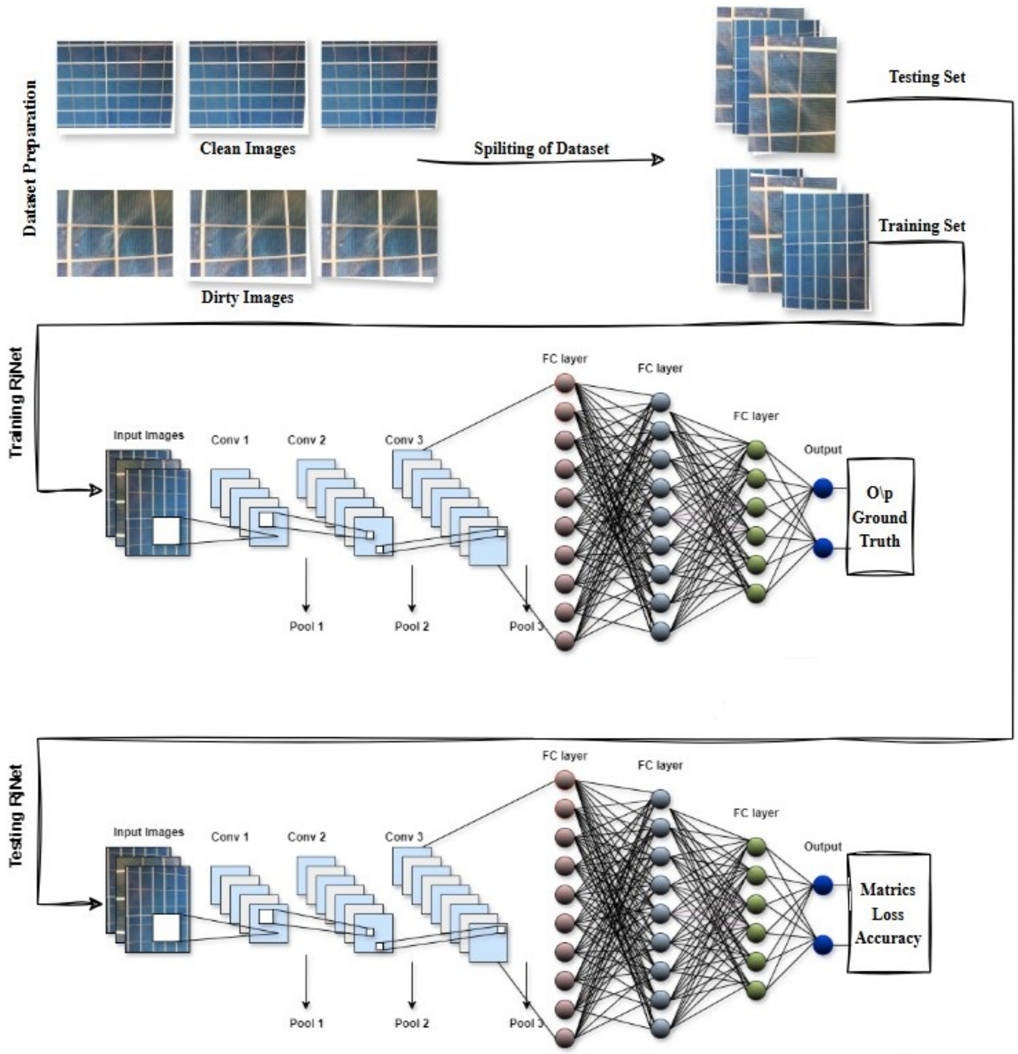


Figure 4.2: Workflow of Proposed Model.

4.8.1 Dataset Collection and Preprocessing

The collection consists of 1566 RGB images of solar panels that were obtained from Kaggle and different parts of Pakistan. These datasets show a diversity of orientations and environmental circumstances. There are 787 images of dusty panels and 779 images of clean panels. This dataset, which captures the many environmental effects on solar panels in various locations and weather conditions, offers a strong basis for training and evaluating the dust detection algorithm.

Table 4.1: Dataset Overview for Solar Panel Dust Detection

Category	Count
Total Images	1566
Clean Solar Panels	779
Dirty Solar Panels	787
Environmental Conditions	Diverse (e.g., weather and orientations)
Image Type	RGB

4.8.2 Data Augmentation Techniques

Many techniques for data augmentation were used in the development of the RjNet model for dust monitoring on solar panels, which improved the model's resilience and ability to generalize. By using these techniques, we were able to overcome the dataset size restriction and improve the model's performance in a range of environmental scenarios.

Applied Augmentation:

In this work, data augmentation was carried out using the Image Data Generator class in Keras, resulting in improved images that were produced in real-time throughout the training phase. The following transformations were applied:

- **Rotation Range**: To display different object views, images were randomly rotated by up to 30 degrees.
- **Width and Height Shifts**: Images were subjected to random adjustments up to 30% of their height and width in both the horizontal and vertical directions, producing a range of object placements.
- **Shear Transformation**: To allow the model to detect items in multiple geometrical orientations, slanted duplicates of the images with a shear range of 0.3 were produced.
- **Zoom Range**: The model learned from both zoomed-in and zoomed-out images, enhancing its capacity to identify objects at various sizes by employing a zoom range of 0.3.

- **Horizontal Flip**: The generation of mirror images by horizontal flipping is highly advantageous for image classification applications requiring symmetric objects, which were applied.
- **Fill Mode**: Once modifications were made, the fill_mode='nearest' option was used to fill in any newly created pixels with the closest pixel value.

The implementation of data augmentation techniques has led to enhanced precision and stability for the RjNet model, rendering it a viable option for dust identification on solar panels.

4.8.3 RjNet: Proposed Model

In this study, a unique CNN-based architecture called RjNet is presented, which is intended to distinguish between clean and dusty solar panels. The architecture consists of three convolutional layers, three pooling layers, and three dense layers. This approach aims to achieve high dust detection accuracy at reduced processing costs by reducing the number of trainable parameters. The model was designed to process input images and has 128×128 pixel dimensions. To preserve every detail, the images were first captured in an arbitrary format. Finally, the square-shaped images in the dataset can certainly be used with any kind of neural network after being reshaped. This made it possible to test models using our dataset that had various input shape variations. Figure 4.3 displays some labeled images of the dataset.

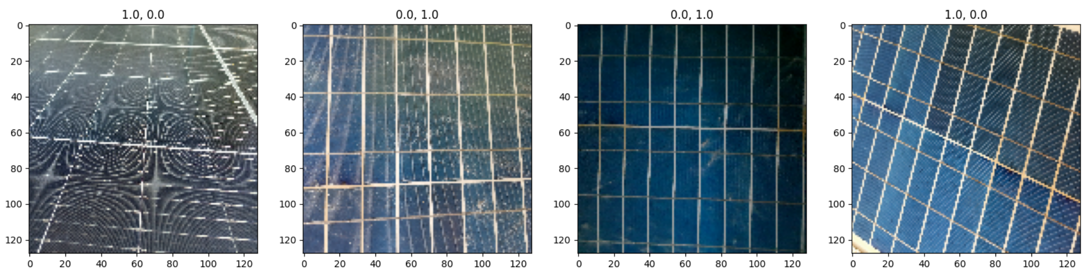


Figure 4.3: Images of Clean and Dusty Solar Panels from the Dataset.

Following the input layer, the architecture consists of convolutional and pooling layers. Each convolutional layer is followed by a batch normalization layer, which normalizes the previous layer's activations to enable faster and more stable training by decreasing internal covariate shifts. This normalization improves parallel processing capabilities and reduces the number of required training epochs, considerably accelerating the training process. The data is flattened after passing through the convolutional and pooling layers before being input into the dense layers. The last dense layer employs a sigmoid activation function to produce a binary classification result indicating whether the solar panel is clean or dusty.

The RjNet architecture is meticulously crafted to optimize both performance and efficiency. Convolutional layers extract hierarchical features from the input images while pooling layers decrease spatial dimensions and lessen computational demands. Batch normalization improves training efficiency and stability. The dense layers at the network's end combine the extracted features to produce the final classification decision.

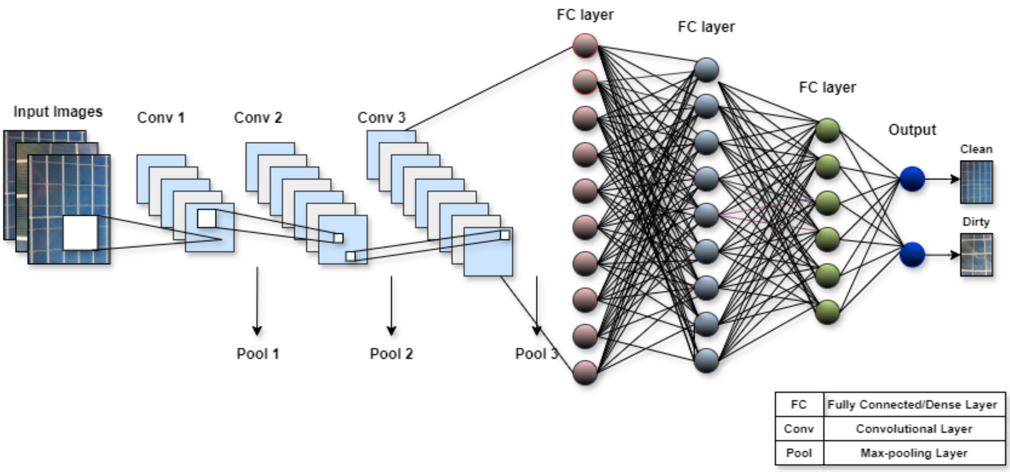


Figure 4.4: RjNet: Architecture.

A model's complexity is mostly determined by the amount of trainable parameters. This comprises all of the neurons that are utilized to create the layer-to-layer connection. A dense layer with input and output nodes m and n will have $(n+1)\times m$ trainable parameters. Convolutional layers are built with p and q as inputs and outputs. Upon including a filter of size $i\times j$, the resultant feature maps contain trainable parameters totaling $((i\times j\times p)+1)\times q$. For our suggested RjNet architecture, the computations provide a total of 2.14 million trainable parameters.

The model's performance was optimized using a loss function for binary classification applications. Following equation

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{4.1}$$

describes the sigmoid function, that is characterized by its S-shaped curve. This function is widely utilized in a variety of domains, most notably in machine learning as the activation function in neural networks, where it translates every real-valued integer to a range of 0 to 1, thus converting outputs into probabilities [226]. Equation 4.2,

$$\sigma_h(z) = \max(0, z) \tag{4.2}$$

specifies the rectified linear unit (ReLU) activation function, which is essential for modern deep learning architectures. ReLU is used because it is computationally efficient and can alleviate the vanishing gradient issue [227]. Here is equation, 4.3

$$\text{class} = \arg\max[\sigma\left(\mathbf{W}_i^\top \times \phi(\mathbf{X}_j) + b^i\right)] \tag{4.3}$$

represents the output of a neural network. The model predicts the class label by applying an activation function σ to the weighted sum of inputs modified by a feature extraction function ϕ. This formulation is essential for classification tasks of this work because it allows the network to transfer input data to discrete categories by choosing the class from the output layer that has the highest probability. The application of weights W_i and biases b_i enables learned representations that increase prediction accuracy through backpropagation training [228]. Given Equation 4.4,

$$\text{loss} = \frac{1}{N}\sum_{i=1}^{N} -\{y_i \times \log(P_i) + (1-y_i) \times \log(1-P_i)\} \tag{4.4}$$

represents the binary cross-entropy loss function, which was used for evaluating how well binary classification models perform. By calculating the difference between the true labels y_i and the predicted probabilities P_i, the loss function effectively quantifies the degree to which the model's predictions match the actual results. It is essential to train neural networks to improve model accuracy throughout the learning process. It achieves this by directing optimization by severely penalizing incorrect predictions [229].

4.8.4 Training Environment, Tools and Settings

The RjNet operates as a function dependent on biases and weights that are adjusted throughout the training phase. The algorithm requires two types of input: the dataset and the hyperparameters, which can be modified before training. During training, the weights are refined as errors are minimized through forward and backward propagation. Hyperparameters are essential for training models; while they are typically set via experimentation, well-established methods from previous studies are also taken into consideration. The training environment is shown in the following table.

Table 4.2: Summary of the Training Process and Key Hyperparameters

Environment	Value
Hardware	GPU, Intel Core i7
Operating system	Windows 11
Programming Language	Python 3.12.0
Deep Learning Framework	TensorFlow 2.17.0
IDE	Google Colab
Training Dataset	Custom Dataset of solar panel images
Batch Size	32
Learning Rate	0.0001
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Number of Epochs	30
Early Stopping	Applied
Total Dataset	1566 RGB Images
Validation Method	80-20 Train-Test Split
Data Augmentation Methods	Applied
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score

4.9 Selection Criteria for Pre-trained CNN Models

There are a few important factors to consider when selecting pre-trained models to evaluate the RjNet architecture. Based on the model's performance on image classification tasks including ResNet50, InceptionV3, VGG16, and MobileNetV2, its design efficacy needs to be widely recognized. Models that demonstrate greater accuracy on common datasets like ImageNet are considered reliable performance benchmarks. Furthermore, computational efficiency is crucial; real-time processing necessitates rapid inference abilities; and efficient models with fewer trainable parameters are preferred.

Pre-trained weights facilitate transfer learning, while the model's data sources and deep learning framework integration enable adaption. Evaluation of scalability and requirements for hardware is also crucial to ensure the model can handle increasing amounts of datasets. These components work together to allow for a thorough comparison between the recommended model (RjNet) and the pre-trained models.

4.10 Experimental Results

This section presents a performance comparison between our proposed RjNet model and the pre-trained models (VGG16, InceptionV3, ResNet50, and MobileNetV2). By using bar graphs to display each model's accuracy, precision, recall, and f1-score, the superiority of the RjNet model is demonstrated. A tabular comparison is also provided to provide a comprehensive examination of the performance metrics for each model.

4.10.1 VGG16

Simonyan et al. [198] proposed the VGG16 convolutional neural network model in 2014. It has a 16-layer structure, 3×3 convolutional layers, and a default input image size of 224×224 pixels. The VGG16 model achieved 92.357% accuracy on our dataset by utilizing 21.14 million trainable parameters. By changing the last classification layer, the pre-trained VGG16 model was tuned to anticipate dust deposition on solar panels. This change increased its effectiveness in the dust-detecting task.

4.10.2 InceptionV3

Google presented the Inception architecture, a revolutionary convolutional neural network (CNN) built as a layered feature extractor. Within the same module, this architecture executes numerous feature extractions using different filter sizes and parallel convolutional layers. The 22-layer Inception approach utilizes all learned filters, creating sparse structures that reduce computational costs. Szegedy et al. [200] developed the InceptionV3 CNN architecture, which achieved an accuracy of 54.94% on our dataset with 23.854 million parameters. InceptionV3 processes input images at a resolution of 229×229 pixels using three color channels, allowing it to capture detailed features across different scales.

4.10.3 ResNet50

Kaiming et al. [202] developed the Residual Neural Network (ResNet50), which enhances neural network architecture through the use of skip connections and shortcuts that bypass certain layers. This design avoids non-linearity and batch normalization issues. The skip connections simplify the network, particularly in the early stages of training, by using fewer layers. In our study, the ResNet model, comprising 50 layers and 25.451 million trainable parameters, achieved an accuracy of 72.66%. The network was trained with input images of size $224 \times 224 \times 3$, representing three color channels.

4.10.4 MobileNetV2

An improved MobileNetV2 architecture, presented by Sandler et. al [204], reached an accuracy of 51.39% in image classification tasks with 2.422 million parameters. The main modifications involved using separable convolutions instead of depthwise separable convolutions, incorporating drop-activation, and applying random erasing regularization. The model processed $224 \times 224 \times 3$ dimensions of input images. However, the architecture did not achieve high accuracy, only attaining 51.39%.

4.11 Analyzing of Results

In the following sections, we will examine and compare the performance of our proposed model to several pre-trained CNN models. We seek to illustrate the efficacy of our model in comparison to existing architectures by assessing important metrics including accuracy, precision, recall, f1-score, and computational cost. This comparison analysis will reveal the strengths and limitations of each approach, thereby proving the robustness of our solution.

4.11.1 Accuracy

Accuracy is defined as the ratio of correctly classified records to total records. Machine Learning and Deep Learning models are regarded as superior in terms of accuracy.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.5}$$

The accuracy is evaluated on the datasets used for testing and training. The proposed RjNet model outperformed the other models, achieving 99.325% accuracy on the training dataset and 99.218% on the testing dataset. VGG16 had the second-greatest accuracy on the training and testing datasets showing 92.66% and 92.35%, respectively.

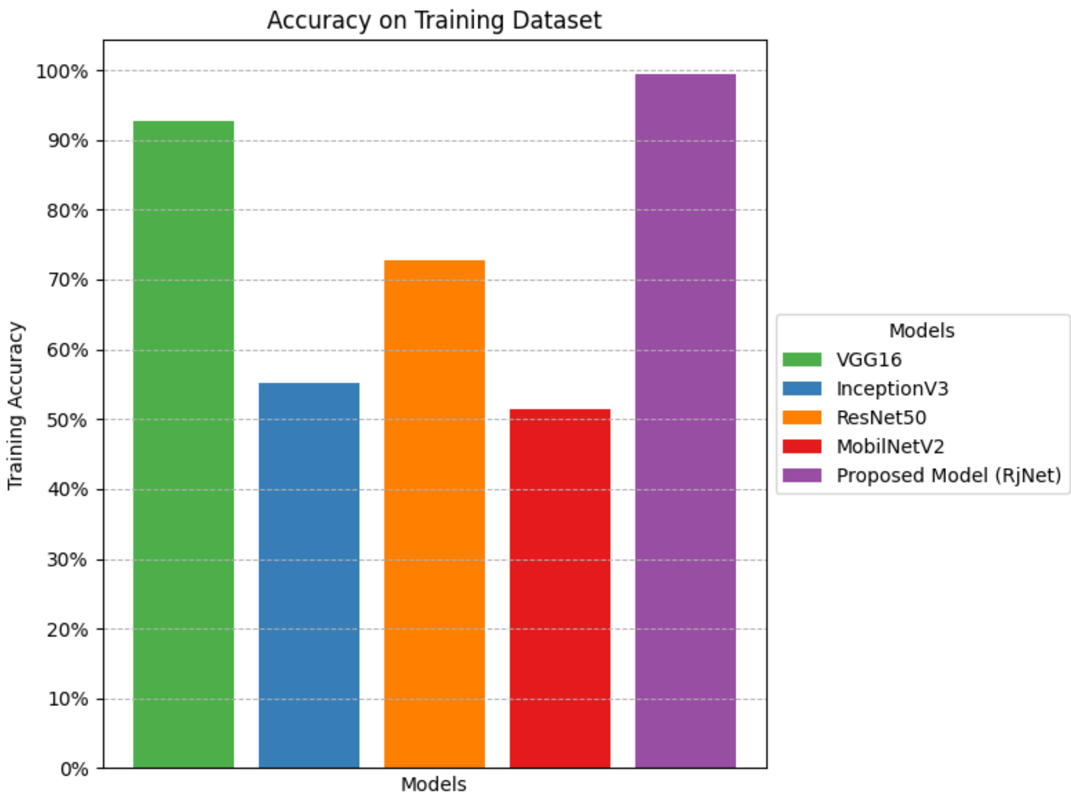


Figure 4.5: Accuracy of Models on Training Dataset

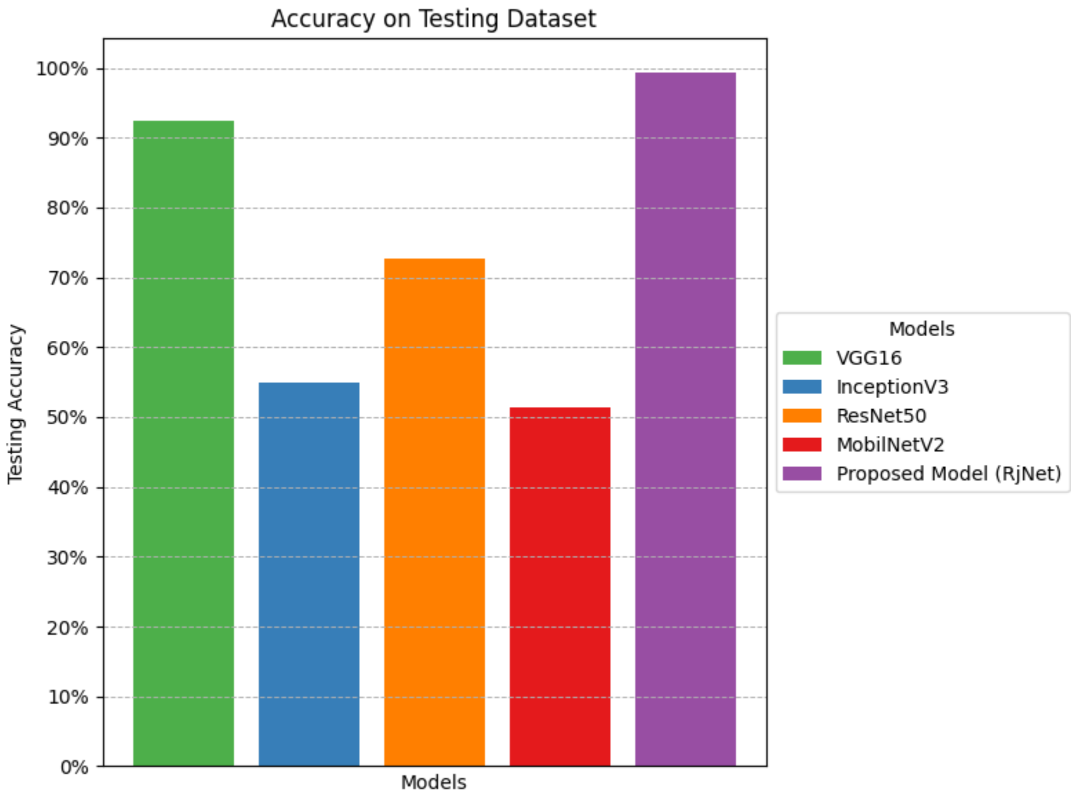


Figure 4.6: Accuracy of Models on Testing Dataset

4.11.2 Precision

The precision ratio is calculated by dividing the number of correctly categorized solar panels by the total number of classified solar energy panels.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4.6}$$

The proposed model achieved 99.217% precision on the testing dataset and 99.319% precision on the training dataset, as illustrated in Fig 4.7 and Fig 4.8.

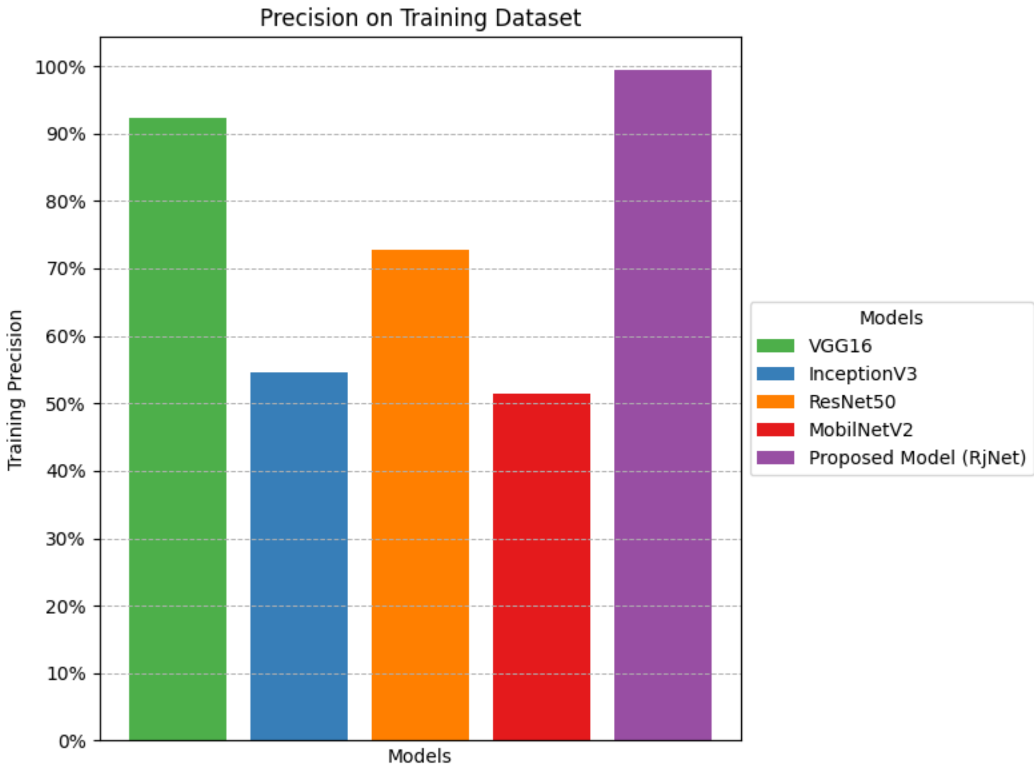


Figure 4.7: Precision of Models on Training Dataset

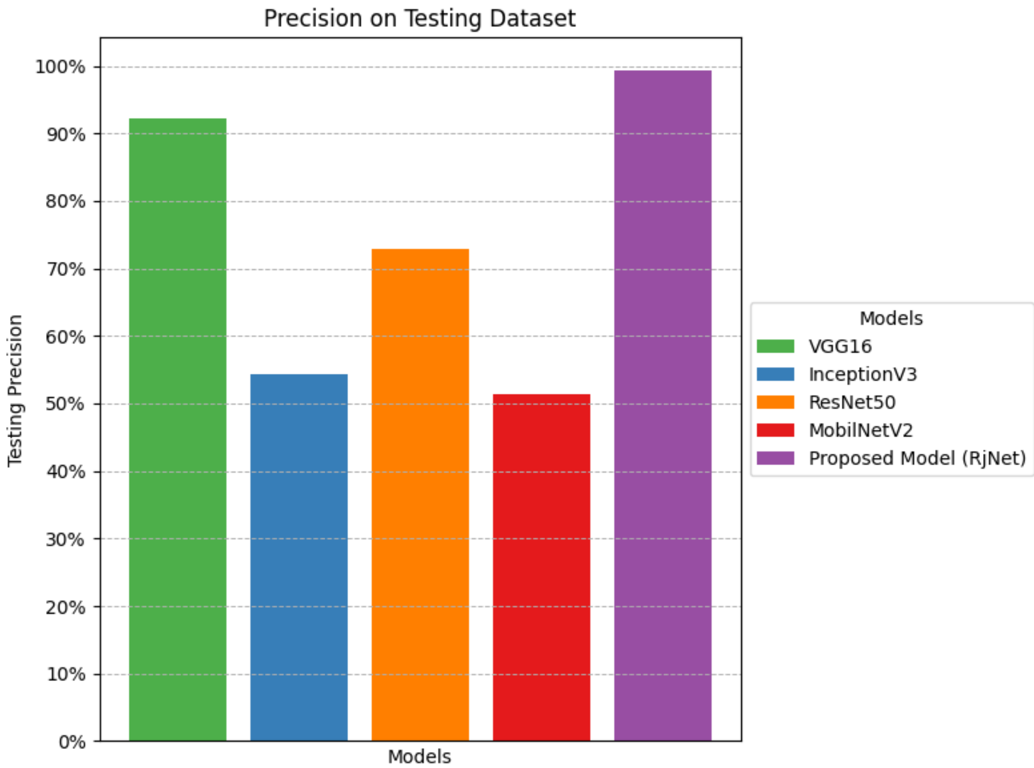


Figure 4.8: Precision of Models on Testing Dataset

4.11.3 Recall

Recall is described as the ratio of true to positive and the total of true positive to false negative.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4.7}$$

The recall of the RjNet model is 99.325% for the training dataset and 99.218% for the testing dataset. However, VGG16 has the second-highest recall score for training and dataset, 92.96%, and 92.67% for testing.

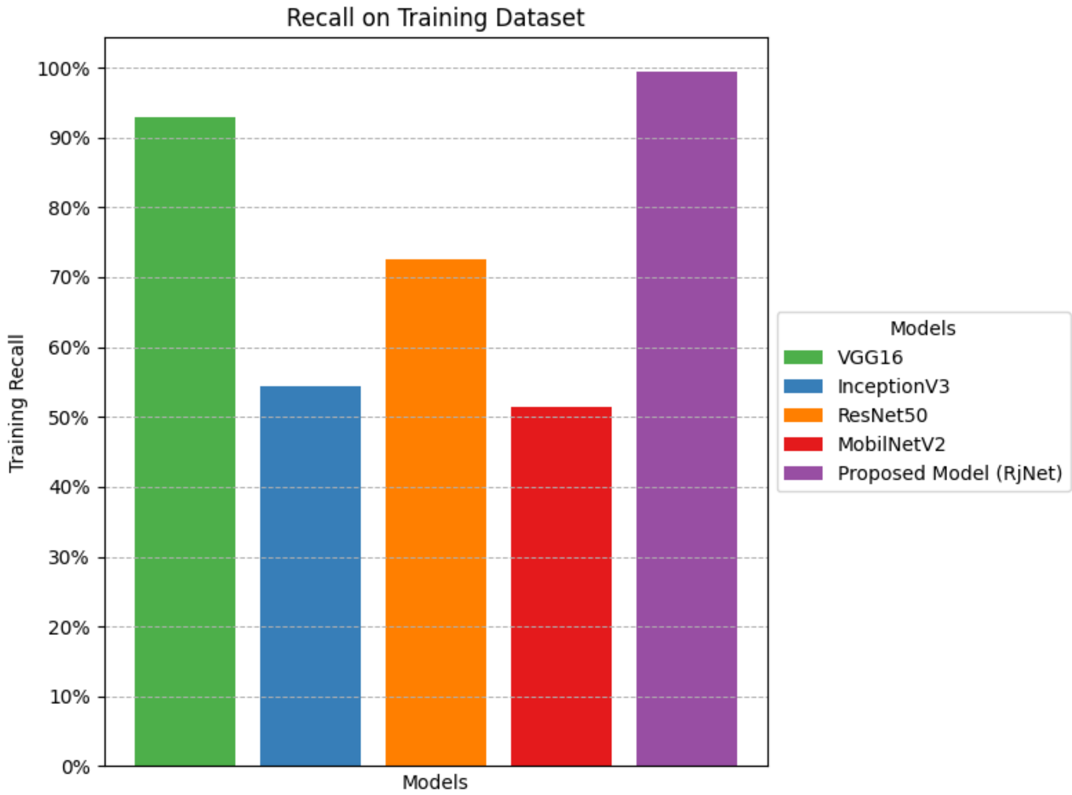


Figure 4.9: Recall of Models on Training Dataset

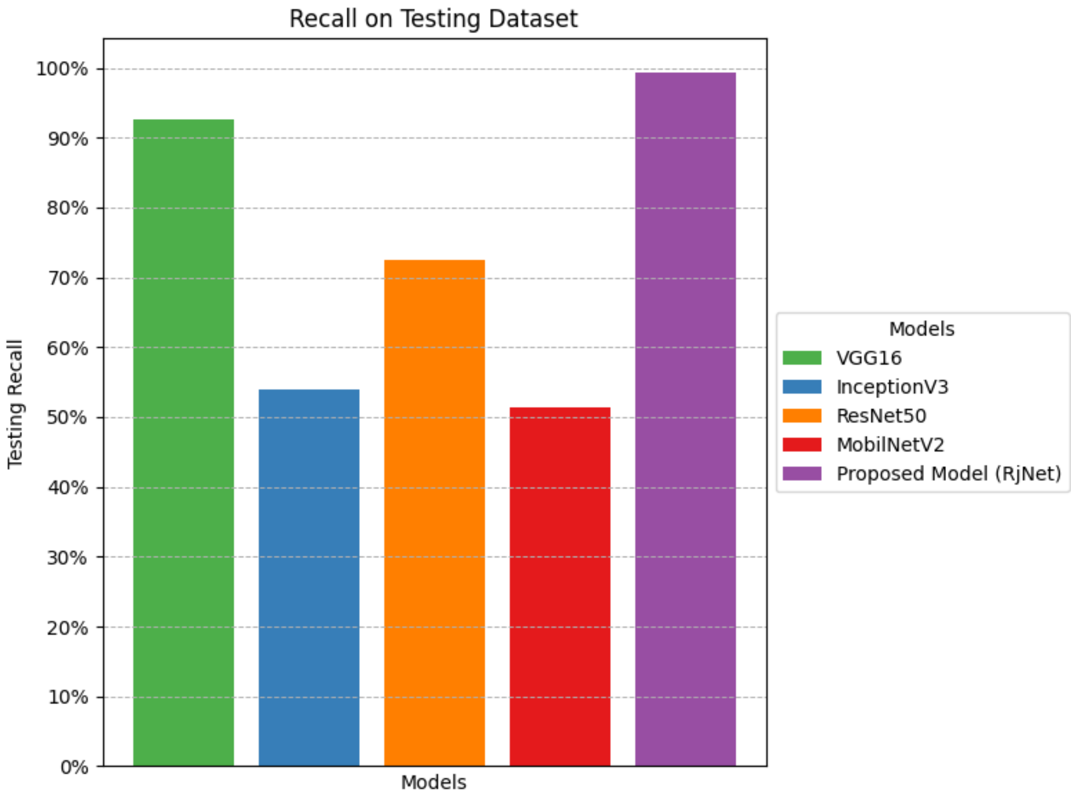


Figure 4.10: Recall of Models on Testing Dataset

4.11.4 F1-Score

The F1-score is the weighted mean of recall and precision.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4.8}$$

The proposed model achieved the F1-Scores of 99.327% for training and 99.219% for testing datasets.

Figure 4.11: F1-score of Models on Training Dataset

Figure 4.12: F1-score of Models on Testing Dataset

4.11.5 Loss

The loss graph compares the performance of multiple CNN models, including VGG16, InceptionV3, ResNet50, MobileNetV2, and the proposed RjNet model, according to their loss values on the testing dataset. The proposed model, RjNet, has a significantly lower loss (0.0261) than the other models, indicating better performance and more accurate predictions.

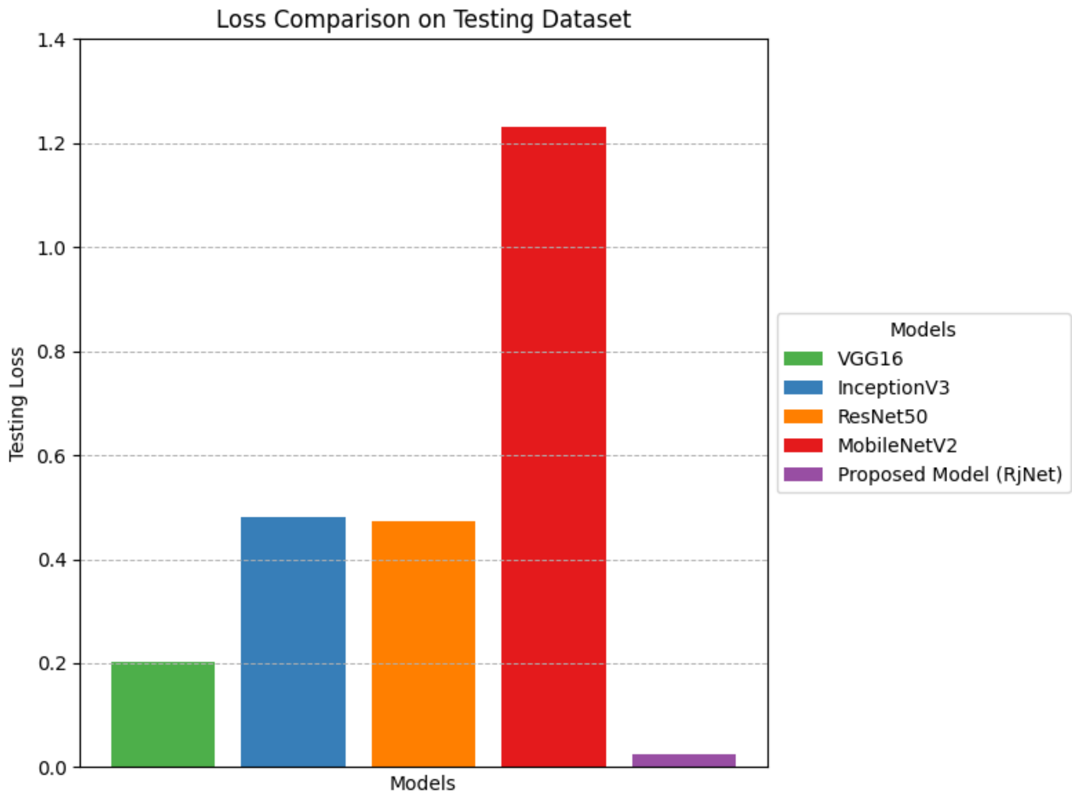


Figure 4.13: Loss of Models on Testing Dataset

Performance is evaluated using both the training and testing datasets. The training dataset performance demonstrates how the model performed on the training dataset, whereas the testing dataset performance demonstrates how the model performed on the test dataset. Tables 4.3 and 4.4 display a comparison of the model's performance on training and testing datasets, respectively.

Table 4.3: Training Performance of Models.

Model	Training Accuracy (%)	Training Precision (%)	Training Recall (%)	Training F1-Score (%)
VGG16	92.66	92.36	92.96	92.67
InceptionV3	55.14	54.53	54.44	54.97
ResNet50	72.85	72.77	72.56	72.68
MobilNetV2	51.48	51.39	51.48	51.53
RjNet	99.325	99.319	99.325	99.327

Table 4.4: Testing Performance of Models.

Model	Testing Accuracy (%)	Testing Precision (%)	Testing Recall (%)	Testing F1-Score (%)
VGG16	92.35	92.12	92.67	92.56
InceptionV3	54.94	54.26	53.99	54.96
ResNet50	72.66	72.84	72.54	72.58
MobilNetV2	51.39	51.38	51.39	51.41
RjNet	99.218	99.217	99.218	99.219

4.11.6 Difference Between Training and Testing Performance of RjNet Model

A comparison of the training and testing performance of our proposed (RjNet) model is presented in Table 4.5. The suggested model is generalized and resolves the problems of overfitting and underfitting because of minimal differences between training and test scores.

Table 4.5: Difference Between Training and Testing Performance of RjNet.

Model	Accuracy	Precision	Recall	F1-Score
Proposed Model (RjNet)	0.107	0.102	0.107	0.108

4.11.7 Confusion Matrix of RjNet

The confusion matrix demonstrates the effectiveness of the classification model with a high accuracy of 99.218%. The model correctly identified 99.2% of solar panels as clean, misclassifying the remaining 0.8% as dirty. Similarly, 99.1% of dirty panels were predicted correctly, whereas 0.9% were incorrectly classified as clean. This minimal error demonstrates the model's great prediction ability to distinguish between clean and dirty solar panels, showing its potential application in real-world scenarios where correct classification is critical for optimizing solar panel maintenance.

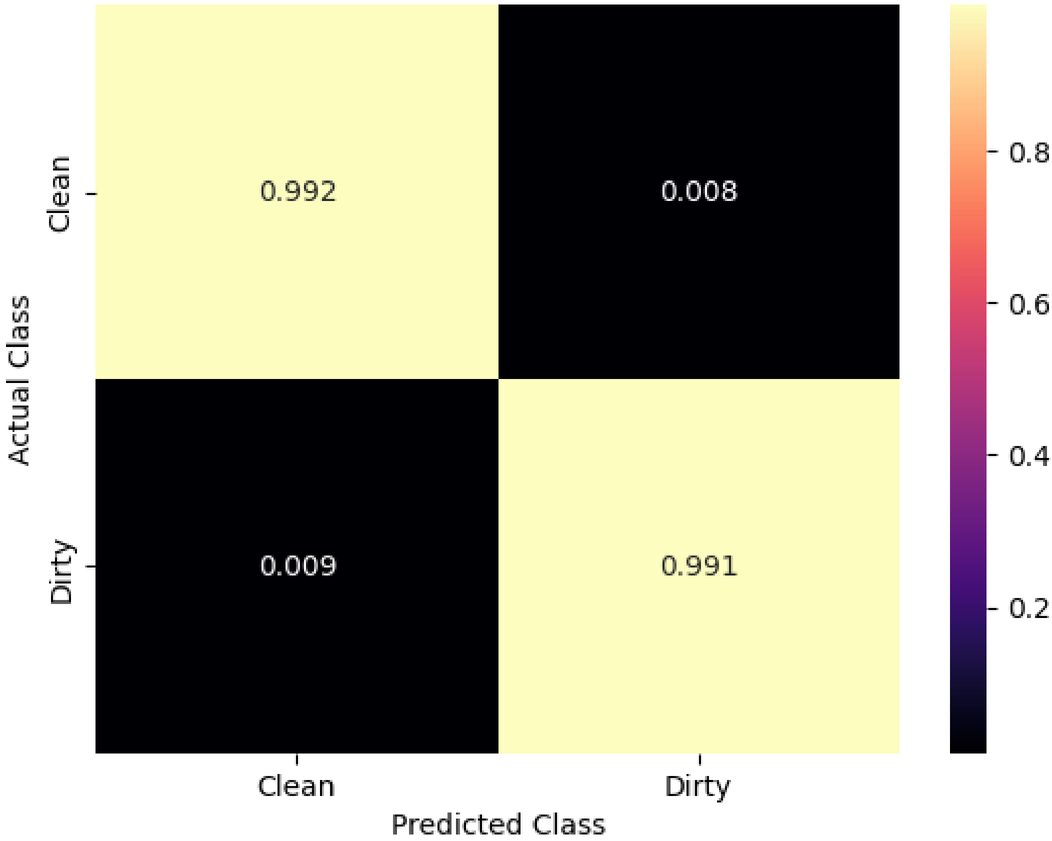


Figure 4.14: Confusion Matrix

4.11.8 Graphically Representation of Accuracy of RjNet Model

The presented accuracy graph represents the performance of a model over 30 epochs of training and validation. The training accuracy of the model (blue line) initially rises quickly, getting close to 100% in the first few epochs. However, the model's performance on unseen data is measured by the validation accuracy (yellow line), which starts quite low and continues to rise dramatically after epoch 5. By epoch 15, the validation accuracy has stabilized and is approximately aligned with the training accuracy, showing that the model is learning and generalizing well. Starting with epoch 15, the model's training and validation accuracy consistently remain nearly 100%, indicating that it has achieved peak performance with minimal overfitting. The consistent alignment of both accuracies indicates a strong model that performs well on both the training and testing datasets.

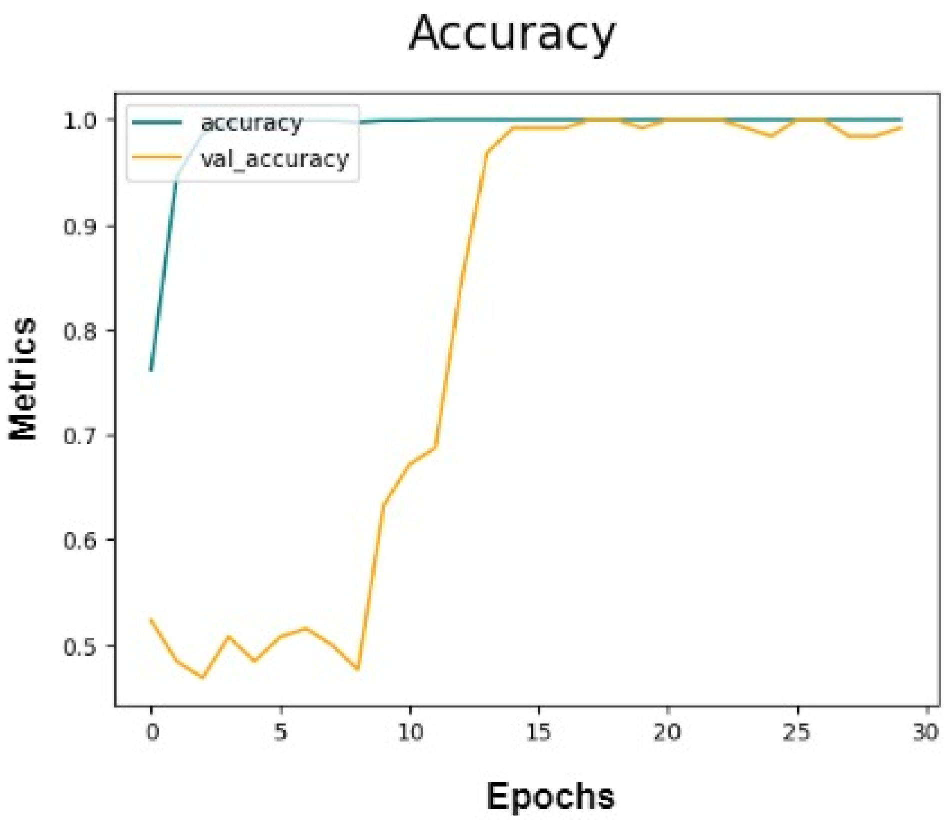


Figure 4.15: Accuracy Graph

4.11.9 Graphically Representation of Loss of RjNet Model

Figure 4.16 illustrates a graph of a model's training and validation loss over 30 epochs. Initially, both losses are significant, with the training loss reducing rapidly as the model learns. Early in the epoch, the validation loss marginally increases; but, by the 10th epoch, it begins decreasing and approaches the training loss. This suggests that the model consistently performs better than the validation and training sets. The fact that both losses get close to zero after the 15th epoch indicates that the model has successfully trained and achieved peak performance across all data sets.

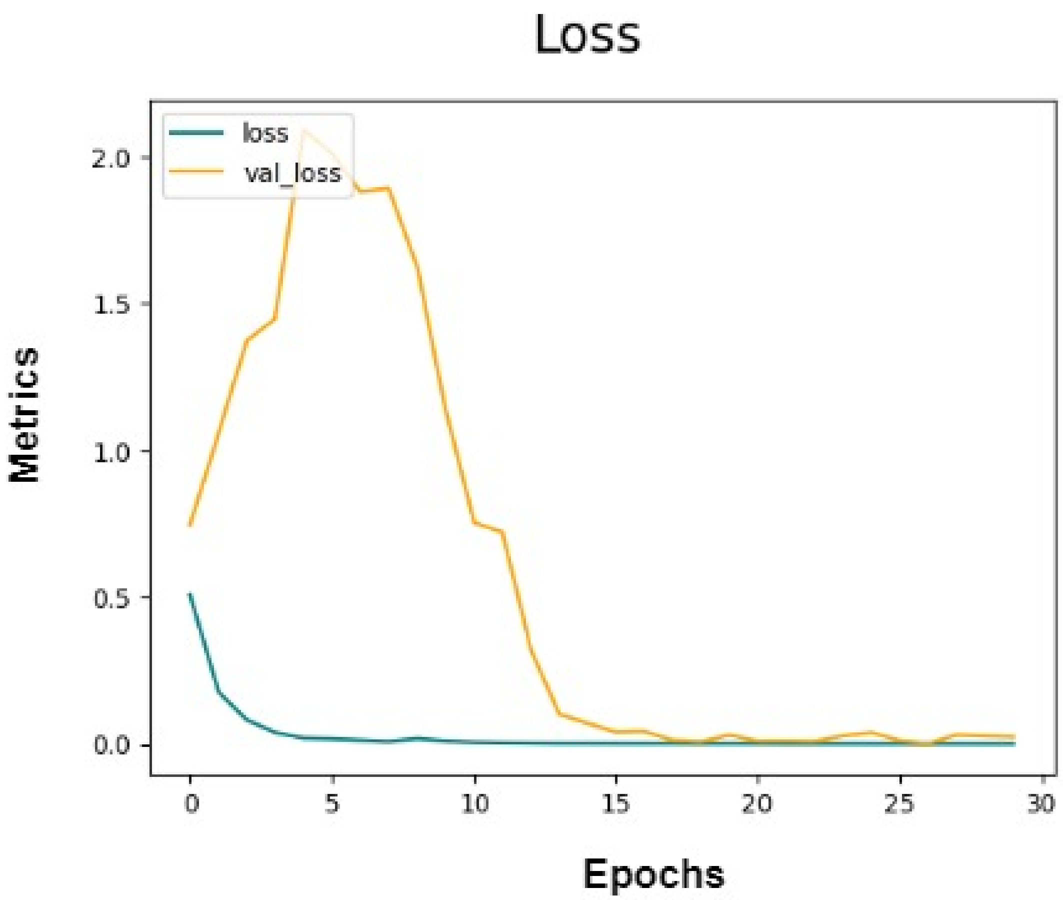


Figure 4.16: Loss Graph

4.12 Comparison of Computational Cost

A comparison of the state-of-the-art convolutional neural network, models offers important information on the trade-offs between computational complexity and accuracy. Compared to other models, RjNet provides excellent predictions at low computational cost, which makes it especially useful in scenarios with limited resources and real-time applications. Fewer trainable parameters further strengthen the RjNet model as the best option for dust detection on solar panels by reducing the risk of overfitting and underfitting and resulting in quicker training periods. Table 4.6 provides a summary of the comparison of trainable parameters.

Table 4.6: Testing Accuracy Comparison Between RjNet and SOTA Models Using Our Dataset Collection.

Authors	Model	Accuracy	No: of Trainable Parameters
Simonyan et al. [198]	VGG16	92.357%	21.14M
Szegedy et al.[201]	InceptionV3	54.94%	23.854M
Kaiming et al. [202]	ResNet50	72.66%	25.451M
Sandler et al. [204]	MobileNetV2	51.39%	2.422M
Proposed Model	RjNet	99.218%	2.14M

4.13 Discussion

A well-curated dataset is crucial for training any model effectively. In this research, we obtained a dataset of solar panels (clean and dusty) from Kaggle and developed an additional dataset from Pakistan, which was subsequently merged for this study. The dataset's robustness was confirmed by its performance with state-of-the-art (SOTA) models, indicating its suitability for solving additional classification problems using machine learning and deep learning. This dataset was subsequently used to train the proposed RjNet model, which achieved a 99.128% accuracy rate with only 2.14 million trainable parameters. As a result, the RjNet model outperformed SOTA models, including VGG16, Inception V3, ResNet50, and MobileNetV2, in the specified evaluation metrics. Moreover, the RjNet model demonstrated better performance compared to similar studies by other researchers using various datasets. Specifically, it outperformed the CNN LeNet model reported by Maity et al. [133], the AlexNet model developed by Zyout et al. [230], and the SolNet model by Saif et al. [139], which achieved accuracies of 80%, 93.3%, and 98.2%, respectively, in dust detection.

Table 4.6 shows that the RjNet model significantly outperformed the other models regarding accuracy. Additionally, the reduced number of parameters in RjNet compared to many well-known models highlights its lower complexity, which in turn reduces computational demands and training time. Consequently, RjNet achieved higher accuracy with shorter training periods and less complexity. Although MobileNetV2 has fewer parameters and a shorter runtime, however, its accuracy is inferior.

RjNet used early stopping to address overfitting, a typical problem while creating robust models. This technique helps assess the model's performance across different data variations [231]. Figures 4.15 and 4.16 illustrate the accuracy and loss plotted against epochs to determine that 30 epochs were optimal. Adjustments to other hyperparameters were also made to prevent overfitting and underfitting on unseen data.

The RjNet model performs exceptionally well in real-time scenarios because of its efficient design, which minimizes computational complexity and training times. Its streamlined architecture is ideal for applications that require quick and effective results. The model's optimized structure supports high performance and operational speed, making it well-suited for tasks that are both demanding and time-sensitive.

4.14 Summary

This chapter provides a comprehensive performance evaluation of the proposed RjNet model. The evaluation is thoroughly detailed using various metrics. The proposed model demonstrated superior accuracy compared to pre-trained models while requiring fewer computational resources (trainable parameters) for both training and testing datasets.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

The goal of this study is to identify dust on solar photovoltaic panels. As the globe transitions to renewable energy sources to reduce the environmental effects of fossil fuels, solar panel efficiency becomes increasingly important. Additionally, dust accumulation significantly reduces the performance of PV panels. This work addresses this problem by presenting an innovative solution that utilizes deep learning technology. An in-depth analysis of the pros and cons of existing dust detection techniques, such as thermal imaging, Internet of Things sensors, and image processing, exposes several drawbacks, such as expensive maintenance requirements and uneven accuracy. This emphasizes the significance of using more advanced and potent methods. To address these issues, the study uses a dataset of 1566 images of solar power plants (clean and dirty) collected from Kaggle and combined with an additional collection of images of solar panels from Pakistan. We used diverse lighting conditions to make the dataset more complete, allowing the model to perform effectively in a variety of real-world scenarios. To ensure that both categories are well represented, the dataset is rigorously labeled to distinguish between clean and dusty panels.

The main contribution of this study is the development of a unique convolutional neural network model named RjNet, which is meant to detect dust on solar panels. The RjNet architecture consists of three convolutional layers, three pooling layers, and three fully connected layers that have been rigorously tuned to provide the greatest possible combination of processing speed and accuracy. RjNet outperformed state-of-the-art models including VGG16, InceptionV3, ResNet50, and MobileNetV2, as shown by extensive testing on an unseen dataset. RjNet demonstrated remarkable efficacy and usefulness for real-time dust detection on solar power plants, with 99.218% accuracy with just 2.14 million trainable parameters.

This research enhances both the academic and practical aspects of dust detection on solar photovoltaic (PV) panels through deep learning. The RjNet model represents a significant improvement in dust detection by offering a solution that is both highly accurate and computationally efficient. Additionally, this approach supports a seamless shift from detecting dust to initiating the cleaning process, ensuring that solar panels consistently achieve optimal performance.

5.2 Limitations

This study identifies some limitations and challenges that should be addressed in future research. The dataset, which consists of 1,566 RGB images of solar panels, is collected exclusively from various locations in Pakistan and Kaggle, limiting the model's relevance to other regions of the world with different environmental conditions. While the dataset covers some variation in environmental factors and panel orientations, it may not fully account for the broad range of conditions that solar panels experience worldwide. Moreover, the dataset features a nearly balanced number of clean and dirty images (779 clean and 787 dirty), which may not accurately represent the often skewed real-world distributions. This balance could pose difficulties for the model in handling different levels of class imbalance.

5.3 Future Work

Future research should focus on diversifying the dataset for multi-class classification by including images from various global regions and climates, utilizing automated data collection methods such as drones, and incorporating environmental factors such as humidity, wind speed, and pollution levels into the model, as well as addressing class imbalances within the dataset, which will enhance overall performance.

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