NEAR EAST UNIVERSITY

INSTITUTE OF GRADUATE STUDIES

DEPARTMENT OF MECHANICAL ENGINEERING

EFFECTS OF GEOGRAPHICAL PARAMETERS IN PREDICTING THE DIRECT NORMAL IRRADIANCE OF AFRICA USING MACHINE LEARNING MODELS

M.Sc. THESIS

MUSTAPHA TANIMU ADAMU

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MUSTAPHA TANIMU ADAMU
20215363

Supervisor

Assoc. Prof. Dr. Youssef Kassem

Nicosia
June 2023

Approval

We certify that we have read the thesis submitted by Mustapha Tanimu Adamu titled **"Effects of Geographical Parameters in Predicting the Direct Normal Irradiance using Machine Learning Models"** and that in our combined opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Mechanical Engineering.

Examining Committee	Name-Surname	Signature
Head of the Committee:	Prof. Dr. Hüseyin Gökçekuş	....
Committee Member*:	Assoc. Prof. Dr. Hüseyin Çamur	....
Supervisor:	Assoc. Prof. Dr. Youssef Kassem	....

Approved by the Head of the Department

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Assoc. Prof. Dr. Hüseyin Çamur

Head of Department

Approved by the Institute of Graduate Studies

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Prof. Dr. Kemal Hüsnü Can Başer

Head of the Institute

Declaration

I hereby declare that all information in this thesis has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Mustapha Tanimu Adamu
20/06/2023

Acknowledgments

All praises and thanks are due to the designer and creator of the universe, Almighty ALLAH, who gave me the courage and opportunity to successfully complete my thesis

It is pertinent that I offer my special prayers to my parents who since I was born have been taking good care of me supported my education in all aspect, may ALLAH reward you in abundance. My special regard goes to my supervisor, Assoc. Prof. Dr Youssef Kassem for the support and guidance he rendered throughout my thesis. My regards go Prof. Huseyin Camur, my course advisor for the support he rendered, Thank You

To all the people who directly or indirectly supported me in one way or the other towards completing this work, I say a very big Thank You. May ALLAH bless us.

Mustapha Tanimu Adamu

Abstract

Effects Of Geographical Parameters in Predicting the Direct Normal Irradiance of Africa Using Machine Learning Models

Mustapha Tanimu Adamu

M.Sc., Department of Mechanical Engineering
Supervisor's Name: Assoc. Prof. Dr. Youssef Kassem

20/June/2023 83 pages

The switch from conventional to renewable energy (RE) resources has been prompted by the sharply rising global energy desire, the sharp decline in fossil fuel reserves, global warming, climate change, and energy security concerns. In Africa, With the high population of about 1.3 billion, most of the people who stay in remote areas in Africa do not have access to electricity. It is on record that nearly two-thirds of Africa's population, which is estimated to be 620 million and increasing, lack access to electricity, which limits the continent's ability to develop. With this rising concern, the need to shift to a reliable alternative energy is imminent. One of the most important factors in designing solar power is the Direct Normal Irradiance which is the quantity of solar radiation received by a surface that is constantly held perpendicular (or normal) to the rays that arrive in a straight line from the direction of the sun at its current location in the sky. In this study, the effect of geographical parameters was seen using machine learning models in predicting this important component of solar energy. Three models, FFNN ENN and LRNN were used and from the results obtained based on the calculated R^2 indicated that for, scenario 1 with geograpchical parameters, the best model was found to be FFNN with a value of 0.9294. But for scenario 2 with nongeographical parameters, the best model with R^2 value of 0.9604 was FFNN. For all the scenarios, ENN was the model with least RMSE and MAE values. The percentage error for FFNN, ENN and LRNN were found to be 4.95%, 3.20% and 1.70%. This result indicated that the geographical parameters do not any significant effects on the accuracy of the models for the prediction of DNI in africa.

Keywords: *Renewable Energy, Africa, DNI, Prediction, Machine Learning*

Özet

Makine Öğrenimi Modellerini Kullanarak Afrika'nın Doğrudan Normal Işınımını Tahmin Etmede Coğrafi Parametrelerin Etkileri

Mustapha Tanimu Adamu

Yüksek Lisans, Makine Mühendisliği Bölümü
Danışmanın Adı: Assoc. Prof. Dr. Youssef Kassem

20/ Haziran/2023 83 sayfa

Konvansiyonelden yenilenebilir enerji (YE) kaynaklarına geçiş, hızla artan küresel enerji isteği, fosil yakıt rezervlerindeki keskin düşüş, küresel ısınma, iklim değişikliği ve enerji güvenliği endişeleri tarafından tetiklendi. Afrika'da, yaklaşık 1,3 milyar gibi yüksek bir nüfusa sahip olan Afrika'da ücra bölgelerde yaşayan insanların çoğunun elektriğe erişimi yok. 620 milyon olduğu tahmin edilen ve artmakta olan Afrika nüfusunun yaklaşık üçte ikisinin elektriğe erişimden yoksun olduğu kayıtlara geçmiştir ve bu da kıtanın gelişme kabiliyetini sınırlamaktadır. Artan bu endişeyle, güvenilir bir alternatif enerjiye geçiş ihtiyacı yakındır. Güneş enerjisi tasarımındaki en önemli faktörlerden biri, güneş yönünden düz bir çizgide gelen ışınlara sürekli dik (veya normal) tutulan bir yüzey tarafından alınan güneş radyasyonu miktarı olan Doğrudan Normal Işınımdır. gökyüzündeki mevcut konumunda. Bu çalışmada, güneş enerjisinin bu önemli bileşenini tahmin etmede coğrafi parametrelerin etkisi makine öğrenimi modelleri kullanılarak görülmüştür. FFNN ENN ve LRNN olmak üzere üç model kullanılmış ve hesaplanan R2'ye göre elde edilen sonuçlardan coğrafi parametrelere sahip senaryo 1 için en iyi modelin 0,9294 değeri ile FFNN olduğu görülmüştür. Ancak coğrafi olmayan parametrelere sahip senaryo 2 için, R2 değeri 0,9604 olan en iyi model FFNN idi. Tüm senaryolar için ENN, RMSE ve MAE değerlerinin en az olduğu model olmuştur. FFNN, ENN ve LRNN için yüzde hatası %4.95, %3.20 ve %1.70 olarak bulunmuştur. Bu sonuç, coğrafi parametrelerin Afrika'da DNI tahmini için modellerin doğruluğu üzerinde önemli bir etkiye sahip olmadığını göstermiştir.

Anahtar Kelimeler*: Yenilenebilir Enerji, Afrika, DNI, Tahmin, Makine Öğrenimi*

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List of Abbreviations

MFFNN	Multilayer Feed-Forward Neural Network
CFNN	Cascade Feed-Forward Neural Network
RBFNN	Radial Basis Function Neural Network
WANN	Wavelet-Ann
WELM	Wavelet- Elm
WRBF	Wavelet-Rbf
ARIMA	Autoregressive Integrated Moving Average
DNN	Deep Neural Networks
FFNN	Feedforward Neural Network
KNN	K-Nearest Neighbors
MLM	Minimal Learning Machine
RF	Random Forests
GPR	Gaussian Process Regression
KNN	K-Nearest Neighbors.
ELM	Extreme Learning Machines
RBF	Radial Basis Function
BMA	Bayesian Model Averaging
GMDH	Group Method Of Data Handling
LSSVM	Least Squares Support Vector Machine
ENN	Emo- Tional Neural Network
RBFNN	Radial Basis Function Neural Network
BPNN	Backpropagation Neural Network
RNN	Recurrent Neural Network
MLP	Multi-Layer Perception

SVM	Support Vector Machine
GWO	Grey Wolf Optimization
MLR	Multiple Linear Regression
SVR	Support Vector Regression
DTR	Decision Tree Regression
RFR	Random Forest Regression
GBR	Gradient Boosting Regression
LSTM	Long-Short-Term Memory

CHAPTER I

Introduction

Energy is a component of our life since it is necessary for man's household and industrial activities and depends heavily on its accessibility(Phoumin & Kimura, 2019). The primary goal of all energy systems is to deliver energy services that are necessary for man, from residential tasks like heating, cooling, and cooking to commercial operations like manufacturing and building(Amir & Khan, 2022). For the sake of sustainability and progress, energy is a necessity for any society, and for many decades the majority of the energy used by humans came from the burning of fossil fuels. Oil, gas, coal, and low-carbon sources will make up about four equal portions of the energy supply mix by 2040 as the world's energy consumption is projected to increase by 37% (Abdullahi, 2015).

Energy may be derived from a variety of sources that are generally categorized as renewable and non-renewable sources. The non-renewable sources include resources that are located in the earth's crust. The rate at which these energy supplies replenish is not the same as the rate at which they are utilized. It takes millions of years for them to regenerate. Coal, oil, and natural gas are the key non-renewable resource examples. High world reliance on these conventional sources of energy has brought many negative effects which include air pollution, climate change, and rising fuel prices. This change in climate is a major concern as it causes problems such as shortage of water, damage from storms and floods, the evolution of illness, the annihilation of some species, etc. Another problem with relying only on traditional energy sources is that fossil fuels are finite and, at the current rate of usage, might run out within a few years. The release of greenhouse gases (such as carbon dioxide and methane) from the burning of fossil fuels by vehicles, factories, electricity generation, etc. has been proven to be the cause of the climatic change linked to global warming(Ramsami & Oree, 2015). The global community is adopting various measures to speed up the process to decrease the impact of these environmental and social challenges. To overcome these problems, the need for another source of energy is paramount.

Renewable energy sources are numerous and sustainable in nature(Mufutau Opeyemi, 2021). These energy sources are environmentally friendly and can be renewed organically. The following renewable energy sources are a few examples: solar, wind, hydro, geothermal, biomass, and tidal energy.

Renewable energy is generated from natural resources that recuperate more quickly than they are depleted. Sunlight, often known as solar energy, and wind, which may be used sparingly, make up renewable energy sources. Compared to burning fossil fuels, producing renewable energy produces less emissions(Razmjoo et al., 2021) Without running out, renewable energy can be utilized repeatedly. Renewable energy is considered as a clean energy source. The most prevalent sort of renewable energy that was available was solar energy(Qazi et al., 2019).

Solar energy is defined as the sun's rays that are capable of igniting chemical processes, producing heat, or creating electricity(Mekhilef et al., 2011). A feasible and inexpensive energy option for addressing long-term difficulties with the current energy crisis is solar energy, in addition to other renewable energy sources. (Kannan & Vakeesan, 2016). Due to the high demand for energy and the expensive and restricted supply of the primary energy source, fossil fuel, the global solar market is gradually expanding(Izam et al., 2022). It is now considered a major tool in advancing the economic standards of developing countries and sustaining the lives of many disadvantaged people because of the substantial, intensive research done to fasten its development. It is now inexpensive as a result of this. (Rathore & Panwar, 2022). It is important to emphasize that the solar industry would unquestionably profit from meeting future energy demand because it excels in terms of accessibility, affordability, capacity, and efficiency compared to other renewable energy sources. (de Almeida et al., 2022).

In solar energy research, solar radiation is a very important parameter. Solar radiation is a catch-all phrase describing the electromagnetic radiation that the sun emits. Other names for it include solar resources or just sunlight. Various kinds of devices may be employed to collect solar radiation and then transform it into usable forms of energy like heat and electricity. However, the technological viability and cost-effectiveness of these systems are based on the solar resource available at the particular location and in most cases, high cost and difficulty in measuring this parameter make it not readily available(Elminir et al., 2005). Depending on certain factors, every location on the earth receives its portion of the solar radiation at different parts of the year with certain times higher than others. These factors include geographical location, time of day, season of the year and weather conditions(Lopes et al., 2018). Therefore, alternative ways are needed to be developed to in generating this data. In this regard, Regression models based on sunshine duration were first applied to this problem Later, regression models incorporated with trigonometric functions were also used. Both methods had shown limitations when used to model nonlinear systems. Harmonic analysis techniques have also been used to describe radiation data which happens to be time-dependent. To overcome this, Artificial Neural Networks were then used due to their ability to learn from multidimensional data and because it has shown suitability in solving the problem of identifying noisy data(Elminir et al., 2005).

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Statement of the Problem

Solar energy can be used as electricity in developing countries, especially in African countries. solar energy can be used as heat, cooling, lighting, and electricity to host appliances moreover solar technologies change the sunlight into electrical energy through photovoltaic panels or through mirrors that concentrate solar radiation which then can be used as electricity in African countries. Most of the people who stay in remote areas in Africa do not have access to electricity (Chakamera & Alagidede, 2018). It is on record that nearly two-thirds of Africa's population, which is estimated to be 620 million and increasing, lack access to electricity, which limits the continent's ability to develop (Ogah, 2022).

Moreover, a minority of people located in sub-Saharan have access to electricity. A lot of individuals who have access are concentrated in high-income households, businesses, and industries. Unfortunately, due to insufficient and poor maintenance and upgrading of the electrical infrastructure, both rural and urban are depreciating (Wolde-Rufael, 2006). A rise in energy demand is being caused by the emergence of wind and solar energy as viable solutions to alleviate the lack of electricity in African countries. This further exacerbates the problem of climate change and drives up the price of fossil fuels (Ramsami & Oree, 2015). Due to the rapid growth and demand for electricity photovoltaic technologies that directly change solar radiation to electricity have increased in recent years (Tripathi et al., 2022; Veisi et al., 2022)because of their abundance, clean, and inexhaustible. This shift in alternative source of energy with Solar with the highest trend, have brought about exploring all possibilities to make the best use of this energy. As stated earlier, solar radiation is an important factor in determining the design of solar technologies in a specific location and due to its unavailability and expensive nature in getting the measured data, the need to use alternative methods in getting this data comes into play.

Aim of the Study

To fully understand the aims of this study, consider the table below:

Table 1

List of Input Parameters

Scenario 1	Scenario 2
Latitude	Year
Longitude	Surface Pressure (kPa)
Altitude	Temperature at 2 Meters (C)
Slope	Relative Humidity at 2 Meters (%)
Azimuth	Wind Speed at 2 Meters (m/s)
Year	Wind Direction at 10 Meters (Degrees)
Surface Pressure (kPa)	Wind Speed at 10 Meters (m/s)
Temperature at 2 Meters (C)	Dew/Frost Point at 2 Meters (C)
Relative Humidity at 2 Meters (%)	Wet Bulb Temperature at 2 Meters (C)
Wind Speed at 2 Meters (m/s)	Temperature at 2 Meters Maximum (C)
Wind Direction at 10 Meters (Degrees)	Temperature at 2 Meters Minimum (C)
Wind Speed at 10 Meters (m/s)	Cloud Amount (%)
Dew/Frost Point at 2 Meters (C)	Wind Speed at 10 Meters Maximum (m/s)
Wet Bulb Temperature at 2 Meters (C)	Wind Speed at 10 Meters Minimum (m/s)
Temperature at 2m Max (C)	Precipitation Corrected (mm/day)
Temperature at 2m Min (C)	Year
Cloud Amount (%)	
Wind Speed at 10m Max (m/s)	
Wind Speed at 10m Min (m/s)	
Precipitation Corrected (mm/day)	

From the above table, the aims of the study are:

1. To predict Direct Normal Irradiance for the selected cities of Africa using machine learning models

2. To propose 2 scenarios with various input parameters as seen in the above table.

3. To compare and predict the accuracy of the models and to observe if there is any effect the geographical parameters latitude, longitude, altitude, slope and azimuth angle have on the models.

Significance of the Study

1. Solar Technology Planning: predicting the DNI will bring about effective planning and assessing the potential of solar energy in Africa.
2. Energy Generation: by effectively predicting the DNI, energy generation and efficiency in Africa will be improved. In addition, by understanding the effect of these geographical parameters on DNI, this study will help in providing insights into having the optimal design of energy systems.
3. Environmental Impact: Solar energy has been an alternative source of energy and by predicting the DNI effectively, it will improve the use of solar energy which in return will contribute to reducing greenhouse gas emissions. The findings can help to move Africa to a greener and more sustainable source of energy.
4. Research Advancement: this study can help in the area of machine learning and prediction of DNI. Also, the study will add to the existing knowledge and will help in advancing the understanding of solar energy resource assessment. The research results will surely inspire further investigations and research

Justification

Solar Energy has become a crucial part of Africa's sustainable development and energy transition. As the continent is facing a rise in an energy crisis and seeks to minimize the high dependant on fossils fuel, the need for adequate solar resource assessment is paramount. By focusing on the prediction of the DNI, which is a very important parameter in designing solar energy systems, this study addresses a critical issue in harnessing solar energy potential in Africa.

Limitations of the Study

This study is limited to the use of input data gotten from the NASA database. Limited availability of other data may pose a challenge in accurately predicting the DNI of African cities and training and evaluating the machine learning models. Additionally, the accuracy of geographical parameters such as latitude, longitude, altitude, slope and azimuth angle could vary based on the data source used

CHPATER II

Literature Review

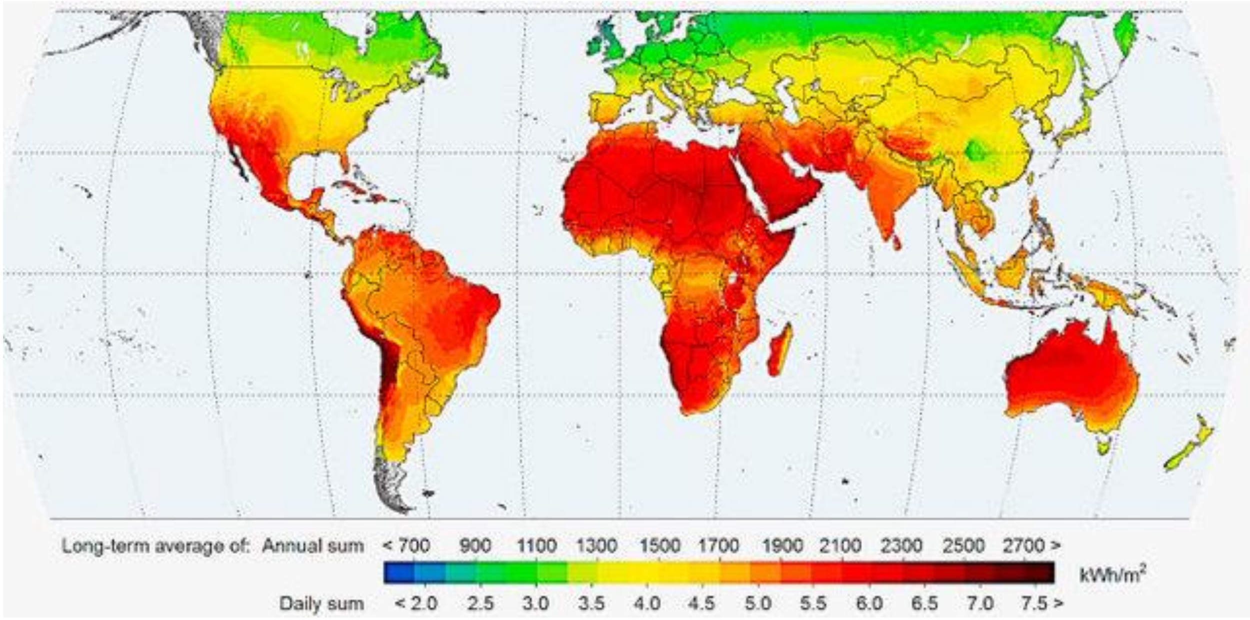
Introduction

The switch from conventional to renewable energy (RE) resources has been prompted by the sharply rising global energy desire, the sharp decline in fossil fuel reserves, global warming, climate change, and energy security concerns (Fang et al., 2018). More than 75% of China's power is still produced using "dirty" coal, which emits large amounts of NOx, CO_2, and SO_2 into the atmosphere(Bi et al., 2018). Researchers are looking for alternative energy sources that can both provide energy and preserve the environment as a result of the environmental issues brought on by the growing use of fossil fuels.(Kassem, Cąmur, et al., 2021). Due to its economic viability and few negative effects on the environment, renewable energy sources like solar energy are quickly expanding (Kassem, Gökçekuş, et al., 2021). Also, due to its sustainability and financial advantages, solar energy has become one of the most popular alternative energy sources. Additionally, it has been determined that the quantity of solar energy on the earth is 157 times greater than coal reserves and 516 times greater than the world's oil reserves(Nordell, 2003). In modern years, studies have evaluated solar energy potentials as a good power source for electric generations.

Solar energy is defined as the sun's rays that are capable of igniting chemical processes, producing heat, or creating electricity(Mekhilef et al., 2011). A feasible and inexpensive energy option for addressing long-term difficulties with the current energy crisis is solar energy, in addition to other renewable energy sources. (Kannan & Vakeesan, 2016). Due to the high demand for energy and the expensive and restricted supply of the primary energy source, fossil fuel, the global solar market is gradually expanding(Izam et al., 2022). It is now considered a major tool in advancing the economic standards of developing countries and sustaining the lives of many disadvantaged people because of the substantial, intensive research done to fasten its development. It is now inexpensive as a result of this. (Rathore & Panwar, 2022). It is important to emphasize that the solar industry would unquestionably profit from meeting future energy demand because it excels in terms of accessibility, affordability, capacity, and efficiency compared to other renewable energy sources. (de Almeida et al., 2022)

Figure 1

World Solar Energy Map



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Solar Power

Solar power is the conversion of this energy into electricity directly using photovoltaic technology or indirectly using concentrated solar panels (CSP)(Hayat et al., 2019). Photovoltaic technology converts sunlight using the photovoltaic effect into electric current while CSP uses mirrors, lenses and other solar tracking systems to capture the sunlight over a large and wider location(Guney, 2016). The generation of the electricity by both systems is dependent on the solar radiation received at a given period.

Photovoltaic System

Using a photovoltaic (PV) system, solar radiation may be converted into power. The photovoltaic effect is a principle that the PV system uses to convert sunlight into electrical power. The energy from photons is transferred to the charge carriers every time light strikes a photovoltaic cell. The electric field across the junction caused the charge carriers to divide into positively charged holes and negatively charged electrons at that point. If a closed channel is given to the circuit by attaching a load, current will flow as a result (Venkateswari & Sreejith, 2019).

Figure 2

Photovoltaic System

Concentrated Solar Power

The technology of concentrated solar power (CSP) harnesses heat produced by solar radiation that is focused on a tiny area to produce electricity. Sunlight is reflected off of mirrors and directed to a receiver, where heat is captured by a thermal energy carrier (primary circuit) and utilized either directly (in the case of water or steam) or indirectly (through a secondary circuit) to drive a turbine and produce electricity. Particularly in areas with high DNI, CSP is a viable technology

Figure 3

Concentrated Solar Power

Solar Irradiance

Solar irradiance is defined as the amount of solar radiation that reach a certain area. The unit of solar irradiance is watts per square meter (W/m^2). It is a representation of the intensity or power density of sunlight a specified location and time. The amount of solar irradiance in a given location is a key factor in determining how much energy is produced. As a result, a site with high solar irradiance will produce more energy, whereas a location with low irradiance will produce less energy.

Understanding this pattern is very crucial in designing and optimization of solar energy systems. By assessing this, engineers and designers can choose the best technology and establish ideal sizes and orientation of the solar panels. It also gives the ability to analyze and predict the energy production at a given time.

Factors affecting Solar Irradiance

Solar Irradiance is affected by many factors which include longitude, latitude, cloud cover, atmospheric conditions and seasonal variations(Rathod et al., 2017)

1. Atmospheric Conditions: factors such as cloud cover, air pollution dust particles and water vapour can impact the amount of solar irradiance at a given location. A location with clear skies tends to have higher amount of solar irradiance(Rathod et al., 2017).
2. Time of the year: Due to Earth's axial tilt, solar irradiance varies throughout the year. In summer, solar irradiance becomes higher and becomes lower during winter(Stanciu & Stanciu, 2014)
3. Time of the day: as the Sun's angle changes, the amount of solar irradiance also changes. In morning and evenings, the amount is very much lower and becomes peak at noon(Chu et al., 2015).
4. Geographical parameters: Latitude and longitude greatly affect solar irradiance. Locations that are closer to the equator will have higher amount and as locations move closer to the poles, the amount of solar irradiance decreases(Rathod et al., 2017)

Components of Solar Irradiance

Direct Normal Irradiance (DNI)

The quantity of solar radiation received by a surface that is constantly held perpendicular (or normal) to the rays that arrive in a straight line from the direction of the sun at its current location in the sky is known as direct normal irradiance (DNI). A surface may often get the most irradiance per year by maintaining a normal angle to incoming radiation. Both concentrated solar thermal plants and installations that follow the location of the sun are particularly interested in this parameter(Boutahir et al., 2022). Pyrheliometer is the device used to measure this component

Diffuse Horizontal Irradiance (DHI)

Diffuse Horizontal Irradiance (DHI) is the quantity of radiation received by a surface (that is not in any shade or shadow) per unit area that is not arriving from the sun directly, but is instead evenly distributed from all directions by atmospheric molecules and particles(Haase, 2016). This component is measured using a device named Pyranometer

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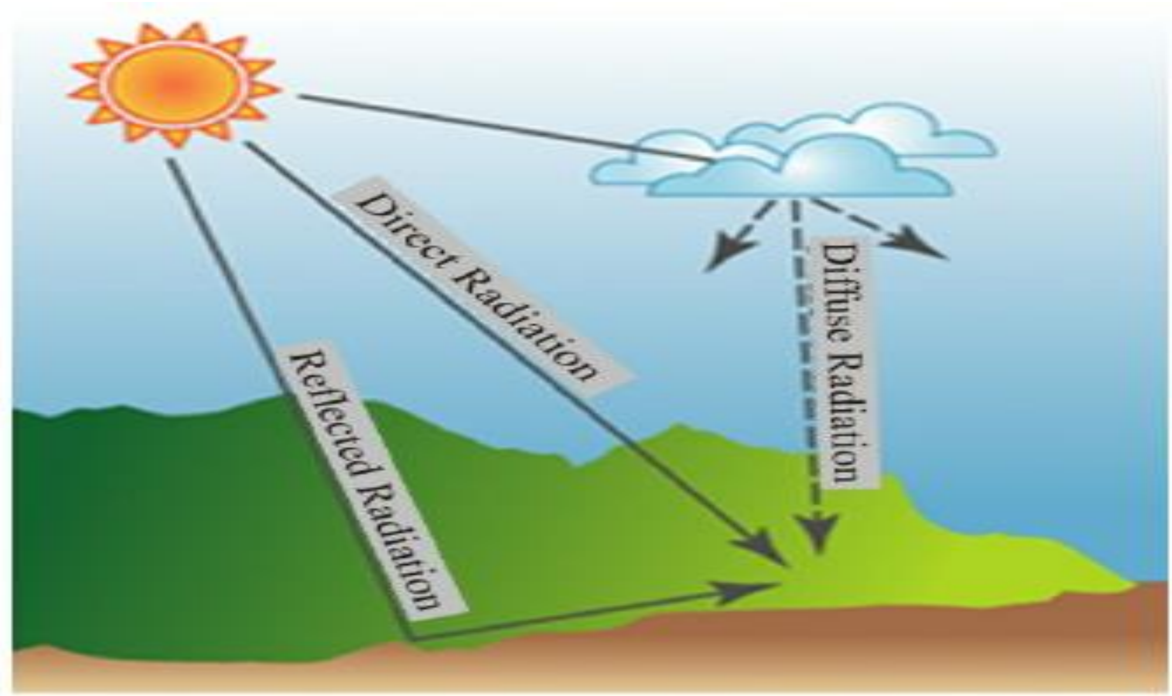
Global Horizontal Irradiance (GHI

A surface horizontal to the ground receives all of the shortwave radiation from above, which is known as global horizontal irradiance (GHI). Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) are both included in that value, which is of particular significance to solar systems(Boutahir et al., 2022)

Figure 4

Components of Solar Radiation

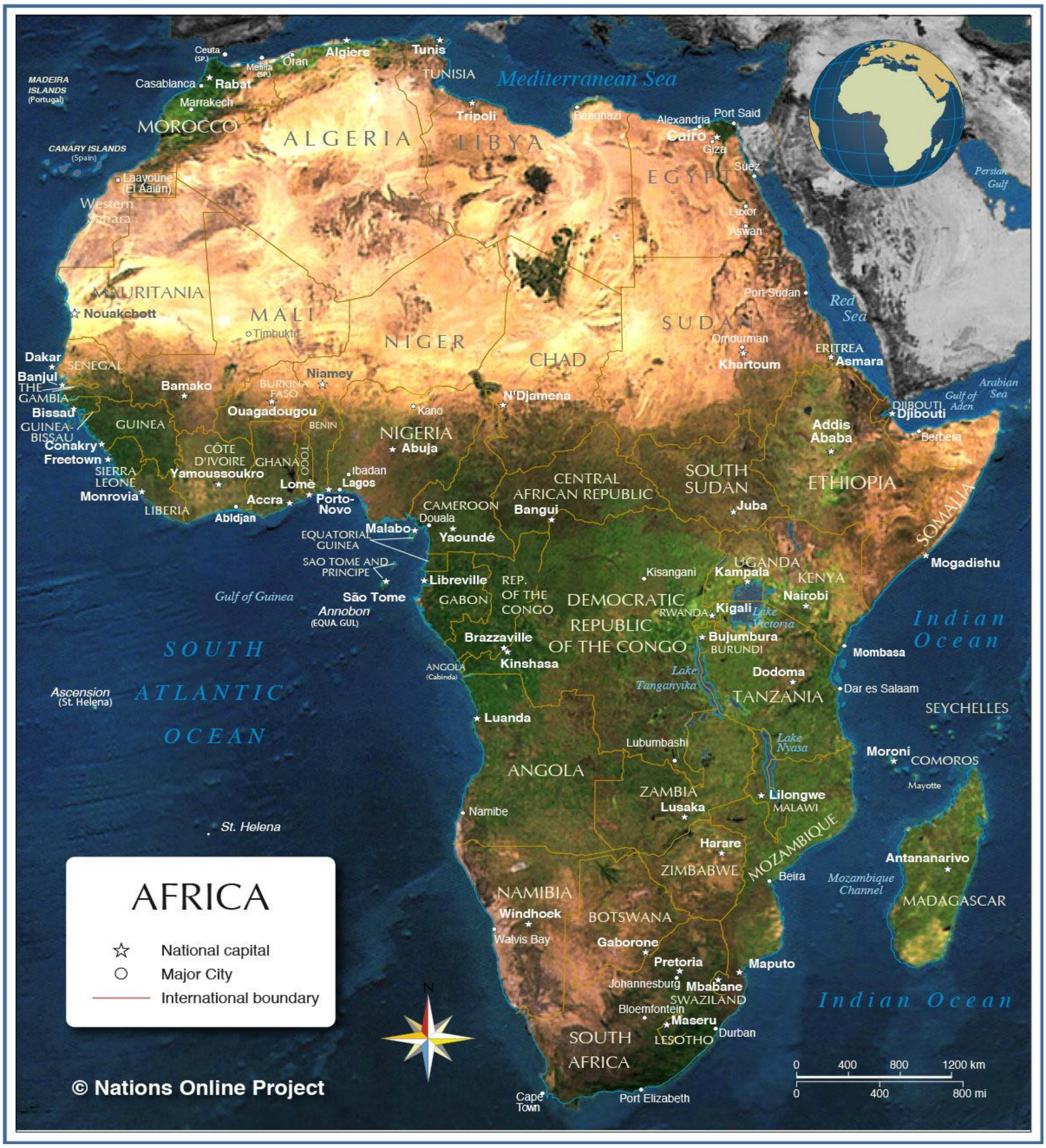


Africa

Africa is the second largest by land mass and the second most populated continent on earth. It has a land mass of about 11.72 million square miles (30.3 million km^2). It covers one-fifth of the total Earth land mass. It has boundaries from the west with Atlantic Ocean, from the north, Mediterranean Sea, from the east, Red Sea and from south, Atlantic and Indian Oceans. It is situated on a latitude and longitude of 9.1021^0N and 18.2812^0S. Africa has a population of about 1.3 billion as of 2019. This value represents 16% of the world's population. There are 54 countries in the African continent. From north to south, the continent is around 5,000 miles (8,000 km) long, and from east to west, it is about 4,600 miles (7,400 km). Africa typically has a humid and warm environment with the northern part mostly covered by dryness and very high temperature. Because of the Equator's almost equal division of the continent, the majority of Africa is located in a tropical area that is bordered on the north by the Tropic of Cancer and on the south by the Tropic of Capricorn. The majority of Africa's land is located north of the Equator due to the bulge that western Africa has created. The prime meridian (0° longitude) runs through Africa from north to south, passing close to Accra, Ghana, to the east.

Figure 5

Map of Africa



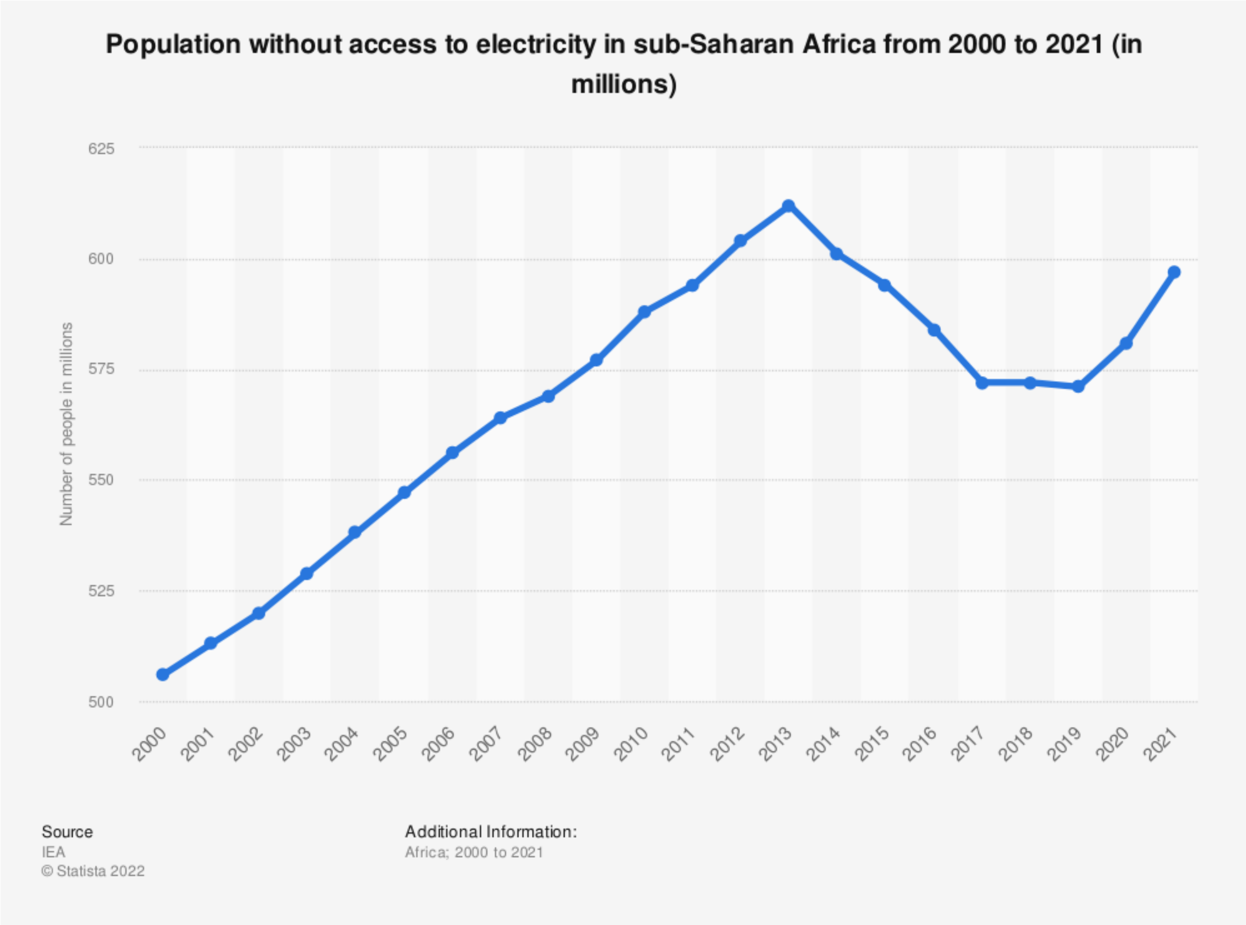
Energy Crisis in Africa

With the high population of about 1.3 billion, most of the people who stay in remote areas in Africa do not have access to electricity (Chakamera & Alagidede, 2018). It is on record that nearly two-thirds of Africa's population, which is estimated to be 620 million and increasing, lack access to electricity, which limits the continent's ability to develop (Ogah, 2022). Despite the fact that Africa as a continent normally has severe electrical problems, Sub-Saharan Africa is the area that suffers the most from these issues because it is presently home to more than two-thirds of the world's people who do not have access to power(*Africa Energy Outlook 2022 – Analysis* - *IEA*, n.d.). In addition, inadequate maintenance has rendered around 15% of Sub-Saharan Africa's installed capacity inoperable. Furthermore, because accessing the national electrical grid is expensive, an estimated 700 million individuals in Africa still generate their own electricity using traditional biomass(Adenle, 2020). Africa's anticipated population rise is a serious problem. By 2050, it is predicted that there will be 2 billion people living in sub-Saharan Africa alone. Despite this, the region's energy demand is expected to increase by 3% annually(Bugaje, 2006). Rising energy costs and the increased need for climate change mitigation strategies may also provide new difficulties(Maji et al., 2019). With all these issues only 1.48% of the world's capacity for solar energy is occupied by Africa, despite the continent having 40% of the world's solar power potential(*IRENA: Renewable Capacity Statistics 2019* - *Google Scholar*, n.d.). This problem is mostly attributed to the following reasons:

1. Lack of Access to Electricity: like stated earlier, almost two third of Africa’s population don’t have access to electricity. The number is even more severe in rural areas with people mostly relying on expensive and insufficient sources (*Access to Electricity – SDG7: Data and Projections – Analysis* - *IEA*, n.d.)

Figure 6

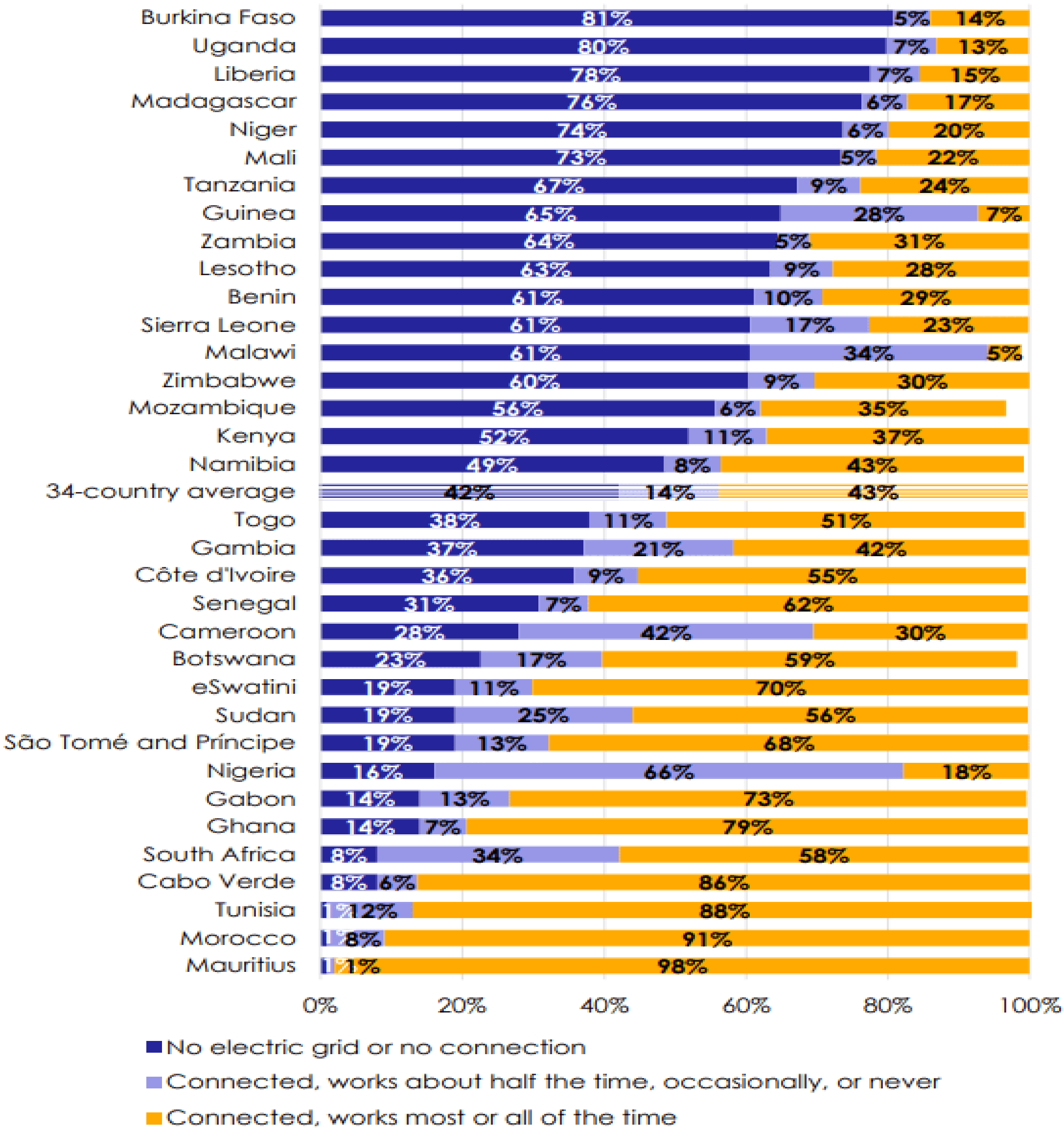
Population without access to electricity



2. Insufficient Infrastructure: in Africa, the energy infrastructure in mostly in adequate and insufficient to fulfil the high and rising population demand. In most areas of the continent, there is power outages and blackout due to inadequate and poorly maintained distribution networks. The flow of energy effectively from production sites to end users is mostly hindered by this problem(Abdullahi, 2015)
3. Lack of funding: the funding of the energy sector in most African countries have been marred by lack of funding by most governments(González-Eguino, 2015). In cases where there is funding, it is mostly characterised by corruption and embezzlement which at long last, the aim is not achieved(Abdullahi, 2015).

Figure 7

Grid Connection in some African Countries



Therefore, increasing solar power and using renewable energy sources to deliver power in Africa is a realistic choice

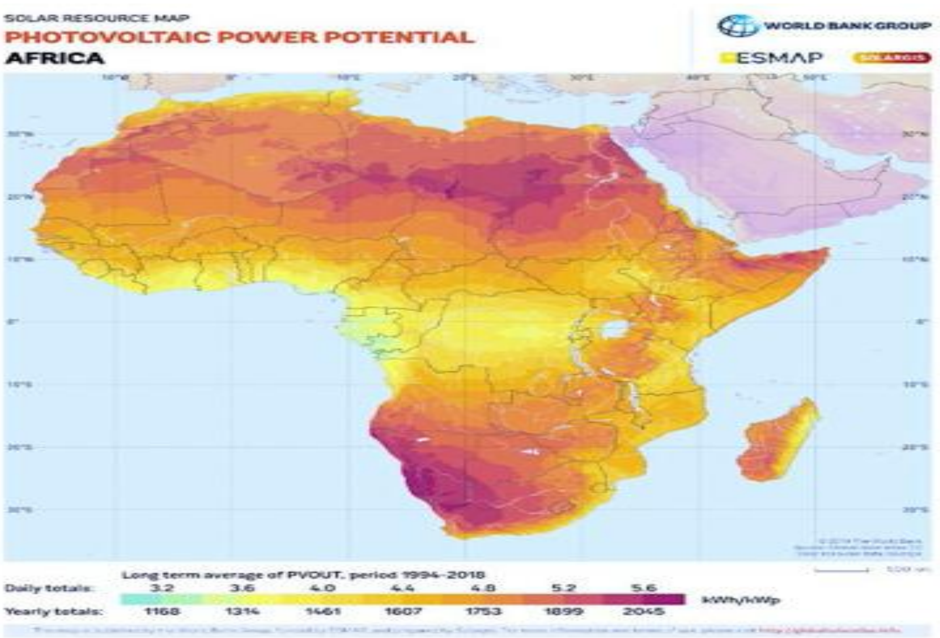
Solar Potential in Africa

Africa faces numerous obstacles and dangers, including its susceptibility to climate change, a rapidly increasing population compared to other nations, and insufficient electrification to support the shift towards renewable energy(Abdelrazik et al., 2022). To tackle these issues, renewable energy is a practical solution. To optimize solar power, comprehensive knowledge of solar resources is crucial in the midst of changing climatic conditions(Goliatt & Yaseen, 2023). Africa, due to its proximity to the equator and profusion of sunshine, Africa experiences high amounts of daily global solar radiation. Africa receives between 4 and 6 kWh/m2 of solar energy on average every day, with specific quantities varying throughout the continent's various areas. This enormous sun resource offers a big opportunity for solar energy harvesting and can aid in the continent's sustainable development(*IRENA: Renewable Capacity Statistics 2019 - Google Scholar*, n.d.).

Africa has enormous solar energy potential. This is brought about by a variety of elements, including its close closeness to the equator and its abundance of sunny, dry days (*The Solar Revolution in Africa*, n.d.) For instance, South Africa has a solar PV potential of 42,243 TWh/year and a concentrated solar potential of 43,275 TWh/year(Adenle, 2020). With an average insolation of 220 W/m2, most of South Africa experiences more than 2500 hours of sunlight annually(Ayodele & Munda, 2019). . In North Africa, solar power facilities occupy twice as much territory as the entire European Union of Africa, according to the German Aerospace Center, a pioneer in the field of renewable energy technology. It is claimed that the power use may be met(*The Solar Revolution in Africa*, n.d.). Figure 8 illustrates how North Africa is advantageously situated in the Sunbelt area, where solar energy is abundant. The quantity of yearly solar radiation reflects this; for instance, the annual total solar radiation in Algeria, Morocco, Egypt, and Tunisia is 2700 KWh/m2, 2600 KWh/m2, and 2800 KWh/m2, respectively(Zhao et al., 2018).

Figure 8

Photovoltaic Potential in Africa

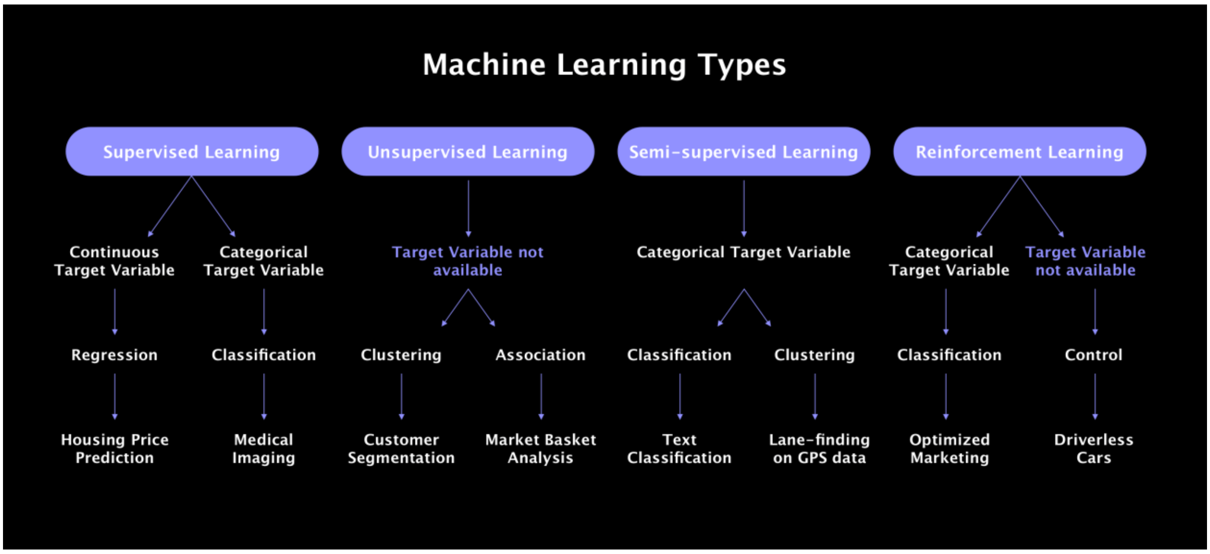


Machine Learning

Data are considered new life of the 21st century, amounting to significant information, insights and potential, and they are now a vital part of all entities that are driven by data. In a variety of areas, including research, health, industries, educational areas, financial services, cybersecurity, law enforcement, governance, and marketing, information may be extracted from data to develop varieties of smart applications(Sarker, 2019). As a result, there is an urgent demand for data management systems that can rapidly and shrewdly extract relevant insights from data. Machine Learning (ML), which is one of the most important tools for intelligently analyzing such data and creating related practical applications, has advanced significantly in recent years.(Koteluk et al., 2021; Sarker et al., 2020). The picture below shows the different type of machines learning.

Figure 9

Types of Machine Learning



Types of Machine Learning

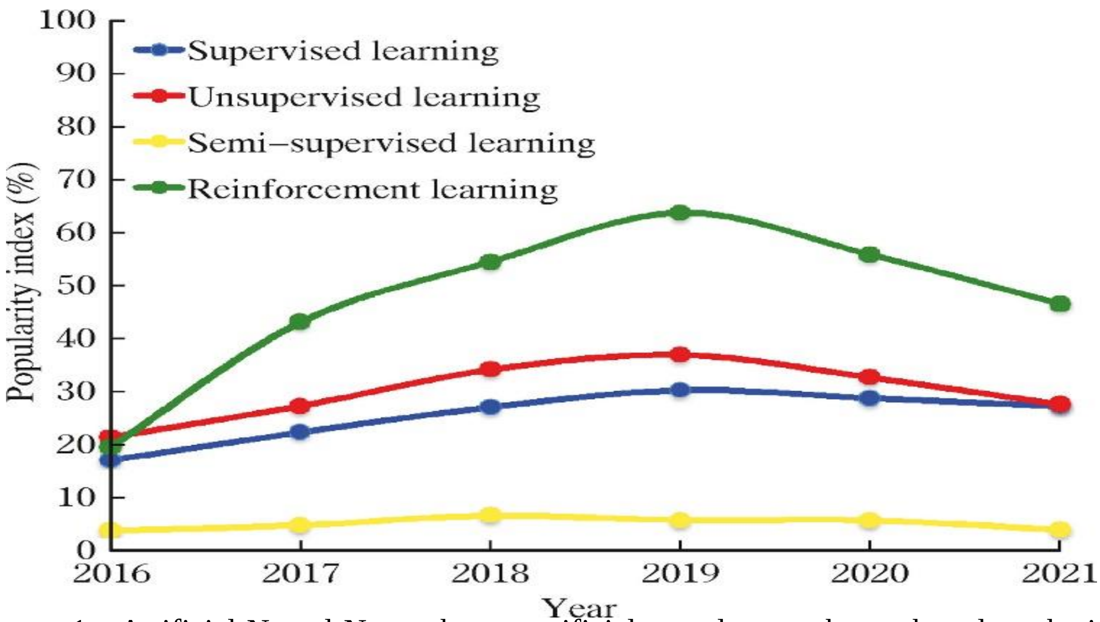
1. Supervised Learning: Base on test input to output pair, supervised learning uses Machine Learning tasks in training a function that translates inputs to outputs. As a result, this learning processes is founded on linking the derived outputs and projected

outputs; hence, learning is the process of calculating the errors and modifying the errors to produce the desired outputs(Pugliese et al., 2021). The automatic response to incoming communications (valuable for large businesses), facial recognition for ATM security, surveillances areas, closed-circuits cameras, the criminals justice system, and picture tag on social networking platforms like meta's Facebook are examples of applications of this learning(Li et al., 2015; Pugliese et al., 2021).

2. Unsupervised Learning: Without human intervention, unsupervised learning examines unlabeled datasets. In this learning, the algorithms splits the sample into several class according to only the characteristic of data to be trained, without assigning matching labels(Jia et al., 2022; Pugliese et al., 2021).
3. Semi-supervised Machine Learning: Given that it use data that are both labeled and unlabeled, semi-supervised learning may be seen as a hybridization of supervised and unsupervised approach outlined above(Jia et al., 2022; Pugliese et al., 2021).
4. Reinforcement Learning: An environment-driven technique, or reinforcements learning, relies on collection of algorithms that generally run in sequence to analyze automatically the ideal behaviors in certain environments and increase its effectiveness(Buşoniu et al., 2010).

Figure 10

Popularity Index of Machine Learning

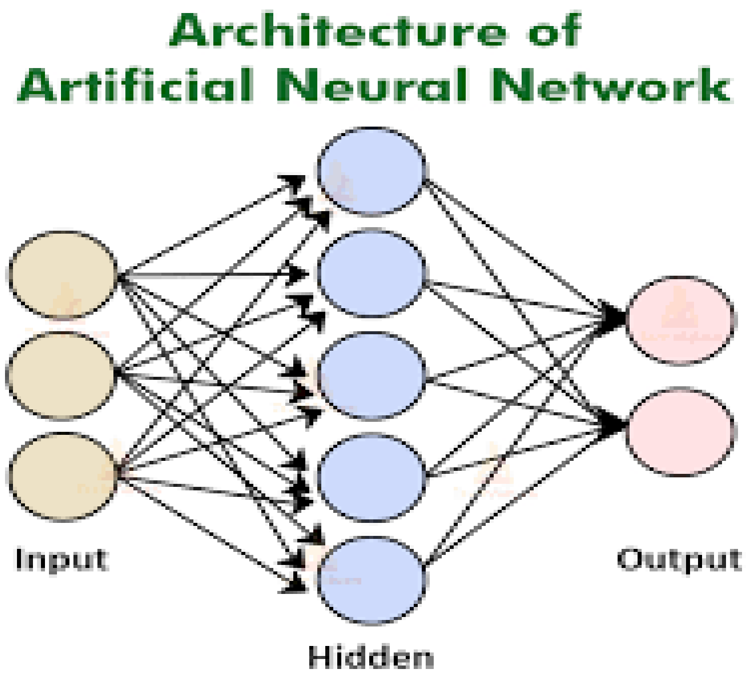


1. Artificial Neural Networks: an artificial neural networks are based on the ideas of a human neurons(Han et al., 2018). Artificial neurons, comprised of a group of cluster members that resemble the neurons found in a biological brain, make up the central

component of an ANN. (Zakaria et al., 2014). Each link may communicate with surrounding neurons, much like the junctions in the human brain. A synthetic neuron takes inputs, analyses them, and then sends messages to neurons nearby(Rashid, 2016).

Figure 11

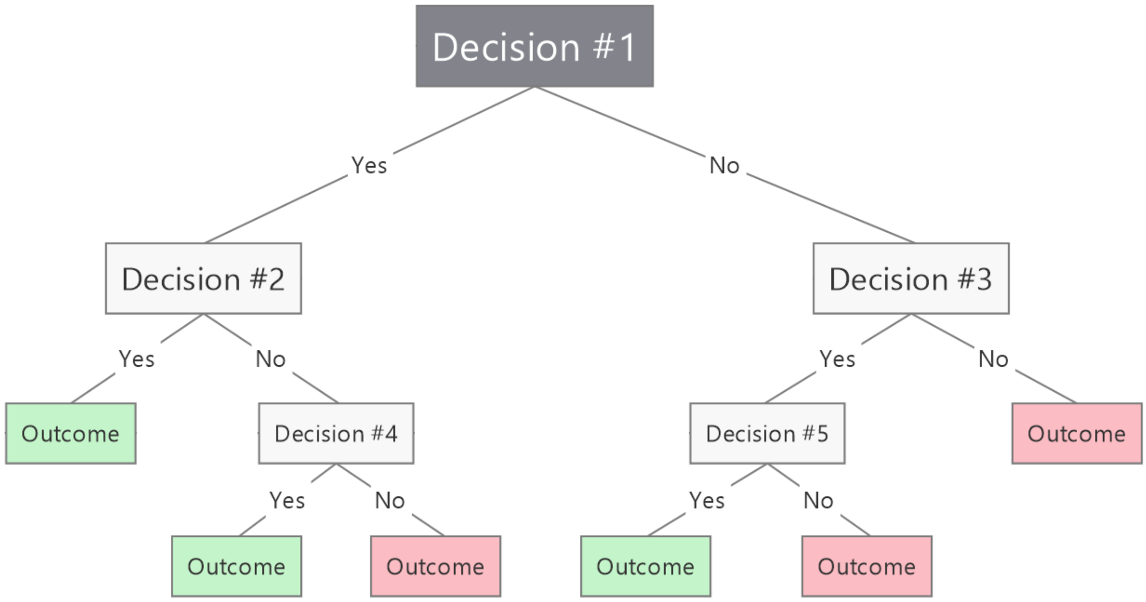
Architecture of ANN



2. Decision Tree: Two most common usage of the decisions tree approach are the creations of categorization system dependent on a number of different factors and the building of predictions algorithms for a target variables. (Song & Lu, 2015). In order to develop an inverted tree with a root nodes, internal node, and leaf node, this algorithm divides a population into segments that resemble branches. (Bhukya & Ramachandram, 2010). The methods, which are non-parametric, might successfully handle different, complicated dataset against generating a difficult parametric framework. Once the sample sizes are large enough, the research's data may be split into trainings and validations dataset. The best final model is produced by building a decisions tree model using the training datasets and choosing the optimum tree sizes using the validation dataset.(Loh, 2014).

Figure 12

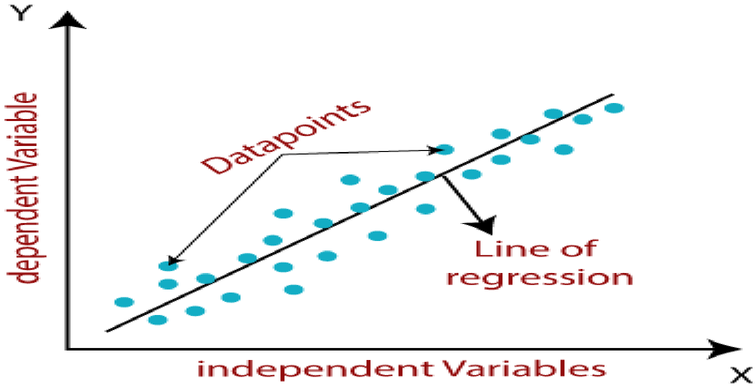
Architecture of Decision Tree



3. Linear Regression: A continuous target variable is predicted using linear regression using one or more input features. The model implies that the input and target variables have a linear relationship (Ray, 2019)

Figure 13

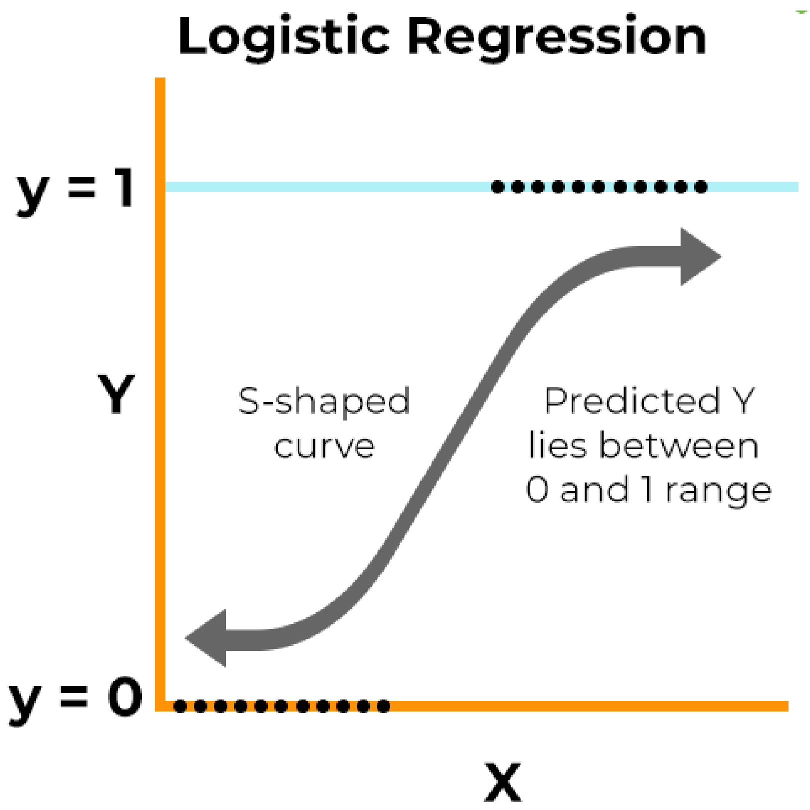
Architecture of Linear Regression



4. Logistic Regression: When the target variable has two classes, logistic regression is the model used to solve binary classification issues. Calculate the likelihood that a certain instance belongs to a certain class(Ray, 2019)

Figure 14

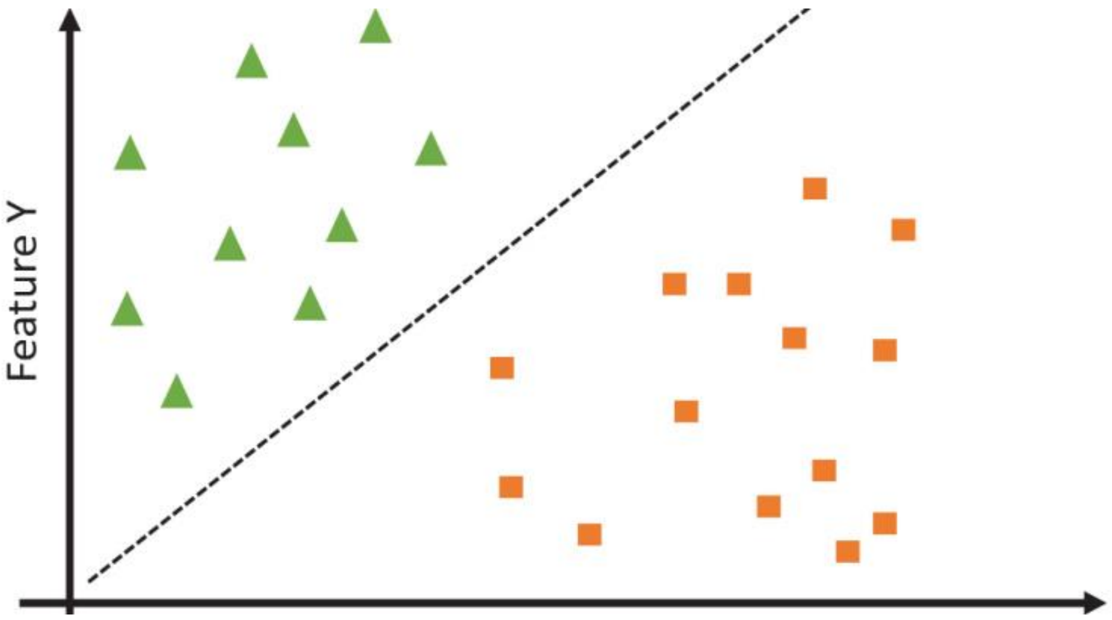
Logistic Regression



5. Support Vector Machine (SVM): SVM is a well-liked model for both regression and classification tasks. Find the ideal hyperplane with the biggest margin of separation between data points from distinct classes(Ray, 2019).

Figure 15

Architecture of SVM



Review of existing Literature on the Prediction of Solar Radiation Using Machine Learning Models

The switch from conventional to renewable energy (RE) resources has been prompted by the sharply rising global energy desire, the sharp decline in fossil fuels reserves, global warming, climate change, and energy security concerns (Fang et al., 2018). More than 75% of China's power is still produced using "dirty" coal, which emits large amounts of NOx, CO_2, and SO_2 into the atmosphere(Bi et al., 2018). Researchers are looking for alternative energy sources that can both provide energy and preserve the environment as a result of the environmental issues brought on by the growing use of fossil fuels.(Kassem, Cąmur, et al., 2021). Due to its economic viability and few negative effects on the environment, renewable energy sources like solar energy are quickly expanding (Kassem, Gökçekuş, et al., 2021). Also, due to its sustainability and financial advantages, solar energy has become one of the most popular alternative energy sources. Additionally, it has been determined that the quantity of solar energy on the earth is 157 times greater than coal reserves and 516 times greater than the world's oil reserves(Nordell, 2003). In modern years, studies have evaluated solar energy potentials as a good power source for electric generations. For example, taking Nahr El-Bared, Lebanon as a case study, (Camur et al., 2021) assessed the performances photovoltaic (PV) systems. The findings showed that the yearly generation of power might meet the area's energy needs and lower its electricity costs. (Tripathi et al., 2022) predicted the resulted output power of a solar photovoltaic system using different machine learning models taking into consideration different input parameters such as temperature, relative humidity, solar radiation, on and time of the day. Their study concluded that of all the models employed, the multiple linear regression algorithm demonstrated better performances considering mean squared error and mean absolute error. Similarly, (Kassem, Cąmur, et al., 2021) tested the viability of a small-scale grid-connected Photovoltaic system using various technology in Amman, Jordan. The result of their study showed that the power obtained would significantly reduce the consumption of fossil fuels and emissions of CO_2. In another study of (Jia et al., 2022), machine learning model was used to estimate the daily global and diffuse solar radiation. Their result from the models employed indicated that the SVM models showed reliability in the prediction of radiation under slight pollutions and weather condition. In his paper, (Zazoum, 2022) explored the relationships between certain inputs and Photovoltaic systems using different machine learning model. The result indicated that these input parameters which included ambient temperature, solar flux, day time and relative humidity are basic factors that influence the energy outputs of a Photovoltaic system. Additionally several of other studies have employed machine learning models to forecast PV system power as a function of variations in climate (Omubo-Pepple et al., 2009). The solar radiation of about 200 cities in Nigeria were estimated using different machine learning models that are dependent of feed forward and multilayered network using different weather condition(Teke et al., 2015). came up with a model using ANN to predict the solar radiation in Saudi Arabia. Using back propagation algorithm, the various patterns of the multilayer feed neural network were trained. The best result was determined considering the minimum mean absolute percentage error.

Table 2

Summary of some existing Literature

Reference	Area of Study	Aim	Data Used	Models Used
(Kassem & Othman, 2022b)	Amman, Jordan	-the developed models for predicting the output power of 68 kW grid-connected PV system	- the mean daily average temperature, -minimum and Maximum temperatures, -wet-bulb temperature -relative humidity, -global solar radiation - wind speed	-MFFNN -CFNN -RBFNN -ENN -QM -MLR
(Kisi et al., 2020)	Antakya/Adana Turkey	-for estimating monthly solar radiation	-maximum temperature -maximum temperature -sunshine hours -wind speed -relative humidity	-ANN -ELM -RBF -WANN -WRBF -BMA -WELM

Table 2(Continued)

(Belmahdi et al., 2022)	Tetouan, Morocco	- the prediction of hourly global solar radiation data at one meteorological weather station (MWS) installed on the rooftop in the Faculty of Sciences, University Abdelmalek Essadi, Tetouan, Morocco	-humidity -pressure -maximum temperature -temperature ratio -average temperature	-ARIMA -FFNN-BP -k-NN -SVM
(Banerjee et al., 2022)	Eastern India	- the net radiation, global solar radiation (GSR) and canopy temperature (CT) were measured over fve different types of crops, namely cowpea, maize, rice, chickpea and mustard.	-thermometer -Canopy temperature	-DNN -RR -SR -RF -GBR
(Sohani et al., 2022)	-Tehran, Iran	-an enhanced design for the solar still system, which was originally introduced by Sohani , is investigated, and the experimental data for that are employed as the input data for obtaining different types of ANN model.	-water temperature - hourly distillate production -Wind speed -Depth of water in the basin, -Ambient temperature	-FF -BP -RBF

Table 2(Continued)

(de Amorim Neto et al., 2022)	-Ceará, Brazil	-predicting the thermal response of a solar wall.	- ambient temperature -solar radiation temperature -date -time -direct difuse -	-kNN -MLM -SVM -RF
(García-Cuesta et al., 2022)	-Iberian Peninsula	- to extract features and reduce dimensionality in renewable energy.	-Cloud mixing ratio -Relative humidity -Soil Temperature -component of wind	-SLMVP -PCA -LPP -LOL -SNMF
(Verma & Patil, 2021)	-France	-the estimation of ground solar radiation based on satellite images	-altitude - latitude - longitude - month -day - time -solar zenith angle - solar azimuth angle -viewing zenith angle -viewing azimuth angle	-ANN -SVM -EVM

Table 2(Continued)

(Demir & Citakoglu, 2023)	-Turkey.	- investigated the potentialof new ensemble method, Bayesian modelaverag-ing (BMA), in modeling monthly solar radiation based on climatic data	-minimum temperature -maximum temperature -sunshine hours -wind speed -relative humidity -	-ELM -RBF - WANN -WELM -WRBF -BMA
(Janković et al., 2021)	-China	- develop the prediction models of the EF.	-natural gas sources, -coal sources, - oil sources - wind Sources -solar photovoltaic sources, -hydropower sources -nuclear sources	-KNNR -RFR
(Ofori-Ntow Jnr et al., 2022)	Ghana	- handling long-term photovoltaic power Forecasting	-wind speed -air temperature -sun height -	-BPNN -GMDH -ENN -LSSVM -RBFNN

Table 2(Continued)

(Muhammad Ehsan et al., 2017)	Tiruchirappalli India	- the profile of power output of a grid-connected 20-kWp solar power plant	- Atmospheric Temperature - Relative Humidity - Wind speed -Earth Temperature - solar radiation - wind direction - rainfall	
(Park et al., 2021)	- Korea	- RNN model for predicting solar PV power generation using the neural network toolbox function of MATLAB.	-outdoor air temperature -humidity, -direct solar radiation -diffuse solar radiation - wind speed	- RNN
(Kumar et al., 2020)	-India	- A 5 kWp grid-connected PV system is installed at rooftop of the laboratory	-irradiance incident -cell temperature -Linke turbidity - wind speed	- GWO –MLP

Table 2(Continued)

(Arora et al., 2021)	-India	- to improve ANN based prediction model by incorporating technique to normalise input dataset.	- temperature, -relative humidity, -precipitation, -sunshine hours, -clearness index, -pressure, -wind speed	- FFD -
(Shah et al., 2021)	-India	- T to find out the best model for estimation from RBF and MLP	-sunshine duration -relative humidity -temperature, -atmospheric pressure	- RBF -MLP
(Dikmen et al., 2014)	-Turkey	-The thermal performance of the evacuated tube solar collector	-Ambient temperature -Solar radiation -Collector tilt-angl -Mean temperature -Thermal performance	-LM

Table 2(Continued)

(Natsheh et al., 2014)	-Manchester	-The solar irradiance and temperature data are gathered from a 28.8 kW solar power system	- Solar irradiance, -temperature	-LM

From the above table, it was summarised that the the most common data, few data and new data and also the models used are given in tables:

Table 3

Information of Data Used by Previous Studies

Common Data	Few Data	New Data
Pressure	Solar Zenith Angle	Sunrise Hour Angle
Relative Humidity	Maximum City Heights	Extra-Terrestrial
Wind Speed	Longitude	Radiation On A
Wind Direction	Latitude	Horizontal Surface
Sunshine Hours	Temperature Ratio	Temperature Ratio
The Mean Daily Average Temperature	Max Sea Surface Pressure,	Component Of Wind
Minimum Temperatures	Min Sea Surface Pressure	Viewing Zenith Angle
Maximum Temperatures	Mean Sea Surface Pressure	Viewing Azimuth Angle
Wet-Bulb Temperature	Mean Vapour Pressure	Year
Global Solar Radiation	Max Cloudiness	Irradiance Incident
Rainfall	Mean Cloudiness	Cell Temperature
Atmospheric Temperature	Maximum Humidity	Linked Turbidity
	Minimum Humidity	Cloud Mixing Ratio
	Mean Humidity	Soil Temperature
	Sunshine Hours,	Component Of Wind
	Evaporation	
	Mean Dew Point Temperature,	
	Mean Wet Point Temperature,	
	Maximum Air Pressure,	
	Minimum Air Pressure,	
	Mean Air Pressure,	
	Mean Vapour Saturation Pressure	
	Canopy Temperature	

Table 4

Models used by previous studies

Common Models	Few Models
SVR	GWO
DTR	MLP
RFR	RR
GBR	SR
LSTM	RF
GPR	RR
SVM	SR
ANFIS	RF
MLR	BPNN
RBF	FFNN
SVMR	DNN
LSTM	MANN
ELM	ENN
KNN	QM
WANN	CC
WRBF	RMSE
BMA	NS
WELM	
MLM	
SVM	
MLM	
MLM	
SVM	
MFFNN	
CFNN	
RBFNN	

CHAPTER III

Materials and Methods

In this section, the effects of geographical parameters in prediction of solar radiation using machine learning methods were studied utilizing three models of ANN for predicting the results.

Description of the Dataset

The patterns of solar radiation in the region are influenced by a number of climatic factors in Africa, the second-largest continent Earth. There are significant variations in the amount of solar radiation present on Earth because of its large size and diverse geography, with some regions getting high quantities while others receive low levels.

Solar radiation forecasting is crucial for the development of renewable energy projects in Africa, especially in remote and rural areas with little access to grid electricity. Latitude, altitude cloud cover, air pollution, and land cover are just a few of the factors that affect how much solar radiation is received in different parts of Africa.

In order to accurately predict solar radiation in Africa, it is essential to take into account these factors and develop reliable models that take into account the local conditions. Thanks to the rapid advancement of renewable energy technology in Africa, accurate estimates of solar radiation can aid in the deployment of solar power plants and ease the transition to a more sustainable energy future on the continent. In this study, 91 major cities were selected for to check the effect of this parameters in the prediction of the solar radiation of the region.

Cities that were used for training include Cairo Egypt, the Kinshasa Democratic Republic of the Congo, Lagos Nigeria, Giza Egypt, Luanda Angola, Dar es Salaam Tanzania, Khartoum Sudan, Johannesburg South Africa, Abidjan Côte d'Ivoire, Alexandria Egypt Addis Ababa Ethiopia, Nairobi Kenya, Cape Town South Africa, Kano Nigeria, East Rand South Africa, Douala Cameroon, Casablanca Morocco, Ibadan Nigeria, Antananarivo Madagascar, Abuja Nigeria, Kampala Uganda, Kumasi Ghana, Dakar Senegal, Durban South Africa, Lusaka Zambia, Algiers Algeria, Bamako Mali, Omdurman Sudan, the Mbuji-Mayi Democratic Republic of the Congo, Lubumbashi Democratic Republic of the Congo, Accra Ghana, Brazzaville Republic of the Congo, Mogadishu Somalia, Lomé Togo, Benin City Nigeria, Matola Mozambique, Monrovia Liberia, Kananga Democratic Republic of the Congo, Harare Zimbabwe, Onitsha Nigeria, N'Djamena Chad, Nouakchott Mauritania, Mombasa

Kenya, Niamey Niger, Gqeberham South Africa, Fez Morocco, Mwanza Tanzania, Lilongwe Malawi, Kigali Rwanda, the Bukavu Democratic Republic of the Congo, Abomey-Calavi Benin, Nnewi Nigeria, Kaduna Nigeria, Aba Nigeria, Bujumbura Burundi, Maputo Mozambique, Hargeisa Somalia, Bobo Doulas, Burkina Faso, Shubra el-Kheima Egypt, Ikorodu Nigeria, Asmara Eritrea, Marrakesh Morocco, Ilorin Nigeria, Blantyre Malawi, Agadir Morocco, Misratah Libya, Jos Nigeria, Bangui Central African Republic, Nampula Mozambique, Lubango Angola, Cabinda Angola, Libreville Gabon, Maiduguri Nigeria, Enugu Nigeria, Lokoja Nigeria, Benguela Angola For testing data, the data for; Oran Algeria, Ouagadougou Burkina Faso, Owerri Nigeria, Pointe-Noire Republic of the Congo, Port Harcourt Nigeria, Pretoria South Africa, Rabat Morocco, Tangier Morocco, Tripoli Libya, Tshikapa Democratic Republic of the Congo, Tunis Tunisia, Umuahia Nigeria, Uyo Nigeria, Warri Nigeria, Vereeniging South Africa, West Rand South Africa and Yaoundé.

Table 5

Information of the Selected Cities

Location	**Latitude [N°]**	**Longitude [E°]**	**Altitude [m]**
Cairo	30.033	31.562	350
Kinshasa	-4.322	15.313	277
Vereeniging	-26.558	27.908	1526
Giza	29.987	31.212	19
Luanda	-9.518	13.536	201
Dar es Salaam	-6.816	39.28	15
Khartoum	15.603	32.526	387
Johannesburg	-26.205	28.05	1746
Abidjan	5.409	-4.042	105
Alexandria	30.943	29.766	18
Addis Ababa	9	38.750	2315
Nairobi	-1.303	36.826	1657
Cape Town	-33.299	18.417	35

Table 5 (Continued)

Yaoundé	3.869	11.521	715
Kano	11.985	8.536	454
East Rand	-26.395	27.396	1590
Umuahia	5.532	7.492	154
Douala	36.634	4.085	614
Casablanca	33.263	-7.964	189
Ibadan	7.378	3.897	223
Antananarivo	18.985	46.739	1205
Abuja	9.064	7.489	473
Kampala	0.318	32.581	1237
Kumasi	6.698	-1.623	260
Dakar	14.74	-17.334	6
Port Harcourt	4.768	7.019	18
Durban	-29.862	31.01	13
Ouagadougou	12.37	-1.533	299
Lusaka	-15.358	29.165	1149
Algiers	36.775	3.06	31
Bamako	12.649	-8	335
Omdurman	15.645	32.478	391
Mbuji-Mayi	-6.119	23.568	678
Pretoria	-25.746	28.188	1338
Kananga	-5.895	22.409	636
Harare	-17.857	31.06	1483
Onitsha	6.133	6.792	51

Table 5 (Continued)

N'Djamena	12.119	15.05	297
Nouakchott	18.079	-15.978	8
Mombasa	-4.039	39.684	10
Niamey	13.525	2.11	207
Pointe-Noire	-4.816	11.887	16
Gqeberha	-33.962	25.621	52
Cabinda	-5.056	12.321	103
Fez	33.833	-4.856	971
Uyo	5.032	7.925	71
Mwanza	-2.455	32.713	1134
Lilongwe	-14.041	33.735	1071
Kigali	-1.886	30.13	1575
Bukavu	-2.498	28.887	1533
Abomey	6.415	2.303	30.02
Nnewi	5.96	6.981	163
Tripoli	32.773	13.332	31
Kaduna	10.382	7.853	661
Aba	5.113	7.364	64
Bujumbura	-3.349	29.363	798
Maputo	-25.966	32.568	14
Hargeisa	9.562	44.062	1267
BoboDioulass	11.176	-4.296	420
Shubra el-Kheima	30.124	31.238	28
Ikorodu	6.619	3.505	36

Table 5 (Continued)

Asmara	15.339	38.933	2342
Marrakesh	31.626	-7.989	468
Tshikapa	-2.981	23.822	505
Ilorin	8.496	4.548	318
Blantyre	-15.78	35.01	698
Agadir	30.703	-9.570	454
Misratah	32.375	15.092	9
Lubumbashi	-11.664	27.483	1262
Accra	5.81	0.1	39
Brazzaville	-2.981	23.822	505
Monrovia	6.328	-10.798	6
Tunis	33.844	9.4	43
Rabat	33.967	-6.843	87
Lomé	6.13	1.216	14
Benin City	6.333	5.622	90
Owerri	5.48	7.022	74
Warri	5.517	5.75	5
Jos	9.918	8.898	1182
Bangui	4.378	18.554	355
Nampula	-15.119	39.262	430
Oran Algeria	35.622	-0.702	162
West Rand	-26.223	27.513	1589
Lubango	-14.919	13.49	1774

Artificial Neural Network

ANN is the most commonly utilized model to solve non-linear functions and describe a complex system (de Amorim Neto et al., 2022; García-Cuesta et al., 2022) An artificial neural network (ANN) is a network of linked nodes that is used to solve complicated issues and show the intricate relationship between causes and effects(Kassem, Gökçekuş, et al., 2021). A "black box" of linked artificial neurons makes up an artificial neural network (ANN), a type of computer model. These neurons, which can be organized in one or more layers, don't function linearly. An ANN's operation is modelled after how the human brain functions. It has input, hidden, and output layers, with nodes connecting each neuron. Data is sent from input nodes to hidden neurons, integrated, and processed by activation functions, and finally it is delivered to the output neurons. This is how information flows in an ANN. Different ANN approach have been created and used in a variety of sectors, including engineering and research. Long short-term memory, feed-forward neural networks, multi-layered perceptron neural networks, generalized regression neural networks, support vector machines, K-nearest neighbor algorithms, and extreme learning machines are a few examples. In this study, three machine learning models, **feed-forward neural network, Elman neural network and Layer Recurrent Neural Network,** were used for predicting the yearly of the African countries. The performance of these models was tested on 91 cities in Africa with the six main climate zones, namely, Equatorial, Humid Tropical, Tropical, Semi-desert (Sahalian), Mediterranean, and Desert, which are subject to the high solar radiation zone.

Feed Forward Neural Network:

The term "FFNN" stands for "Feed-Forward Neural Networks," and it refers to a model that is widely used for issue analysis across many different fields(Iravanian et al., 2022). Using this model, the Levenberg-Marquardt algorithm and the backpropagation approach are frequently employed. (Meshram et al., 2019). Trials and error is used to determine the number of hidden layers and numerous neurons. The training algorithm's effectiveness is evaluated using mean squared error. The data are normalized between 0 and 1, so take note of that. In this research, the learning algorithm is the backpropagation algorithms. The structure of the proposed model is given in figure 16 (Kassem & Othman, 2022a).

Figure 16

Architecture of FFNN

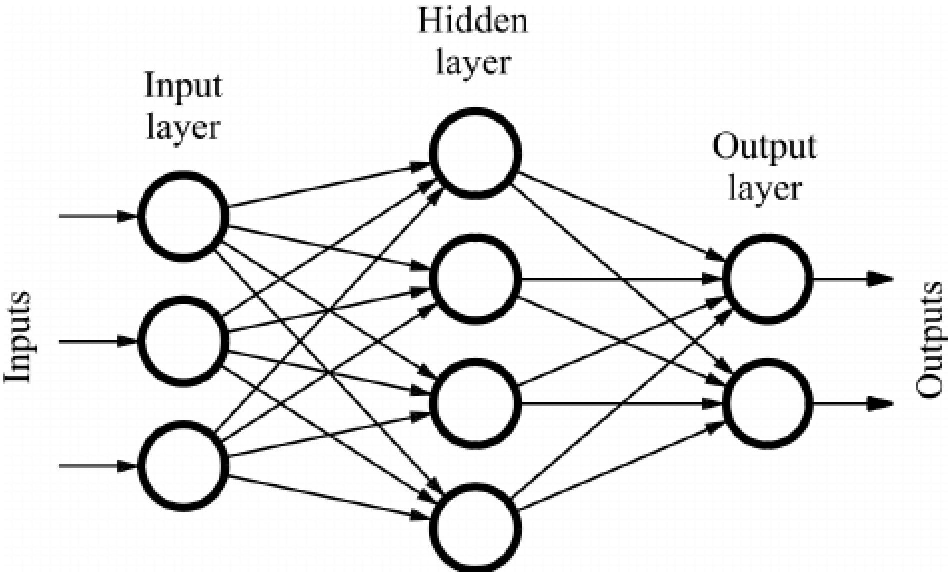
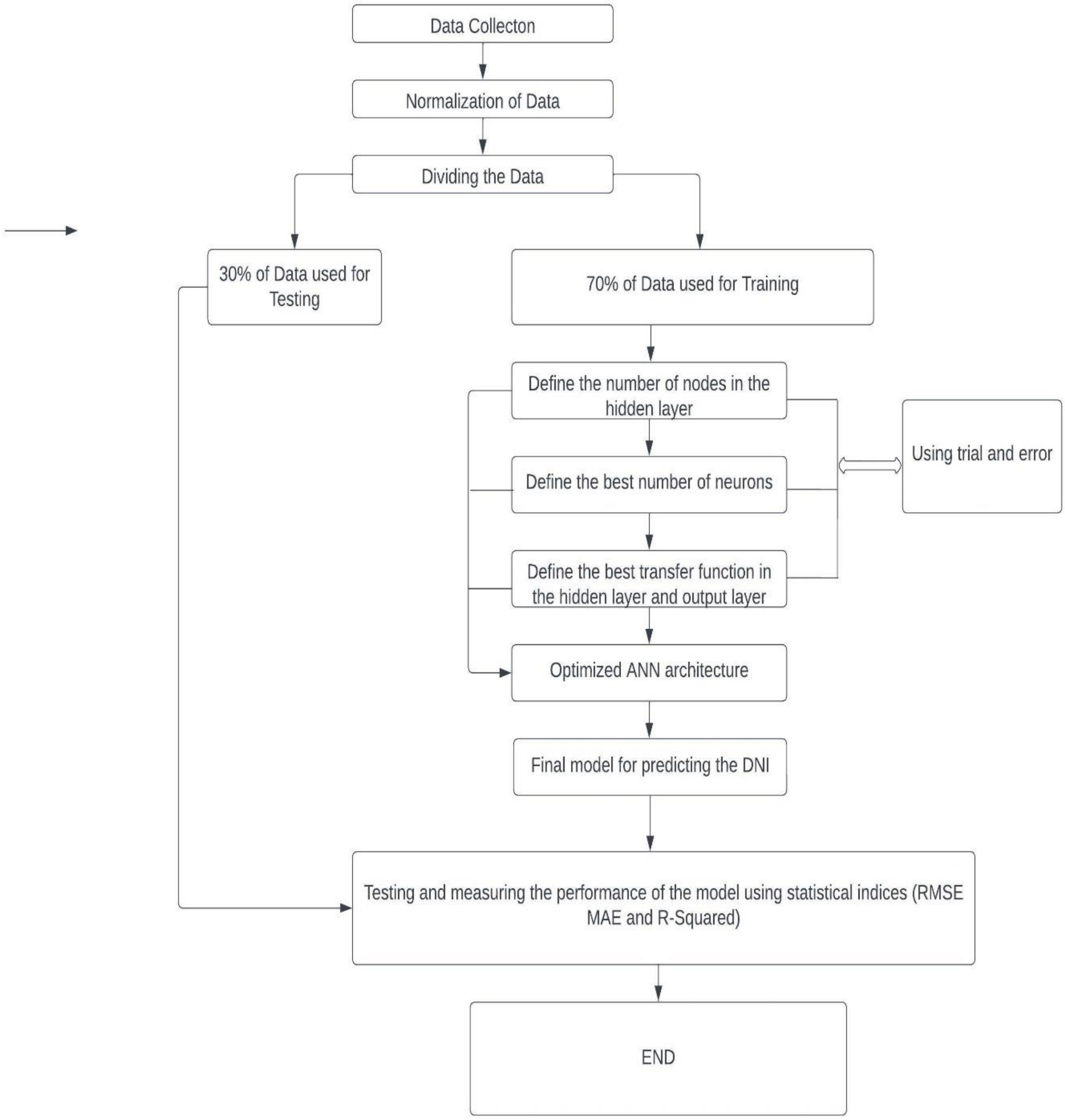


Figure 17

Flowchart of FFNN



Elman Neural Network

ENNs are highly computationally powerful feedback neural networks. The first four levels are the input layers, hidden layers, context layers, and output layers (Tripathi et al., 2022). The input layer is responsible for signal transmission tasks. The output layer, on the other hand, simply includes linear weighting effects. The context layer distinguishes backpropagation neural networks from Ellman Neural Networks (ENN) (Tripathi et al., 2022; Verma & Patil, 2021).

Figure 18

Architecture of ENN

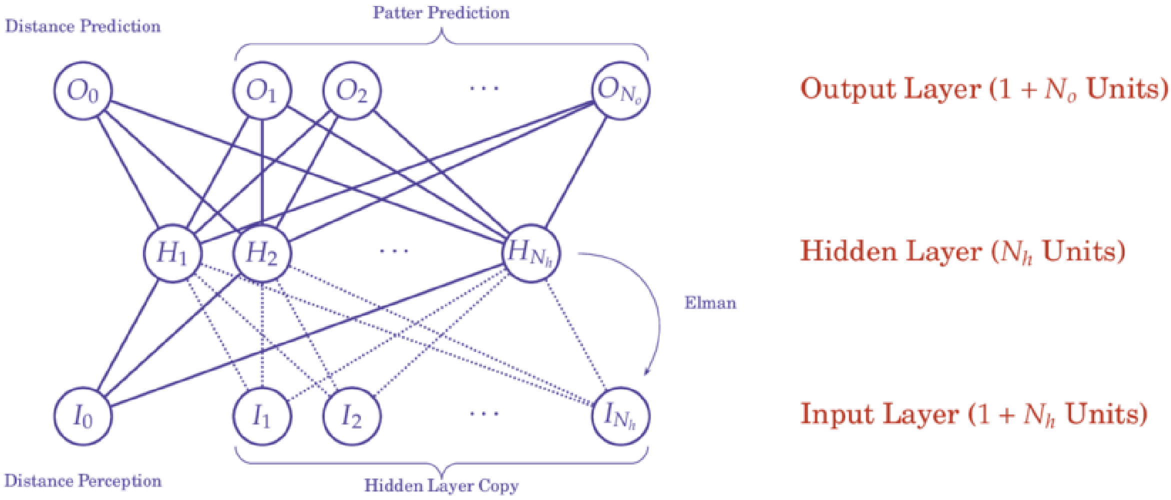
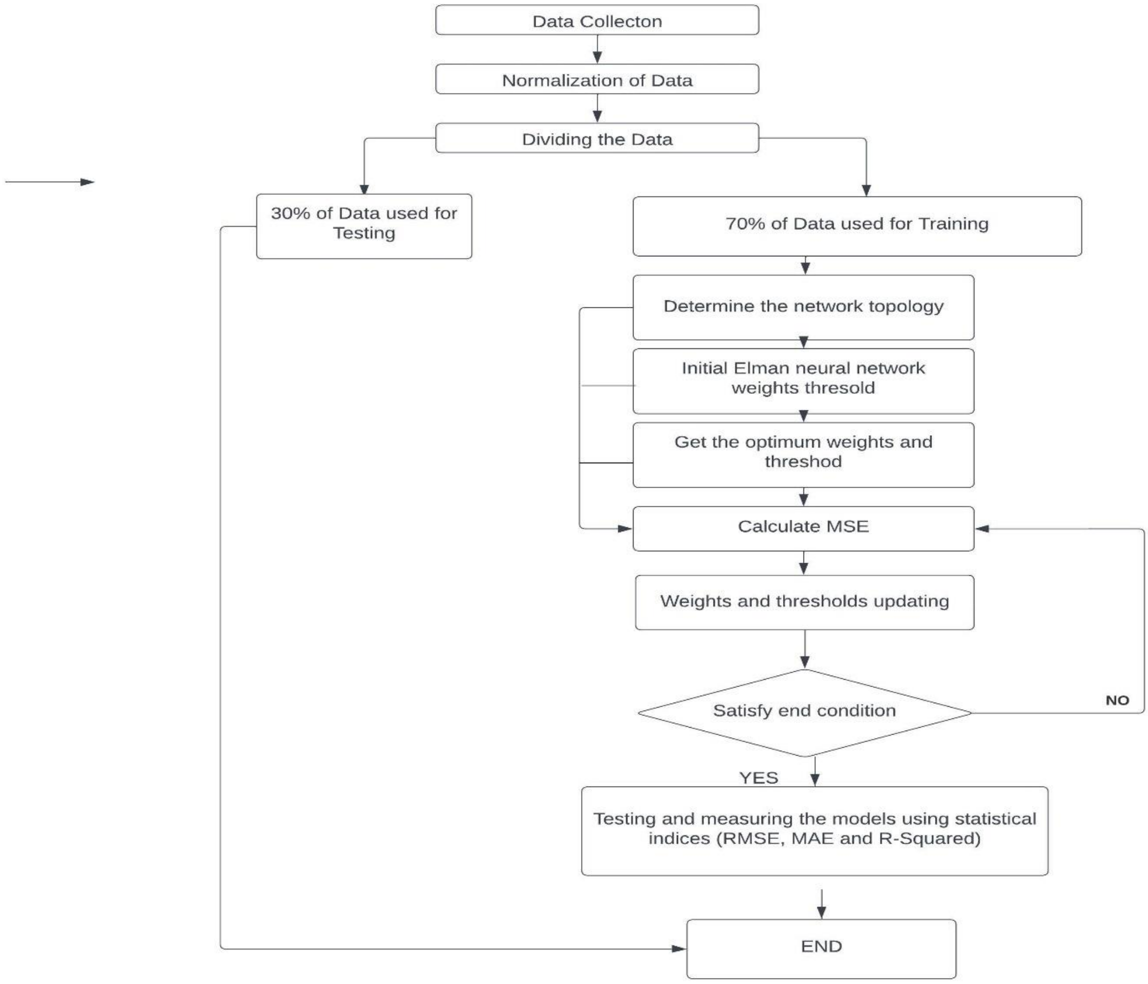


Figure 19

Flowchart of ENN



Layer Recurrent Neural Network

The fundamental version of an RNN achieves "memory" by using its internal state. The fundamental RNN, however, lacks gates in contrast to the more complex varieties. It should be noted that Keras may be used to implement the fundamental RNN as a simple RNN. The Long Short-Term Memory (LSTM) is a more advanced RNN than the standard RNNLSTM employs gates to increase memory depth. The shared states of LSTM neurons may be categorized as long-term and short-term states, respectively. As memories are deleted and added, long-term states pass via gates of oblivion and addition. The long-term state is then transmitted to the following neuron, but the output gate copies and filters it beforehand. This results in a transient condition (Verma & Patil, 2021). Prior to that, four completely linked layers pass the previous short-term state and the current input vector, altering the long-term state's makeup as necessary. In a nutshell, LSTM neurons are made to recognize long-term patterns and are particularly beneficial for continuous or time-series data (Tripathi et al., 2022).

Figure 20

Architecture of LRNN

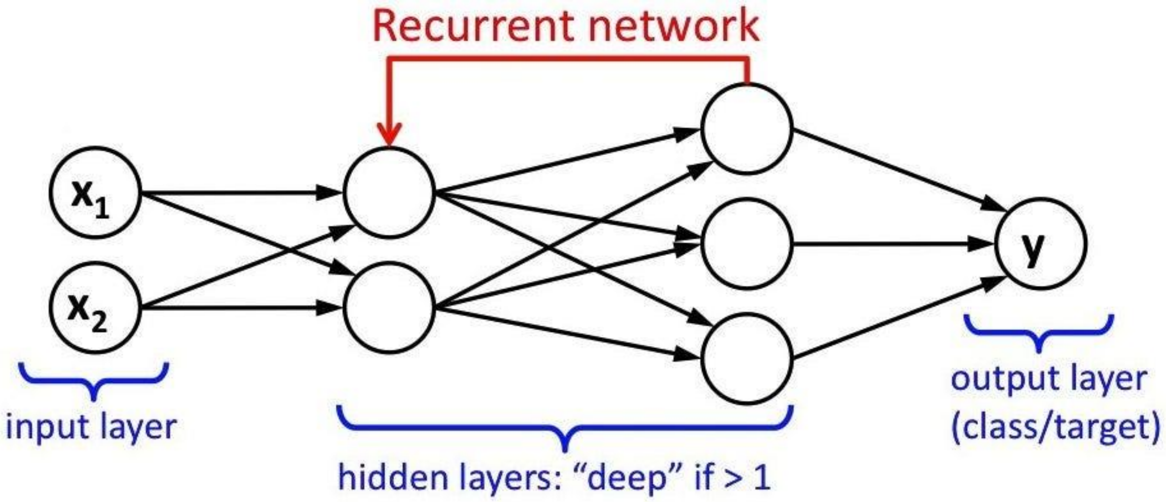
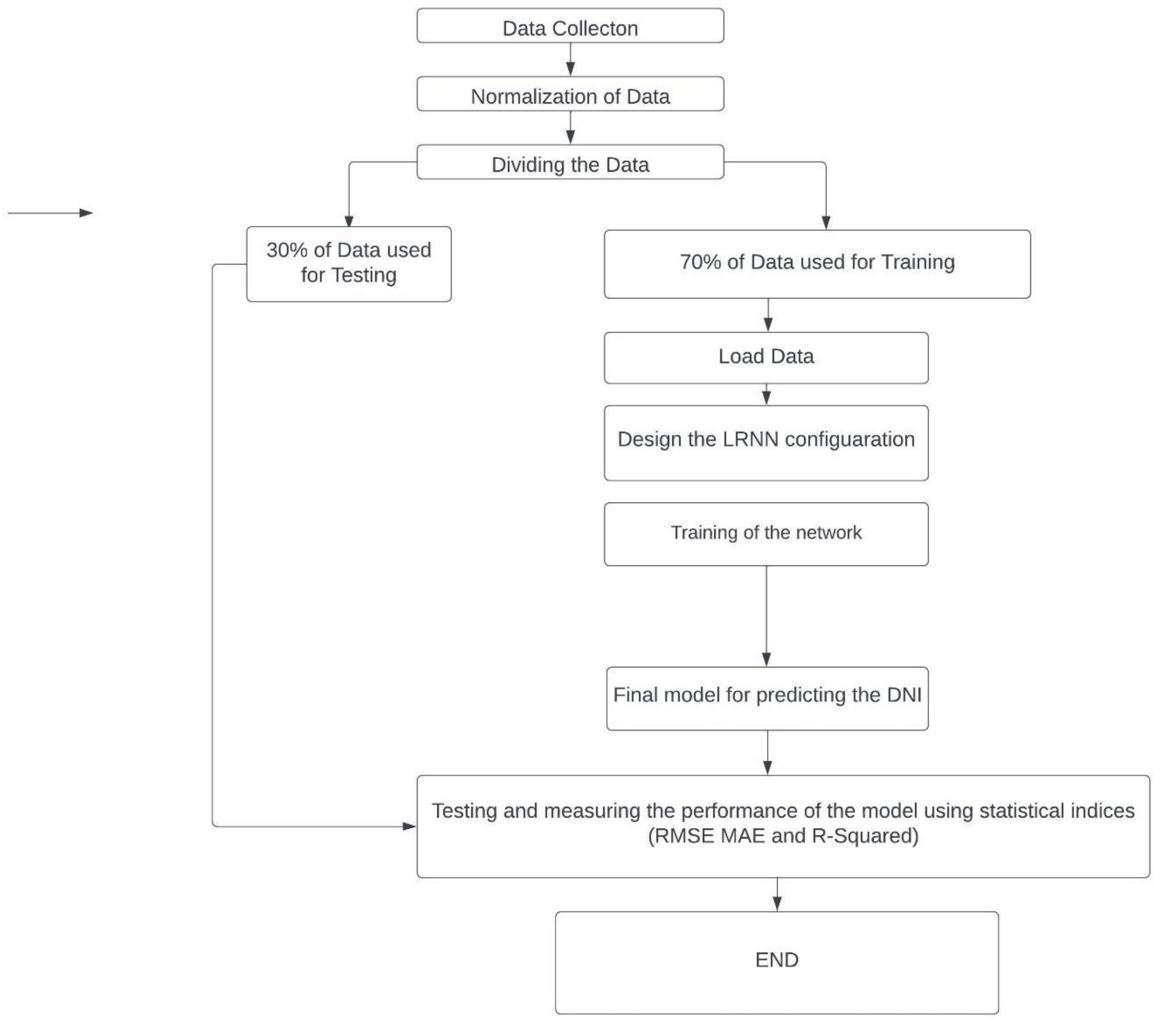


Figure 21

Flowchart of LRNN



Dataset

The NASA POWER (Prediction of Worldwide Energy Resource) dataset is a comprehensive collection of solar and meteorological data. It provides information on various parameters that are crucial for studying and analyzing renewable energy resources and their potential. The dataset covers locations worldwide, allowing researchers and analysts to access solar and meteorological data for virtually any location on Earth. The NASA POWER dataset includes a wide range of parameters related to solar radiation and meteorological conditions. These data are solar radiation including Global Horizontal Irradiance (GHI), Direct Normal

Irradiance (DNI), Diffuse Horizontal Irradiance (DHI), and Clear Sky GHI as well as meteorological data including: temperatures, relative humidity, wind speed, wind directions, precipitation, clouds cover, atmospheric pressures, and more. The dataset offers both hourly and daily temporal resolutions. Hourly data is available for certain parameters, allowing for a more detailed analysis of solar and meteorological conditions throughout the day. Daily data provides aggregated values for each parameter. The spatial resolution of the NASA POWER dataset varies depending on the specific parameter and the data source used. Generally, the dataset provides information at a spatial resolution of approximately 1 km. The dataset integrates data from various sources, including satellite observations, ground measurements, and atmospheric models. NASA incorporates data from multiple sensors and instruments to provide accurate and reliable information. The NASA POWER dataset is freely accessible to the public through the NASA POWER web portal (https://power.larc.nasa.gov/).

Therefore, the annual data including Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Surface Pressure, average, maximum and minimum temperature, Relative Humidity, Wind Speed at 2m height, average, maximum and minimum wind speed at 10m height, Wind Direction at 10m height, Dew/Frost Point, Wet Bulb Temperature, cloud amount, and precipitation were collected for all selected cities in Africa.

Figure 22

NASA Power Access Data Viewer

Data Normalization

A preprocessing method used in machine learning to normalize the range of features or variables is known as data normalization, often referred to as feature scaling. Data normalization aims to scale all characteristics uniformly while preserving their individual distinctions and interrelationships(Ali et al., n.d.).

Normalization is crucial since it aids in preventing the dominance or distortion of particular characteristics in the learning algorithm. When the input data is of similar scale, several machine learning algorithms operate more effectively or converge more quickly(Singh et al., n.d.).

It is calculated mathematically using the formula:

$$\frac{X - X_{minimum}}{X_{maximum} - X_{minimum}}$$

Data Randomization

The process of randomizing the order of data instances inside a data collection is referred to as data randomization, also known as shuffling. It is frequently used in machine learning to prevent data during training from being distorted or biased by innate ordering or patterns(Adams & Anthony, 1996).

Because some machine learning algorithms might be sensitive to the sequence of training samples, the random order of data examples is crucial. The ordering of the data might lead to biased or inefficient learning.

Table 6

Descriptive Statistics of the Training Datasets

Variable	Mean	Median	SD	Minimum	Maximum
Long	3.618	6.131	16.951	-33.962	36.775
Long	16.257	14.543	16.087	-17.334	46.739
Alt.	555.7	352.5	597.6	6.0	2342.0
Slop	17.619	16.000	15.724	-1.000	90.000
Azimuth	930317	-2	7842303	-2099	66988885
YEAR	2011.0	2011.0	6.06	2001.0	2021.0
PS	96.063	97.950	5.636	81.400	101.700
T2M	23.625	24.690	3.620	8.380	30.120

Table 6(Continued)

RH2M	68.820	71.910	15.201	23.810	89.190
WS2M	2.4182	2.3000	1.1292	0.4500	6.0500
WD10M	195.17	211.25	94.24	0.44	359.50
WS10M	3.4027	3.2750	1.2156	1.0200	7.1900
T2MDEW	15.994	15.440	5.570	4.120	24.300
T2MWET	19.810	19.755	3.923	7.190	25.670
T2M-MAX	36.476	36.105	4.942	25.250	46.940
T2M-MIN	11.895	12.120	5.895	-8.700	23.520
CLOUD-AMT	54.354	55.755	15.929	11.360	86.880
WS10M-MAX	10.045	10.050	3.603	2.810	22.850
WS10M-MI	0.06226	0.05000	0.06463	0.00000	1.41000
PRECTOTCORR	2.8400	2.6350	1.9214	0.0100	20.2800
ALLSKY-SFC-SW-DNI	4.2669	4.3000	1.3801	1.9700	7.7400
ALLSKY-SFC-SW-DWN	5.2555	5.2450	0.6825	2.5800	6.8000

Table 7

Descriptive Statistics of the Testing Datasets

Variable	Mean	Median	SD	Minimum	Maximum
Long	8.77	5.50	20.85	-26.56	35.62
Long	11.410	8.662	11.565	-6.843	31.238
Alt.	403.9	120.5	528.1	5.0	1589.0
Slop	19.765	17.000	11.415	0.000	34.000
Azimuth	-131.1	1.0	427.8	-1871.0	18.0
YEAR	2011.0	2011.0	6.06	2001.0	2021.0
PS	97.158	99.925	5.223	84.700	101.580
T2M	22.427	23.125	3.410	15.800	28.580
RH2M	70.830	71.685	15.565	39.250	90.250
WS2M	2.0017	2.0000	1.0286	0.0800	4.3600
WD10M	228.72	235.22	101.01	0.94	360.00
WS10M	2.9572	3.0700	1.1067	0.6600	5.3200
T2MDEW	15.557	14.230	6.789	4.450	24.080
T2MWET	18.992	18.475	4.885	10.800	25.040

Table 7 (Continued)

T2M-MAX	36.992	35.905	4.785	29.050	47.770
T2M-MIN	8.881	10.235	7.843	-6.200	21.190
CLOUD-AMT	54.298	49.990	18.914	22.770	84.550
WS10M-MAX	9.883	9.500	4.379	1.730	20.880
WS10M-MI	0.05415	0.05000	0.04694	0.01000	0.47000
PRECTOTCORR	3.028	2.175	2.337	0.030	11.020
ALLSKY-SFC-SW-DNI	4.2447	4.5450	1.6901	1.8300	7.0900
ALLSKY-SFC-SW-DWN	5.0012	4.9500	0.5872	3.9800	5.9600

CHAPTER IV

Results and Discussion

Description of the Dataset

The data obtained for the 91 cities of different part of Africa from the NASA database were divided into training and testing with the training data taking 70% of the cities while testing was 30% of the cities. Data of 21 years (2000 to 2020) were utilized for this study. To start the training process, three (3) networks were created with different configurations. The training process was done by trial and error and were utilized to find the best neural network model and the best combination of input variables and hidden layer neurons. In this regard, the number of layers, neurons and iterations were between the range of 1-2, 5-15 and 10000-100000. Also, the, transfer function was changed between TANSIG and LOGSIG while the Training Function and Adaption Learning function was kept constant for all different configuration of networks. After the training, the optimal best network was then selected and the testing data was inputted to simulate the network.

Table 8

Optimum network configuration

ANN model	Scenario	Number of hidden layers	Number of neurons	Transfer function
FFNN	1	1	15	TANSIG
	2	1	15	TANSIG
ENN	1	2	5	LOGSIG
	2	1	15	TANSIG
LRNN	1	1	5	TANSIG
	2	2	10	LOGSIG

Results of the ANN

For every configuration, the input was varied with the first case including geographical parameters while the second scenario has no geographical parameters. To assess the best model, various statistical indices were employed such as the R^2, MAE, and RMSE. These statistical equations have been described as widely used when determining the best model (Arora et al., 2021; Kumar et al., 2020; Park et al., 2021). A model with a value of the R^2 that is close to 1 and RMSE and MAE close to 0 indicates the best model (Kassem & Gökçekuş, 2021). When comparing to other statistical indices, the R^2 is the most informative and thereby employed as the best when determining the performance of a model (Chicco et al., 2021). For models with a 0.5 R^2, the value is considered to be moderated and ca be accepted (Van Liew et al., 2003) The mathematical expressions for the indices are given below:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

Where n is Number of Datasets, Y_i is Actual Datasets and $\widehat{Y_i}$ is the Predicted Datasets and $\bar{Y}$ is the mean of actual values.

First Scenario

Based on the calculated results for the first scenario, the R^2 values for all the cities was between the range of 0.9151 to 0.9294. The values show that the models can be used to predict the DNI for the selected locations. ENN was found to be the best models with the highest value of the R^2 of 0.9294. The values of RMSE and MSE for all the cities were found to be in the range of 0.0679 to 0.0802 and 0.0546 to 0.0621. The best model that is closest to 0 was found to be ENN.

For Oran, the value of R^2 range from 0.8093 to 0.8561 with LRNN having the highest value. Any value of the R^2 that is above 0.5 id considered accepted and the model is considered good for the prediction according to (Veisi et al., 2022). Also, for Tangier, all the models used in the studies were having a value of R^2 above 0.5 (0.75-0.86). For this city, LRNN was found to be the best model for prediction

For Pretoria, Shubra El- Kheims, West Rand, Vereeniging and Tripoli, the R^2 values was between the range of 0.1 to 0.87. Some of the models were not suitable for the prediction (Van Liew et al., 2003) but in all the cites, ENN was found to be the best models with values above 0.5 which is considered accepted(Veisi et al., 2022).

Results of Rabat and Yaoundé, the value of R^2 was found within the range of 0.1 and 0.63. the best model was the LRNN with the cities having values of 0.6357 and 0.5577 respectively.

For Warri, Tshikapa and Tunis, the best model was found to be FFNN base on the calculated value of the R^2. The values for the FFNN were all above 0.5 which rendered the model suitable and acceptable(Veisi et al., 2022)

For Ouagadougou, Owerri, Pointe Noire, Port Harcourt, Umuahia and Uyo the value of R^2 range from 0.01 to 0.49 but in this case, all values were below 0.5 and is concluded that the models employed in the prediction did not predict the values for this particular city thus unacceptable (Van Liew et al., 2003)

The calculated RMSE and MAE Values for cites Ouagadougou, Owerri, Pointe Noire, Pretoria, Rabat, Umuahia, and Uyo were having LRNN as the model with value closest to 0. A value closest to 0 indicates that the models have the least error. For Cities Oran, Shubra El-Kheims, Tangier, Tripoli, Tshikapa, Tunis and Vereeniging were all having ENN as the models with the least error considering the calculated values of the RMSE and MAE.

The least values of RMSE and MAE for cities Port Harcourt, Warri, West Rand and Yaoundé was calculated in the model FFNN.

Second Scenario

As per the calculated results, it was found that the used models have predicted the values of R^2 for all the cities significantly well. The values were in the range of 0.9364 and 0.9604. The FFNN was found to be the best models with highest value closest to 1. Similarly, the 3 models employed in the study all predicted closely the values of Warri and having a very high $R^{2.}$ The FFNN model was found to be the best with a value of 0.6467.

For cities Oran, Rabat, Shubra El-Kheims, Tangier, and Vereeniging have some models below 0.5 and some models above 0.5. but in all the cities, the ENN was found to be the best models having the R^2 value closest to 1.

For cities Pretoria, Tripoli, Tshikapa, Umuahia, West Rand and Yaoundé were all having the best model for the prediction as FFNN. It was considered best due to the highest value of the calculated R^2, a value greater than 0.5 and closest to 1 in all the cities.

The calculated R^2 value for Cities Ouagadougou, Owerri, Pointe Noire, Tunis and Uyo indicated that all the models poorly predicted the original values. Thus, the R^2 Values were all considered not accepted because of their distance to 1 and below 0.5(Van Liew et al., 2003).

Considering the RMSE and MAE, cities Oran, Ouagadougou, Owerri, Shubra El-Kheims, Tangier, Tripoli, Umuahia, Vereeniging, Warri, and West Rand were all having the least value; closest to 0 indicating a minimal error in the model. For cities Pointe Noire, Rabat, Tunis, and Yaoundé were having the FFNN as the least values. For Cities Tshikapa and Uyo, the least value of the RMSE and MAE was calculated in the model LRNN.

Table 9

Calculated Results

Location	Case	Statistical Index	FFNN	ENN	LRNN
All Cities	1	R^2	0.9151	0.9294	0.9208
		RMSE	0.0734	0.0679	0.0802
		MAE	0.0621	0.0546	0.0617
	2	R2	0.9604	0.9595	0.9364
		RMSE	0.1260	0.0568	0.3051
		MAE	0.1172	0.0507	0.2896
Oran	1	R2	0.8093	0.8112	0.8561
		RMSE	0.0734	0.0679	0.0802
		MAE	0.0621	0.0546	0.0617
	2	R2	0.8292	0.9007	0.2590
		RMSE	0.1260	0.0568	0.3051
		MAE	0.1172	0.0507	0.2896
Ouagadougou	1	R2	0.0641	0.0456	0.0109
		RMSE	0.2410	0.0773	0.0706
		MAE	0.2218	0.0610	0.0585
	2	R2	0.0027	0.0049	0.0003
		RMSE	0.1097	0.0798	0.1374
		MAE	0.0951	0.0633	0.1285
Owerri	1	R2	0.2388	0.1347	0.1705
		RMSE	0.0986	0.1009	0.0776
		MAE	0.0969	0.0989	0.0746
	2	R2	0.4282	0.2446	0.2452
		RMSE	0.0382	0.0251	0.0259
		MAE	0.0342	0.0185	0.0214

Table 9 (Continued)

Pointe Noire	1	R2	0.0954	0.0034	0.2933
		RMSE	0.0755	0.0643	0.0564
		MAE	0.0632	0.0518	0.0509
	2	R2	0.1493	0.0077	0.0318
		RMSE	0.0594	0.0712	0.0623
		MAE	0.0511	0.0623	0.0547
Port Harcourt	1	R2	0.0679	0.0024	0.0001
		RMSE	0.0504	0.0638	0.0549
		MAE	0.0478	0.0621	0.0524
	2	R2	0.1950	0.1626	0.0434
		RMSE	0.0496	0.0336	0.0376
		MAE	0.0366	0.0282	0.0311
Pretoria	1	R2	0.3775	0.8602	0.7989
		RMSE	0.1131	0.0944	0.0413
		MAE	0.0865	0.0759	0.0331
	2	R2	0.7678	0.6814	0.3699
		RMSE	0.1153	0.1256	0.1326
		MAE	0.0904	0.1127	0.1090
Rabat	1	R2	0.3207	0.1855	0.6357
		RMSE	0.1397	0.2820	0.0597
		MAE	0.1309	0.2735	0.0502
	2	R2	0.4846	0.5685	0.3974
		RMSE	0.0513	0.0695	0.0687
		MAE	0.0416	0.0572	0.0544
Shubra el Kheims	1	R2	0.3817	0.6739	0.6057
		RMSE	0.0635	0.0304	0.1109
		MAE	0.0525	0.0234	0.1023
	2	R2	0.6013	0.6574	0.0275
		RMSE	0.0954	0.0446	0.1370
		MAE	0.0903	0.0383	0.1260

Table 9 (Continued)

Tangier	1	R2	0.7572	0.7830	0.8656
		RMSE	0.1358	0.0902	0.1200
		MAE	0.1216	0.0743	0.0996
	2	R2	0.5297	0.9457	0.4718
		RMSE	0.1823	0.0536	0.1777
		MAE	0.1618	0.0444	0.1582
Tripoli	1	R2	0.1481	0.7538	0.3328
		RMSE	0.1593	0.0583	0.1479
		MAE	0.1188	0.0480	0.1055
	2	R2	0.5952	0.3853	0.1051
		RMSE	0.1151	0.1000	0.2340
		MAE	0.1004	0.0835	0.2066
Tshikapa	1	R2	0.5356	0.4031	0.2636
		RMSE	0.1188	0.0575	0.1011
		MAE	0.1149	0.0486	0.0950
	2	R2	0.5051	0.3310	0.4130
		RMSE	0.0457	0.0440	0.0397
		MAE	0.0398	0.0368	0.0311
Tunis	1	R2	0.5128	0.2775	0.2824
		RMSE	0.1504	0.0510	0.1655
		MAE	0.1471	0.0417	0.1619
	2	R2	0.3015	0.0049	0.0588
		RMSE	0.0573	0.0911	0.1232
		MAE	0.0448	0.0801	0.1154
Umuahia	1	R2	0.2172	0.0638	0.2965
		RMSE	0.0978	0.0886	0.0632
		MAE	0.0959	0.0862	0.0599
	2	R2	0.5148	0.2155	0.2096
		RMSE	0.0334	0.0216	0.0274
		MAE	0.0289	0.0173	0.0232

Table 9 (Continued)

Uyo	1	R2	0.1589	0.0366	0.2573
		RMSE	0.0845	0.0969	0.0831
		MAE	0.0816	0.0946	0.0808
	2	R2	0.2501	0.0353	0.2455
		RMSE	0.0617	0.0275	0.0225
		MAE	0.0535	0.0220	0.0182
Vereeniging	1	R2	0.6417	0.6565	0.4356
		RMSE	0.0604	0.0411	0.1576
		MAE	0.0515	0.0334	0.1444
	2	R2	0.6547	0.4438	0.3149
		RMSE	0.1246	0.0828	0.1423
		MAE	0.1127	0.0710	0.1266
Warri	1	R2	0.5329	0.3308	0.1886
		RMSE	0.0240	0.0538	0.0422
		MAE	0.0213	0.0498	0.0370
	2	R2	0.6467	0.5157	0.5625
		RMSE	0.0439	0.0297	0.0457
		MAE	0.0356	0.0259	0.0424
West Rand	1	R2	0.0815	0.7520	0.0433
		RMSE	0.0809	0.0964	0.1491
		MAE	0.0530	0.0580	0.1311
	2	R2	0.6215	0.4579	0.0098
		RMSE	0.1247	0.0634	0.1397
		MAE	0.1114	0.0504	0.1223
Yaounde	1	R2	0.5019	0.4403	0.5577
		RMSE	0.0283	0.0377	0.0406
		MAE	0.0239	0.0301	0.0355
	2	R2	0.5759	0.4039	0.4409
		RMSE	0.0582	0.0780	0.0820
		MAE	0.0531	0.0732	0.0768

Discussions of the Result

The results obtained after calculating the statistical indices indicated that all the models have showed reliability in predicting the solar radiation of African Cities. In the first scenario, the three models were having a value within the range of 0.9151 to 0.9294 while the second scenario were having values in the range of 0.9364 and 0.9604. These obtained results have shown a correspondence with previous studies that used machine learning approaches to predict solar radiation. For instance, (Demir & Citakoglu, 2023) had used machine learning approaches to forecast solar radiation in turkey. In his study LSTM, SVMR, GPR, ELM and KNN models were used. Their results indicated that the average value of R^2 valued were in the range of 0.50 to 0.89. Also, (Kisi et al., 2020) estimated solar radiation using ELM, RBF and BMA in the Mediterranean climate and there results of the R^2 were with the range of 0.7 to 0.95. These results have showed that the models predicted the solar radiation nearly accurate. In another study of (Belmahdi et al., 2022), machine learning and time series models were used to predict the global solar radiation, from the results obtained, the ARIMA and FFNN Models were best in approximating the intended output. (Banerjee et al., 2022) have also used machine learning approach to predict solar radiation. The results obtained indicated that for all the five models used in their study, the R^2 value was within the range of 0.60 to 0.9. These showed that machine learning models can be employed to predict the solar radiation. Using SVM and ANN models in selecting the best input parameters for determining the global solar radiation, the results obtained by (Biazar et al., 2020) were within the range of 0.6 to 0.99. this result is a clear indication of the applicability of machine learning in prediction of solar radiation.

In addition to the above studies, other studies showed the predictability of solar radiation using machine learning models. (Geetha et al., 2022) have predicted hourly solar radiation in Tamil Nadu. The results proved that ANN models have accuracy and improvement in the prediction of the radiation. The results of all the algorithms used were between the range of 0.7 to 0.99. Also, (Fadare, 2009) in his study to estimate the mean monthly solar radiation in Nigeria, the R^2 valued obtained was 0.971.

The studies above and other studies used to predict solar radiation have showed a similar R^2 values from the values obtained in this research. It is an indication that machine learning algorithms can be effectively used to predict the solar radiation not only in Africa but different locations in the globe.

Comparison of the Calculated Values for All Cities

From the calculated results, it could be seen that all the models used in this study for scenario 2 have a higher value of R^2 than that of scenario 1. On this note, it was observed that the value of FFNN for scenario 2 was 0.9604 against 0.9151 of scenario 1. Likewise, the R^2 value for ENN in the 2nd scenario was found to be 0.9595 against 0.9294 of the 1st scenarios. Finally, 0.9364 was the R^2 value of LRNN in the 2nd scenario which was greater than 0.9208 of the 1st scenarios.

Percentage Error

To understand the effect of these changes and determine the accuracy of the models, the percentage error was calculated.

The formular for percentage error is given as:

$$\delta = \frac{v_A - v_E}{v_E} x \ 100$$

Where v_A is actual value observed

v_E is expected value

For FFNN: $\frac{0.9604-0.9151}{0.9151} x \ 100$ = 4.95%

For ENN: $\frac{0.9595-0.9294}{0.9294} x \ 100 = 3.20\%$

For LRNN: $\frac{0.9364-0.9208}{0.9208} x \ 100 = 1.70\%$

Based on the above errors, it was observed that the accuracy of the models was not affected significantly by the geographical parameters.

CHAPTER V

Conclusion and Recommendations

Conclusions

Base on the studies, can be concluded that:

1. Direct normal radiation predictions for Africa are not significantly impacted by geography. In this note, DNI levels are not significantly influenced by the climate, latitude, longitude, and altitude of different geographical areas.
2. Effective machine learning algorithms can forecast her DNI in Africa. These models offer precise predictions of solar irradiance and support effective planning and utilization of solar energy resources by utilizing geographic characteristics and climatic data.
3. Geographic characteristics and machine learning models trained on previous DNI data may recognize these fluctuations and produce accurate forecasts for specific places.
4. The performance of various machine learning methods in forecasting DNI for Africa varies. It's crucial to assess and contrast several models in order to choose the most precise and reliable strategy for a certain area.

Recommendations

1. By adding other parameters including atmospheric conditions, cloud cover, and aerosol index, research should continue to focus on improving the precision and accuracy of DNI predictions. This may be accomplished by collaborating with organizations that deal with meteorology and remote sensing experts.
2. To improve the performance of machine learning models, the DNI dataset must be updated and increased on a regular basis. In order to collect and distribute DNI data across Africa, cooperation is crucial.
3. Frameworks for designing and deploying solar energy systems may use newly created machine learning models. Governments, energy organizations, and renewable energy companies could utilize these models to identify high-potential locations for solar energy projects, boost energy output, and create intelligent policy decisions.

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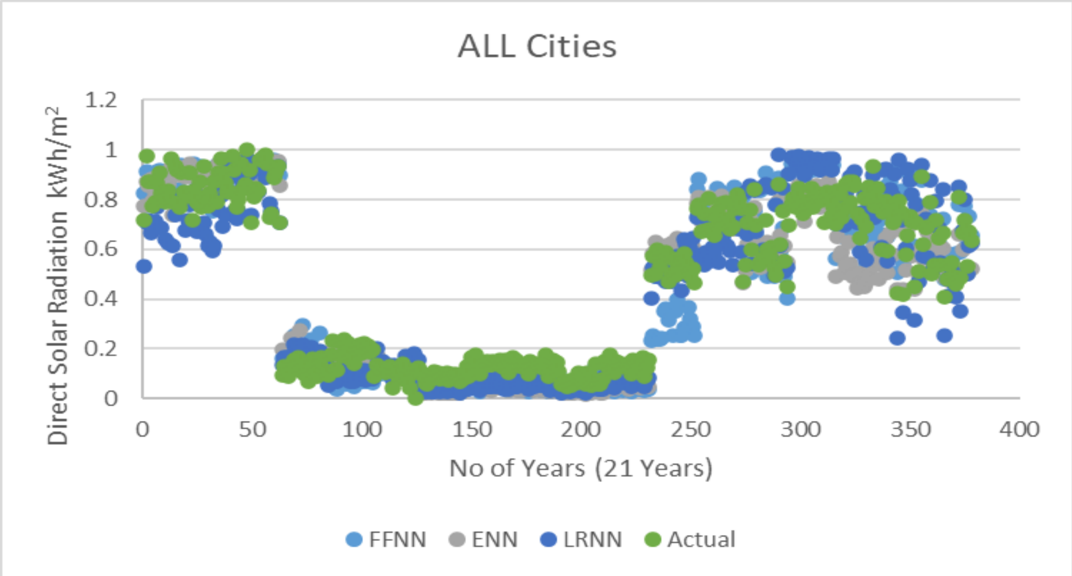
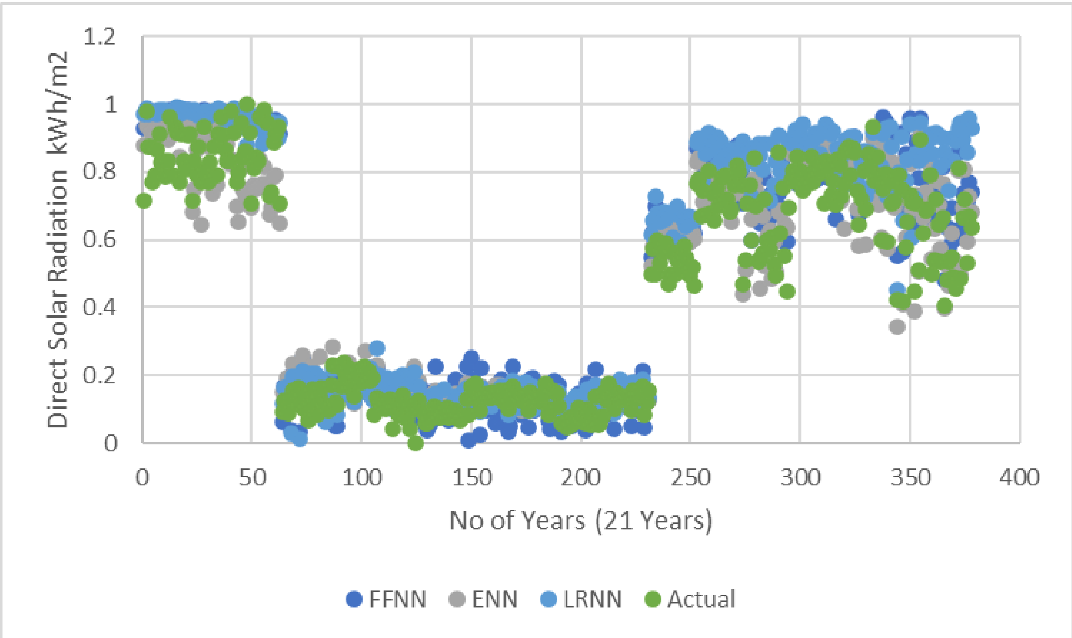
APPENDIX A

Time Series Plot for All Cities with Geographical Parameters



Time Series Plot for All Cities with nongeographical parameters



APPENDIX B

Thesis

ORIGINALITY REPORT

13%	7%	8%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	link.springer.com Internet Source	2%
2	Maryam K. Abdelrazik, Sara E. Abdelaziz, Mariam F. Hassan, Tarek M. Hatem. "Climate action: Prospects of solar energy in Africa", Energy Reports, 2022 Publication	1%
3	Proceedings of ISES World Congress 2007 (Vol I – Vol V), 2009. Publication	1%
4	Weiwei Jiang, Jiayun Luo. "An evaluation of machine learning and deep learning models for drought prediction using weather data", Journal of Intelligent & Fuzzy Systems, 2022 Publication	1%
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6	Ali Sohani, Siamak Hoseinzadeh, Saman Samiezadeh, Ivan Verhaert. "Machine learning prediction approach for dynamic performance modeling of an enhanced solar still	<1%

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