A Project Report on

EFFECTIVE PREDICTION OF GLOBAL SOLAR RADIATION USING MACHINE LEARNING ALGORITHMS AND SATELLITE IMAGES

Submitted in partial fulfillment of the requirement
For the award of the degree of

BACHELOR OF TECHNOLOGY
IN
CSE (DATA SCIENCE)

Submitted by

T. Sahana	21A31A4430
S. Yamini Satya Sai Priya	21A31A4428
Jafari Kulsum	21A31A4412
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Under the esteemed guidance of
Mrs. K. Harika **M.Tech**
Assistant Professor of CSE (Data Science)

DEPARTMENT OF CSE (DATA SCIENCE)

PRAGATI ENGINEERING COLLEGE
(AUTONOMOUS)
(Approved by AICTE, Permanently Affiliated to JNTUK, KAKINADA, Accredited by NBA& NAAC with 'A+' Grade)
ADB Road, Surampalem, Near Peddapuram, Kakinada District, AP- 533437

2021-2025

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CERTIFICATE

DEPARTMENT OF CSE (DATA SCIENCE)

విద్యా పరా దేవతా

Learning is Supreme Deity

This is to certify that the project report entitled **“EFFECTIVE PREDICTION OF GLOBAL SOLAR RADIATION USING MACHINE LEARNING ALGORITHMS AND SATELLITE IMAGES”** is being submitted by **T.SAHANA (21A31A4430),S.YAMINI SATYA SAI PRIYA (21A31A4428), JAFARI KULSUM (21A31A4412), T.SIVA VENKATA SAI KUMAR (21A31A4461), SHAIK SAMEERUDDIN (21A31A4458)** in partial fulfilment for the award of the Degree of **Bachelor of Technology**, during the year **2021-2025** in Data Science of Pragati Engineering College, for the record of a bonafide work carried out by them.

Project Supervisor:	Head of the Department:
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ABSTRACT

Accurate prediction of Daily Global Solar Radiation (DGSR) is crucial for applications in renewable energy, agriculture, and climate studies. Reliable forecasting enables better planning and utilization of solar energy resources, improving efficiency in power generation and environmental monitoring. This study explores the effectiveness of Machine Learning (ML) algorithms combined with satellite imagery to enhance DGSR forecasting. Traditional ML models rely on meteorological parameters such as temperature, wind speed, atmospheric pressure, and sunshine duration, as well as radiometric parameters like aerosol optical thickness and water vapor. However, incorporating additional sources of data can lead to more precise predictions.

In this study, the integration of normalized reflectance from satellite images across multiple spectral channels is examined to improve prediction accuracy. This approach leverages remotely sensed data to capture atmospheric and surface characteristics that influence solar radiation. Two ML techniques— Artificial Neural Networks (ANN) and Support Vector Machines (SVM)—are employed as regression models to estimate DGSR based on diverse input features. The effectiveness of these models is analyzed by evaluating their performance across different datasets.

The findings indicate that the choice and number of input parameters significantly impact forecast accuracy. A comprehensive selection of features enhances the model's ability to capture complex relationships between atmospheric variables and solar radiation levels. Among the two approaches, ANN demonstrated superior performance over SVM, highlighting its capability to learn intricate patterns and provide more reliable predictions. These results emphasize the potential of ML-driven methodologies in advancing solar energy forecasting, paving the way for more sustainable and efficient energy management strategies.

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CHAPTER-1

INTRODUCTION

INTRODUCTION

Solar radiation plays a crucial role in various natural and artificial processes, including climate regulation, weather patterns, and renewable energy production. Understanding and predicting solar radiation levels are essential for optimizing solar energy systems, enhancing optical communication efficiency, and improving climate change research. However, the complex interaction between atmospheric components, cloud cover, and geographical conditions makes accurate solar radiation estimation challenging. Traditional methods, such as empirical and mathematical models, rely on extensive ground-based measurements, which are often impractical due to high costs, maintenance requirements, and limited spatial coverage.

Recent advancements in artificial intelligence (AI) and satellite technology have opened new possibilities for improving solar radiation forecasting. Machine learning (ML) techniques, including Artificial Neural Networks (ANN) and Support Vector Machines (SVM), have demonstrated their ability to process large datasets and identify complex patterns within atmospheric and radiometric parameters. By integrating satellite data, such as zenith angle and reflectance values from multiple spectral bands, these models can offer more accurate and scalable predictions. This integration eliminates the reliance on costly ground-based stations and enables precise estimations in remote and inaccessible locations.

The adoption of AI-driven solar radiation prediction models has significant implications for energy management, environmental sustainability, and climate research. More accurate forecasts will enhance the efficiency of solar energy farms, reducing dependence on fossil fuels and lowering greenhouse gas emissions. Additionally, improved solar radiation modeling can aid policymakers in designing sustainable energy strategies while contributing to the development of advanced optical communication systems. Given the increasing global focus on renewable energy, leveraging ML-based predictive models with satellite data presents a promising approach to optimizing solar resource utilization.

Problem Statement

Accurately predicting solar radiation remains a major challenge due to atmospheric variability, cloud cover, and geographical differences. Traditional ground-based measurement techniques are costly, time- consuming, and geographically limited, making them impractical for large-scale applications. Existing empirical and mathematical models often lack adaptability to different climatic conditions and sky states. To overcome these limitations, this study proposes the development of a machine learning-based approach using Artificial Neural Networks (ANN) and Support Vector Machines (SVM) with satellite-derived data.

Significance of the Proposed System

The proposed system integrates machine learning algorithms with satellite-derived parameters to improve the prediction of solar radiation under various sky conditions. This system offers several advantages over traditional methods, including enhanced accuracy, scalability, and cost-effectiveness. By utilizing satellite data, the model eliminates the need for extensive ground-based measurements, making it a viable solution for remote and inaccessible regions. Furthermore, reliable solar radiation predictions will significantly benefit solar energy management, enabling efficient power generation, grid stability, and resource planning.

Objectives of the Project

1. To develop an accurate solar radiation prediction model using Artificial Neural Networks (ANN) and Support Vector Machines (SVM).
2. To integrate satellite-derived parameters, such as zenith angle and reflectance data, into the predictive framework.
3. To evaluate the performance of the proposed models under different sky conditions, including clear and overcast conditions.
4. To reduce dependency on ground-based measurement stations by leveraging satellite data for continuous and scalable solar radiation estimation.

CHAPTER -2

LITERATURE SURVEY

LITERATURE SURVEY

“Traditional models for solar radiation prediction rely on empirical and mathematical methods but often lack accuracy due to their dependence on ground-based measurements.”

In [1], early models for solar radiation estimation primarily relied on empirical and mathematical methods using ground-based measurements. These models use standard meteorological parameters such as temperature, humidity, sunshine duration, and wind speed. While straightforward, these approaches often suffer from limitations in accuracy and are costly due to the need for extensive manual data collection. As stated in [1], “the inefficiency of conventional models in handling complex weather patterns makes large- scale solar radiation prediction challenging.” Studies like Gurel et al. (2023) highlight the limitations of these traditional models in capturing variations in atmospheric conditions.

“Hybrid models integrate statistical and mathematical techniques to improve solar radiation estimation, yet they remain constrained by the necessity of ground-based input data.”

In [2], hybrid models combining mathematical approaches with statistical techniques have been explored to improve accuracy. Alizamir et al. (2023) introduced hybrid deep learning models combining Long Short- Term Memory (LSTM) networks with wavelet transforms to enhance predictive power. However, these approaches still depend significantly on ground-level data, which limits their scalability. According to [2], “although hybrid techniques enhance prediction accuracy, their reliance on location-specific meteorological data reduces their effectiveness for global applications.”

“Machine learning models offer advanced capabilities for solar radiation forecasting, yet their effectiveness depends on the selection of appropriate input features.”

In [3], machine learning (ML) approaches have been increasingly adopted for more reliable solar radiation prediction. Studies by Zaiani et al. (2021) and Ghimire et al. (2022) demonstrate the use of Support Vector Machines (SVM) and Artificial Neural Networks (ANN) for solar radiation prediction.

radiation models depends on comprehensive data input, with deficiencies leading to suboptimal performance.”

“Satellite data presents an opportunity to enhance solar radiation prediction by providing continuous spatial and temporal coverage.”

In [4], recent research emphasizes the use of satellite data to overcome the limitations of ground-based measurements. Satellite imagery provides extensive spatial and temporal coverage. Studies such as Chen et al. (2022) explore satellite-derived radiometric parameters for solar radiation estimation, showing significant improvements in prediction accuracy. In [4], it is stated that “satellite-derived radiometric data eliminates geographical limitations, offering a scalable and precise solution for solar radiation forecasting.”

“Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are widely used in prediction models, each with its advantages and limitations.”

In [5], Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are among the most popular ML models for prediction. However, the performance of these models varies with input data complexity. Quej et al. (2017) demonstrated that input feature selection significantly affects ANN and SVM performance, with ANN often outperforming SVM in complex datasets but at the cost of computational complexity and a higher risk of overfitting. As mentioned in [5], “ANN models excel in capturing complex patterns, but they require careful tuning to prevent overfitting, whereas SVM provides robustness in cases with fewer data points.”

CHAPTER-3

SYSTEM ANALYSIS

SYSTEM ANALYSIS

3.1 Existing System

The existing system for predicting global solar radiation primarily relies on conventional methods using **empirical and mathematical models** based on **ground-based meteorological and radiometric measurements**. These models require parameters such as wind speed, temperature, sunshine duration, and humidity, among others. Ground-based data collection poses challenges due to the **high cost, time consumption, and limited geographical coverage**. Recent advancements have incorporated **machine learning (ML) models**, using algorithms like Linear Regression, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) to predict solar radiation using meteorological data. However, these systems still depend heavily on ground-based measurements, making them less practical for large-scale or remote locations**.**

LIMITATIONS OF EXISTING SYSTEM

- Dependence on Ground-based Data: Predictions rely on ground-based stations, which are costly and impractical for continuous global coverage.
- Limited Accuracy with Meteorological Inputs: Using only meteorological parameters limits the prediction accuracy compared to more comprehensive satellite data.
- Inconsistent Performance of Machine Learning Models: Performance varies across different ML models, with some models like SVM underperforming compared to ANN.
- Scalability Issues: Ground-based systems are not easily scalable for large-scale or global prediction.
- Limited Use of Satellite Data: Conventional systems do not fully utilize the potential of satellite imagery for improved accuracy and global coverage.
- Computational Complexity: ANN models offer higher accuracy but come with increased computational demands and potential overfitting issues without sufficient data**.**

3.2 Proposed System

The proposed system presents a machine learning-based solution for predicting global solar radiation using satellite imagery data combined with advanced algorithms. The system utilizes normalized reflectance values from multiple channels of the Meteosat Second Generation (MSG) satellite (VIS06, VIS08, HRV, and IR016) as primary input features. These inputs are processed using supervised machine learning models, including Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to enhance predictive accuracy. Data preprocessing steps ensure data consistency, and hyperparameter tuning optimizes model performance. A real-time prediction interface can provide dynamic solar radiation forecasts based on live satellite data. Ethical principles, such as data privacy, fairness, and transparency, are integrated into the system to ensure responsible use. This system offers a robust, accurate, and scalable framework for solar radiation forecasting, supporting energy management and climate research

ADVANTAGES

Improved Prediction Accuracy: Integrating satellite data with machine learning models, especially ANN, significantly improves the accuracy of global solar radiation forecasts.

Scalability: The system handles large-scale datasets and allows for future feature enhancements to accommodate broader geographic regions.

User-Friendly Interface: Real-time prediction capabilities allow users to dynamically visualize solar radiation levels, enhancing decision-making for energy applications.

Faster Decision-Making: Automated prediction models reduce processing time compared to manual or traditional statistical methods.

Customization and Flexibility: Input features can be updated, and models retrained to adapt to evolving data patterns and technological advances.

Transparency and Interpretability: Use of clear performance metrics and explainable ML models builds trust and accountability in predictions.

CHAPTER – 4

SYSTEM DESIGN

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

The system processes ultrasound (US) images to analyse tendon conditions using deep learning-based segmentation and classification. Initially, the system takes an ultrasound image as input, extracts essential features, and generates a segmentation mask highlighting the tendon structure.

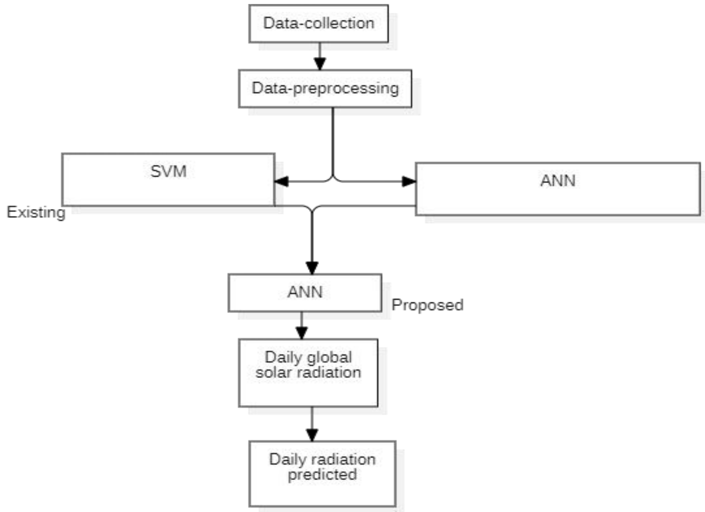
1. **Data Collection:** The system collects ultrasound images from medical imaging devices. These images contain different tendon conditions, including normal and torn tendons, to train the models effectively.

2. **Data Preprocessing:** Before training, the images are resized, normalized, and enhanced using augmentation techniques such as contrast adjustment and rotation to improve model performance.

3. **Feature Extraction & Segmentation:** A fine-tuned InceptionV4 model extracts key features from the ultrasound image. The extracted features are processed by a decoder, which generates a segmentation contour highlighting the tendon.

4. **Segmentation Overlay & Mask Generation:** The segmentation contour is overlaid on the original ultrasound image for visualization. A segmentation mask (224x224) is created, which serves as input for the classification model.

5. **Classification Model Training:** A VGG-16 classification model is trained using segmentation masks to distinguish between intact tendons and torn tendons, learning patterns that differentiate normal and abnormal cases.

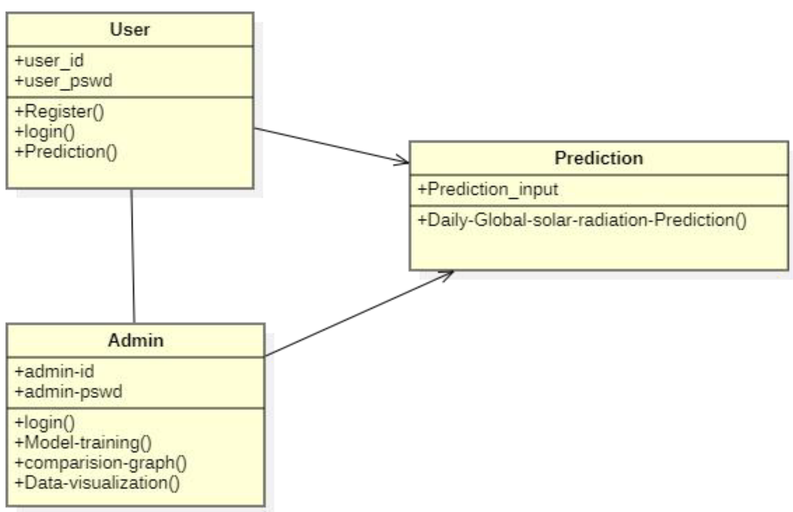


4.1.1 System Architecture

4.2 UML REPRESENTATION ‘

4.2.1 Class Diagram

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes.



4.2.1 Class Diagram

4.2.2 Use case Diagram:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

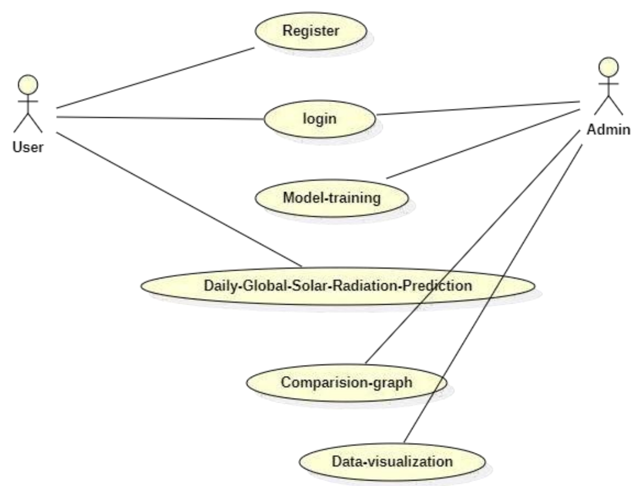


Figure 4.2.2 Use Case Diagram

4.2.3 Sequence diagram:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

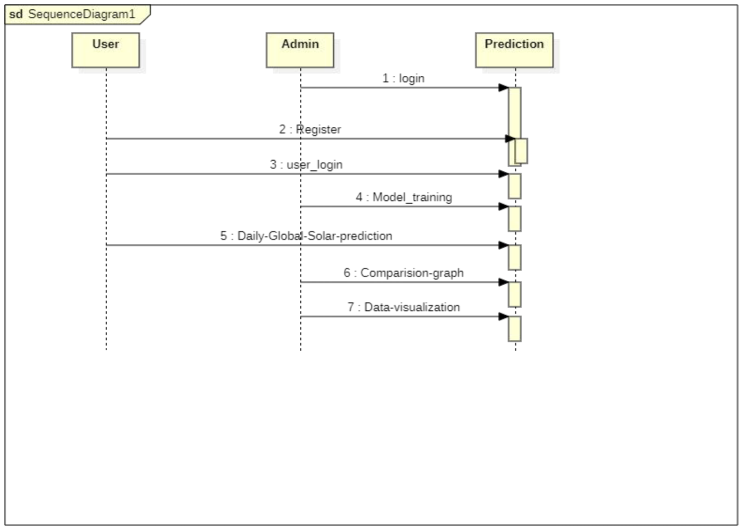
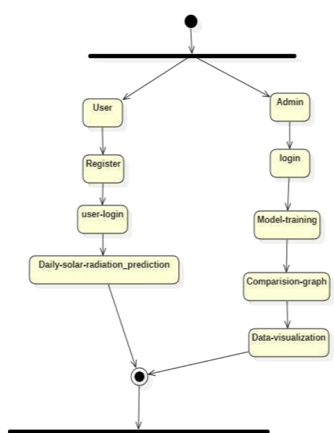


Figure 4.2.3 Sequence Diagram

4.2.4 Activity Diagram:

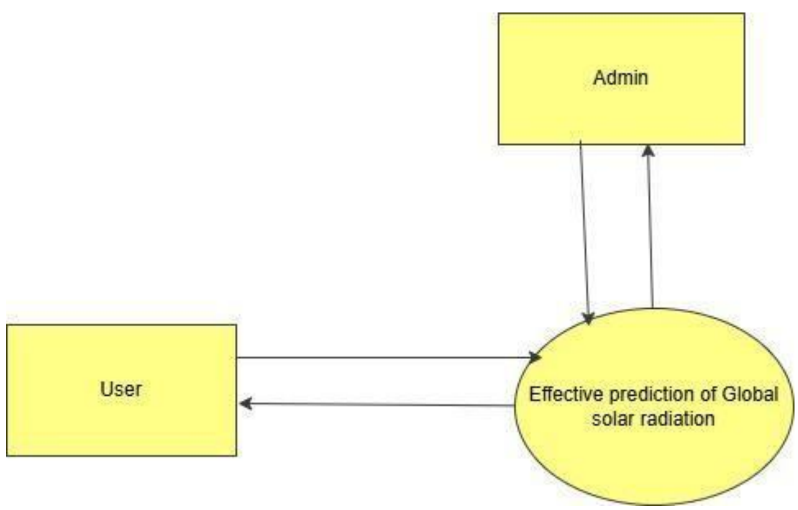
Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



4.2.4 Activity Diagram

4.2.5 Data Flow Diagram :

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



4.2.5 Data Flow Diagram

CHAPTER- 5

SYSTEM IMPLEMENTATION

SYSTEM IMPLEMENTATION

5.1 Modules:

1. Data Preprocessing
2. Feature Extraction
3. Model Training
4. Real-Time Prediction and Performance Analysis
5. Ethical and Fairness Considerations

1. **Data Preprocessing:** Data preprocessing is a crucial step in preparing raw satellite and ground-based solar radiation data for machine learning applications. This step includes cleaning data to handle missing values, outliers, and inconsistencies. Reflectance data from various satellite channels (VIS06, VIS08, HRV, IR016) are normalized to standardize inputs and improve model performance.
2. **Feature Extraction:** Feature extraction involves identifying the most relevant input variables that significantly influence global solar radiation predictions. Important features include zenith angle and normalized reflectance values from multiple satellite channels.
3. **Model Training**: The model training phase utilizes supervised machine learning algorithms to predict global solar radiation. Artificial Neural Networks (ANN) are chosen for their ability to capture complex, non- linear relationships, providing superior predictive power. Support Vector Machines (SVM) are also employed for regression-based modelling.
4. **Real-Time Prediction and Performance Analysis :** This module enables real-time solar radiation prediction using the trained models. Satellite image data are fed into the ANN or SVM models, which generate instant predictions. A graphical user interface (GUI) or integration into a web-based platform allows dynamic interaction for users to visualize predicted solar radiation levels.
5. **Ethical and Fairness Considerations:** Ethical considerations are critical for responsible solar radiation prediction systems. Data privacy must be protected by anonymizing sensitive data, and fairness is ensured by preventing biases related to specific geographical regions. Transparency is promoted through interpretable models or methods that explain predictions, enhancing trust**.**

5.2 SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS:

MINIMUM (Required for Execution)		MY SYSTEM (Development)
System	Pentium IV 2.2 GHz	i3 Processor 7th Gen
Hard Disk	20 Gb	1 TB
Ram	1 Gb	4 Gb

SOFTWARE REQUIREMENTS:

Operating System	Windows 10/11
Development Software	Python 3.10
Programming Language	Python
Integrated Development Environment (IDE)	Visual Studio Code
Front End Technologies	HTML5, CSS3, Java Script
Back End Technologies or Framework	Django
Database Language	SQL
Database (RDBMS)	MySQL
Database Software	WAMP or XAMPP Server
Web Server or Deployment Server	Django Application Development Server
Design/Modelling	Rational Rose

CHAPTER - 6

SYSTEM TESTING

SYSTEM TESTING

6.1 TYPES OF TESTING

Functional Testing: Functional testing is a crucial part of software testing that focuses on verifying that a system or application meets its functional requirements. In the context of our project, functional testing ensures that the system behaves as expected and correctly identifies fraudulent activities. Here's how you can perform functional testing for such a system:

- **Test Case Identification:** Identify functional requirements: Review the system's specifications, user stories, and use cases to understand the expected behavior of the fraud detection system. Develop test cases based on different scenarios that the system should support, such as detecting various types of fraudulent activities (e.g., fake reviews, malware-containing apps, coordinated fraud schemes).

- **Test Environment Setup:** Set up a testing environment that closely resembles the production environment, including the necessary infrastructure, data, and dependencies. Ensure that the testing environment is isolated from the production environment to prevent any impact on real users or data.

- **Test Execution:** Execute the identified test cases systematically, following the predefined test scenarios. Provide input data or stimuli to the system and observe its responses. Verify that the system behaves according to the expected outcomes specified in the test cases. Record any deviations, defects, or unexpected behaviors encountered during testing.

1) Unit Testing

Unit testing is a type of software testing which is done on an individual unit or component to test its corrections. Typically, Unit testing is done by the developer at the application development phase. Each unit in unit testing can be viewed as a method, function, procedure, or object. Unit testing is important because we can find more defects at the unit test level. Unit testing in our project involves testing individual units or components of the software in isolation to ensure they function correctly.

Unit testing in the context of a project like "Credit Card Transaction Fraud Detection using Transaction History using Machine Learning" would focus on testing individual units or components of the system in isolation. Since this project likely involves various components such as data preprocessing, feature engineering, model training, and prediction, each of these would be subject to unit testing. Here's how unit testing could be approached for each component:

Data Preprocessing Unit Testing: Test individual data preprocessing functions/methods such as data cleaning, normalization, and encoding. Verify that each function/method handles edge cases and unexpected inputs correctly. Mock input data to simulate different scenarios (e.g., missing values, outliers) and validate the output.

Model Training Unit Testing: Test functions/methods responsible for training machine learning models. Mock training data and verify that models are trained successfully. Validate that hyperparameter tuning functions/methods work as expected. Ensure that model evaluation metrics are computed correctly.

Prediction Unit Testing: Test functions/methods responsible for making predictions on new transaction data. Mock input data and verify that predictions are generated accurately. Test edge cases such as empty input or unexpected data formats. Validate that prediction outputs adhere to expected formats and conventions.

System Testing: System testing is types of testing where tester evaluates the whole system against the specified requirements.

2) End to End Testing

It involves testing a complete application environment in a situation that mimics real-world use, such as interacting with a database, using network communications, or interacting with other hardware, applications, or systems if appropriate. System testing in our project involves testing the integrated system as a whole to ensure that it meets its specified requirements and functions correctly in its intended environment.

6.2 TEST CASES

Test Case ID	Pre Conditions	Test Steps	Test Result	Pass/Fail
DGSR_A1	Verify successful admin login with valid credentials	Enter a valid email Enter a valid password Click "Login"	Admin should be logged in successfully and redirected to the admin dashboard	Pass
DGSR_A2	Verify login with invalid email	Enter an invalid email Enter a valid password 1. Click "Login"	Error message: “login credentials was incorrect. ”	Fail
DGSR_A3	After successful Login of Admin	Login to the admin app Open dashboard Click on Models Run Algorithms	Algorithms run successfully	Pass
DGSR_UR 1	Verify successful user registration	Enter a valid email Enter a strong password Enter a valid contact number Upload a valid image Click “Register”	User should be registered successfully and redirected to the login page.	Pass
DGSR_UR 2	Verify registration with an already registered email	Enter an email that is already registered Enter a password Click "Register"	Error message: " Email already registered. Please Login"	Pass

DGSR_U1	Verify successful user login	Enter a valid email Enter a valid password Click "Login"	User should be logged in successfully and redirected to the homepage	Pass
DGSR_U2	Verify login with an unregistered email	Enter an unregistered email Enter any password Click "Login"	Error message: “login credentials was incorrect. ”	Pass
DGSR_U3	Verify login with a registered email but wrong password	Enter a registered email Enter an incorrect password Click "Login"	Error message: “login credentials was incorrect. ”	Pass
DGSR_U4	After successful Login of user	Login to the user app Enter the values you want Click on Predict Button	Prediction Successful	Pass

CHAPTER -7

SCREENSHOTS

SCREENSHOTS

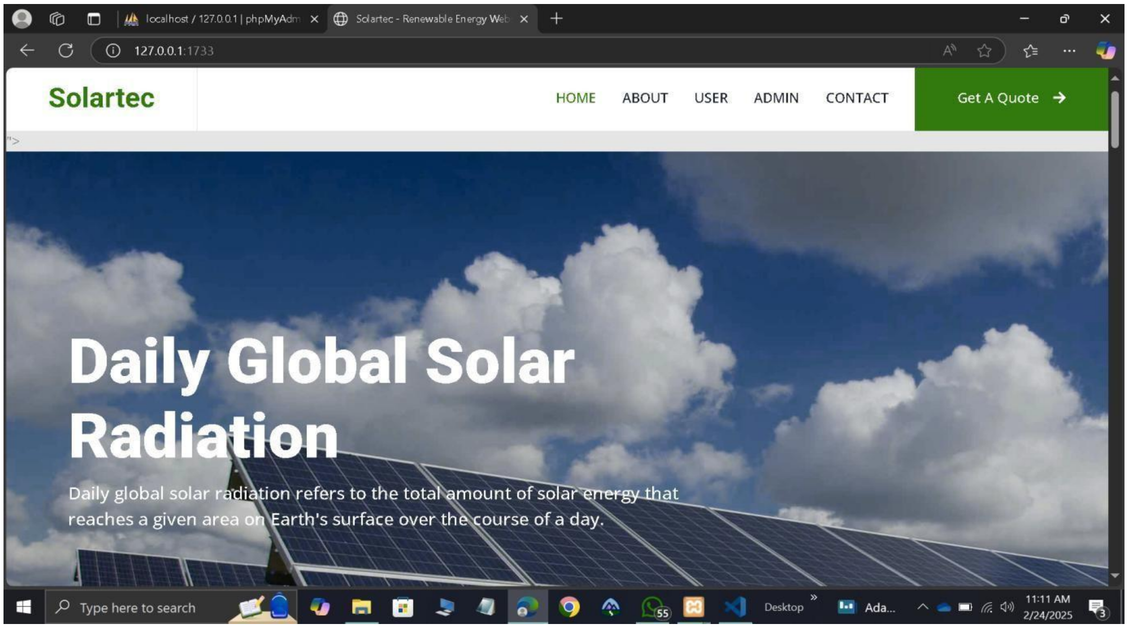


Fig7.1This fig shows the first screen of our project

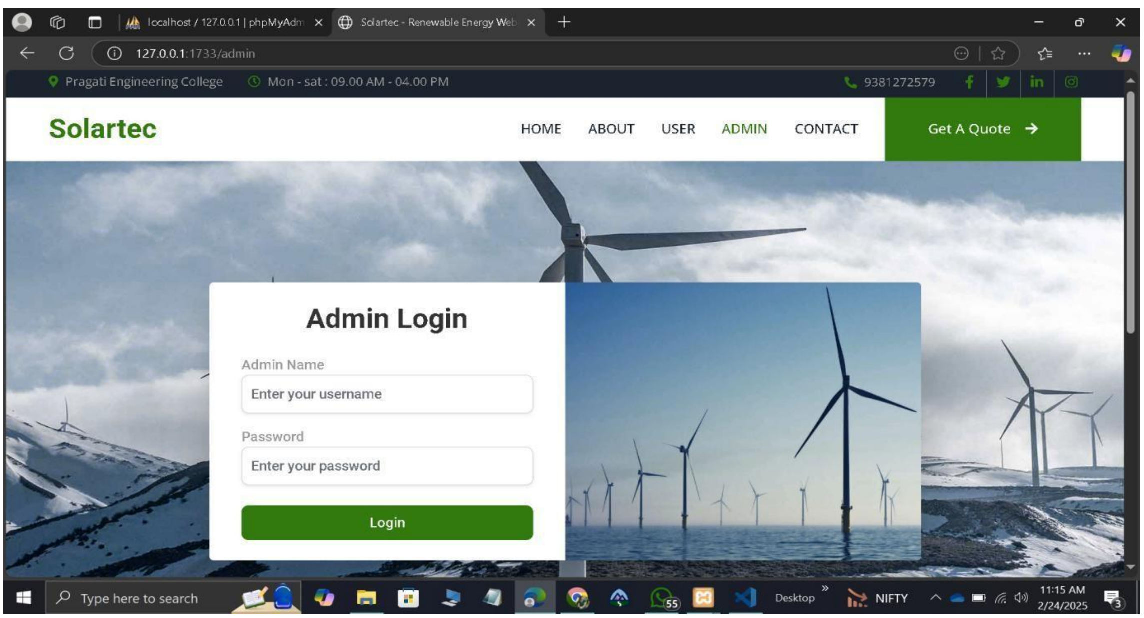


Fig7.2 Admin Login

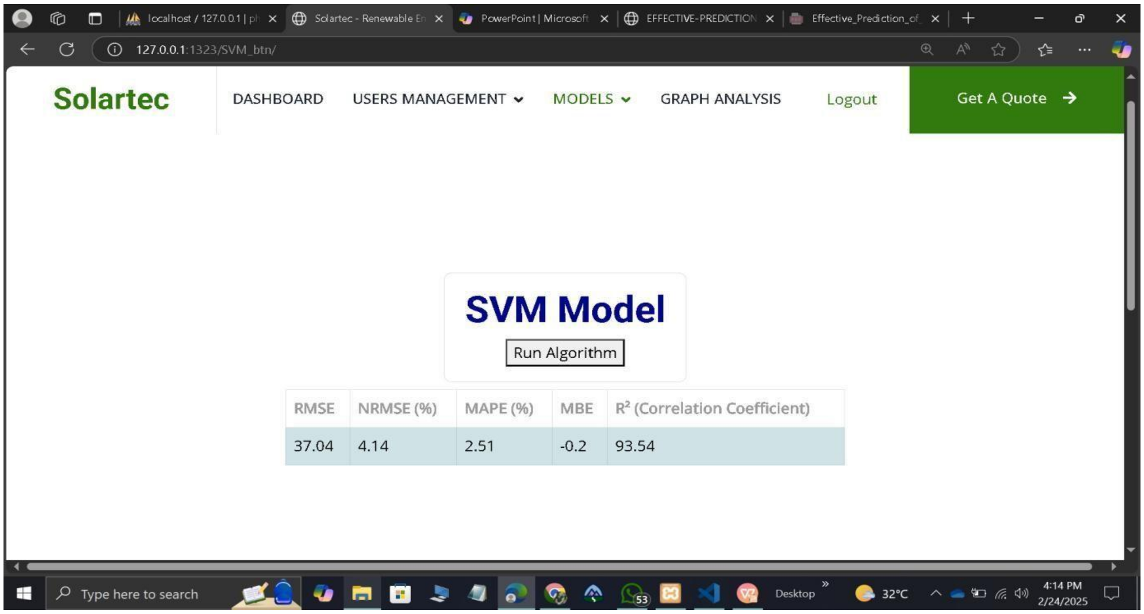


Fig7.3 SVM Algorithm

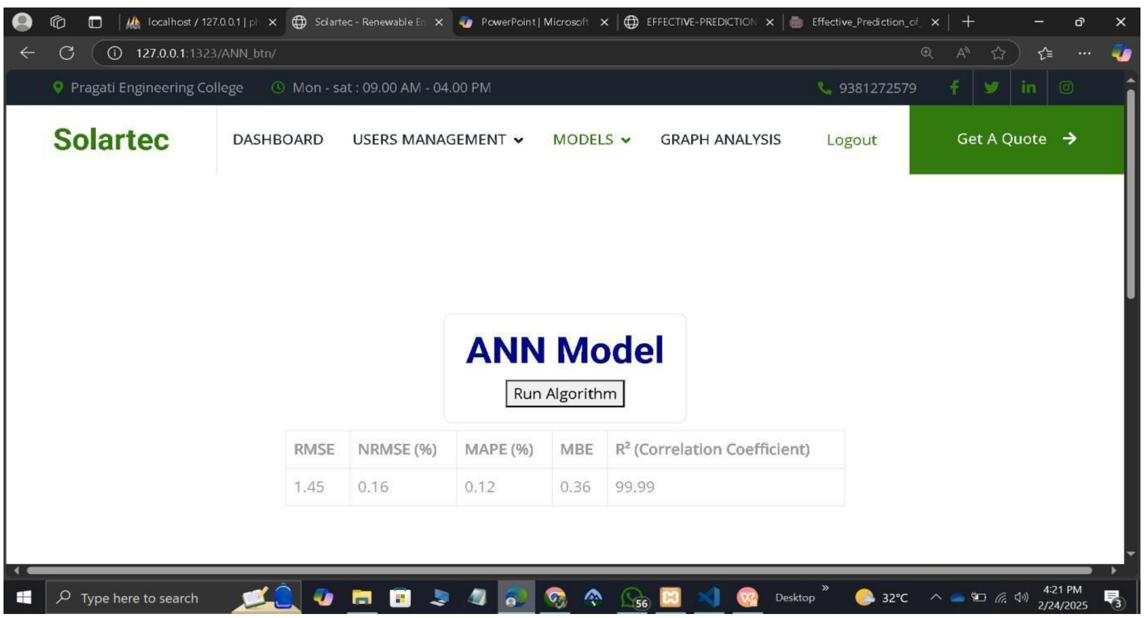


Fig7.4 ANN Algorithm

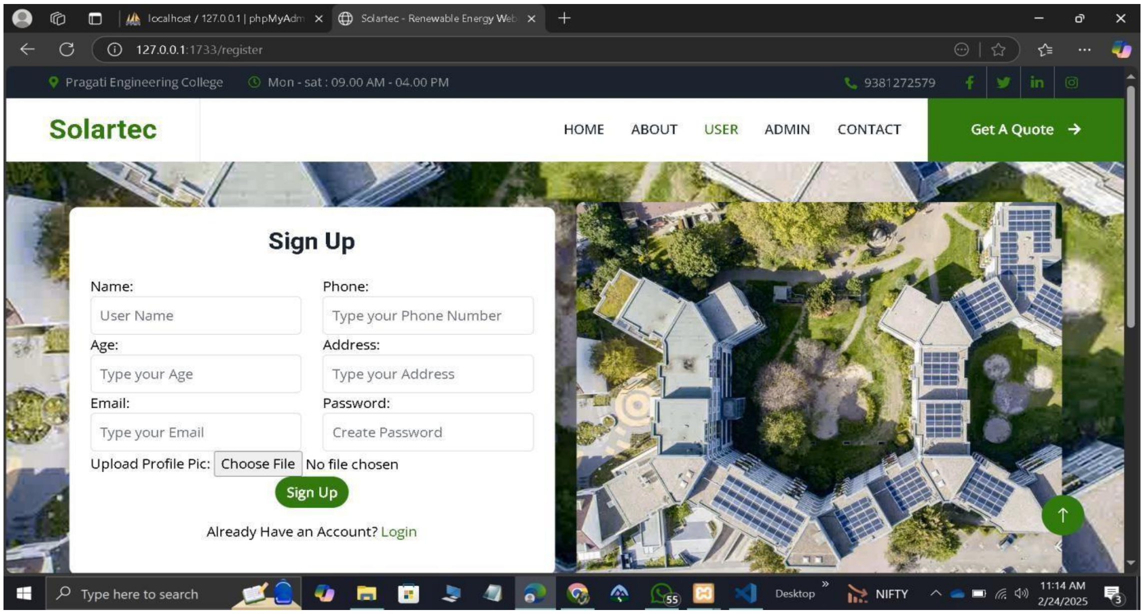


Fig7.5 User Registration

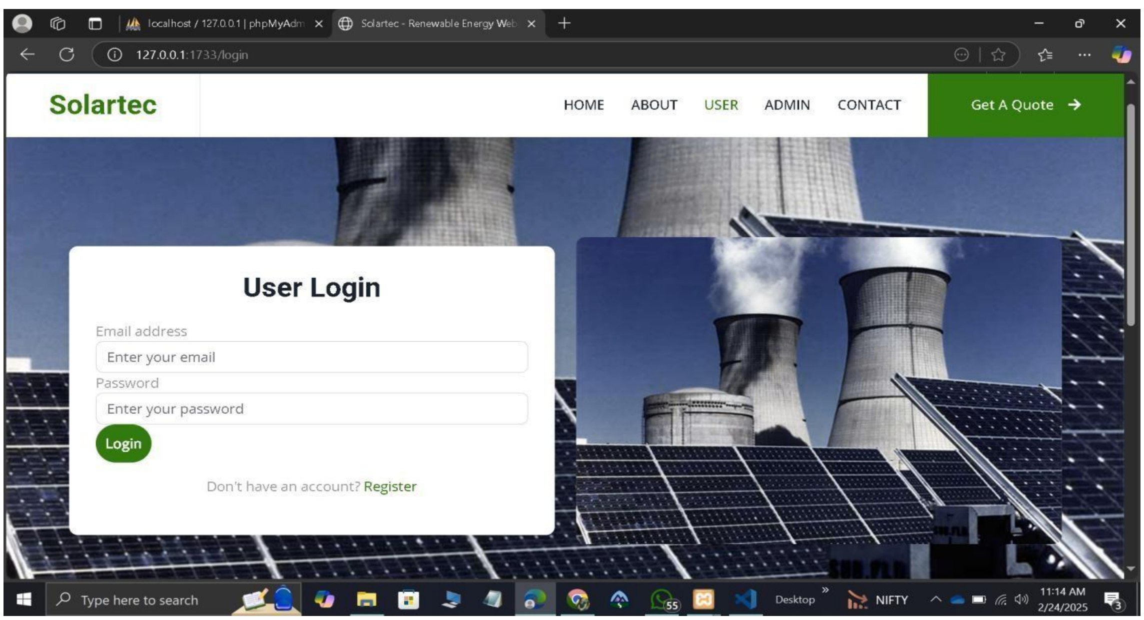


Fig7.6 User Login

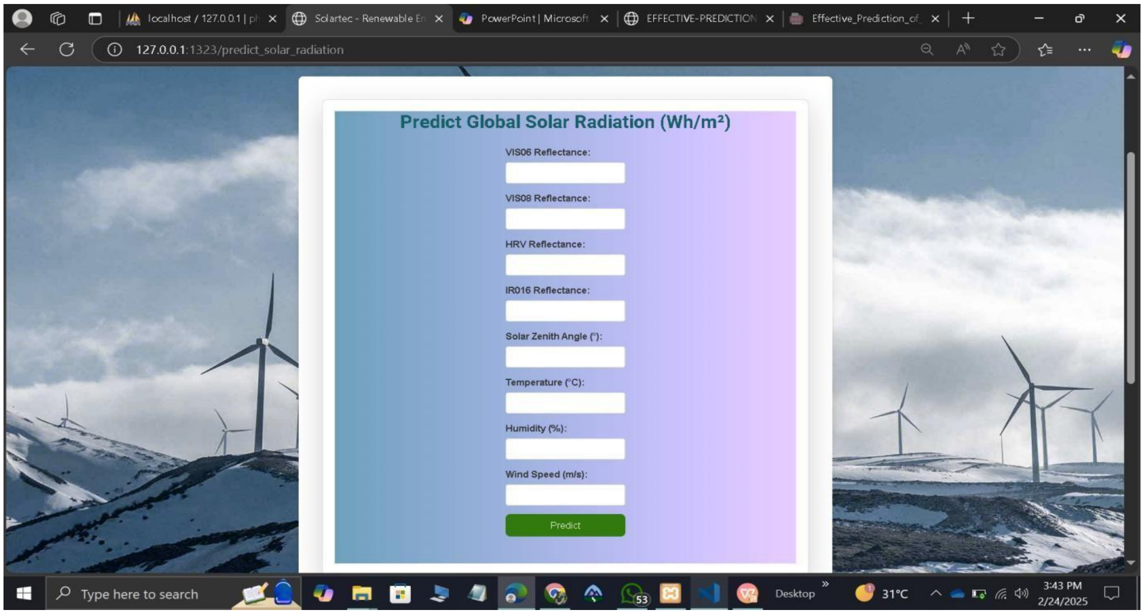


Fig7.7 User Prediction Page

Fig7.8 Result Page

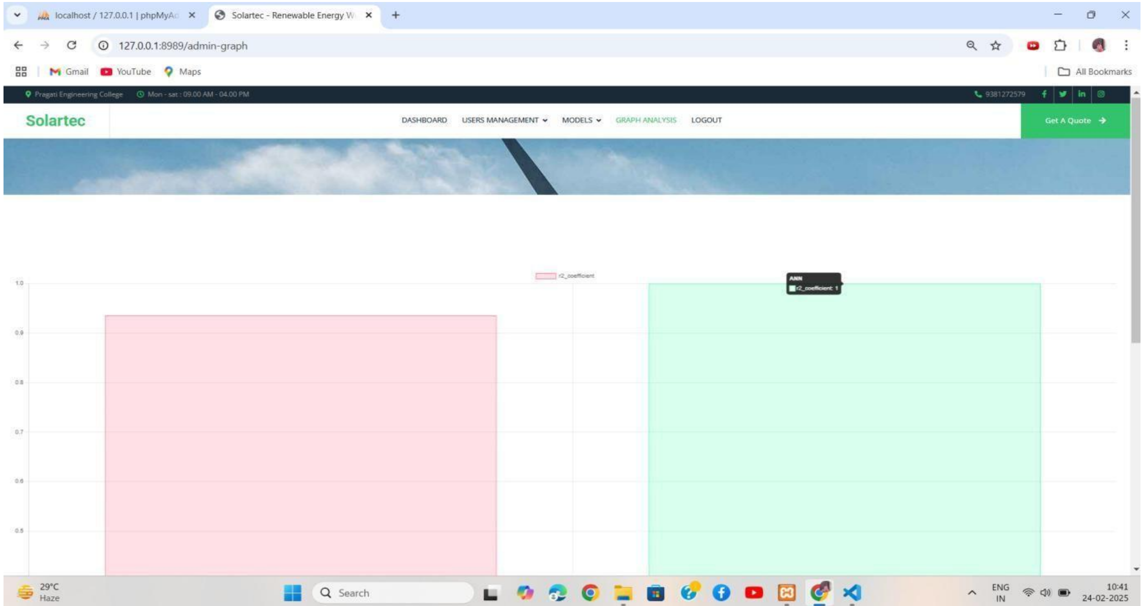


Fig7.9 Comparison Graph

CHAPTER- 8
CONCLUSION AND FUTURE WORK

CONCLUSION AND FUTURE WORK

In this study, we performed a comparative analysis of the performance of Artificial Neural Networks (ANN) and Support Vector Machine (SVM) techniques for predicting daily global solar radiation (DGRS) in Ghardaïa, Algeria. The normalized reflectance obtained from the Meteosat Second Generation (MSG) images taken between 2014 and 2017 was used as the main input variable in the Machine Learning (ML) models. DGSR measurements carried out in Ghardaïa during the same period 2014-2017 were used to compare with model estimates. We used various statistical metrics, including Root Mean Square Error (RMSE), Normalized RMSE (NRMSE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE), and the correlation coefficient (R) to evaluated the performances of the models. R is obtained from the linear regression carried out between the prediction values and the measurements. Different combination of input data for the ML models were tested to assess their impact on the results. The

first lesson to be deduced is that the choice of input variables significantly influenced the results. The results also reveal that the optimal combination for ANN and SVM models is to use the four inputs VIS06, VIS08, HRV, and IR016. Indeed, the data provided by the ANN model give an RMSE of 212.21 $W\ h/m2$, an NRMSE of 3.46%, a MAPE of 2.85% and an MBE of -7.26$W\ h/m2$ while those of the SVM model give RMSE, NRMSE, MAPE, and MBE values of 441.95$W\ h/m2$, 6.6%, 5.62% and 69.46$W\ h/m2$, respectively. Although the two models demonstrated a very good agreement during the training phase with the DGSR predictions and measured very close, our results show that the ANN model slightly exceeds the SVM model in the prediction of the DGSR for Ghardaïa, Algeria. The ANN model systematically has lower error values than the SVM model and a

correlation coefficient of 0.99, which is slightly higher to that obtained with SVM which is 0.98. In summary, this study has shown interesting and promising perspectives of the contribution of machine learning to predict ground observations from satellite images, in particular to predict solar radiation at the ground level in land areas where there is no solar monitoring instrument providing measurement data.

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APPENDIX – A : SOURCE CODE

SOURCE CODE

Views.py

```
from django.shortcuts import render,redirect
from Mainapp.models import *
from Userapp.models import Feedback,Dataset
from Adminapp.models import *
from django.contrib import messages
import time
from django.core.paginator import Paginator
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from django.core.files.storage import default_storage
from django.conf import settings import numpy as
np from tensorflow.keras.models import
load_model from tensorflow.keras.preprocessing
import image
from tensorflow.keras.applications.inception_v3 import
preprocess_input from tensorflow.keras.models import load_model
from tensorflow.keras.optimizers import Adam
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from django.shortcuts import render, redirect
from django.contrib import messages
from .models import User, Feedback # Ensure your models are imported
from django.shortcuts import render
```

```
import pandas as pd

from sklearn.model_selection

import train_test_split, GridSearchCV, cross_val_score

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_squared_error,

r2_score

import numpy as np

def userdashboard(req):
images_count = User.objects.all().count() print(images_count) user_id
= req.session["User_id"]
user = User.objects.get(User_id = user_id)
return render(req,'user/user-dashboard.html')
def profile(req):
user_id = req.session["User_id"]
user = User.objects.get(User_id = user_id) if
req.method == 'POST':
user_name = req.POST.get('userName')
user_age = req.POST.get('userAge')
user_phone = req.POST.get('userPhNum')
user_email = req.POST.get('userEmail')
user_address =
req.POST.get("userAddress") # user_img =
request.POST.get("userimg")

user.Full_name = user_name

user.Age = user_age

user.Address = user_address

user.Phone_Number=user_phone
```

```
        if len(req.FILES) !=
0: image =
req.FILES['profilepic']
user.Image = image
user.Full_name = user_name
user.Age = user_age
user.Address = user_address
user.Phone_Number = user_phone
user.Email=user_email user.Address=user_address
user.save()
messages.success(req, 'Updated SUccessfully...!')
 else:
 user.Full_name = user_name
user.Age =   user_age user.save()
messages.success(req, 'Updated SUccessfully...!')
def userlogout(req):
user_id = req.session["User_id"]
user = User.objects.get(User_id = user_id) t =
time.localtime()
user.Last_Login_Time = t
  current_time = time.strftime('%H:%M:%S', t)
user.Last_Login_Time = current_time current_date =
time.strftime('%Y-%m-%d') user.Last_Login_Date =
current_date user.save() messages.info(req, 'You are
logged out..')
   return
redirect('index') def
```

```
 id=req.session["User_id"]
 uusser=User.objects.get(User_id=id)
if req.method == "POST":
 rating=req.POST.get("rating")
 review=req.POST.get("review
 ") if not rating:
 messages.info(req,'give rating')
 return redirect('userfeedbacks')
 sid=SentimentIntensityAnalyzer()
 score=sid.polarity_scores(review
 ) sentiment=None
 if score['compound']>0 and score['compound']<=0.5:
 sentiment='positive'
elif score['compound']>=0.5:
 sentiment='very positive'
elif score['compound']<-0.5:
 sentiment='very negative'
 elif score['compound']<0 and score['compound']>=-0.5:
 sentiment='negative'
 else :
   sentiment='neutral' #
 print(sentiment)
 # print(rating,feed)
 Feedback.objects.create(Rating=rating, Review=review, Sentiment=sentiment, Reviewer=uusser)
 messages.success(req,'Feedback recorded')
 return redirect('userfeedbacks')
```

```
return render(req,'user/user-feedbacks.html')
import joblib
import numpy as np
import pandas as pd
from django.shortcuts import render
import tensorflow as tf
from sklearn.preprocessing import
StandardScaler # Load the ANN model

# ann_model = joblib.load("D:/DGSR/DGSR/ANN.pkl")

ann_model = tf.keras.models.load_model("D:\DGSR\DGSR\ANN_model.h5") # Assuming ANN

is in  SavedModel format

scaler = joblib.load("D:\DGSR\DGSR\scaler.pkl")
# If a scaler was used, load it as well (assuming you saved the scaler)
# scaler = joblib.load("D:/DGSR/DGSR/scaler.pkl")
def predict_solar_radiation(request): if

request.method == 'POST':

# Collect feature values from form submission

user_input = {

'VIS06_Reflectance':float(request.POST['VIS06_Reflectance']),
'VIS08_Reflectance':loat(request.POST['VIS08_Reflectance']),

'HRV_Reflectance':float(request.POST['HRV_Reflectance']),

'IR016_Reflectance': float(request.POST['IR016_Reflectance']),

'Solar_Zenith_Angle_deg':float(request.POST['Solar_Zenith_Angle_deg']),

'Temperature_C': float(request.POST['Temperature_C']),

'Humidity_%':

float(request.POST['Humidity_%']),

Humidity_%
```

```
}

# Convert to DataFrame for prediction
user_df = pd.DataFrame([user_input])

# Apply scaling if the model was trained with standardized data
# user_df = scaler.transform(user_df)  # Uncomment if scaling was used during training

# Make prediction
prediction = ann_model.predict(user_df)[0][0]  # Extract the single predicted value

# Render prediction result
return render(request, 'user/predict_solar_radiation.html', {'prediction': prediction})

# Render the form if request is not POST
return render(request, 'user/predict_solar_radiation.html
```

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AI-Powered Global Solar Radiation Forecasting: Fusing Machine Learning with Satellite Vision

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Abstract- Accurately predicting Daily Global Solar Radiation (DGSR) is crucial for applications in renewable energy, agriculture, and climate research. This study explores the potential of Machine Learning (ML) algorithms combined with satellite imagery to enhance DGSR forecasting. Traditional ML-based approaches rely on meteorological parameters such as temperature, wind speed, atmospheric pressure, and sunshine duration, along with radiometric factors like aerosol optical thickness and water vapor. In this work, we investigate the integration of normalized reflectance from satellite images across multiple spectral channels to refine solar radiation predictions. Two ML models, Artificial Neural Networks (ANN) and Support Vector Machines (SVM), were employed as regression techniques. The findings highlight that the selection and quantity of input parameters significantly impact the accuracy of DGSR predictions. Furthermore, ANN demonstrated superior performance over SVM, achieving an RMSE of 212.21 W h/m^2, NRMSE of 3.46%, MAPE of 2.85%, MBE of -7.26 W h/m^2, and an R-value of 0.99. In contrast, the SVM model produced an RMSE of 441.95 W h/m^2, NRMSE of 6.6%, MAPE of 5.62%, MBE of 69.46 W h/m^2, and an R-value of 0.98. These results underscore the effectiveness of leveraging satellite imagery alongside ML techniques to improve the accuracy of DGSR forecasting.

Keywords- Deep learning, Satellite imagery, Solar irradiance

I. INTRODUCTION

significantly to carbon emission reduction and fostering job creation, particularly in developing

Solar radiation that reaches the Earth's surface plays countries. Over the past few decades, substantial a fundamental role in numerous chemical, physical, efforts have been dedicated worldwide to and biological processes essential for sustaining life. advancing solar energy applications, with Algeria Its utilization is also crucial for fulfilling global being one of the regions emphasizing its energy demands, making solar radiation monitoring development. Accurate solar radiation forecasting is highly valuable for various applications, including vital across multiple domains, including sustainable optimizing solar energy system installations, energy production, climate research, and enhancing optical satellite communication links, environmental impact assessments. Researchers and studying atmospheric conditions in the context have long focused on improving solar radiation of climate change. Additionally, solar energy is prediction models under diverse sky conditions, recognized for its minimal environmental impact ranging from clear to overcast. Traditionally, solar compared to conventional fossil fuels, contributing radiation has been estimated using various

meteorological parameters such as wind speed, temperature, sunshine duration, atmospheric pressure, and humidity. Several predictive models have been proposed in the literature, including empirical and mathematical methods, as well as more advanced machine learning (ML) and hybrid approaches. A significant challenge associated with conventional models is their reliance on groundbased meteorological and radiometric data, which can be costly, time-intensive, and difficult to obtain, especially in remote or inaccessible regions. To overcome these limitations, satellite-based data offer an effective alternative, providing continuous and high-resolution spatial and temporal coverage of solar radiation on both regional and global scales. Unlike ground-based measurements, satellite observations ensure greater consistency and completeness, making them highly valuable for radiation estimation. Given the potential of ML techniques in predictive modelling, this study investigates the use of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for solar radiation prediction. The models incorporate zenith angle and normalized reflectance data extracted from multiple satellite channels as input features, aiming to enhance prediction accuracy across varying atmospheric conditions.

II. LITERTURE REVIEW

Early solar radiation estimation models primarily relied on empirical and mathematical techniques that utilized ground-based meteorological data, including parameters such as temperature, humidity, sunshine duration, and wind speed. While these models offer a fundamental approach, they often struggle with accuracy due to their reliance on manually collected data, which is both timeintensive and expensive. Research by Gürel et al. (2023) underscores the inefficiency of these traditional models, particularly in dealing with complex and highly variable weather patterns. To enhance predictive accuracy, hybrid models combining conventional mathematical methods with statistical approaches have been developed. Alizamir et al. (2023) proposed a hybrid deep learning approach that integrates Long Short-Term Memory (LSTM) networks with wavelet transforms to refine solar radiation predictions. While these models improve accuracy, their dependence on ground-based meteorological data presents a challenge in terms of scalability and application across diverse geographical regions.

The adoption of machine learning (ML) techniques has significantly improved the reliability of solar radiation forecasting. Studies conducted by Zaiani et al. (2021) and Ghimire et al. (2022) explored the effectiveness of models like Support Vector Machines (SVM) and Artificial Neural Networks (ANN) for solar radiation prediction using meteorological data. Although these ML models exhibit strong predictive capabilities, their performance remains constrained due to the limited availability of input features, particularly in complex atmospheric conditions.

Recent advancements in solar radiation forecasting emphasize the role of satellite-derived data in overcoming the limitations of ground-based observations. Satellite imagery offers extensive spatial and temporal coverage, allowing for more comprehensive assessments. Research by Chen et al. (2022) highlights the potential of satellitederived radiometric parameters in improving solar radiation estimates, leading to significantly enhanced prediction accuracy.

Among machine learning models, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are widely used for solar radiation forecasting. However, their efficiency depends heavily on input data complexity and feature selection. Quej et al. (2017) demonstrated that ANN tends to outperform SVM when handling complex datasets, though at the cost of increased computational demand and a higher risk of overfitting, necessitating careful model tuning.

One of the key challenges in solar radiation prediction is ensuring both accuracy and scalability. While sophisticated ML models improve prediction quality, their reliance on localized ground-based data limits their applicability on a broader scale. Additionally, factors such as computational cost,

crucial concerns in advancing solar radiation or global applications due to their reliance on forecasting methodologies. localized data sources.

III. SYSTEM ANALYSIS

information, which offers more

data availability, and model generalization remain

Existing System

Current approaches for global solar radiation prediction predominantly rely on traditional empirical and mathematical models that use ground-based meteorological and radiometric measurements. These models require input parameters such as wind speed, temperature, sunshine duration, and humidity. However, collecting ground-based data presents several challenges, including high operational costs, timeintensive processes, and limited spatial coverage.

In recent years, machine learning (ML) techniques have been integrated into solar radiation forecasting, utilizing algorithms such as Linear Regression, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) to enhance prediction accuracy. While these ML models improve forecasting capabilities, they still heavily depend on meteorological data collected from ground stations. This reliance makes them less effective for large-scale or remote area applications where data availability is sparse.

Limitations of the Existing System

- **Dependence on Ground-Based Measurements:** The accuracy of predictions is constrained by the availability of ground-based data, which is expensive to collect and lacks continuous global coverage.
- **Limited Accuracy Using Meteorological Inputs Alone:** Predictive models based solely on meteorological parameters do not achieve optimal accuracy compared to approaches that incorporate satellite data.
- **Inconsistent Machine Learning Model Performance:** Different ML models exhibit

- **Underutilization of Satellite Data:** Existing methods do not fully leverage the potential of satellite-derived

varying levels of accuracy, with some, like SVM, underperforming relative to ANN in complex scenarios.
- **Scalability Constraints:** Traditional systems struggle to scale efficiently for broader regional comprehensive spatial and temporal coverage.
- **Computational Challenges:** While ANN models demonstrate superior accuracy, they require high computational resources and are prone to overfitting when trained on insufficient data.

Proposed System

The proposed system introduces a machine learning-driven approach for global solar radiation prediction, leveraging satellite imagery to enhance forecasting accuracy and scalability. Instead of relying solely on ground-based meteorological data, this system integrates satellite-derived normalized reflectance values from multiple channels of the

Meteosat Second Generation (MSG) satellite, including VIS06, VIS08, HRV, and IR016, as key input features. These inputs are processed using advanced supervised learning models, such as Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to refine predictive capabilities.

To ensure reliability, the system employs rigorous data preprocessing for consistency and applies hyperparameter tuning to optimize model performance. Additionally, a real-time prediction interface enables dynamic visualization of solar radiation forecasts using live satellite data. Ethical considerations, including data privacy, fairness, and transparency, are embedded in the system design, promoting responsible and equitable AI usage. This approach offers a high-accuracy, scalable, and userfriendly solution for solar radiation forecasting, benefiting energy planning, climate research, and environmental monitoring.

Key Advantages

- **Enhanced Predictive Accuracy:** Incorporating satellite imagery with ML models, particularly ANN, significantly boosts the precision of solar radiation forecasts.
- **Scalability:** The system efficiently processes large datasets, making it adaptable for broader geographical coverage and future model enhancements.
- **Intuitive User Interface:** Real-time forecasting allows users to monitor solar radiation patterns dynamically, aiding decision-making in energy and climate-related applications.
- **Faster Computational Efficiency:** Automated ML-based predictions reduce processing time compared to traditional empirical or statistical models.
- **Customization and Adaptability:** The system allows modifications in input features and model retraining, ensuring adaptability to new data trends and technological advancements.
- **Transparent and Interpretable Predictions:** Explainable AI techniques and performance metrics provide clarity and build trust in the prediction outcomes.
- **Bias Mitigation:** The inclusion of diverse datasets ensures fair and unbiased predictions across different regions and timeframes.
- **Ethical AI Implementation:** The system upholds privacy and data protection standards, ensuring responsible use and compliance with regulatory guidelines.

By integrating satellite imagery with cutting-edge ML techniques, this system offers a reliable and scalable solution for improving solar radiation predictions, with broad applications in sustainable energy management, climate analysis, and environmental research.

System Design System Architecture

Below diagram depicts the whole system architecture.

System Implementation Modules

Data Preprocessing:

Preparing raw satellite and ground-based solar radiation data is an essential step before feeding it into machine learning models. This process involves handling missing values, removing outliers, and resolving inconsistencies to ensure data quality.
Reflectance values from satellite channels (VIS06, VIS08, HRV, IR016) are standardized to maintain uniformity and enhance model efficiency. The dataset is systematically split into training (80%), validation, and testing (20%) sets to evaluate model performance objectively. Effective preprocessing ensures data reliability, leading to more precise and consistent solar radiation forecasts.

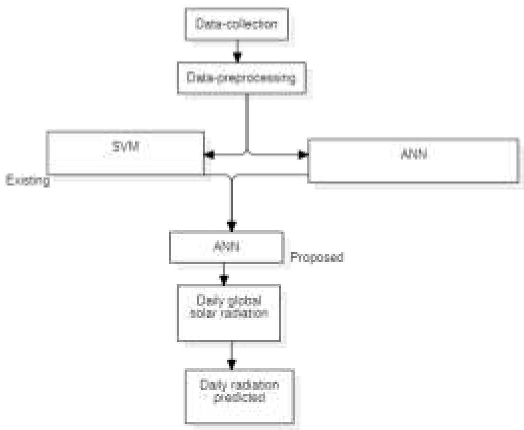


Fig 1. Methodology followed for proposed model

Feature Extraction

Identifying key input variables that significantly impact solar radiation prediction is crucial for model accuracy. Important features include the zenith angle and reflectance values from different satellite bands. The combination of reflectance data from VIS06, VIS08, HRV, and IR016 channels contributes to better prediction reliability. Feature selection techniques, such as correlation analysis, are employed to filter out less relevant data, minimizing noise and maximizing the effectiveness of machine learning models.

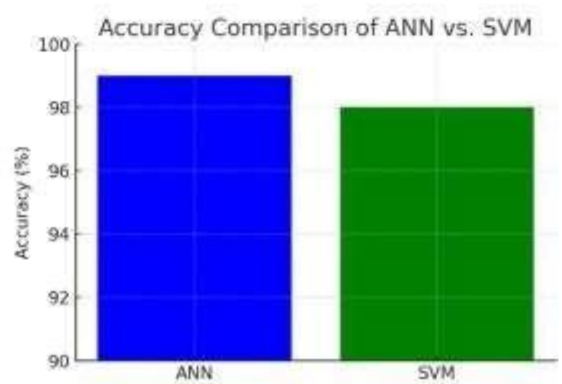
Model Training:

Supervised machine learning techniques are used to train predictive models for solar radiation estimation. Artificial Neural Networks (ANN) are selected for their ability to capture complex, nonlinear relationships in data, while Support Vector Machines (SVM) serve as a complementary regression model. During training, hyperparameter tuning is performed to optimize model performance and reduce error rates. Key performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and correlation coefficients, are utilized to assess accuracy. This stage ensures the development of reliable and high-performing models for solar radiation forecasting.

Real-Time Prediction and Performance Analysis: This module facilitates real-time solar radiation estimation using trained models. Incoming satellite data is processed through the ANN or SVM models to generate instantaneous predictions. A userfriendly interface, such as a graphical dashboard or web-based platform, allows users to visualize realtime solar radiation trends dynamically. Comparative analysis is performed to evaluate the performance of ANN and SVM models, demonstrating the effectiveness of satellite-based data over traditional ground-based methods.

Ethical and Fairness Considerations: Ensuring ethical responsibility in solar radiation prediction systems is a fundamental aspect of this study. Data privacy measures, such as anonymization, protect sensitive information, while fairness mechanisms prevent biases related to specific geographical locations. Model transparency is prioritized through interpretable AI techniques, fostering trust and accountability. The use of diverse and balanced datasets mitigates potential biases, promoting equitable and reliable forecasting results. By adhering to ethical guidelines, the system upholds fairness, accuracy, and responsible AI deployment.

IV. RESULTS AND DISCUSSION



In above diagram a discribes about verious algorithmic accuracy comparion graph

V. CONCLUSIONS

This study conducted a comparative analysis of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for predicting Daily Global Solar Radiation (DGSR) in Ghardaïa, Algeria. The models utilized normalized reflectance data from Meteosat Second Generation (MSG) satellite imagery collected between 2014 and 2017, with ground-based DGSR measurements from the same period serving as reference data. Various statistical metrics, including RMSE, NRMSE, MAPE, MBE, and the correlation coefficient (R), were employed to assess model accuracy. The study revealed that the selection of input features significantly impacted prediction performance. The optimal input combination for both ANN and SVM models consisted of VIS06, VIS08, HRV, and IR016 reflectance data. ANN demonstrated superior performance, achieving an RMSE of 212.21 W h/m², NRMSE of 3.46%, MAPE of 2.85%, and MBE of -7.26 W h/m², whereas the SVM model yielded higher error values, with an RMSE of 441.95 W h/m², NRMSE of 6.6%, MAPE of 5.62%, and MBE of 69.46 W h/m². While both models exhibited strong correlation with actual measurements, ANN consistently outperformed SVM, achieving a correlation coefficient of 0.99 compared to 0.98 for SVM. These findings highlight the potential of machine learning in solar radiation estimation using satellite imagery, particularly in regions lacking ground-based measurement instruments.

For future work, further enhancements can be made by incorporating additional satellite-derived features and experimenting with hybrid ML models that integrate deep learning techniques. Investigating the impact of different atmospheric conditions and seasonal variations on model performance could improve prediction accuracy. Additionally, extending the study to multiple geographic locations would help validate the generalizability of the approach. Implementing realtime DGSR prediction systems using cloud-based platforms could facilitate large-scale deployment and practical applications in renewable energy management and climate studies.

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