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FORECASTING ELECTRICAL POWER GENERATED FROM SOLAR PV SYSTEMS BY INNOVATIVE DL PRINCIPLES

Adnan Salam ABBAS

Master’s Thesis

Supervisor

Asst. Prof. Dr. Sefer KURNAZ

Istanbul, 2023

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The thesis titled FORECASTING ELECTRICAL POWER GENERATED FROM SOLAR PV SYSTEMS BY INNOVATIVE DL PRINCIPLES, prepared by ADNAN SALAM ABBAS and submitted on 20/04/2023 has been **accepted unanimously** for the degree of Master of Science in Computer Engineering.

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I hereby declare that this thesis meets all format and submission requirements of a Master's thesis. Submission date of the thesis to Institute of Graduate Studies: ___/___/___

I hereby declare that all information presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Adnan Salam ABBAS

Signature

DEDICATION

In this thesis, I would like to dedicate my achievement to my nice parents, who have been tremendously encouraging and supportive of my efforts throughout my master's investigations. Furthermore, thanks are extended to my supervisor and the rest of the computer engineering doctors at Altinbas University for their guidance, support, and overall expertise throughout the duration associated with my work in this master's research. When it came to the numerical analysis, my supervisor also gave me a lot of significant advice and assistance.

In addition, I would like to express my great gratitude to every person at Altinbas University who supported and assisted me with my numerical investigations, which were modified and amended based on their experience and help.

ABSTRACT

FORECASTING ELECTRICAL POWER GENERATED FROM SOLAR PV SYSTEMS BY INNOVATIVE DL PRINCIPLES

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This master's research is implemented to examine and explore the significant contributions and substantial relevances of novel DL algorithms in making predictions with considerable effectiveness, accuracy, reliability, and trustworthiness. The work addressed a case study comprising two solar PV systems in India. Datasets were defined, and two performance evaluation approaches were used to examine the accuracy of the three DL models: LSTM, CNN, and LSTM-CNN. The numerical simulations and mathematical analysis in this work revealed that the LSTM, CNN, and hybrid LSTM-CNN models offered higher accuracy in forecasting clean electrical power produced from the two solar PV systems. Nonetheless, the accuracy of the hybrid scheme provided the most significant accuracy rates compared with the first two algorithms. The research findings also indicated that the values of MAE linked to the training of the three algorithms were more considerable than the MAE amounts related to the testing process across all the epoch ranges. Besides, it was found that the MAE connected with training for the three algorithms started at a maximum value. Then, it declines until it reaches a lower value steadily for a more extended epoch range. However, the MAE value after declination was still larger than the MAE rates of the testing process. Further, the numerical outputs confirmed that the RMSE value of the training and testing procedures for the three algorithms had similar behavior to the MAE in forecasting the clean electrical power of the two solar PV systems.

Keywords: Solar Energy, Electricity Production, Forecasting, Accuracy, Performance, Intelligent Algorithms, DL Arinciples.

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ABBREVIATIONS

ANN	:	Artificial Neural Network
BiLSTM	:	Bidirectional LSTM
BiGRU	:	Bidirectional GRU
CNNs	:	Convolutional Neural Networks
CI	:	Computational Intelligence
CSI	:	Clear Sky Index
DL	:	Deep Learning
EMS	:	Energy Management System
ESS	:	Energy Storage System
EVs	:	Electric Vehicles
GHG	:	Greenhouse Gas
GRU	:	Gated Recurrent Unit
GBT	:	Gradient Boosted Trees
GHI	:	Global Horizontal Irradiance
IoT	:	Internet Of Things
LSTM	:	Long Short-Term Memory
MLP	:	Multi-Layer Perceptron
MAPE	:	Mean Absolute Percentage Error
MSF	:	Multistep Forecasting
MAE	:	Mean Absolute Error
NREL	:	National Renewable Energy Laboratory
PV	:	Photovoltaic
PT	:	Portfolio Theory
PSO	:	Particle Swarm Optimization
RNN	:	Recurrent Neural Network
RF	:	Random Forest
RMSE	:	Root-Mean-Square Error Evaluation Metric
SVR	:	Support Vector Regression
SVM	:	Support Vector Machine
WPD	:	Wavelet Packet Decomposition

1. INTRODUCTION

1.1 RESEARCH BACKGROUND

In recent years, the globe witnessed increasing attention regarding the adoption and implementation of different solar Photovoltaic (PV) plants that play a critical role in providing beneficial impacts and positive advantages for humans and the environment, which include the following aspects:

a. Offering a sustainable coverage of heating and cooling energy requirements for small and large-scale requirements,
b. Reducing the significant budget associated with the electrical bill spent for cooling, heating, and other applications, like cooking, and operation of different domestic and industrial appliances,
c. Saving the total annual electrical power consumed in industrial, commercial, and residential buildings,
d. Alleviating air pollution and degradation of nature and the environment due to the broad utilization of fossil fuel resources,
e. Minimizing the Greenhouse Gas (GHG) emissions generated from the use of crude oil, diesel, and other heavy oil resources to operate power plants and diesel generators.

Solar PV systems differ in their size based on the application they are involved with, beginning from a couple of kilowatts (for small homes), several megawatts (for medium-size organizations and commercial facilities), ten megawatts (associated with industrial firms, manufacturing companies, and factories), and more than hundred megawatts that are necessary to serve large districts, utilities, and large zones.

The networks and online databases related to solar PV systems are tracked, measured, and recorded periodically to make sure that the operation, execution, and clean electrical power generation from solar radiation is achieved successfully and reliably.

Nonetheless, in some situations, scientists and energy engineers may require a prediction process through which the forecasting approach of clean electrical power is carried out for citizens or facilities to solve some issues or provide critical aspects pertaining to the following situations, which include:

a. Predicting the future electrical power generation for a PV system based on the variation of solar radiation in a region.
b. Forecasting the subsequent energy produced from the solar PV framework depending on the fluctuation of the temperature profile.
c. Determining the future production of electricity related to a PV system according to the divergence in the PV module temperature values.

To make those prediction processes, diverse scholars and researchers worldwide rely on the principles of Deep Learning (DL) to make accurate and reliable forecasting processes for solar electrical power [1]–[10]. Figure 1.1 illustrates the forecasting process of clean electrical power from a solar PV system.

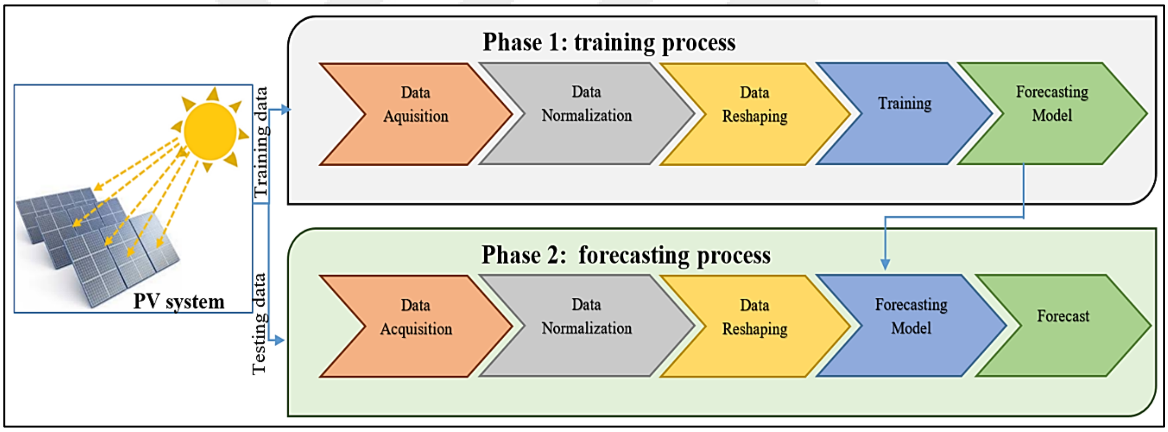

Figure 1.1: A Configuration of Significant Steps Related to the Forecasting Process of Electrical Power from Solar PV System [11].

To make the forecasting process of clean electrical power from the solar PV system, some data should be collected. Figure 1.2 describes an architecture linked to the critical data required to measure and offer for accurate and reliable prediction approach of electricity produced from the PV system.

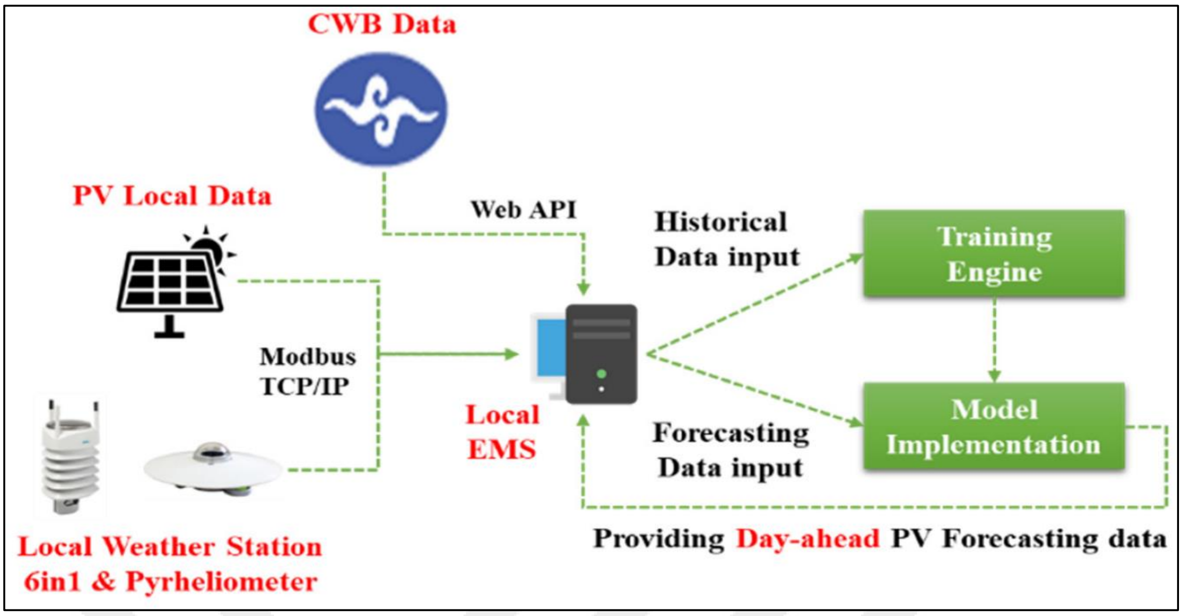

Figure 1.2: Remarkable Data Needed to Offer and Gather to Conduct the Forecasting Process of Electricity from PV Systems [12].

It is worth mentioning that in all prediction processes conducted to forecast the electrical power from solar radiation, the electricity generation differs and variate during the day because of the variation in solar radiation. Also, the electrical power may variate depending on the season. Summer has the largest power production compared with the least amount of clean electricity, which is produced in winter, as described in Figure 1.3.

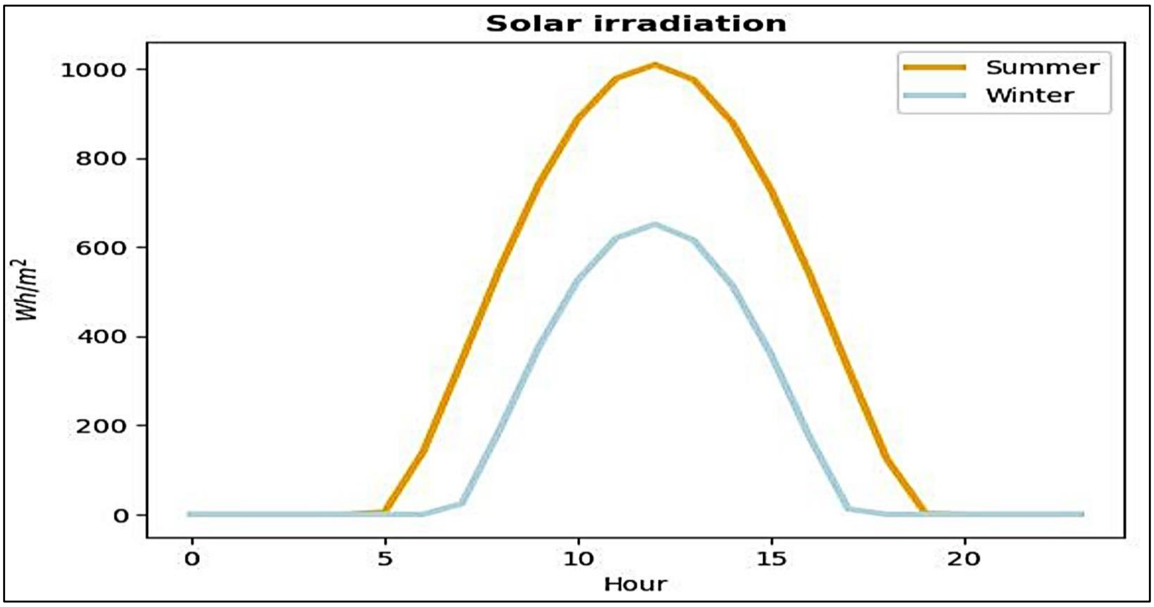

Figure 1.3: The Variation in Solar Radiation During the Day in Summer and Winter Resulting in Different Electrical Power Generation [13].

1.2 PROBLEM STATEMENT

In the last decades, the need for accurate, reliable, high-performance, quick, and trustworthy methods of forecasting clean electrical power from solar energy has been remarkably growing. The reasons are related to the significant development and large-scale adoption of different solar PV systems that require to be monitored and optimized in terms of future clean electric power generation. In addition, the conventional methods and obsolete techniques employed to predict the amount of electricity generated from those innovative solar systems lack the following criteria:

a. Considerable rates of errors (Thus, large amounts of prediction degradation are noted in the accuracy).
b. The slow procedure of prediction.
c. Complicated phases applied to forecast the electrical power.
d. The high amount of risks or problems that may occur when predicting electrical power is followed by complex and old techniques.

In this context, worldwide, scientists and researchers developed novel methods known as DL techniques. Those DL techniques rely on intelligent algorithms and DL models to conduct different types of prediction techniques based on high-performance, quick, and accurate measures [14]–[23].

This work will apply some innovative DL algorithms to achieve this goal and forecast clean electrical power from a solar PV system.

1.3 RESEARCH SIGNIFICANCE

This research comes with some relevant contributions and vital significances that may benefit the global society in carrying out accurate and reliable prediction processes. For instance, this master’s work will provide crucial numerical results and substantial outcomes that are obtained from the simulation process and mathematical analysis. Those important findings would lead computer engineers and international researchers to employ the principles of DL approaches and intelligent algorithms in predicting clean electrical power with higher rates of speed, effectiveness, and reliability.

Furthermore, this research is crucial to help researchers and energy engineers who are interested in predicting electricity from solar energy to learn and implement those novels and practical DL techniques and models to forecast electricity, providing different vital advantages and relevances.

1.4 RESEARCH MAJOR AIM AND MINOR OBJECTIVES

The primary objective of this study is to examine and pinpoint the vital functions and benefits of DL algorithms employed to determine future amounts of electricity accurately. To help achieve the primary goal of this master's thesis, some specific (minor) objectives are adopted and executed, including the following aspects:

a. To review and address the vital merits and advantageous effects of intelligent algorithms that rely on DL principles to forecast clean electrical power depending on global experience.
b. To choose a case study representing a solar PV system.
c. To develop a new algorithm and compare its accuracy with other existing models that operate on DL fundamentals to determine future values of electricity production.
d. To use Python code, simulations, and numerical analysis and define historical datasets to help the algorithm function correctly and accurately.
e. To validate and modify the numerical research findings according to a panel of DL specialists, computer experts, DL professionals, and computer science academicians' points of view.

1.5 THESIS STATEMENT

The title of this study is "FORECASTING ELECTRICAL POWER GENERATED FROM SOLAR PV SYSTEMS BY INNOVATIVE DL PRINCIPLES."

1.6 RESEARCH QUESTION

This master's thesis seeks to answer the following research questions:

a. What are the significant characteristics and vital features that distinguish modern DL algorithms from traditional electricity forecasting approaches?
b. How could the use of modern DL algorithms achieve accurate and flexible prediction of electrical power from solar PV systems?

c. Could the employment of new algorithms and intelligent DL techniques contribute to the fast determination of future clean electrical power from PV frameworks?
d. Do modern and intelligent DL algorithms provide significant levels of performance, precision, speed, and reliability in forecasting clean electrical power from solar radiation?

1.7 RESEARCH ORGANIZATION

The architecture of this master's thesis is organized according to the following consequence:

a. Chapter One has the title INTRODUCTION. It indicates some detailed data related to the research background, research significance, problem statement, research's major goal and specific objectives, and the research questions.
b. Chapter Two has the title of LITERATURE REVIEW. It discusses detailed data and addresses vital information associated with major trends and advanced contributions pertaining to the employment of modern algorithms and beneficial DL techniques in predicting electrical power with higher rates of accuracy, speed, and effectiveness. The data collected in this chapter relies on various peer-reviewed articles and research and academic publications existing in ScienceDirect, ResearchGate, Academia, MDPI, and other internationally recognized web journals.
c. Chapter Three has the title RESEARCH METHODOLOGY. It describes the major steps and research procedures adopted and followed in conducting numerical analysis by virtue of Python code using DL algorithms and mathematical simulations to forecast clean electricity. Also, the dataset and parameters used in this research will be identified and explained.
d. Chapter Four has the title RESULTS AND DISCUSSIONS. It illustrates the substantial numerical research's outputs and provides discussions linked to the outcomes attained from the research findings from other scientists.
e. Chapter Five has the title CONCLUSIONS AND RECOMMENDATION. It illustrates the major study's conclusions attained from the numerical analysis and simulations using the Python code. Also, this chapter will offer some vital recommendations and vital suggestions that help scholars improve the adoption of the DL algorithm in providing accurate electrical power prediction.

2. LITERATURE REVIEW

2.1 CHAPTER GOAL

This chapter provides a comprehensive review, which addresses and discusses a wide range of recent scholarly papers and peer-reviewed articles in order to emphasize the crucial benefits and considerable role of the intelligent DL techniques and algorithms in maintaining significant levels of prediction and forecasting of electrical power from solar energy in various contexts. Hence, several AI techniques can be used to assess the most important factors in harnessing solar power for electricity generation.

2.2 CRITICAL BENEFITS AND MAJOR CONTRIBUTIONS OF INTELLIGENT DEEP LEARNING ALGORITHMS FOR FORECASTING ELECTRICAL POWER FROM SOLAR ENERGY

[24] conducted an analysis investigating the functional merits and active uses of implementing DL methods in detecting an electrical power from solar energy. The scholars reported that they used deep learning to the problem of making long-term predictions in a certain area. Short-term solar energy forecasting using fisheye photos was the motivating application at Electricité de France. They took a look at two potential lines of inquiry for enhancing deep forecasting techniques using additional physics-based information. The function of the training loss in the first direction. They demonstrated that existing models could be improved by using shape and time requirements that are divisible. They proposed the DILATE loss function to address the deterministic setting, and the STRIPE model to handle the probabilistic setting. Their second course of action involves utilizing deep data-driven networks to supplement non-complete physical models for improved foresight. They presented the PhyDNet model for video prediction, which decouples physical dynamics from residual data like texture or details. As a follow-up, they presented a learning framework (APHYNITY) that, given relaxed assumptions, guarantees a principled and unique linear decomposition of physical and data-driven components, improving both forecasting effectiveness and parameter recognition.

[25] guided a study exploring the significant benefits and valuable uses of using DL techniques to identify solar-generated electricity. The authors stated that clean energy, such as solar power, holds the key to producing sufficient amounts of power for the smart grid of the future. Yet, the administration and stable operation of power systems are complicated

by the intermittency and randomness of solar energy resources. Accurately predicting PV power is crucial for minimizing the disruptive effects of PV plant access on power grids. To this end, they offered a hybrid deep learning approach to PV output power forecasting, one that utilized both convolutional neural networks (CNNs) and long-short term memory recurrent neural networks (LSTMs). Use of a convolutional neural network (CNN) model is employed to learn the invariant structures and nonlinear properties hidden in the historical output power data, hence improving the accuracy of PV power forecasting. Modeling the temporal variations in the most recent PV data, the LSTM can then forecast the PV power at the following time step. Then, to get the predicted output power, both models' prediction findings were taken into careful consideration. Numerical results showed that the suggested technique could provide high predictive accuracy in PV systems, and the approach is extensively examined on real PV data from Limberg, Belgium.

[26] published a manuscript inspecting the advantageous influences and important applications of utilizing DL approaches to the task of solar power detection. The scientists mentioned that PV power integration has several positive economic and environmental effects. As a result of its intermittent and sporadic nature, PV power generation poses a challenge to the operation and planning of the current power system, which could be exacerbated by a high penetration of PV power. Accurate PV power generation forecasts are crucial for ensuring the consistent delivery of high-quality electricity to consumers and for bolstering the safety and stability of the power grid. Their research was inspired by the promising results achieved by contemporary deep learning approaches in the energy sector, and it was proposing a hybrid deep learning model that combines wavelet packet decomposition (WPD) and long short-term memory (LSTM) networks. For PV power forecasting one hour in advance at five-minute intervals, the hybrid deep learning model was used. Initially, the PV power series was broken down using WPD. Following that, four separate LSTM networks were built to handle these individual series. At the end, the outputs of each LSTM network are reconstructed, and a linear weighting algorithm is used to obtain the final forecast. As illustrated in Figure 2.1; a framework of the suggested WPD-LSTM scheme for short-term PV power detection.

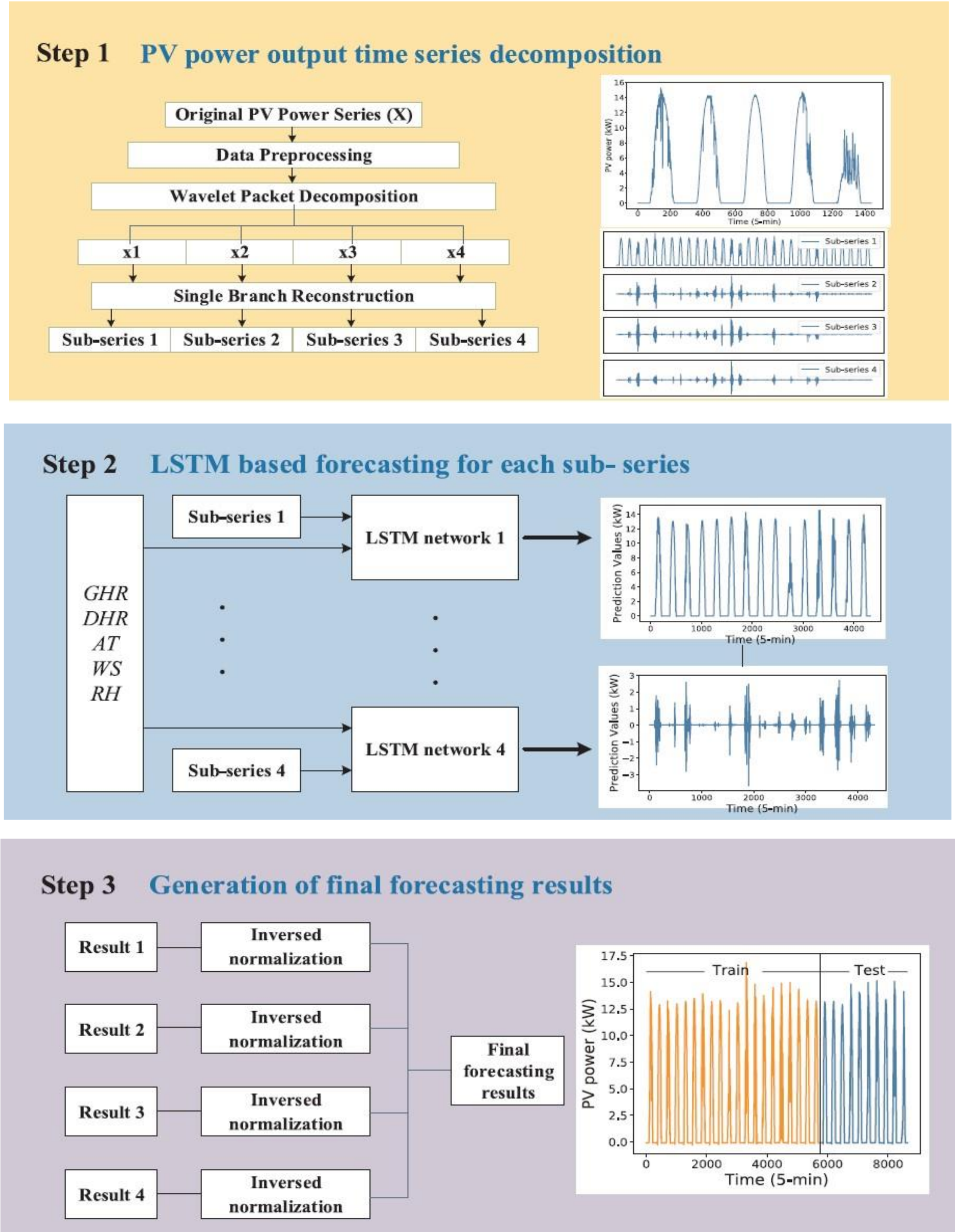

Figure 2.1: Framework of the Suggested WPD-LSTM Scheme for Short-Term PV Power Detection.

Case study data from Alice Springs, Australia was used to illustrate the efficacy of the proposed strategy. There were additional comparisons made to stand-alone versions of the multi-layer perceptron (MLP), gated recurrent unit (GRU), recurrent neural network (RNN), and long short-term memory (LSTM) models. The suggested hybrid deep learning model has higher performance in terms of both predicting accuracy and stability, as evidenced by the results of three effectiveness evaluation indicators: MAPE, MBE, and RMSE. In addition, the suggested hybrid deep learning model takes into account both current and past weather conditions and electricity outputs. This way, we can take into account the connection among PV power outputs and climate. Since it is currently impossible to reliably predict the weather, the PV power outputs forecasting method uses historical meteorology data as input rather than weather forecasting data.

[27] carried out a study classifying the significant benefits and valuable uses of applying DL techniques to forecast solar-generated electricity. The scholars reported that the widespread acceptance of solar power as a viable renewable energy option that may help meet global energy demands was a major achievement. Solar energy was a promising form of renewable energy, but its intermittent nature in electricity production makes it challenging to operate the electrical system. Therefore, they suggested using Deep Learning (DL), a hot topic in AI right now, to forecast the sun's behavior. The method's efficacy was demonstrated by contrasting it against well-established methods of solar forecasting, including the Multilayer Perceptron, the Radial Basis Function, and the Support Vector Regression. Additionally, their paper proposed a new adaptable topology based on the Portfolio Theory (PT) to improve solar forecasts by incorporating AI technologies. When one asset in the forecast exhibits prediction flaws, PT can counteract them with another. The results of the experiments conducted using data from Spain and Brazil demonstrated that the Mean Absolute Percentage Error (MAPE) for forecasts using DL was 6.89%, while the MAPE for the suggested integration (named PrevPT) was only 5.36% with respect to Spanish data. While making predictions on the Brazilian dataset, MAPE for DL is 6.08 percent and for PrevPT it was 4.52%. PrevPT and DL both produced superior results compared to the alternatives.

[28] managed a study examining the vital role and critical benefits of implementing DL methods in detecting an electrical power from solar energy. The authors stated that solar power was a significant renewable energy option that could help meet the world's growing energy needs. Yet, due to the resource's intermittent nature, solar energy was challenging to incorporate into the grid. In their study, they proposed and evaluate two machine learning

methods, support vector regression (SVR) and deep learning (DL), to test their performance for solar forecasting. Data from their Spanish experiments showed that DL and SVR had mean absolute percentage errors of 7.9% and 8.52%, respectively, when making predictions. While the DL performed best in terms of solar energy forecasting, it was important to note that the SVR also produced respectable outcomes.

[29] directed an analysis exploring the practical advantages of using DL techniques to forecast solar-generated electricity. The researchers claimed that for microgrids to be controlled and designed with efficiency, smart energy management systems required precise short-term forecasts of photovoltaic (PV) electricity. Bidirectional LSTM (BiLSTM), Long Short-Term Memory (LSTM), Bidirectional GRU (BiGRU), Gated Recurrent Unit (GRU), One-Dimensional Convolutional Neural Network (CNN1D), and other hybrid configurations like CNN1D-LSTM and CNN1D-GRU were all types of DLNN that have been developed and compared in their paper for short-term output Pv energy forecasting. The neural networks were trained and tested with data gathered from the microgrid at the University of Trieste (Italy), which has recorded the amount of PV electricity generated by the solar panels. One-Step and multi-step forward performance has been measured over four timespans (1, 5, 30, and 60 mins). The results demonstrated that the examined DLNNs provided very good accuracy, especially in the case of 1 min timeframe including one step ahead (coefficient of correlation is nearer to 1), whereas for the case of multi-step ahead (up to eight steps ahead) the results were found to be acceptable (coefficient of correlation ranges from 96.9% to 98.0%).

[30] directed an analysis exploring the positive effectiveness of utilizing DL approaches to the task of solar power detection. The scientists mentioned that distributed photovoltaic (PV) power generation calls for accurate predictions of sun irradiance at both the hourly and daily timescales. The UTSA SkyImager was created by employing a Raspberry Pi computer and camera to create a low-cost all-sky imaging device. It has been put into use in a variety of places, including the Joint Base San Antonio, National Renewable Energy Laboratory (NREL), and two areas in the Canary Islands, thanks to its adaptability to a wide range of operational conditions. The initial plan included optical flow for extrapolating cloud locations, and ray-tracing for foreseeing where shadows would fall on solar panels. Mathematically, the latter issue was poorly posed. Their research described a different

approach that makes use of AI to predict solar radiation levels using an extracted sub image of the solar atmosphere. Gradient Boosted Trees and Deep Learning were just two of the AI models that were compared there. 147 days of data from NREL were analyzed, from 10/2015 to 5/2016, the findings and error metrics were reported for that time span. Scatter plots of observed GHI against predicted GHI are displayed in Figure 2.2 for a number of machine learning models, including Deep Learning (DL), Random Forest (RF), Gradient Boosted Trees (GBT), and Multi-Layer Perceptron (MLP).

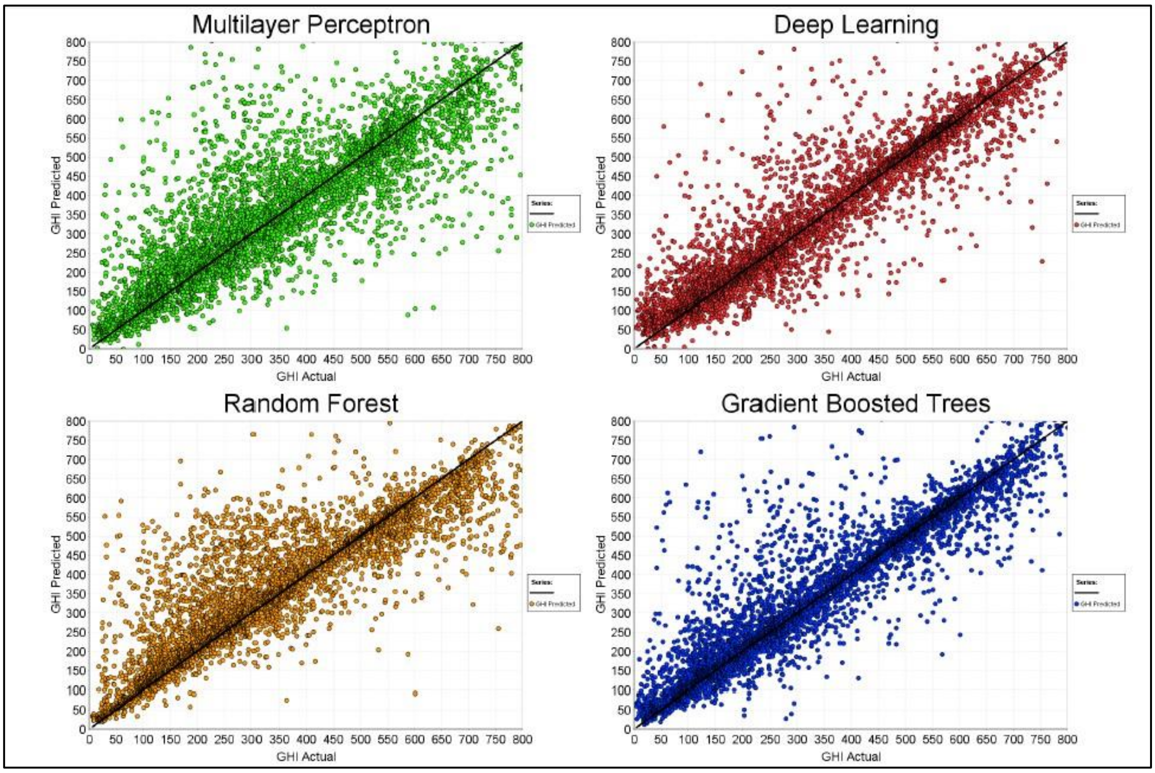

Figure 2.2: Comparison of 10/2015 Global Horizontal Irradiance (GHI) Measurements to Those Anticipated by Numerous Artificial Intelligence Models.

[31] executed an investigation identifying the functional merits of applying DL techniques to forecast solar-generated electricity. The scholars reported that the use of cutting-edge digital technologies was speeding up the evolution of power systems. Deep Learning (DL) approaches were becoming most ideal technologies for its upcoming growth and success as a result of the increasing complexity of power systems and the collection of enormous volumes of data. Improved algorithms, larger datasets, and faster processing speeds have all contributed to a new era of progress in the field of deep learning (DL). Their article gave a fresh study case on the solar radiation forecasting necessary for PV generation and

introduced the state-of-the-art implementation of Deep Learning in energy systems. Their case study involved a year-ahead estimate of hourly, daily, and overall solar irradiation utilizing Long-Short Term Memory forecasting (LSTM). Information for the coming year was crucial for installation planning and the market.

[32] guided a study exploring the relevant impacts of implementing DL methods in detecting an electrical power from solar energy. The authors stated that wind power, solar energy, and fuel cells were just a few examples of the sustainable and renewable energy sources that have been advocated for worldwide as part of a larger movement away from fossil fuels. It was prudent to proceed with caution when implementing systems for renewable energy and regulations that rely on wind and solar power, due to their unpredictability and complexity. In light of that, the Korean energy policy served as a case study as their research created a model for energy forecasting with renewable energy technology. Variability in electricity generation and demand might be predicted using deep learning-based models, which was essential in a system of renewable energy but was beyond the capabilities of traditional models. The gated recurrent unit outperformed the other forecasting models in terms of prediction accuracy; as a result, it was chosen as the foundational model upon which to assess four other renewable energy strategies. Economic and environmental cost benefit analysis were used to rank the scenarios. With an integrated combined cycle gasification, offshore and onshore wind farms, fuel cell plants, and solar power stations the best-case scenario achieved a policy of 100% renewable energy while also showed the lowest economic and environmental costs. An optimal scenario evaluation was conducted by analyzing the scenario's SWOT characteristics and took into account the current domestic and international energy technological, economic, and environmental conditions.

[33] carried out a study classifying the considerable characteristics of using DL techniques to forecast solar-generated electricity. The scientists mentioned that due of rising demand for power and the finite nature of fossil fuels, a transition to sources of renewable energy was inevitable. The intermittent nature of renewable energy sources could be mitigated by utilizing several generators. If the major source was unable to supply the required amount of energy, the secondary source would take over. In their study, they designed and implemented an energy management system (EMS) that made use of a hybrid renewable energy source for the purpose of energy forecasting. Their study's overarching goal was to

find the best way to manage the three interrelated processes of energy generation, grid interaction, and storage system at the same time. In their research, they combined battery state-of-charge data alongside control objectives to develop strategies for optimizing grid-feeding power injection. It was anticipated that the controlling inputs received at the beginning of the prediction window would remain constant for the full duration of the window. The RMSE data showed an enhanced rate of accuracy when utilizing EMS, with errors lower than 0.3%.

[34] executed an investigation identifying the substantial advantages of utilizing DL approaches to the task of solar power detection. The scientists mentioned that the expansion of solar power since the year 2000 has allowed it to meet the rising need for electricity in homes, businesses, farms, and other uses. Forecasting the power generation of solar power plants was crucial for the growth of solar energy since it has allowed for more steady operation, better planning, and more balanced electricity production. Short-term, intermediate-term, and long-term solar generation predictions have all been addressed by a wide variety of models and approaches. Artificial Neural Network (ANN) based prediction models outperformed other models due to its capacity to address complicated nonlinear issues, as evidenced by studies conducted between the years 2000 and the present. When the two models were used together in prediction or processing input data, their accuracy was greatly enhanced. In their study, they evaluated the ANN model's prediction popularity, forecasting scope, and accuracy in comparison to other models often used for predicting solar power output. Forecasting the power generation of solar power plants relied heavily on the present robust development of combined prediction models of Gate Recurrent Unit (GRU) and Long Short-Term Memory (LSTM).

[35] conducted an analysis investigating the advantageous influences and important applications of applying DL techniques to forecast solar-generated electricity. The scholars reported that based on the precision of deep learning approaches, they were a viable choice for solar energy forecasting. In their article, they took a look at deep learning approaches for dealing with time-series data, specifically for the purpose of forecasting photovoltaic (PV) and solar irradiance output. For the purpose of their discussion, they had focused on four distinct models: the recurrent neural network (RNN), the long short-term memory (LSTM), the gated recurrent unit (GRU), and the convolutional neural network-LSTM hybrid (CNN–

LSTM). Accuracy, input data, predicting horizon, season and weather type, and training time were compared amongst the models chosen for further analysis. The analysis of performance revealed the advantages and disadvantages of those models under various circumstances. In terms of the root-mean-square error evaluation metric (RMSE), LSTM often performed better for solo models. Yet, while requiring more time to train data, the hybrid model (CNN-LSTM) surpassed the three solo models. The most important result was that deep learning models were superior to more traditional machine learning predictions of solar radiation and PV power. To further ease accuracy comparability across research, they advocated for the use of the related RMSE as the typical evaluation statistic.

[36] directed an analysis exploring the critical contributions of implementing DL methods in detecting an electrical power from solar energy. The scholars suggested that a model for predicting the performance of renewable energy sources was established using a modeling system based on machine learning. Producing and optimizing renewable energies have both benefited greatly from the application of Computational Intelligence (CI) techniques. Large amounts of variables and data were covered, adding complexity to the analysis of that form of energy. Their research presented a novel taxonomy for classifying and comparing the efficacy of Deep Learning (DL) methods used to analyze data from renewable energy sources like solar and wind. Furthermore, it has discussed important difficulties and prospects for further research and provided a state-of-the-art overview of the literature that led to an evaluation of DL methods' efficacy and effectiveness. Different levels of accuracy, robustness, precision values, and generalization ability were among the most frequently encountered obstacles in the application of DL approaches. When dealing with a sizable dataset, DL methods outperformed conventional CI methods by a wide margin. Therefore, it was recommended that hybrid DL methods be used and developed alongside other optimization methods to enhance and optimise the framework of the methods. Due to combining the strengths of multiple strategies, hybrid networks always outperform their single-network counterparts. While employing DL strategies, a mix of traditional and cutting-edge approaches was advised.

[37] led research evaluating the functional merits and active uses of DL techniques to forecast solar-generated electricity. The researchers claimed that for effective grid distribution and planning, accurate predictions of incident solar-radiance on a panel were

crucial. Standard practice has it that coarse-grained radiometric tiles measured by geo-satellites were used to fine-tune the parameters of meteorological physics models used for making such forecasts. In their study, researchers provided a unique deep neural network technique for estimating the impact of short-term weather on outdoor video footage. To directly quantify and forecast solar irradiance, they employed time-lapsed films (sky-videos) captured by upward-facing wide-lensed cameras (sky-cameras). They showed 2 huge datasets available to the public, collected by stations of weather in two locations of North America utilizing low-cost optical technology, and they discussed their findings. To the best of their knowledge, those datasets were the largest collections of their kind, each including more than a million photographs spanning one and twelve years. The suggested deep learning approach significantly decreased the normalized mean-absolute-percentage error when compared to satellite-based methods for both nowcasting (predicting the solar irradiance at the moment the frame was captured) and forecasting (predicting the solar irradiance up to 4 hours in the future).

[38] carried out a study classifying the vital effects of utilizing DL approaches to the task of solar power detection. The scholars stated that with the world's ever-increasing demand for energy, it only makes sense to turn to solar power, which was both sustainable and inexhaustible. A substantial approach of solar energy forecasting was required for both large and small organizations due to the uncertainties inherent in the forecasting of solar radiation due to its dependence on meteorological conditions. In their research, they proposed Deep Learning-based models that could be used to forecast solar PV total energy in the power sector. In their research, they provided a comparison of many deep learning methods. Long short-term memory (LSTM) and gated recurrent unit (GRU) models fare well on average. The usage of RNNs, LSTMs, and GRUs in solar energy forecasting has become commonplace. Furthermore, the efficiency of their hybrid vehicles has risen. The findings provided a comparison of the aforementioned three models.

[39] managed a study examining the practical advantages of Applying DL techniques to forecast solar-generated electricity. The scholars reported that because of the unpredictability of cloud behavior, short-term predictions of solar power output were fraught with uncertainty and could impede the efficient operation of today's power grids. In order to forecast minute-averaged PV output 15 minutes into the future, their paper

presented a specific convolutional neural network (CNN) called "SUNSET." Hybrid input, temporal history, and rigorous regularization were hallmarks of that approach. The "baseline" model outperformed a smart persistent forecast by 16.3% in overcast conditions and by 15.7% throughout all weather situations on a 1-year database. The best possible combinations of inputs and outputs were discussed, and recommendations were made. It was determined that sky photos and the output history of PV systems were both essential inputs. When comparing outputs, training with PV output has an obvious advantage over clear sky index (CSI). If down-sampling was done correctly, it could cut training time by up to 83% without sacrificing accuracy. The very same length of past as the prediction horizon was a solid heuristic for lag term setups, whereas in this case a little shorter history gave a minor 0.5-0.9% improvement. The project's code base could be found at Github/YuchiSun/SUNSET, ensuring its repeatability and making it easier to build upon in the future.

[40] published a manuscript inspecting the vital role and critical benefits of implementing DL methods in detecting an electrical power from solar energy. The authors stated that within the scope of their work, they investigated the problem of forecasting the half-hourly output of electricity from photovoltaic solar systems over the course of the following day. For massive data time series, they presented DL, a deep learning technique utilizing feed-forward neural networks that breaks down the prediction problem into smaller, more manageable chunks. Using 2 years of solar data collected in Australia, they conducted a thorough evaluation of DL's performance, comparing it to that of two other cutting-edge approaches based on pattern sequence similarity and neural networks. They looked into the impact of various historical window sizes and the usage of several sources of data (weather data for the past days, solar power, and weather predictions for the future day). The findings demonstrate that DL achieves competitive accuracy and scales well, making it an ideal technique for use with large datasets.

2.3 THE VITAL ADVANTAGES AND SUBSTANTIAL IMPACTS OF DL TECHNIQUES FOR SOLAR ENERGY PREDICTION

[41] carried out a study classifying the significant benefits and valuable uses of employing DL techniques to forecast solar-generated electricity. The scientists mentioned that increasing the precision of renewable energy prediction was essential for power system

management, operations, and planning as that form of clean energy gained popularity in the worldwide electric energy grid. Unfortunately, this was difficult because renewable energy data was inconsistent and unpredictable. To date, many approaches have been developed to enhance the predictability of renewable energy, including artificial intelligence methods, statistical methods, physical models, also their hybrids. Among these, deep learning has been widely described in the literature as a potential sort of machine learning capable of detecting the high-level invariant structures, and inherent nonlinear features in data. In order to investigate the efficacy, efficiency, and applicability of deep learning for renewable energy forecasting, their study provided a complete and extensive evaluation of existing methodologies. They categorized the present deep learning-based probabilistic and deterministic forecasting approaches into four classes: deep belief networks, stack auto-encoders, deep recurrent neural networks, and others. They also analyzed practical data preparation strategies and error post-correction approaches to enhance prediction precision. Many strategies for making predictions using deep learning were analyzed, and their advantages and disadvantages were discussed at length. Lastly, they discussed the ongoing studies, difficulties, and possible future research areas in this area.

Figure 2.3 describes the methodology for predicting the performance of renewable energy sources. It has been demonstrated that it is equipped with tools for data preparation, a deep learning-based feature extractor, regression algorithms, and error post-processing approaches. From the outset, we apply data preprocessing methods to break down the raw time series data from renewable sources into many frequency components. Each subset displays improved outliers and behaviors compared to the raw data. This is followed by the creation of separate feature extractors and regressors for use in the prediction of individual subsystems. Existing optimization methods can be used to fine-tune the network architectures and model parameters. Then, the forecast is reconstructed by adding all of the predicted parts back together. Once the incorrect post-processing procedures are used, the rebuilt forecasts can be corrected.

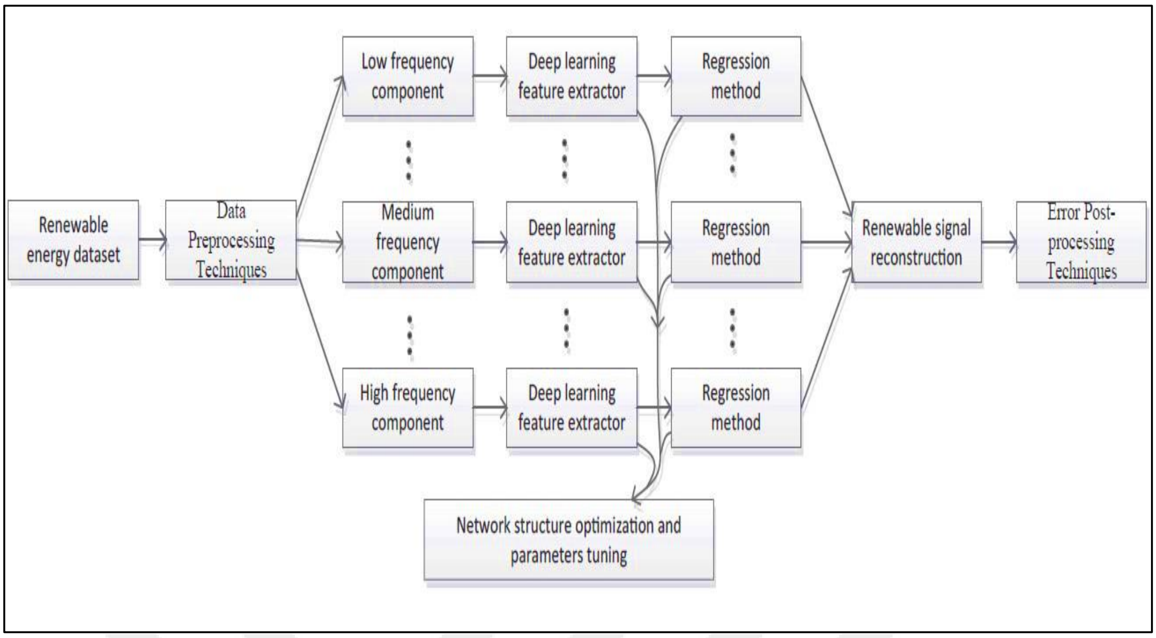

Figure 2.3: Methodology for Predicting the Performance of Renewable Energy Sources.

[42] directed an analysis exploring the considerable characteristics of utilizing DL approaches to the task of solar power detection. The scholars reported that the use of solar concentrators to generate electricity was becoming increasingly common. Even if solar heat might be used safely, its unpredictable thermal output poses significant obstacles to its use. Therefore, it would be crucial for the power grid and the plant to have accurate seasonal forecasts of thermal production. Their research proposed a new type of forecasting system that combined mechanism modeling with deep learning. Mechanism modeling eliminates the subjectivity associated with selecting model input features, allowing for more precise identification of the primary meteorological parameters employed in forecasting. Input features were reconstructed using a convolutional neural network and a long short-term memory network, allowed for a comprehensive investigation of the spatial-temporal coupling features among meteorological elements. When all layers were joined together, thermal power could be released. Over the complete year, the average values of mean absolute error and root mean square error for a forecast of the thermal power of a Solar Two-like concentrated solar power plant based on Zhangbei's weather circumstances were 5.061 MWt and 2.871 MWt, respectively. The outcomes proved the viability of the methodologies described in their research for thermal power prediction of concentrate solar power systems.

[43] managed a study examining the functional merits of applying DL techniques to forecast solar-generated electricity. The authors claimed that forecasting the output of a photovoltaic power generation system with high accuracy was incredibly useful. Predicting the output of photovoltaic systems was challenging since solar energy was unpredictable and inconsistent. Using the information gathered from the DKASC, Alice Springs photovoltaic system, their study proposed and applied three different models: a convolutional neural network, a long short-term memory network, and a hybrid model based on the two. In their study, they evaluated the prediction model using the root mean square error, mean absolute error, and mean absolute percentage error metrics. Increasing the length of the input sequence was shown to improve the model's accuracy, and the hybrid model's prediction effect was found to be superior to that of the convolutional neural network. In spite of its shorter training period, the extended short-term memory network showed the weakest predictive power. Yet it's not true that the greater the sequence of input is, the more accurate the predictions will be. This could be because of some of the time series' inherent properties. In addition, the findings of the deep-learning approach described in their research for predicting the power from photovoltaics showed that deep learning was very beneficial for enhancing the precision with which PV power predictions might be made.

[44] implemented a study analyzing the practical advantages and considerable characteristics of using DL techniques to forecast solar-generated electricity. The researchers suggested that incorporating solar energy into the grid was difficult because of the sun's sporadic and unpredictable output. Prediction of photovoltaic power output with high accuracy was crucial for addressing that issue. As the field of deep learning has progressed, more and more academics have applied successfully the DL model to prediction of time series. In their study, they proposed and implemented a LSTM-Convolutional Network hybrid deep learning model for estimating the output of solar panels. The temporal properties of the data were initially extracted by the long-short term memory network, followed by the spatial features by the convolutional neural network model, in the suggested hybrid prediction model. Comparisons were made between the results of the proposed hybrid prediction model and those of the single approach (convolutional neural network, long-short term memory network), as well as the results of the hybrid network (Convolutional-LSTM Network), and eight error evaluation indices were provided to

demonstrate the superior performance of the suggested hybrid prediction model. The results demonstrated that the hybrid prediction model outperformed the individual prediction models, and that the suggested hybrid model (extract the temporal features of data first, and then extract the spatial features of data) outperformed the Convolutional-LSTM Network (extract the spatial features of data first, and then extract the temporal features of data).

[45] carried out a study classifying the positive effectiveness and relevant impacts of implementing DL methods in detecting an electrical power from solar energy. The authors stated that in order to deal with the unpredictability of photovoltaic (PV) power generation, solar forecasting was a viable method. In their paper, they offered a new multistep forecasting (MSF) scheme for controlling the ramp rate of photovoltaic (PV) power output (PRRC). More suited to industrial applications, that method employed an ensemble of deep ConvNets without the use of time series models (such a recurrent neural network (RNN) or long short-term memory) and other exogenous variables. Although conventional methods produced a single forecasting point, the MSF system could generate many forecasts that share the same high temporal resolution. Moreover, stacked sky photos were employed to enhance the forecasting performance by integrating temporal-spatial information about cloud motions. As shown by the findings, the best skill score achieved by the model was 17.7%, which was better than the accuracy of the currently available forecasting models. When compared to traditional forecasting-based control, the MSF-based PRRC has a better control rate (98.9%) in the PRRC application and could detect more ramp-rate violations. Thus, the suggested method might effectively smooth the PV generation with reduced energy restriction on both cloudy and clear days.

[46] carried out a study classifying the significant benefits and valuable uses of applying DL techniques to forecast solar-generated electricity. The authors stated that to predict the total power load and the PV power output in a community microgrid, a deep recurrent neural network with long short-term memory units (DRNN-LSTM) approach was built. Additionally, under three distinct time-of-use frameworks, an optimum load dispatch model for grid-connected community microgrid was constructed, which incorporated PV arrays, residential power load, energy storage system (ESS), and electric vehicles (EVs). By incorporating the forecasting findings, the model took into account the uncertainties of both PV power generation and residential power load, which helped to enhance the supply-

demand balance. The suggested forecasting model was evaluated on two independent real-world data sets, with the DRNN-LSTM model outperforming both the multi-layer perception (MLP) network and the support vector machine (SVM). In conclusion, a particle swarm optimization (PSO) technique was applied to the grid-connected community microgrid in order to optimize the load dispatch. As shown by the data, EES and coordinated mode charging of EVs could facilitate peak load shifting and cut daily expenditures by 8.97%. Using load and renewable energy forecasts, their research aided in the most efficient microgrid operation. Total costs were reduced and system reliability was enhanced by the optimal load dispatch of a community microgrid using deep learning-based load and solar power forecasting.

[47] directed an analysis exploring the considerable characteristics and practical advantages of utilizing DL approaches to the task of solar power detection. The scholars stated that predicting solar irradiance accurately helped with a few different things: cutting down on energy waste from photovoltaic power plants, protecting systems from the wear and tear that comes from extreme solar irradiance fluctuations, and stabilizing the integration of power output from various power grids. In order to predict the shifts in solar irradiance over the four seasons, a hybrid deep learning model was suggested. That model combined a gated recurrent unit (GRU) neural network with an attention mechanism to account for the randomness and numerous dimensions of meteorological data. In their first phase, they created a feature extraction network using the ResNet and Inception neural network. The second step was to feed the retrieved features into a recurrent neural network (RNN) to train the model. The suggested hybrid deep learning scheme successfully predicted short-term shifts in solar irradiance, as demonstrated by experimental findings. Plus, the model outperformed more conventional deep learning models at making predictions (such as LSTM and GRU).

[48] published a manuscript inspecting the valuable uses and significant benefits of employing DL techniques to forecast solar-generated electricity. The researchers claimed that the influence of unpredictable fluctuations in PV output on the reliable operation of the power grid was becoming increasingly important as the proportion of renewable energy sources like solar PV grows. Accommodating photovoltaic (PV) electricity generation on the grid could be aided by accurate forecasting of PV output. PV power and Surface

irradiance are both significantly affected by cloud cover. Obtaining the surface irradiance in accordance with the sky cloud observation data was essential for the ultra-short-term solar PV power forecast taking cloud movement into account. Their paper proposed a hybrid mapping approach based on deep learning applied to solar PV power forecasting to precisely achieve the real-time mapping link among surface irradiance and sky image. The preprocess stage began with the clustering of the sky image data using the feature extraction of a convolutional autoencoder and a K-means clustering method. Second, a hybrid mapping approach for surface irradiance was developed using deep learning techniques. Finally, several deep learning approaches were evaluated and compared using the simulation findings (LSTM, ANN, and CNN). The findings in their article's proposed model demonstrated its superior accuracy and its ability to remain robust in a wide range of environmental settings.

2.4 SUMMARY OF THE PREVIOUS STUDIES

Table 2.1 represents a summary of the major results obtained from the review of the articles in this chapter.

Table 2.1: The Vital Findings Obtained from the Review of the Articles in this Chapter.

Author(s)	Year	Title	Substantial Outcomes
Le Guen, V.	2022	Deep learning for spatio-temporal forecasting--application to solar energy.	The authors stated that they presented a learning framework (APHYNITY) that, given relaxed assumptions, guarantees a principled and unique linear decomposition of physical and data-driven components, improving both forecasting effectiveness and parameter recognition.
Li, G., Xie, S., Wang, B., Xin, J., Li, Y., & Du, S.	2020	Photovoltaic power forecasting with a hybrid deep learning approach.	Numerical results showed that the suggested technique could provide high predictive accuracy in PV systems, and the approach is extensively examined on real PV data from Limberg, Belgium.

Table 2.2: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Li, P., Zhou, K., Lu, X., & Yang, S.	2020	A hybrid deep learning model for short-term PV power forecasting.	The results revealed that the suggested hybrid deep learning model has higher performance in terms of both predicting accuracy and stability, as evidenced by the results of three evaluation indicators: MAPE, MBE, and RMSE.
Lima, M. A. F., Carvalho, P. C., Fernández-Ramírez, L. M., & Braga, A. P.	2022	Improving solar forecasting using Deep Learning and Portfolio Theory integration.	The results of the experiments conducted using data from Spain and Brazil demonstrated that the Mean Absolute Percentage Error (MAPE) for forecasts using DL was 6.89%, while the MAPE for the suggested integration (named PrevPT) was only 5.36% with respect to Spanish data. While making predictions on the Brazilian dataset, MAPE for DL is 6.08 percent and for PrevPT it was 4.52%. PrevPT and DL both produced superior results compared to the alternatives.
Lima, M. A. F., Fernández Ramírez, L. M., Carvalho, P. C., Batista, J. G., & Freitas, D. M.	2022	A comparison between deep learning and support vector regression techniques applied to solar forecast in Spain.	Data from their Spanish experiments showed that DL and SVR had mean absolute percentage errors of 7.9% and 8.52%, when making predictions. While the DL performed best in terms of solar energy forecasting, the SVR also produced respectable outcomes.

Table 2.3: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Mellit, A., Pavan, A. M., & Lughi, V.	2021	Deep learning neural networks for short-term photovoltaic power forecasting.	The results demonstrated that the examined DLNNs provided very good accuracy, especially in the case of 1 min timeframe including one step ahead (coefficient of correlation is nearer to 1), whereas for the case of multi-step ahead (up to eight steps ahead) the results were found to be acceptable (coefficient of correlation ranges from 96.9% to 98.0%).
Moncada, A., Richardson Jr, W., & Vega-Avila, R.	2018	Deep learning to forecast solar irradiance using a six-month UTSA SkyImager dataset.	The findings showed that 147 days of data from NREL were analyzed, from 10/2015 to 5/2016, the findings and error metrics were reported for that time span.
Muhammad, A., Lee, J. M., Hong, S. W., Lee, S. J., & Lee, E. H.	2019	Deep learning application in power system with a case study on solar irradiation forecasting.	The scholars stated that their case study involved a year-ahead estimate of hourly, daily, and overall solar irradiation utilizing Long-Short Term Memory forecasting (LSTM). Information for the coming year was crucial for installation planning and the market.

Table 2.4: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Nam, K., Hwangbo, S., & Yoo, C.	2020	A deep learning-based forecasting model for renewable energy scenarios to guide sustainable energy policy: A case study of Korea.	The outcomes demonstrated that economic and environmental cost benefit analysis were used to rank the scenarios. With an integrated combined cycle gasification, offshore and onshore wind farms, fuel cell plants, and solar power stations the best-case scenario achieved a policy of 100% renewable energy while also showed the lowest economic and environmental costs.
Nayagam, V. S., Jyothi, A. P., Abirami, P., Femila Roseline, J., Sudhakar, M., Al-Ammar, E. A., ... & Sisay, A.	2022	Deep learning model on energy management in grid-connected solar systems.	The scientists reported that it was anticipated that the controlling inputs received at the beginning of the prediction window would remain constant for the full duration of the window. The RMSE data showed an enhanced rate of accuracy when utilizing EMS, with errors lower than 0.3%.
Nguyen, T. A., Pham, M. H., Duong, T. K., & Vu, M. P.	2021	A Recent Invasion Wave Of Deep Learning In Solar Power Forecasting Techniques Using Ann.	The results confirmed that forecasting the power generation of solar power plants relied heavily on the present robust development of combined prediction models of Gate Recurrent Unit (GRU) and Long Short-Term Memory (LSTM).

Table 2.5: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Rajagukguk, R. A., Ramadhan, R. A., & Lee, H. J.	2020	A review on deep learning models for forecasting time series data of solar irradiance and photovoltaic power.	The most important result was that deep learning models were superior to more traditional machine learning predictions of solar radiation and PV power. To further ease accuracy comparability across research, they advocated for the use of the related RMSE as the typical evaluation statistic.
Shamshirband, S., Rabczuk, T., & Chau, K. W.	2019	A survey of deep learning techniques: application in wind and solar energy resources.	The findings affirmed that due to combining the strengths of multiple strategies, hybrid networks always outperform their single-network counterparts. While employing DL strategies, a mix of traditional and cutting-edge approaches was advised.
Siddiqui, T. A., Bharadwaj, S., & Kalyanaraman, S.	2019	A deep learning approach to solar-irradiance forecasting in sky-videos.	The researchers mentioned that the suggested deep learning approach significantly decreased the normalized mean-absolute-percentage error when compared to satellite-based methods for both nowcasting (predicting the solar irradiance at the moment the frame was captured) and forecasting (predicting the solar irradiance up to 4 hours in the future).

Table 2.6: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Sivanand, R., Singh, J., Ali, A., Khan, A., & Hoda, M. F.	2021	A comparative study of different deep learning models for mid-term solar power prediction.	The outcomes affirmed that the usage of RNNs, LSTMs, and GRUs in solar energy forecasting has become commonplace. Furthermore, the efficiency of their hybrid vehicles has risen. The findings provided a comparison of the aforementioned three models.
Sun, Y., Venugopal, V., & Brandt, A. R.	2019	Short-term solar power forecast with deep learning: Exploring optimal input and output configuration.	The results demonstrated that when comparing outputs, training with PV output has an obvious advantage over clear sky index (CSI). If down-sampling was done correctly, it could cut training time by up to 83% without sacrificing accuracy. The very same length of past as the prediction horizon was a solid heuristic for lag term setups, whereas in this case a little shorter history gave a minor 0.5-0.9% improvement. The project's code base could be found at Github/YuchiSun/SUNSET, ensuring its repeatability and making it easier to build upon in the future.

Table 2.7: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Torres, J. F., Troncoso, A., Koprinska, I., Wang, Z., & Martínez-Álvarez, F.	2019	Big data solar power forecasting based on deep learning and multiple data sources.	The findings demonstrate that DL achieves competitive accuracy and scales well, making it an ideal technique for use with large datasets.
Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J.	2019	A review of deep learning for renewable energy forecasting.	The scholars mentioned that many strategies for making predictions using deep learning were analyzed, and their advantages and disadvantages were discussed at length. Lastly, they discussed the ongoing studies, difficulties, and possible future research areas in this area.
Wang, J., Guo, L., Zhang, C., Song, L., Duan, J., & Duan, L.	2020	Thermal power forecasting of solar power tower system by combining mechanism modeling and deep learning method.	The authors reported that the average values of mean absolute error and root mean square error for a forecast of the thermal power of a Solar Two-like concentrated solar power plant based on Zhangbei's weather circumstances were 5.061 MWt and 2.871 MWt, respectively. The outcomes proved the viability of the methodologies described in their research for thermal power prediction of concentrate solar power systems.

Table 2.8: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Wang, K., Qi, X., & Liu, H.	2019	A comparison of day-ahead photovoltaic power forecasting models based on deep learning neural network.	The scientists mentioned that the findings of the deep-learning approach described in their research for predicting the power from photovoltaics showed that deep learning was very beneficial for enhancing the precision with which PV power predictions might be made.
Wang, K., Qi, X., & Liu, H.	2019	Photovoltaic power forecasting based LSTM-Convolutional Network.	The results demonstrated that the hybrid prediction model outperformed the individual prediction models, and that the suggested hybrid model (extract the temporal features of data first, and then extract the spatial features of data) outperformed the Convolutional-LSTM Network (extract the spatial features of data first, and then extract the temporal features of data).
Wen, H., Du, Y., Chen, X., Lim, E., Wen, H., Jiang, L., & Xiang, W.	2020	Deep learning based multistep solar forecasting for PV ramp-rate control using sky images.	The findings illustrated that when compared to traditional forecasting-based control, the MSF-based PRRC has a better control rate (98.9%) in the PRRC application and could detect more ramp-rate violations. Thus, the suggested method might effectively smooth the PV generation with reduced energy restriction on both cloudy and clear days.

Table 2.9: The Vital Findings Obtained from the Review of the Articles in this Chapter 'Tables Continued'.

Wen, L., Zhou, K., Yang, S., & Lu, X.	2019	Optimal load dispatch of community microgrid with deep learning based solar power and load forecasting.	The authors mentioned that as shown by the data, EES and coordinated mode charging of EVs could facilitate peak load shifting and cut daily expenditures by 8.97%. Using load and renewable energy forecasts, their research aided in the most efficient microgrid operation. Total costs were reduced and system reliability was enhanced by the optimal load dispatch of a community microgrid using DL-based load and solar power forecasting.
Yan, K., Shen, H., Wang, L., Zhou, H., Xu, M., & Mo, Y.	2020	Short-term solar irradiance forecasting based on a hybrid deep learning methodology.	The suggested hybrid deep learning scheme successfully predicted short-term shifts in solar irradiance, as demonstrated by experimental findings. Plus, the model outperformed more conventional deep learning models at making predictions (such as LSTM and GRU).
Zhen, Z., Liu, J., Zhang, Z., Wang, F., Chai, H., Yu, Y., ... & Lin, Y.	2020	Deep learning based surface irradiance mapping model for solar PV power forecasting using sky image.	The scholars stated that several deep learning approaches were evaluated and compared using the simulation findings (LSTM, ANN, and CNN). The findings in their article's proposed model demonstrated its superior accuracy and its ability to remain robust in a wide range of environmental settings.

2.5 SUMMARY OF THE CHAPTER

Based on the comprehensive review conducted in this chapter, different ideas and critical aspects were discussed and addressed from recent scholarly papers and peer-reviewed articles. Various beneficial effects and pivotal influences of DL techniques and intelligent DL algorithms were explored in forecasting electrical power from solar energy with significant levels of accuracy, performance, precision, and speed. The next chapter represents the methodological framework to detect electrical power using those practical methods.

3. RESEARCH METHODOLOGY

3.1 CHAPTER GOAL

This chapter provides critical illustrations and a broad explanation regarding the research phases and primary procedures and approaches adopted and implemented to conduct the numerical analysis and simulation process by virtue of a Python code developed to carry out the validation of DL and ML vital contributions in predicting the clean electrical power associated with a solar energy system in India. Also, the research parameters linked to the intelligent ML and DL algorithms employed in the solar energy prediction process are illustrated.

3.2 RESEARCH METHOD

This master's thesis will rely on a thorough review through which critical secondary databases will be collected and addressed. The secondary data collection process will comprise the beneficial impacts and substantial rationale of implementing different types of ML algorithms, DL simulations, and AI concepts to help scholars predict the production and clean generation of electrical power based on solar radiation depending on historical dataset definition that is related to the solar radiation and electrical power generation in previous years. After this step, a case study will be addressed and investigated, representing two solar Photovoltaic (PV) systems located in India, operating according to the Indian weather conditions and solar radiation. Then, a numerical analysis and mathematical simulation process will be executed with the help of a numeric code developed, written, and processed using the Python software package. After this step, validation of the numerical findings will be applied to modify, adjust, and verify the numerical research outputs. Thereafter, conclusions and recommendations will be proposed to help scientists and engineers predict the amount of clean electrical generation in future from solar energy to help make effective decisions that can provide good matching of citizens' energy demands. Figure 3.1 represents the master's thesis research methodology and its critical phases implemented and executed in this study.

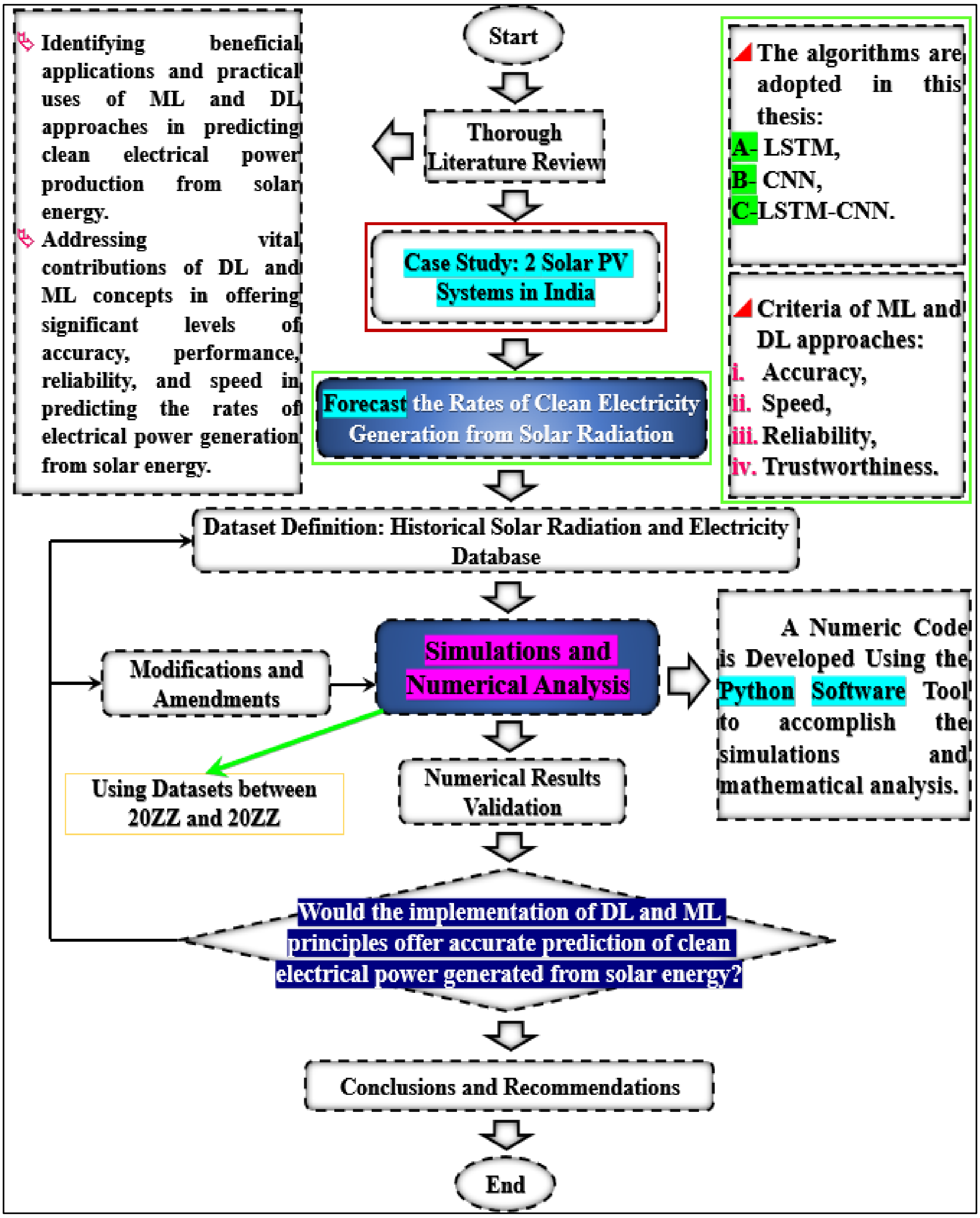

Figure 3.1: The Master's Thesis Methodology Flowchart.

3.3 RESEARCH PHILOSOPHY

The philosophy of this work is reflected in gathering two major types of data, which include (A) Primary and (B) Secondary data collection. In the secondary data collection, international web journals and excellent-rating peer-reviewed articles are addressed and considered to discuss the pivotal roles of various functional impacts of DL and ML implementation to help mechanical and electrical engineers forecast and determine future amounts of clean electrical power generated from solar radiation with exceptional levels of accuracy, performance, reliability, and speed.

At the same time, primary data collection is applied to analyze the active contributions and crucial rationale of DL approaches and ML principles in predicting the total load of green electricity generated from solar radiation depending on the Indian solar parameters and weather conditions between May 15, 2020, and June 17, 2020.

The solar energy prediction dataset will be selected and analyzed to verify the role of those intelligent ML algorithms in determining future amounts of clean electrical power.

Meanwhile, this master;'s thesis will rely on some dependent and independent variables that can describe the effectiveness and reliability of some ML and DL algorithms in performing their task effectively, mirrored in quick and accurate clean electricity generation. Figure 3.2 illustrates the master's research dependent and independent variables.

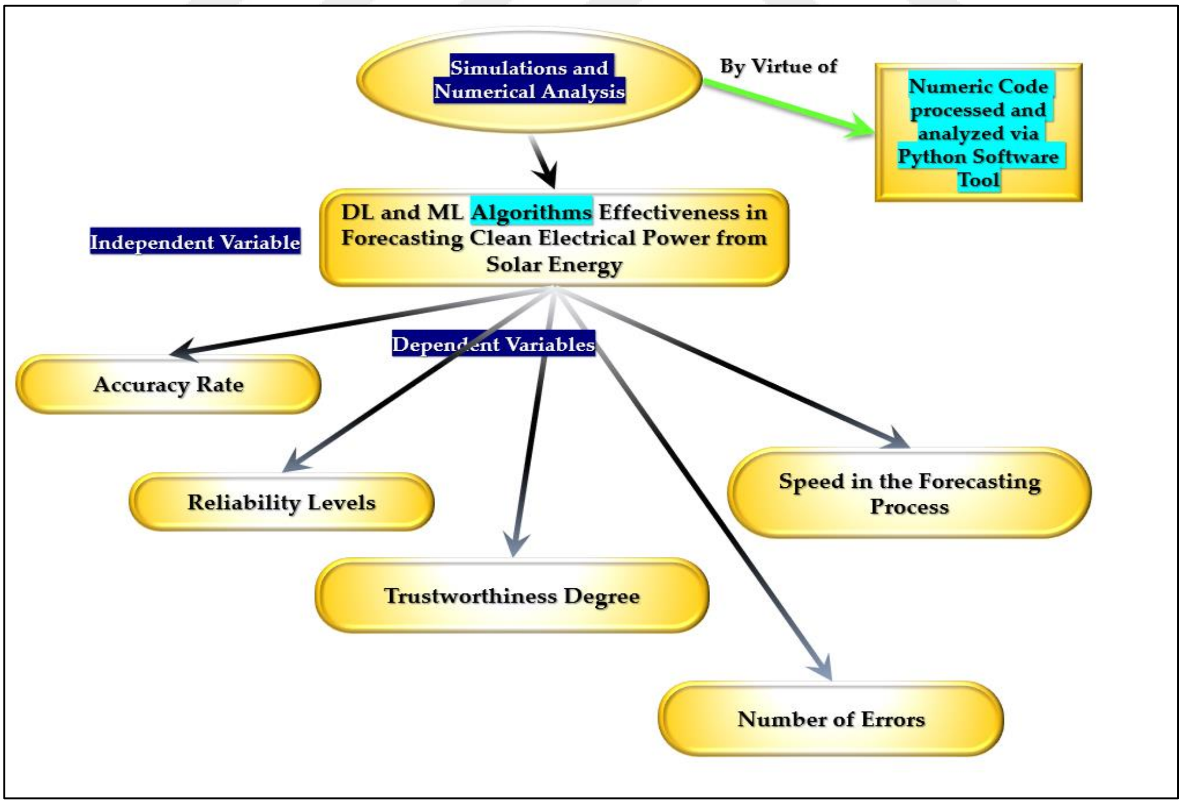

Figure 3.2: The Master's Thesis Dependent and Independent Variables.

It can be inferred from Figure 3.2 that the following parameters:

a. Accuracy Levels.
b. Reliability Degree.
c. Trustworthiness of ML Algorithms.
d. Number of Errors Generated during the Prediction Process, and
e. Speed in Forecasting Electrical Power.

Are essential to identify the performance and effectiveness of ML and DL algorithms in forecasting green electrical power amounts in 2020 according to unprecedented levels of efficiency and robustness.

3.4 DATASET DEFINITION AND PREPARATION

Because of the long duration desired to collect the primary data associated with the measurements and recording of vital variables, like solar radiation, ambient temperature, and overall annual solar PV system production, and other minor variables, like relative humidity, air pressure, and wind speed in Iraq or Turkey, the researcher depended on an open-source website from which available and existing datasets that were previously measured and collected from real PV systems can be employed in this master's thesis. The website is the Kaggle-Open-Source-Dataset-Library, which has the link <https://www.kaggle.com/datasets>.

From this website, the datasets associated with two solar PV systems were considered. The link associated with the dataset and critical input data can be found in the link <https://www.kaggle.com/datasets/anikannal/solar-power-generation-data> [49].

From this website, the dataset associated with three major variables was defined, including:

a. Air temperature.
b. PV module temperature, and
c. Solar radiation.

The duration of the data collection conducted for the two PV power plants lies between May 15, 2020, and June 17, 2020.

The time series analysis of this data took into consideration 3,183 measurements, which were assessed depending on a time variation of 15 minutes (or a quarter of an hour) between each reading. This indicates that the first reading starts on May 15, 2020, at 00:00. At the same time, the following measurement is conducted on May 15, 2020, at 00:15. Thus, 96 readings are recorded per day. Real-time weather sensors and Internet of Things (IoT) data instruments, thermometers, and pyranometers were implemented and used to collect critical data. Excell datasheets were developed according to the datasets created by the measurements between May 15, 2020, and June 17, 2020 [49].

An example of the solar radiation data collection carried out on those days can be represented in Figure 3.3, which represents the solar radiation profile on June 17, 2020.

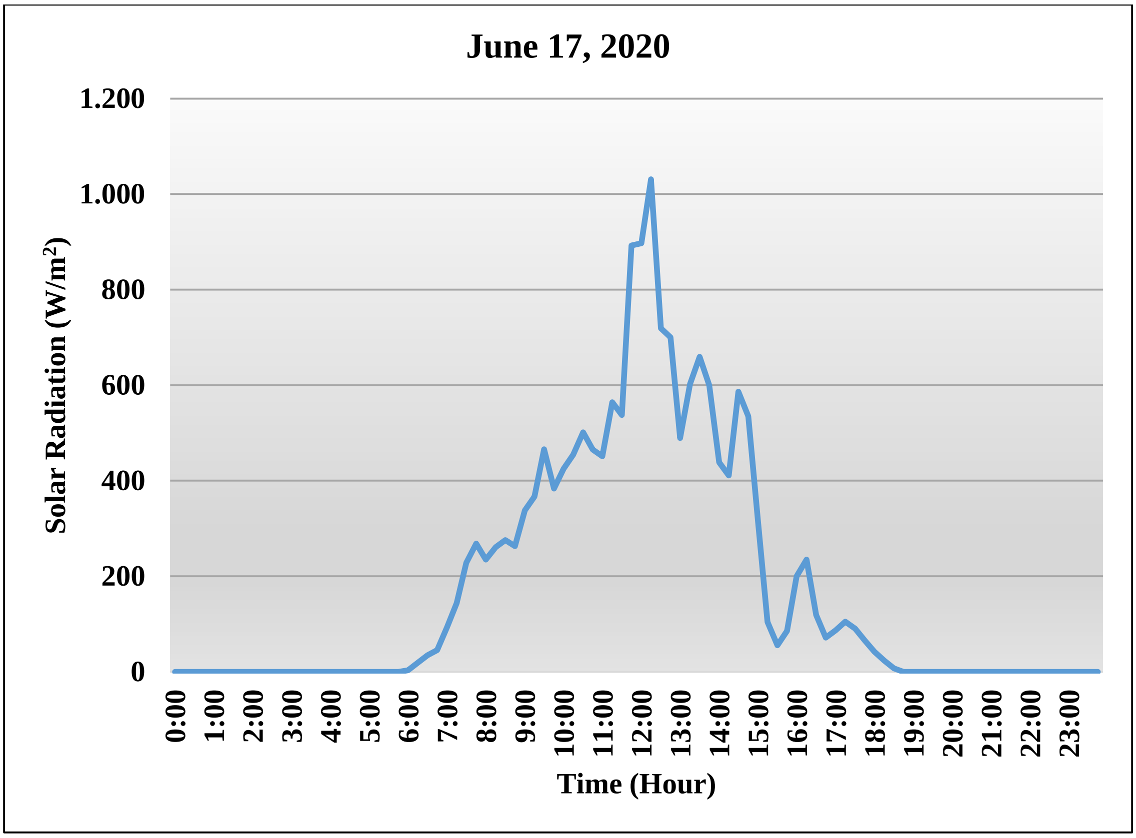

Figure 3.3: The Solar Radiation Profile of the Two Residential PV Power Plants in India [49].

It can be inferred that between around 6:00 am (sunrise) and 6:00 pm (sunset), the solar irradiation recorded a maximum value of just over 1,000 W/m^2.

Another profile was attained by measuring those parameters. This depiction is associated with the ambient temperature, as shown in Figure 3.4 for the same day (June 17, 2020).

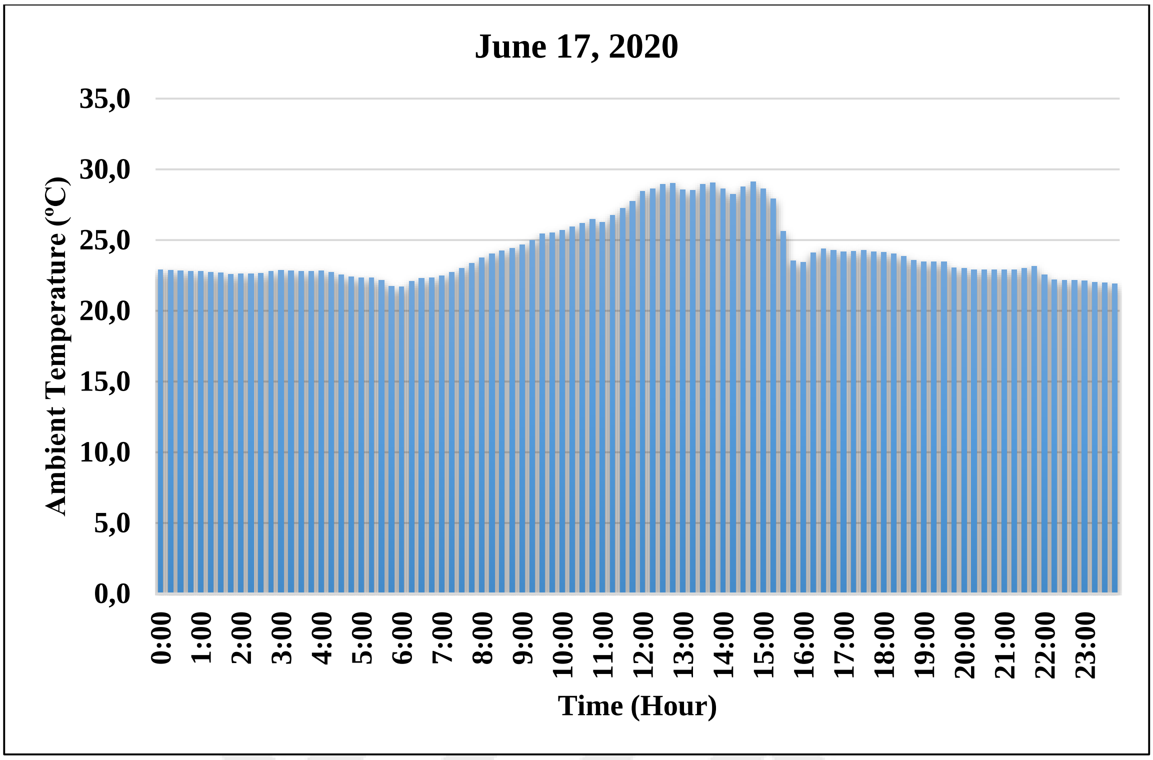

Figure 3.4: The Ambient Temperature Profile of the Two Residential PV Power Plants in India [49].

It can be concluded from the ambient temperature data represented in Figure 3.4 that the minimum air temperature recorded on June 17, 2020, was approximately 22.0 ºC. On the other hand, the maximum recorded temperature value on that day was roughly 29.0 ºC.

In addition, the dataset collected in this case study measured the temperature value of the solar PV module. Those PV modules' temperature values evaluated on June 17, 2020, can be described in Figure 3.5.

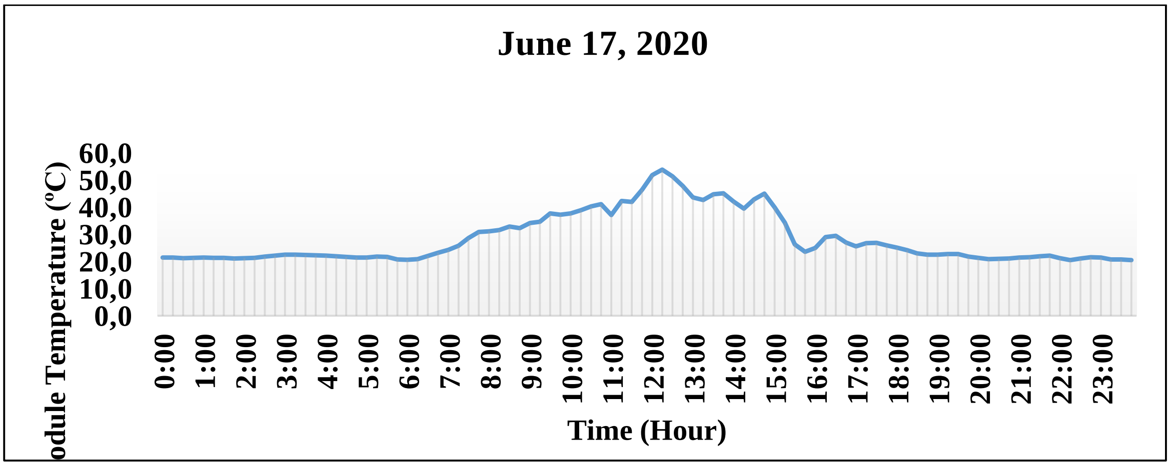

Figure 3.5: The Solar PV Module Recorded on June 17, 2020, for the Two Residential PV Power Plants in India [49].

Furthermore, it is worth mentioning that the datasets addressed in this research contains other dataset that are related to the clean electrical power generation from the two solar PV systems investigated in this numerical analysis. The electrical power production was obtained based on the inverter level. There two investors. Each is connected with a separate PV system and serves a single PV framework. Also, each converter is connected in parallel and series with PV panels according to specific number of arrays in each solar PV system.

More details concerning the description and characteristics of the case study can be illustrated in the following sections.

3.5 CASE STUDY DESCRIPTION

The case study investigated in this research comprises two solar PV systems in India. Those solar two PV systems are operated according to the Indian weather conditions, solar radiation, humidity, and air temperature. The two PV projects are indicated in Figure 3.6.

Those two PV frameworks are installed to provide clean electrical power that can serve a domestic building to achieve the following benefits:

a. Provide more reliability for cooling and heating demands,
b. Cut down the expensive electrical bill spent for the cooling and heating budget,
c. Minimize the overall energy consumption of the domestic building, especially for lighting, refrigeration, cooling, heating, and other energy purposes.
d. Mitigate the dependence on fossil fuel resources,
e. Alleviate the production of Greenhouse Gas (GHG) emissions.

Figure 3.6: An Architecture of the Two Solar PV Systems Investigated in this Research for Two Residential Facilities in India.

The types and capacities of those two systems are illustrated in Table 3.1.

Table 3.1: A description of the thesis's case study.

No.	Category	Value/ Description Details
1	Type of the PV System	On-Grid (Grid-Tied)
2	Wattage - Capacity	8 kW (4 kW each)
3	Location	India
4	Applied for	A residential facility for two apartments (150 m^2 each)

3.6 ML ALGORITHMS EMPLOYED IN THIS WORK

There are three critical types of intelligent ML and DL algorithms employed in this work to validate and confirm the practical contributions of ANN, ML, and DL principles in forecasting the green electrical power produced from solar radiation with considerable degrees of effectiveness and efficiency.

Those ML and DL algorithms include:

a. LSTM,
b. CNN, and
c. LSTM-CNN.

Furthermore, this study will examine the performance and efficacy of those intelligent algorithms based on assessment metrics and evaluation techniques, which are explained in the following sections.

3.6.1 LSTM Model

Long Short-Term Memory (LSTM) networks can be described as intelligent models utilized broadly in ML and DL applications. They comprise various Recurrent Neural Networks (RNNs), which have the potential to learn longer-term data and dependencies associated with sequence forecasting cases and prediction problems [50], [51].

Significant applications of LSTM include its critical role in learning, processing, and classifying sequential databases. Those benefits can be flexibly achieved by virtue of LSTM due to their longer-term dependencies between time indices related to data.

Furthermore, practical LSTM applications are involved in video analysis, speech recognition, language modeling, and sentiment analysis [52]– [54].

Figure 3.7 represents a schematic diagram pertaining to the working principles of the LSTM model in the prediction process.

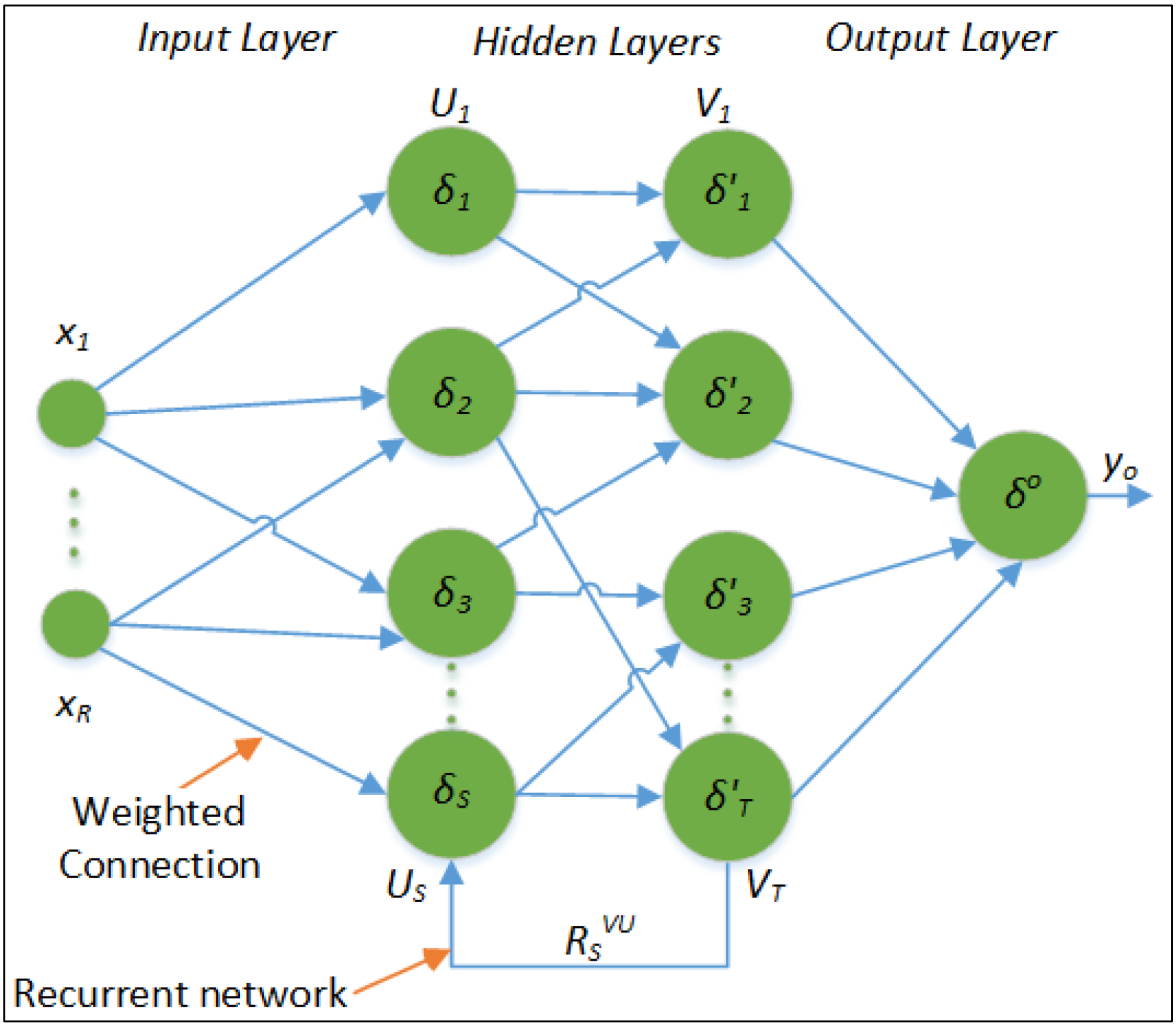

Figure 3.7: A Schematic Illustration Related to the Working Principle of the LSTM Scheme for Making Predictions [55].

[55] conducted a numerical analysis investigating the role of the LSTM model in making predictions and accurate forecasting. The scholars considered a mathematical modeling and theoretical examination of their LSTM model. They reported that a set G has some input and output variables that can be defined by the following formula:

$$G_{In} = (x_1, x_2, x_3, \dots, x_R) \tag{3.1}$$

Where G_{In} is the set comprising the input variables of the group G. x_R is a variable containing the R term that represents the maximum number of variables in the G_{In}. The output group of the set G can be defined as G_{Out}. The threshold or the quantization functions related to the group G can be recognized with the terms δ_i and δ_i', respectively, which are located in the hidden layers.

The LSTM-CNN model or LSTM-Convolutional Neural Network is an exceptional category of RNNs that is associated with image detection and prediction problems connected with images and visual datasets [56].

LSTM-CNN model is also related to time-series forecasting in which previous datasets of the same parameters are required to define. From Figure 3.3, the letters f, o, I, and g represent the forget gate, output gate, input gate, and modulation gate, respectively. Those four gates rely on the current input variable ($x(t)$) and prior quantities of states ($h(t-1)$). The scholars mentioned that the outputs of gates could be computed using the following formula:

$$i(t) = f(W_i x_c(t) + U_i h_c(t-1) + b_i) \tag{3.2}$$

While the f function can be expressed by:

$$f(t) = \tanh(W_c x_c(t) + U_c h_c(t-1) + b_c) \tag{3.3}$$

The g function is illustrated by:

$$g(t) = f(W_f x_c(t) + U_f h_c(t-1) + b_f) \tag{3.4}$$

Where W and U represent the values associated with the input and prior states, respectively. b is the bias. Also, the updated cell state can be given by:

$$O(t) = f(W_o x_c(t) + U_o h_c(t-1) + V_o c(t) + b_o) \tag{3.5}$$

The present cell state, present input values, and prior state related to the cell can be employed to monitor the output gate function. In addition, the state function can be expressed by:

$$h(t) = O(t)\tanh(c(t)) \tag{3.6}$$

3.6.2 CNN Model

As indicated in previous paragraphs, CNN is useful and beneficial for predicting data and forecasting some information associated with different DL problems and differentiating various correlations from the visual data based on biases and importance identification related to learnable parameters [57].

Using Jupyter notebooks in the CNN simulation process can make the simulation process and forecasting procedure more flexible and active by illustrating the prediction phases step by step. Besides, Jupyter notebooks have the ability to arrange the numeric parameters and research data into a good presentation and better order and categorization to facilitate processing and handling the texts, images, and codes. In addition, the Jupyter notebook can document and organize the whole process and numeric data throughout the entire simulation process and code development. This open-source web application can enable researchers and data analysts to write and design numeric codes. Then, share them with different parties, taking into account explanatory texts in separate documents, computational outputs, formulas and equations, and the live simulation code [58]–[60], as indicated in Figure 3.9.

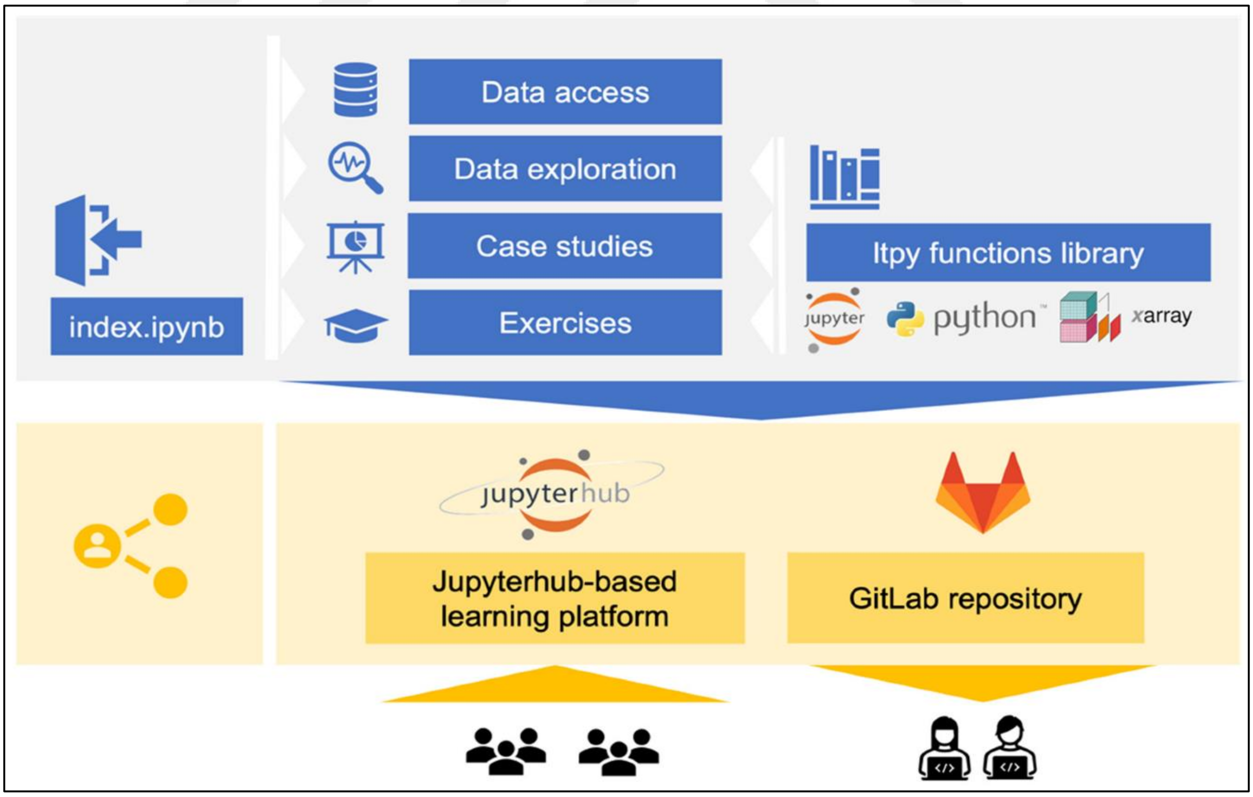

Figure 3.8: An Illustration of CNN Jupyter Model [58].

Some scholars adopted the principles of DL techniques and intelligent CNN algorithm to conduct different prediction processes and forecasting procedures of various cases based on simulation and mathematical analysis executed with the help of numeric codes in variant software tools, like Python and MATLAB software tools. For instance, [61] carried a study investigating the beneficial DL methods and ML approaches in forecasting the clean electrical power of a solar PV system feeding electricity for homes and domestic purposes. They developed a framework by virtue of CNN model to achieve their research goal, as indicated in Figure 3.9.

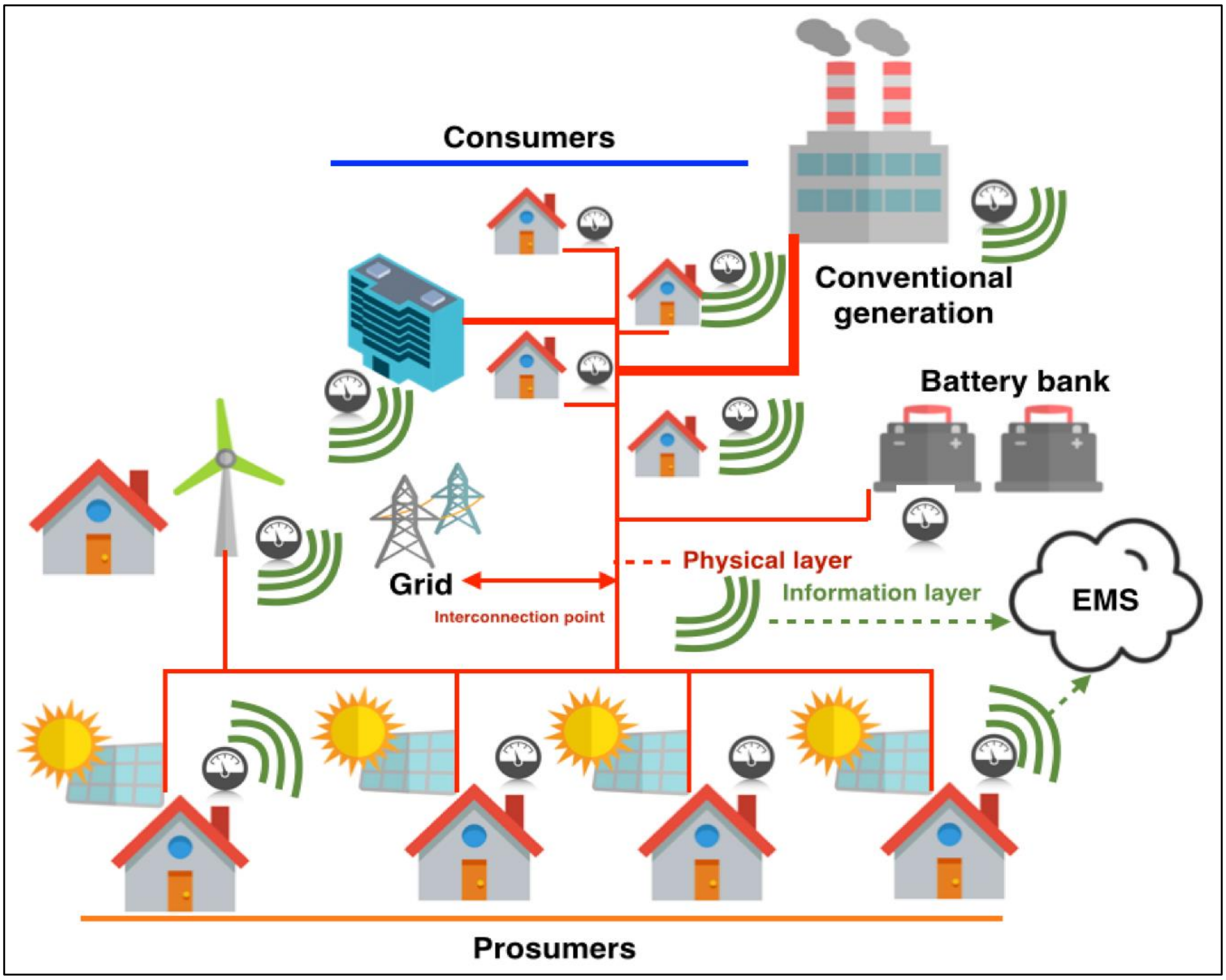

Figure 3.9: Using the CNN Model to Predict the Electrical Power Production in A PV System [61].

3.6.3 LSTM-CNN Model

CNN has the property of focusing on the most prominent properties in the line of sight, so it is widely employed in feature engineering. On the other hand, the LSTM model has the characteristic of expanding according to the sequence of time. Thus, it is broadly employed in time series. According to the characteristics of CNN and LSTM, a stock forecasting model based on CNN-LSTM is established. -e model structure diagram is shown in Figure 3.10, and the main structure is CNN and LSTM, including the input layer, one-dimensional convolution layer, pooling layer, LSTM hidden layer, and complete connection layer.

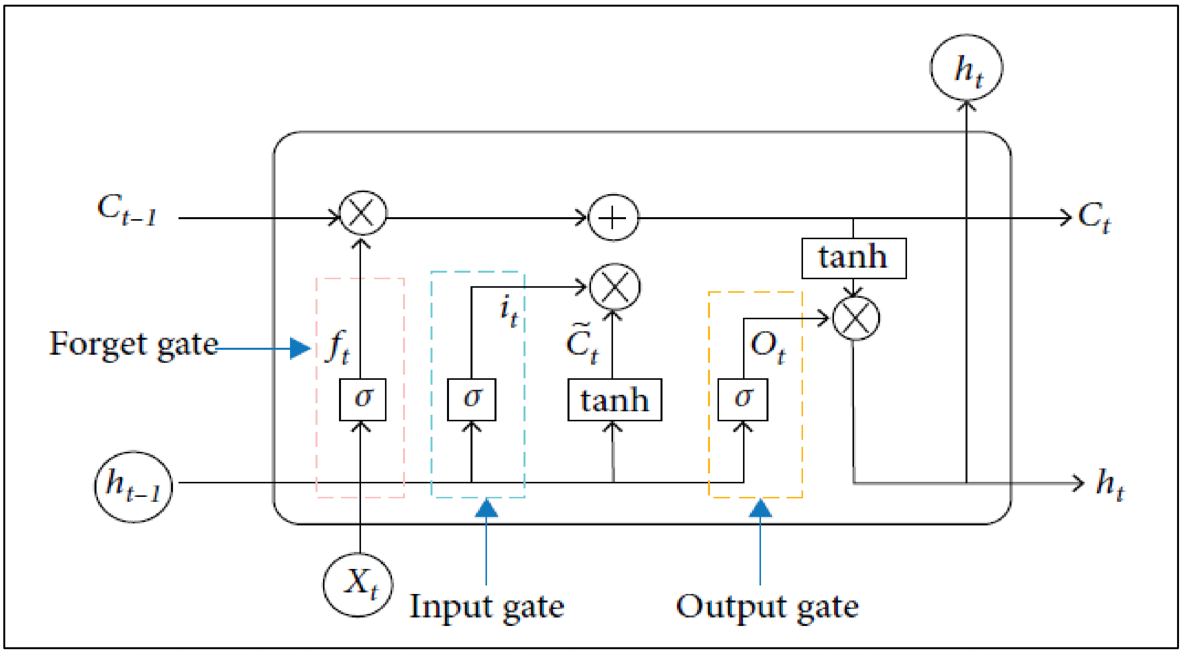

Figure 3.10: A Schematic Representation of the LSTM-CNN Model [56].

[56] guided an analysis investigating the beneficial contributions of a hybrid model consisting of LSTM and CNN algorithms to carry out forecasting the prices of stocks. They developed the new LSTM-CNN model, as shown in Figure 3.11.

They mentioned that designing a model that relies on some substantial research phases and numerical processes can be illustrated in the following points [56]:

a. Input data definition,

b. Standardization of data. It is required to bridge the gap in the input data by making better model training. Thus, the z-score standardization techniques can be implemented to standardize the input data with the help of the following equation:

$$y_i = \frac{x_i - \bar{x}}{s} \tag{3.7}$$

And:

$$x_i = y_i \times s + \bar{x} \tag{3.8}$$

Where y_i is the standardization quantity, x_i is the input data, $\bar{x}$ is represents the mean value related to the input data, and s denotes the standard deviation related to the input data.

a. Initializing the network operating process by defining the biases and weights of every layer linked to the LSTM-CNN model.
b. Calculation process adoption of the CNN layer via the employment of convolution and pooling categories in the CNN layer. Thus, the feature extraction pertaining to the input data can be initiated to obtain the necessary output values.
c. Computing process of the LSTM layer by computing the new output data from the input data of the CNN layer results.
d. A full-connection layer of LSTM and CNN calculation through the computing of new output variables based on the new outputs obtained from the LSTM layer.
e. Error evaluation and results validation by conducting a comparative analysis between the results obtained from the LSTM-CNN model with the real values.
f. Making justification and verification of the results obtained with the end condition.
g. Backpropagation of the error by propagating the computed error in the opposite direction and updating the weight of the bias related to every layer
h. Saving the model.
i. Defining the new data as an input
j. Making data standardization.
k. Forecasting of the new output data depending on the newly trained LSTM-CNN model.
l. Restoring data standardization.
m. Attaining new outputs from the newly trained LSTM-CNN algorithm.

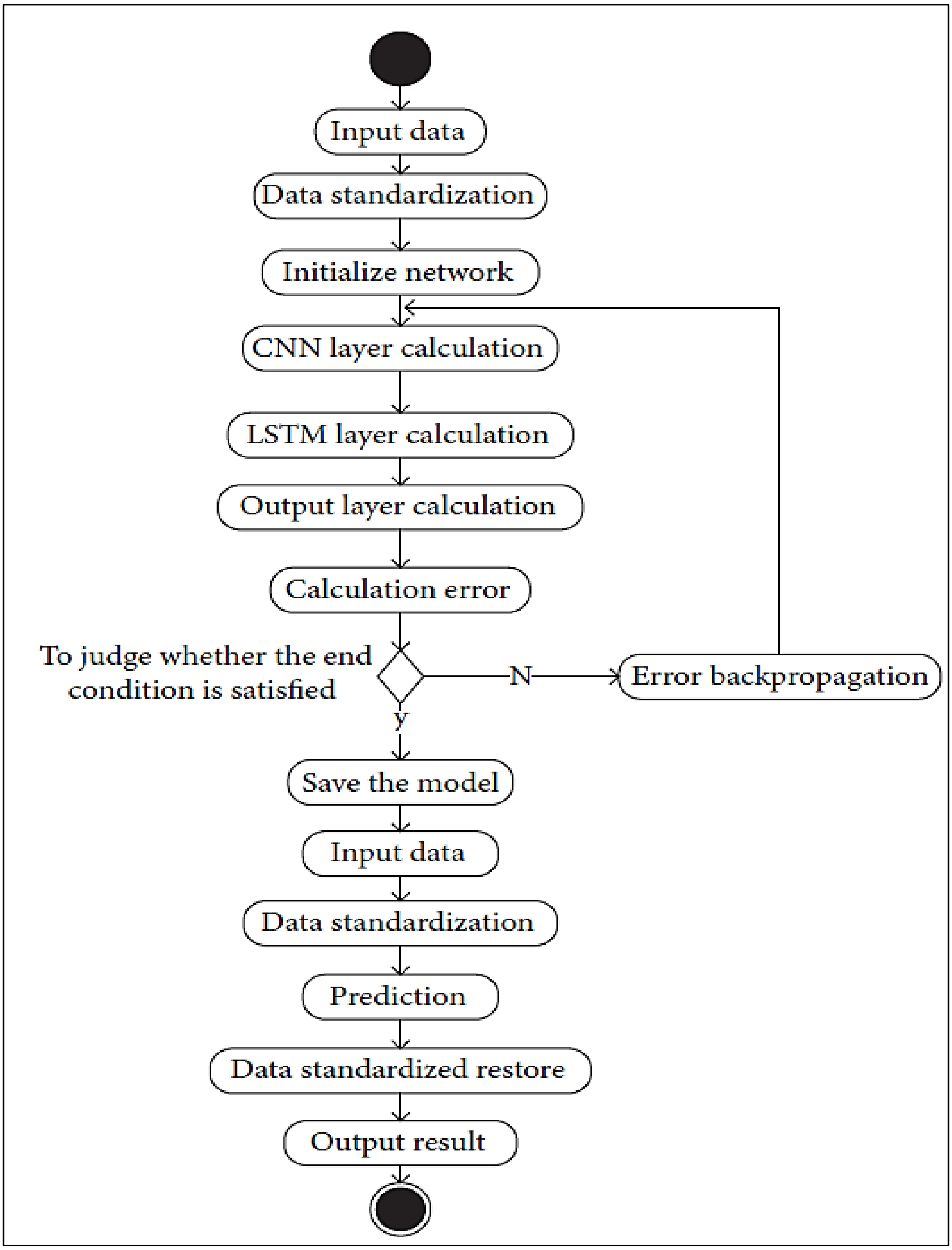

Figure 3.11: The Flow Diagram Related to the Training and Forecasting Process of the LSTM-CNN Model [56].

3.7 PERFORMANCE EXAMINATION OF ML ALGORITHMS

In this work, some evaluation metrics and assessment mechanisms were adopted and applied to help identify the effectiveness and reliability of the LSTM, CNN, and LSTM-CNN algorithms.

Those evaluation approaches include:

a. Mean Absolute Error (MAE), and
b. Root Mean Squared Error (RMSE),

The MAE is vital to assess the mean quantity of a prediction of process or a group of forecasting procedures. But it does not consider directions (negative and positive signs).

IT can be calculated depending on a formula expressed in the following relationship [55]:

$$MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n} \tag{3.9}$$

At the same time, the RMSE approach is beneficial to measure the mean magnitude related to the error of the prediction. It can be computed by finding the difference between the forecasted data and the corresponding noted amounts. The summation of the errors after they were squared is conducted. Then the root is taken. All those steps can be summarized in the following equation [55]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{3.10}$$

3.8 CHAPTER SUMMARY

This chapter was developed and written to describe the fundamental methods and critical research phases adopted in this thesis to carry out a validation and confirmation of a number of intelligent DL algorithms and ML principles to forecast the amount of clean electrical power system for future periods (between May 15, 2020 and June 17, 2020) with remarkable rates of accuracy, speed, and effectiveness. Additionally, this chapter described the dependent and independent parameters needed to assess and examine the performance of the implemented ML algorithms. Besides, the historical dataset definition was applied to define the solar radiation and electrical loads with a period between May and June of 2020.

Those databases are required to conduct the numerical analysis flexibly, verifying the beneficial roles of DL algorithms in predicting clean electrical power from solar radiation. Meantime, the major categories of DL algorithms implemented in this work and associated descriptions of each one was conducted to identify the critical advantageous merits and main characteristics of the implemented ML techniques to offer active solutions for engineers and scientists in terms of accurate and flexible prediction of clean electrical power from solar energy.

4. RESULTS AND DISCUSSIONS

4.1 CHAPTER GOAL

This chapter provides critical illustrations and a detailed explanation regarding the research outcomes and main study findings obtained from the numerical analysis and mathematical simulations conducted on intelligent LSTM, CNN, and LSTM-CNN algorithms to validate the role and positive impacts of adopting ML techniques and DL principles to predict electrical power and forecast some vital parameters related to a typical PV system based on a numeric code developed for the prediction process.

4.2 NUMERICAL RESULTS OF THE LSTM ALGORITHM

Based on the simulations and mathematical analysis carried out to investigate the performance and effectiveness of the LSTM model in forecasting the clean electrical power from the two solar PV systems installed in India, the research findings indicated the values of MAE associated with the forecasting process of clean electrical energy based on training and testing phases.

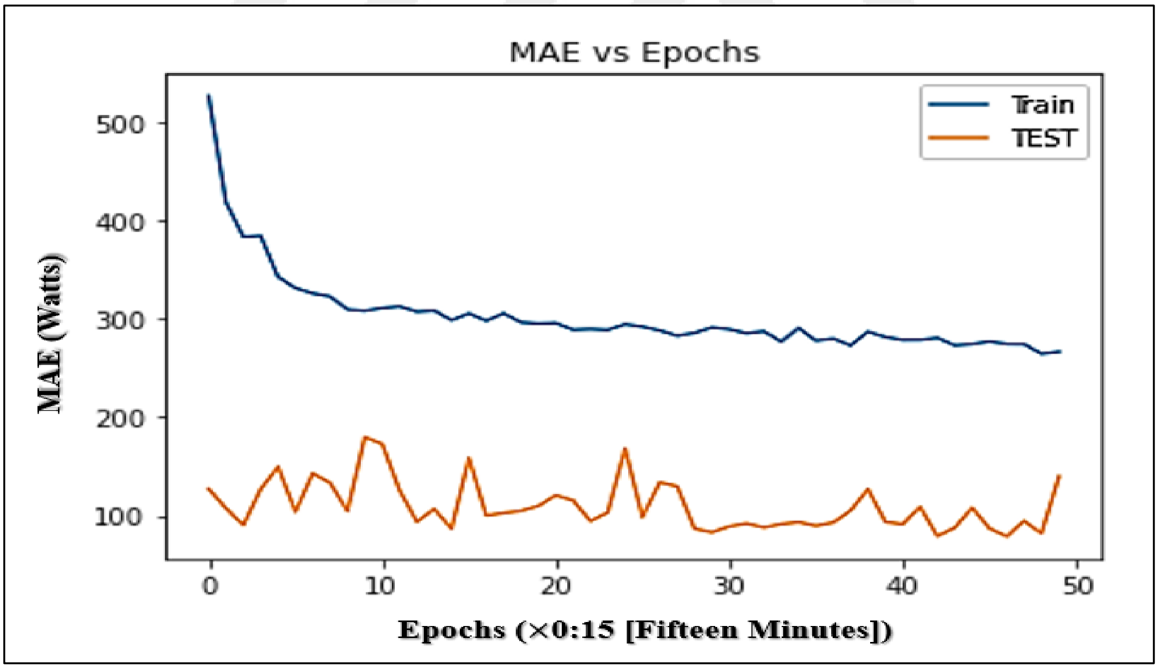

Figure 4.1: The MAE Amounts Related to the Training and Testing Accuracies of the LSTM Model with Time.

It can be inferred from the results illustrated in Figure 4.1 that the MAE values associated with the training process implemented in the LSTM algorithm are more significant than those obtained after the testing phase was accomplished. The amount of MAE for the training process reaches a maximum value of 500 Watts (W). Then, the MAE of training declines to approximately just below 300 W at an epoch of 50 × fifteen minutes. At the same time, the numerical findings indicated the relationship between RMSE and epochs for the LSTM model.

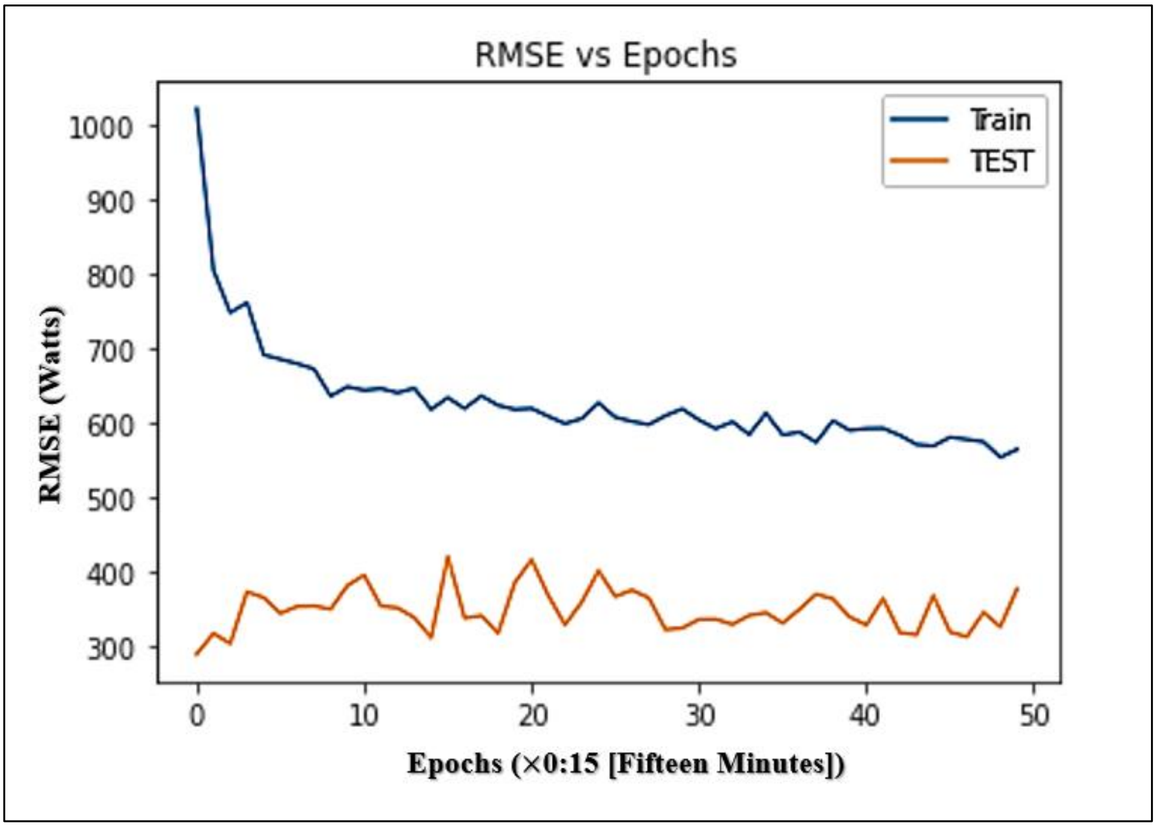

Figure 4.2: The RMSE Amounts Related to the Training and Testing Accuracies of the LSTM Model with Time.

It can be concluded from the data obtained in Figure 4.2 that the RMSE of the training process carried out in the LSTM model that the maximum level reached was 1,000 W. then, the RMSE of training declines to about 600 W at 50 × fifteen minutes. On the other hand, the RMSE attained from the testing procedure ranges between approximately 300 and 400 W. Moreover, Figure 4.3 describes the variation between the original and forecasted values of clean electrical power generated from the two solar PV systems based on the simulations of the LSTM model.

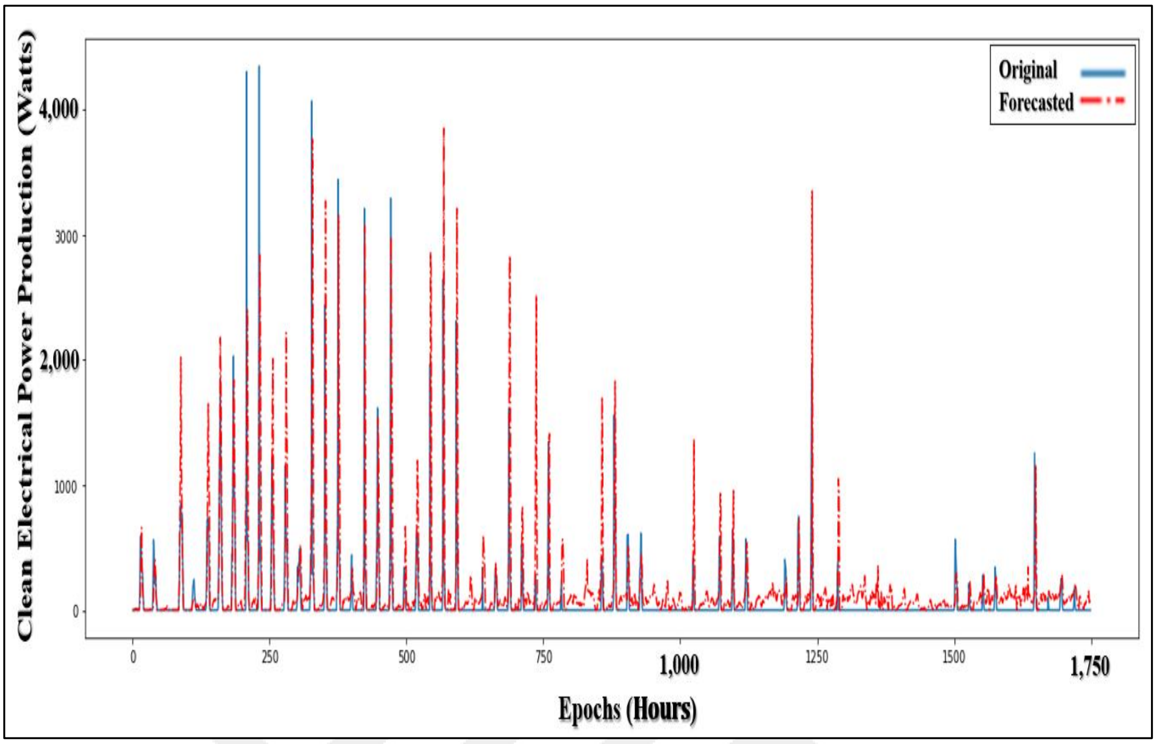

Figure 4.3: The Variation Between the Original and Predicted Clean Electrical Power Generated from the Two PV Systems According to the LSTM Model with Time.

It is deduced from the outputs represented in Figure 4.3 that the rate of accuracy linked to the LSTM model is very high (approximately more considerable than 90%) due to the symmetry and consistency between the two profiles. The blue profile (original clean electrical power quantity) lies perfectly on the forecasted/ predicted green electrical energy according to the simulation outcomes of the LSTM model. However, there are some violations and dissimilarities between the two profiles. Thus, it can be concluded that using the LSTM model would provide a high degree of performance associated with the prediction process. Nonetheless, this degree is not perfect or remarkably significant.

4.3 NUMERICAL RESULTS OF THE CNN ALGORITHM

Based on the simulation process and analytical procedures executed for examining the reliability and effectiveness of the CNN model in forecasting the clean electrical power from the two solar PV systems installed in India, the study outputs revealed the values of MAE associated with the forecasting process of clean electrical energy based on training and testing phases in the CNN model.

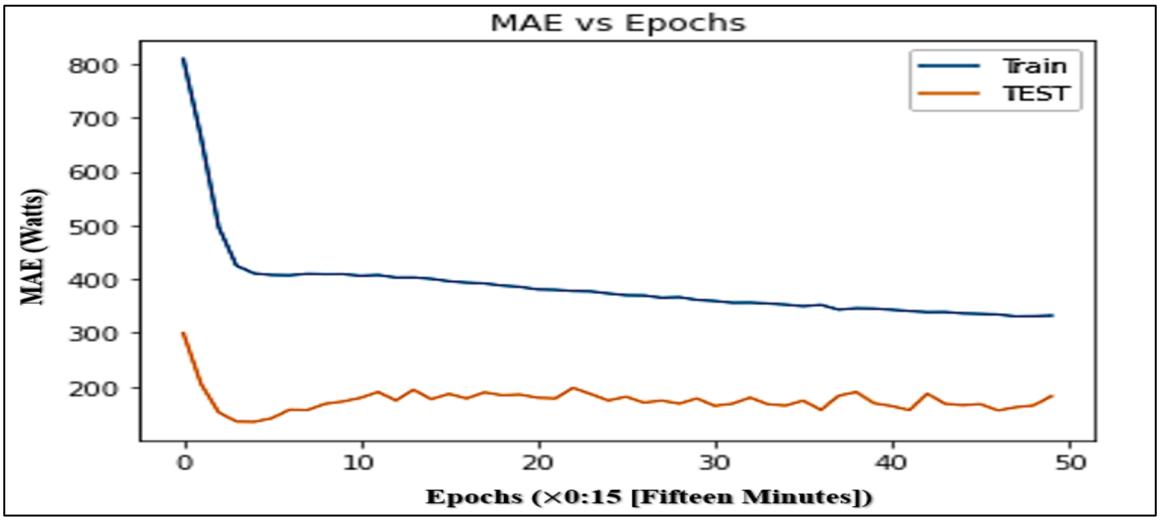

Figure 4.4: The MAE Amounts Related to the Training and Testing Accuracies of the CNN Model with Time.

It can be deduced from the results illustrated in Figure 4.4 that the rate of MAE pertaining to the training process was high for lower epochs (500 to 800 W), corresponding to 0 to 4 × fifteen minutes. However, the MAE declines slightly from around 400 W to 330 W associated with 4 to 50 × fifteen minutes, respectively. At the same time, the MAE attained from the testing procedure ranges between roughly 150 and 200 W after 10 × fifteen minutes. But the MAE registered maximum and minimum values of 300 and just below 150, respectively. Also, Figure 4.5 represents RMSE findings linked to the CNN model training and testing processes.

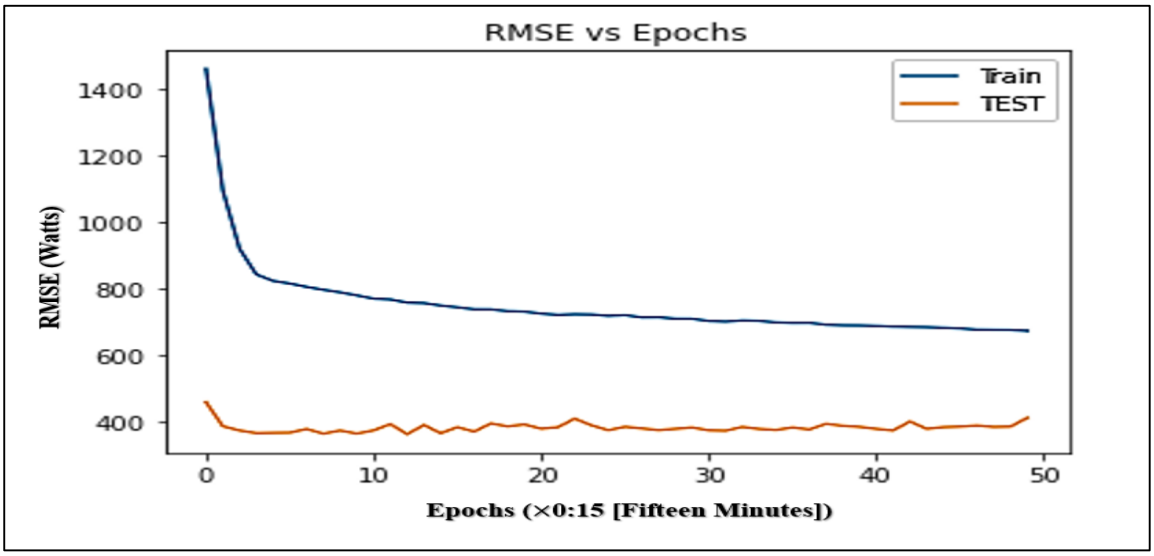

Figure 4.5: The RMSE Amounts Related to the Training and Testing Accuracies of the CNN Model with Time.

It can be indicated from the findings achieved from the simulation of the CNN-testing procedure that RMSE was very high between 0 and 3 × fifteen minutes, corresponding to a maximum RMSE value of around 1,400 W at epochs closer to zero. Then, the RMSE value declines at a steady rate after a period of 3 × fifteen minutes. Approximately, the RMSE value is between 650 and 800 W. Furthermore, the research outcomes provided some findings related to the predicted electrical power from the simulation carried out with the support of the CNN model, as illustrated in Figure 4.6.

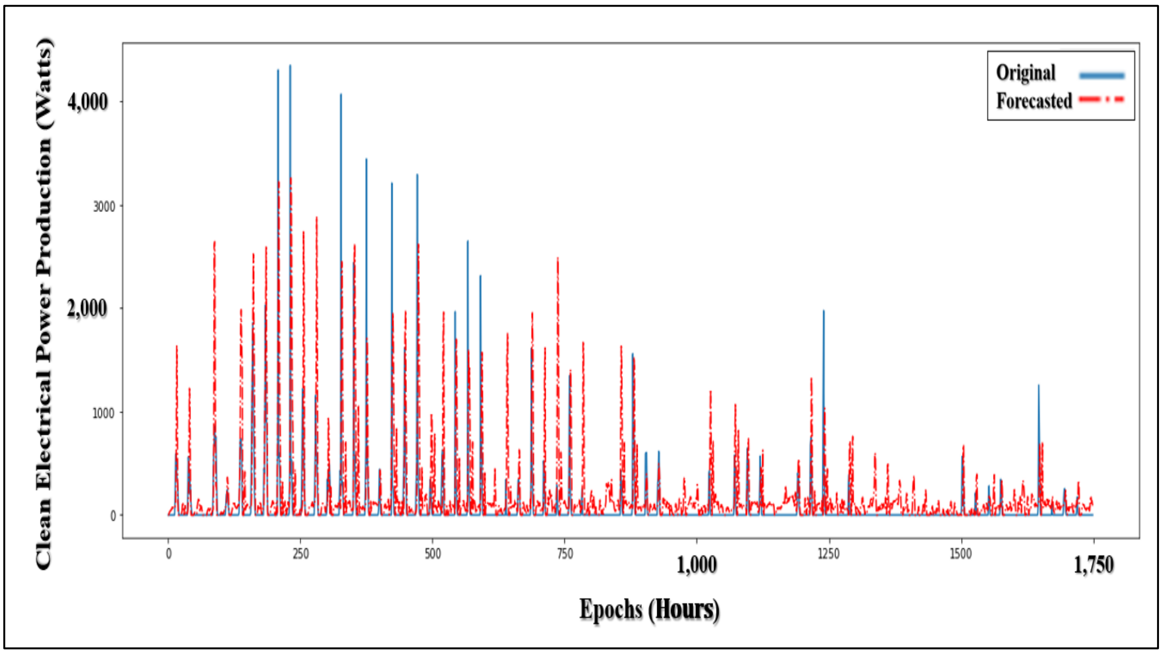

Figure 4.6: The Variation Between the Original and Predicted Clean Electrical Power Generated from the Two PV Systems According to the LSTM Model with Time.

It is inferred from Figure 4.6 that the accuracy of the CNN model in predicting clean electrical power from the two solar PV systems is remarkably significant due to the identical readings and approximate profile behavior of both the original and predicted electrical power output generated from the two PV frameworks. However, there are still some dissimilarities between the forecasted and actual and clean electrical power generation values. Hence, the CNN model is relatively better than the LSTM scheme but does not reach comprehensive perfectness in prediction accuracy.

4.4 NUMERICAL RESULTS OF THE LSTM-CNN ALGORITHM

A third model was developed to compare the effectiveness of clean electrical power production in this work, which is reflected by a hybrid algorithm created from the combination of LSTM and CNN numerical layers. The results of the MAE correlated with the testing and training of the new hybrid algorithm can be shown in Figure 4.7.

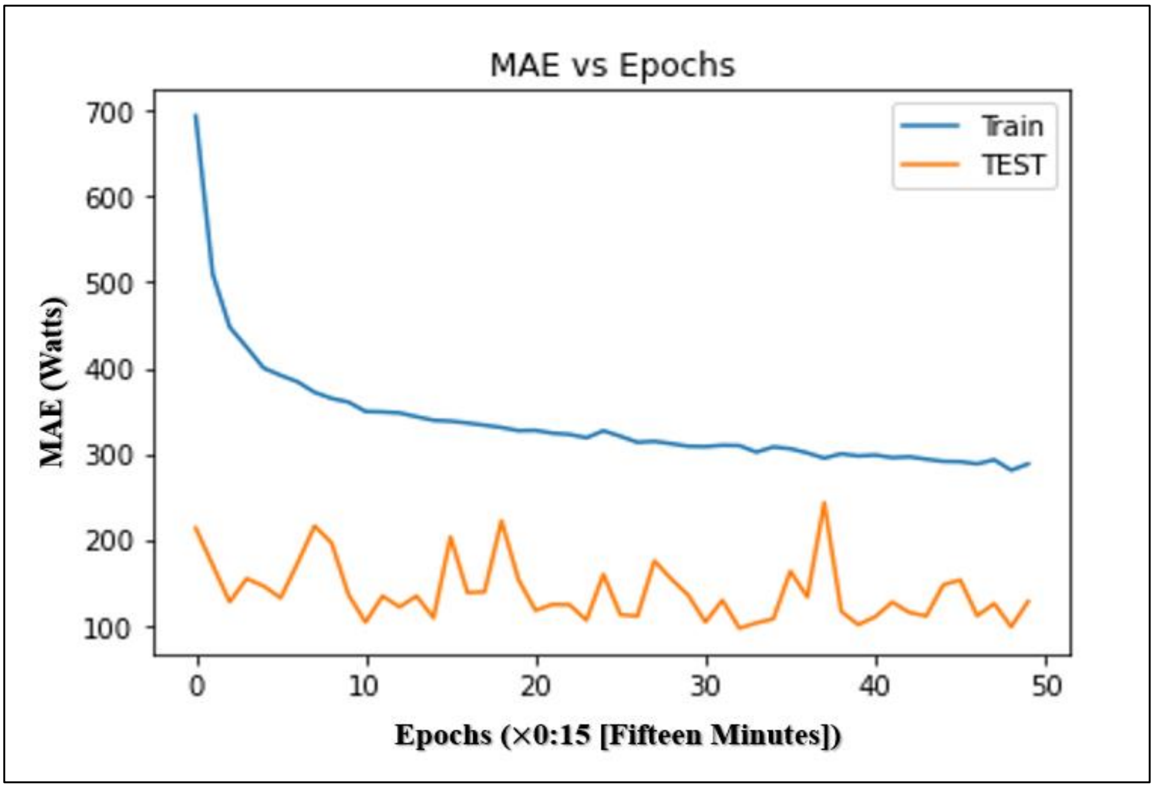

Figure 4.7: The MAE Amounts Related to the Training and Testing Accuracies of the LSTM-CNN Model with Time.

It can be understood from the simulation data obtained and described in Figure 4.7 that the MAE of the training process is generally more significant than that related to the testing procedure of the hybrid LSTM-CNN model. The maximum value attained by the training process was about 700 W. Then, it declines rapidly to an MAE amount of roughly 400. Then, the MAE of the training process continues to decline slightly from 400 to 300 W, corresponding to an epoch of 4 to 50 × fifteen minutes. However, the MAE of the testing process ranges between 100 and 200 W across all the investigated periods. Figure 4.8 depicts the RMSE profile of testing and training processes associated with the hybrid LSTM-CNN algorithm.

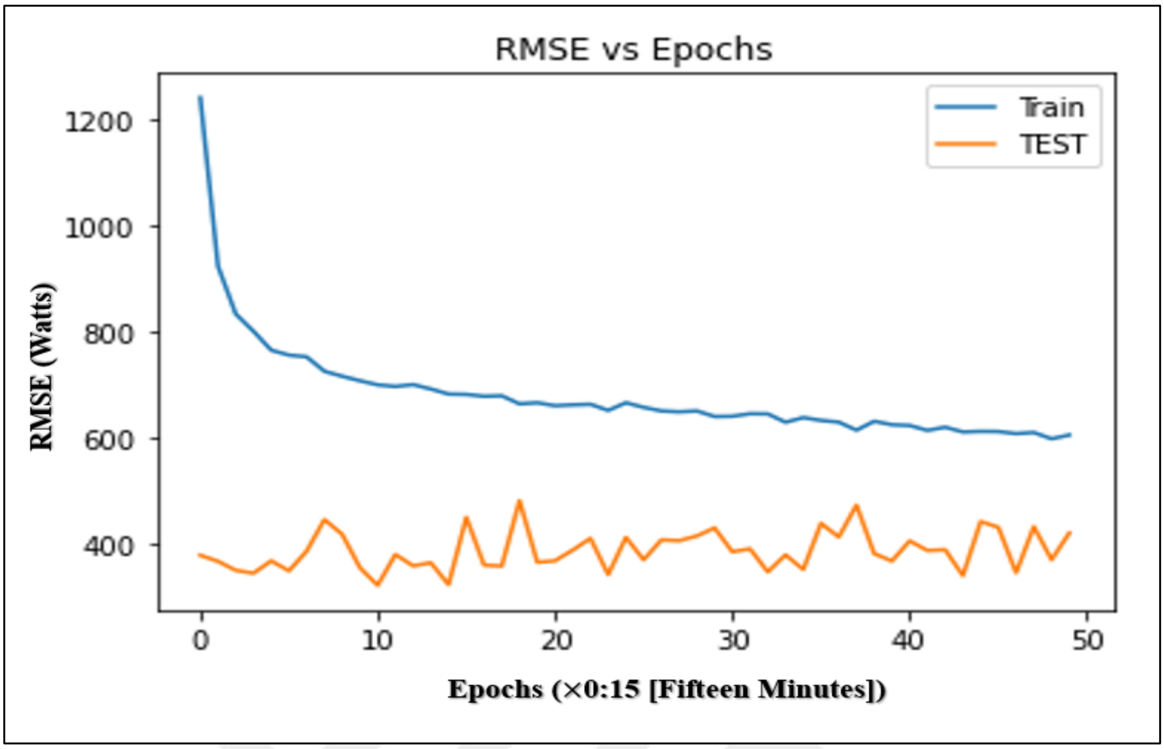

Figure 4.8: The RMSE Amounts Related to the Training and Testing Accuracies of the LSTM-CNN Model with Time.

It can be drawn from the simulation findings accomplished with this new hybrid algorithm that the maximum RMSE quantity attained from the training process in the new hybrid model was 1,200 W. Between 5 and 50 × fifteen minutes, the RMSE related to the training procedure registered an amount of approximately 600 W (minimum) to about 750 W (maximum), corresponding to 5 and 50 × fifteen minutes, respectively. However, the RMSE values range between nearly 150 and 450 W. In addition, Figure 4.9 indicates the results of the clean electrical power obtained from the simulation process of the hybrid LSTM-CNN model compared with the original data.

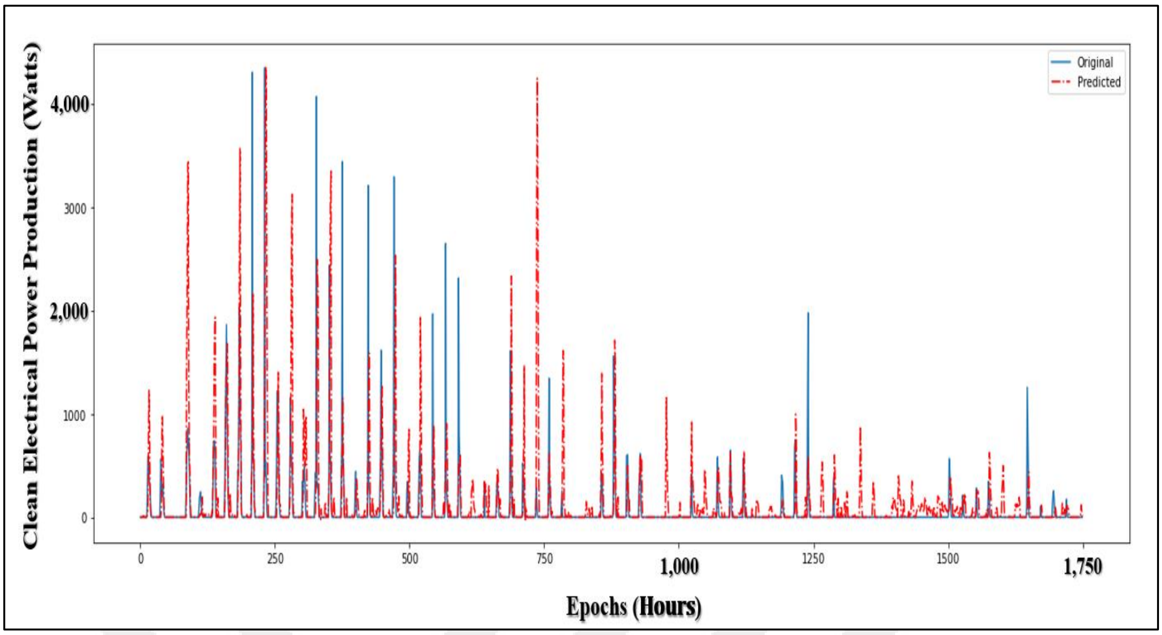

Figure 4.9: The Variation Between the Original and Predicted Clean Electrical Power Generated from the Two PV Systems According to the LSTM Model with Time.

It is deduced from the results attained from the simulation process of the new LSTM-CNN model that approximately all forecasted clean electrical power values associated with the prediction process using this novel hybrid scheme were significantly identical to the original quantities measured from the electronic devices of the two solar PV systems in India. Therefore, it can be concluded that the accuracy of the LSTM-CNN model was remarkably better than LSTM and CNN algorithms.

4.5 COMPARATIVE ANALYSIS BETWEEN THE THREE NUMERICAL MODELS

To provide a good juxtaposition between the three investigated DL models that were applied and implemented to forecast the clean electrical power from solar radiation and PV plants, a comparative analysis was conducted between the three DL schemes, which is shown in Table 4.1.

Table 4.1: A Comparative Analysis Between the Three DL Schemes.

No.	Type of DL Algorithm	Approximate Rate of Accuracy (%)
1	LSTM	85% to 90%
2	CNN	90% to 95%
3	Hybrid LSTM-CNN	95% to 100%

on these comparative analysis results, the new hybrid LSTM-CNN model can be nominated to be actively and functionally employed to forecast electrical power from solar PV systems and make other purposes of prediction applications due to its more significant accuracy compared with other DL algorithms used in this work. A graphical representation of the maximum and minimum accuracy rates obtained from the numerical simulations of this work can be described in Figure 4.10.

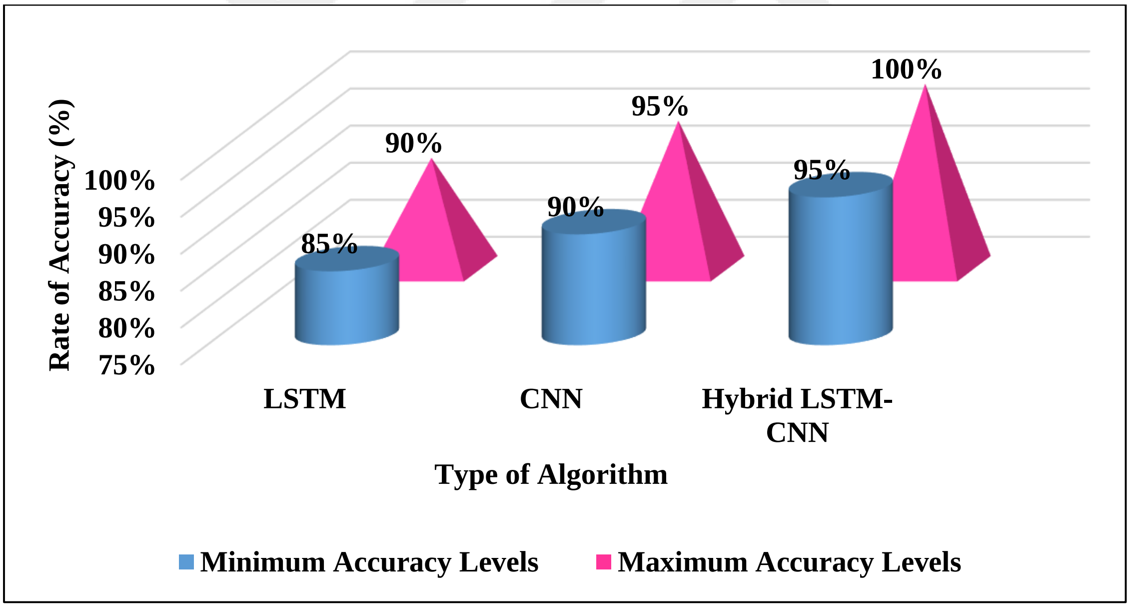

Figure 4.10: Minimum and Maximum Accuracy Levels Associated with Three DL Models Investigated in this Research.

4.6 DISCUSSIONS

The results of this master's thesis revealed that the LSTM, CNN, and hybrid LSTM-CNN models provided a higher degree of accuracy in predicting clean electrical power amounts generated from two solar PV systems. However, the accuracy of the hybrid model offered the most significant accuracy rates compared with the first two algorithms. Furthermore, the results of this work indicated that the values of MAE associated with the training of the three algorithms were more considerable than the MAE amounts related to the testing process across all the epoch ranges. Also, it was found that the MAE connected with training for the three algorithms started at a higher maximum value. Then, it declines until it reaches a lower value steadily for a longer epoch range. But the MAE value after declination was still higher than the MAE rates of the testing process. Moreover, the numerical outputs indicated that the RMSE value of the training and testing procedures for the three algorithms had similar behavior to the MAE in the forecasting process of the clean electrical power of the two solar PV systems. The results of this work are consistent with the research findings of [56], [62]–[65], who carried out numerical analyses and mathematical simulation processes to explore and verify the effectiveness, reliability, and accuracy of a novel model that was created from hybrid layers that take into account LSTM and CNN schemes to formulate the new LSTM-CNN algorithm. The mathematical simulations and research outcomes of those researchers confirmed that using this innovative hybrid LSTM-CNN model gave remarkable levels of performance, trustworthiness, accuracy, and efficacy in forecasting different prediction problems based on the definition of historical datasets.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 CHAPTER GOAL

This chapter provides critical illustrations and a detailed explanation regarding the research outcomes and main study findings obtained from the numerical analysis and mathematical simulations conducted on intelligent LSTM and CNN algorithms to validate the role and positive impacts of adopting ML techniques and DL principles to predict electrical power and forecast some vital parameters related to a typical PV system based on a numeric code developed for the prediction process.

5.2 CONCLUSIONS

This master's research is directed to examine and explore the major contributions and substantial relevances of novel DL algorithms in making predictions with significant rates of accuracy, reliability, effectiveness, and trustworthiness. The study considered a case study representing two solar PV systems operating in India. Some datasets were defined. Two typical performance evaluation approaches were implemented to assess the accuracy of those innovative DL models. LSTM, CNN, and LSTM-CNN algorithms were used. Depending on the numerical simulations and mathematical analysis in this work, the findings revealed the following critical aspects:

a. The LSTM, CNN, and hybrid LSTM-CNN models offered higher degree accuracies in forecasting clean electrical power produced from the two solar PV systems. Nonetheless, the accuracy of the hybrid model provided the most significant accuracy rates compared with the first two algorithms.

b. The values of MAE associated with the training of the three algorithms were more considerable than the MAE amounts related to the testing process across all the epoch ranges.

c. The MAE connected with training for the three algorithms started at a higher maximum value. Then, it declines until it reaches a lower value steadily for a more extended epoch range. But the MAE value after declination was still higher than the MAE rates of the testing process.

d. The RMSE value of the training and testing procedures for the three algorithms had similar behaviour to the MAE in the forecasting process of the clean electrical power of the two solar PV systems.

5.3 RECOMMENDATIONS

Based on the numerical simulations and mathematical analysis carried out in this master's thesis, this work proposes a number of future suggestions that can be considered by computer engineers and energy consultants, and electricity professionals to conduct more enhancements on the adoption and application of DL techniques in computer engineering.

Those critical recommendations include the following points:

a. Executing various active conferences and practical workshops that take into account the implementation of DL principles to forecast different databases associated with varying applications of engineering,
b. Educating employees and junior engineers in engineering companies and computer organizations to apply DL principles in different uses related to real-life problems for predicting various critical data.
c. Making elaborations between DL consultants and business owners to increase the implementation of novel DL algorithms and DL approaches in making high-performance and accurate prediction processes.

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