**笔杆检测报告单** **(全文标明引文)**

**全文标明引文** 全 文 对 照 打印 检测说明

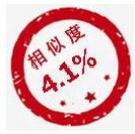
标题：202118020205\_Final\_Report.docx

作者：Li Wanning

报告编号：BG202505061408027801

提交时间：2025-05-0614:08:29

重 复 字 数**：2,369** 总 字 数 ：**57,126**



去除引用文献复制比：4.1%

去除本人已发表文献复制比：4.1%

单篇最大文字复制比：17.2%





**202118020205\_Final\_Report.docx\_** **第1部分**

**原文内容**

UNDERGRADUATE PROJECT REPORT

Project Ttle:Predicting Solar Energy Potential from Radiance SkyImages using Deep Learning

Surname:Li

First Name:Wanning

Student Number:202118020205

Supervisor Name:Gace Ugochi Nneji

Module Code:CHC 6096

Module Name:Project

Date Submitted:May 6,2025

Chengdu University of Technology Oxford Brookes College

Chengdu University of Technology

BSc(Single Honours)Degree Project

Programme Name:Software Engineering

Module No.:CHC 6096

Surname:Li

First Name:Wanning

Project Title:Predicting Solar Energy Potential from Radiance SkyImages using Deep Learning

Student No.:202118020205

Supervisor:Grace Ugochi Nneji

Date submitted:May 6,2025

A report submitted as part of the requirements for the degree of BSc(Hons)in Software Engineering

At

Chengdu University of Technology Oxford Brookes College

Declaration

Student Conduct Regulations:

Please ensure you are familiar with the regulations in relation to Academic Integrity. The University takes this issue very seriously and students have b een expelled or had their degrees witheld for cheating in assessment.It is important that students having ificulties with their work should seek help fro

m their tutors rather than be tempted to use unfair means to gain marks.Students should not risk losing teir degree and underminingal the work they h

ave done towards it.You are expected to have familiarised yourself with these regulations.

<https://www.brookes.ac.uk/regulations/current/appeals-complaints-and-conduct/c1-1/>

Guidance on the correct use of references can be found on [www.brookesac.uk/services/library,and also in a handout in the Library.](https://www.brookesac.uk/services/library,andalsoinahandoutintheLibrary.)

The full regulations may be accessed online at [https://www.brookes.ac.uk/students/sirt/student-conduct/](https://www.brookes.ac.uk/students/sirt/student-conduct/Ifyoudonotunderstandwhatanyofthesetermsmean)

[If you do not understand what any of these terms mean](https://www.brookes.ac.uk/students/sirt/student-conduct/Ifyoudonotunderstandwhatanyofthesetermsmean),<you> should ask your Project Supervisor to clarify them for you.

I declare that I have read and understood Regulations C1.1.4 of the Regulations governing Academic Misconduct,and that the workl submitis full in accordance with them.

Signature Date:06/05/2025

REGULATIONS GOVERNING THE DEPOSIT AND USE OF OXFORD BROOKES UNIVERSITY MODULAR PROGRAMME PROJECTS AND DISSERTATIONS

Copies of projects/dissertations,submitted in fulfilment of Modular Programme requirements and achieving marks of 60%or above,shall normally be kept by the Oxford Brookes University Library.

lagre that thisdisertation may be available for reading and photocopying in accordance with the Regulations governing the use of the Oxford Broo

kes University Library.

Signature Date:06/05/2025

Acknowledgment

I would like to express my sincere gratitude to my supervisor,Dr.Grace Ugochi Nneji,for her invaluable guidance,insightful feedback,and continuous support throughout this project Her expertise and encouragement wereinstrumental in shaping the direction of this research. I am also deeply thankfult

o Joojo Walker,the module leader,for his constructive advice and the structured learning framework that enabled me to develop both technical and analy tical skills essential for this work.

Additionall,I am profoundly grateful to the academic communities at Oxford Brookes University and Chengdu University of Technology for providing me with an inspiring learning environment and valuable research resources.The stimulating discussions with faculty members and fellow researchers signi ficantly contributed to the development of this work.

Finally,to my family and friends,your unwavering support,encouragement,and understanding during thischallenging yet rewarding academic endea vor have been my greatest motivation.

Table of Contents

Declaration ii

Acknowledgment iii

Table of Contents iv

Abstract vi

Abbreviations vii

Glossary viii

Chapter 1 Introduction 9

1.1 Background 9

1.1.1 Risk and Factor 9

1.1.2 Challenge 10

1.2 Aim 11

1.3 Objectives 11

1.4 Project Overview 12

1.4.1 Scope 12

1.4.2 Audience 13

Chapter 2 Background Review 15

2.1 Traditional Method of Solar Radiation Prediction 15

2.2 Machine Learning Method of Solar Radiation Prediction 16

2.3 Deep Learning Method of Solar Radiation Prediction 18

2.3.1 CNN Models 18

2.3.2 Attention Mechanism 18

Chapter 3 Methodology 21

3.1 Approach 21

3.2 Proposed Model Structure 21

3.2.1 CNN Mode 21

3.2.2 Attention CNN Model 21

3.3 Dataset Collection 24

3.4 Data Preprocessing 25

3.4.1 Data Resizing 26

3.4.2 Data Partitioning 26

3.4.3 Evaluation Metrics 26

3.5 Experimental Setup and Technology 27

3.6 Project Version Management 28

Chapter 4Implementation and Result Analysis 29

4.1 Design and Implementation 29

4.2 Model Explainability 34

4.3 Model Visualization-GUI Design 39

4.3.1 Main Pages 39

4.3.2 Core functionality test 39

Chapter 5 Professional lssues 43

5.1 Project Management 43

5.1.1 Activities 43

5.1.2 Schedule 44

5.1.3 Project Data Management 44

5.1.4 Project Deiverables 45

5.2 Risk Analysis 46

5.3 Professional lssues 47

5.3.1 Legal lssues 47

5.3.2 Social lssues 47

5.3.2 Ethical lssues 47

5.3.3 Environmental lssues 48

Chapter 6 Concusion 49

References 51

Abstract

The rapid growth of renewable energy adoption has heightened the need for accurate solar energy prediction to ensure grid stability,particulanly in re gions with high solar penetration.However,traditional forecasting methods relying on historical meteorological data often fail o address short term fluct uations caused by dynamic cloud movements,limiting real time adaptability.To overcome this challenge,this study proposes a deep learning frameworki

ntegrating convolutional neural networks(CNNs)with attention mechanisms to predict photovoltaic(PV)output from radiance sky images.Two datasets c apturing diverse sky conditions were used to evaluate three architectures:a baseline CNN,CNN withSqueeze-and-Excitation(SE)Attention,and CNN with Spatial Attention.The CNN with SE-Attention model significantly outperformed baseline models,reducig prediction errors and improving explanatory po wer,as validated by metrics induding RMSE,MAE,and R².Gradient-weighted Class Activation Mapping (GradCAM)further demonstrated the model s ab ility to prioritize meteorologically critical regions,such as cloud edges and solar disk areas,with distinct attention patterns for sunny and cloudy scenarios. The framework's practical utility was enhanced through deployment in an interactive web-based Graphical User Interface,enabling real-time solar poten tial simulations for energy operators.By combining attention mechanisms with interpretable design,thi work advances short-term solar forecasting accur acy while providing actionable insights for grid management.Future research directions include multi-modal data fusion and hybrid transformer-CNN arc hitectures to improve robustness across diverse cimatic conditions.

**202118020205\_Final\_Report.docx\_ 第2部分**

**原文内容**

Keywords:Solar energy prediction,Deep learning,Attention mechanisms,Grad-Cam,Sky image analysis

Abbreviations

CNN:Convolutional Neural Network

SE-Attention:Squeeze-and-Excitation Attention

PV:Photovoltaic

RMSE:Root mean squared error

MAE:Mean absolute error

R2:Coefficient of Determination

EVSExplained Variance Score

GHI:global horizontal rradiance

IRM:Image Regression Module

LSTM:Long short-term memory

MLP:Multi-Layer Perceptron

ARMA:Autoregressive Moving Average

ARIMA:Autoregressive Integrated Moving Average

NWP:Numerical Weather Prediction

GUI:Graphical User Interface

Grad-CAM:Gradient-weighted Class Activation Mapping

Glossary

Renewable Energy Adoption:The increasing integration of sustainable energy sources like solar and wind into power grids to replace fosil fuel-based generation.

Grid Stability:The ability of an electrical power system to maintain consistent voltage and frequency levels despite fluctuations in energy supply or de

mand.

Solar Penetration:The percentage of total electricity generation provided by solar power in a given grid or region.

Photovoltaic(PV)Output:The actual electrical power produced by solar panels,measured in watt o kilowats,which varies with sunlight availability.

Convolutional Neural Network(CNN):A class of deep neural networks specialized for processing grid-lie data such as images,using convolutional la yers to detect spatial features.

Attention Mechanisms:Neural network modules that compute dynamic feature importance weights (0-1 scaled)through content-based addressing,w ith solar applications particularly benefiting from their ability to focus on transient cloud features while ignoring irelevant sky regions.

Squeeze-and-Excitation(SE)Attention:An efficient channel attention mechanism that first squeezes spatial dimensions via global average pooling,th en excites channelsthrough learned gating weights,typiclly with 4-16×reduction ratio,improving solar forecasting accuracy by 5-15%compared to bas eline CNNs.

Spatial Attention:A computationally efficient 2D attention variant generating pixel-wise importance maps through 1×1 convolutions and sigmoid acti vation,particularly effective for identifying critical sky regions like approaching cumulus clouds or circumsolar areas.

Gradient-weighted Class Activation Mapping(Grad-CAM);:Avisualization method combining forward activation maps,typicallyfrom the last CNN lay er,with backpropagated gradients to produce coarse heatmaps,validating that solar forecasting models properly attend to physically meaningful features like cloud edges

Chapter 1lntroduction

1.1Background

Inrecent years,with the rapid growth of global energy demand and the improvement of environmental protection awareness,the application of dean

energy,especially solar energy,has become the focus of global attention.With its renewable and clean ature,solar energy is seen as an important part of

sustainable energy in the future [1].Accurate solar power forecastingiscriticalto maintaining grid stability especialy in areas with high solar penetration, where grids need to respond in real time to fluctuations in solar radiation due to cloud cover or weather changes t avoid power supply disruptions due t

o sudden drop in sunlight [2].

However,because solar power generation is dependent on the intensity and duration of sunlight,rapid hanges in weather conditions make tradition al forecasting methods challenging.Most of the traditional forecasting methods rely on historical meteorological data,but such methods aredificult to a dapt to the rapidly changing weather conditions in time,especially the dynamic changes of cloud coverin a short period of time,resulting in limited real-t ime and flexible forecasting [3].In order to adresstis chllenge, deep learning technology has made significant progres in the field of image recognitio n and pattern recognition in recent years, making it possible to analyze weather conditions and predict solar radiation in real time using radiated sky imag es [4].

Through real-time analysis of sky images,deep learning models can automaticallyidentify doud type,thickness,coverage and other information,so a s to provide dynamic and accurate data support for solar potential prediction.This image-based forecasting method has shown significant advantages ov er traditional methods,especially in response to short-term weather changes [5].

1.1.1Risk and Factor

Asillustrated in Figure 1,regions with higher solar penetration,such as California and New England,exhibit significantly highereror costs.Althought he curent corelation between error costs and solar penetration levelsi relatively weak,the potential negative impacts of forecasting errors are expected

to become more pronounced as the proportion of solar energy in the energy mix continues to increase [6].Nowadays,ground-based sky imagery and de ep learning models have gradually emerged as effective ways to address these short-term fluctuations,reducing uncertainty by providing fast short-term f orecasts.

Figure 1:Costs of NAM forecasts Errors in 2018 and 2019 by Wang et al.[6]

1.1.2Challenge

The improvement of model performanceis inseparable from the support of high-quality and diverse datasets,which isone of the main challenges fac ing the fild at present.To ensure the reliability of the model,a high-quality dataset representative of a wide range of atmospheric conditionsis essential.

Athough a growing number of open-source sky imagery datasets are becoming available,these datasets vary in coverage,resolution,and quality control, and these factors are critical to training models with high generalization capabilities.Researchers are actively promoting the acesibility of data and the s tandardization of solar prediction datasets,which can help improve model generaization and support further research in energy meteorology and atmos pheric sciences [7]

Predicting solar energy potential by combining radiated sky imagery and deep learning technology,which can not only significantly improve the accu racy of prediction,but also help the grid achieve more efficient power management and dispatch,thereby ensuring tthe stability and reliability of power su pply.This image-based prediction method has strong real-time,low cost and high scalability,which is expected to bring new application prospects and te chnological innovation to the field of solar power generation.

1.2Aim

With the rapid development of renewable energy across the globe,acurate prediction of solar power generation potential is critical for smart grids a nd energy management.To achieve this,many studies employ image-based deep learning models to analyze sky images for solar energy prediction.How ever,traditional methods often struggle to provide real-time,acurate forecasts under rapidly changing weather conditions,such as moving clouds [8].Th erefore,this study proposes a model combining Convolutional Neural Network(CNN)and Attention mechanisms to automatically extract and enhance sp atial features from iradiated sky images.By integrating these features,the nowcasting model aims to corelate sky radiance data with Photovoltaic(PV)o utput,providing efficient and accurate solar energy potential predictions under diverse weather conditions.

1.3Objectives

The main goal of thisproject is to develop a deep learning model combining CNN with Attention mechanisms for real-time prediction of solar energy potential from sky radiation images.To achieve this overall goal,this study focuses on a series of specific tasks,including data processing,model design a nd optimization,evaluation metric seection,and performance validation.

First,this project constructs a diverse sky image dataset covering different meteorological conditions,including sunny and cloudy days.The dataset is pre-divided into trainval (96.16%)and test(3.84%)sets.The trainval set,containing 349,372 samples,is used for 10-fold cross-validation,with 90%of the data used for training and 10%for validation in each fold.To enhance robustness and reduce time-dependent biases,data preprocessing includes groupin g by day blocks,shufling,image normalization,and tensor conversion of PV output.Batch processing is applied to optimize training efficiency.

**202118020205\_Final\_Report.docx\_** **第3部分**

**原文内容**

Secondly,the project designs a CNN-based architecture with integrated Aention mechanisms to extract spatial features,such as cloud density and di stribution patterns,and enhance the focus on relevant regions.Key hyperparameters,including batch size,learning rate,and dropout rate,are optimizedt

o ensure model robustness and accuracy.The Adam optimizer is employed to achieve stable and efficient convergence.These design choices enable the model to perform real-time and accurate predictions,particularly for short-term photovoltaic output under rapidly changing weather conditions.

The model's performance will be assessed using key evaluation metrics,including Root Mean Square Error (RMSE),Mean Absolute Error(MAE),Coeff icient of Determination(R2),and Explained Variance Score (EVS). These metrics will quantify prediction acuracy and generalization ability.urthermore,co mparative experiments with traditional persistence models willdemonstrate the effectiveness of the nowcasting model,particulaly under dynamic weath er conditions.

1.4Project Overview

This section introduces a CNN-based model integrated with Attention mechanisms for real-time solar energy prediction,emphasizing its potential to enhance energy management and the key stakeholders who will benefit from advancements in accuracy predictions of solar energy.

To facilitate a clearer understanding of the project's overall rchitecture,Figure 2 is a schematic representation depicting the key components of the p roject.

Figure 2:Flow chart of whole project

1.4.1Scope

Inrecent years,with the rapid development of deep learning technology,the CNNs have achieved significant sucessin te field of image processing and have been increasingly applied to complex tasks such as weather prediction and energy management. However,standard CNN models may face chall enges when dealing with complex atmospheric conditions and dynamic weather patterns,such as imited adaptability to spatial variations and reduced ro bustness under rapidly changing conditions.To address these limitations,this project introduces a CNN-based model enhanced with Attention mechanis ms.The CNN layers extract spatial features such as cloud density and light intensityfrom sky images,while the Attention modules emphasize relevant regi ons,improving the model's ability to handle dynamic weather scenarios and enabling accurate real-time prediction of solar energy potential.

The potential contributions and practical implications of this project include:

DAccurate prediction of solar power potential:Makes solar energy systems smartr and more reliable by analyzing cloud distribution and light intensit y in radiated sky images to provide round-the-clock real-time predictions.

DImprove the eficiency of renewable energy management Optimize the management and deployment of solar energy in the grid through real-time prediction, reduce energy waste,and improve the stability of power supply.

DPromote the application of solar energy in dynamic weather conditions:provide real-time predictive support for smart grids,photovoltaic power ge neration systems,distributed energy management systems,etc,and enhance the adaptability of solar energy systems.

DImprove forecasting economics and scalability:Reduce backup energy requirements and reduce overal perating costs throug efficient data proce ssing and predictive models.

DProvide technical support for green energy transition:Promote social trust and use of clean energy throughefficient and convenient prediction tool S.

1.4.2Audience

The research provides new ideas for energy management,scientific research,and technology development,and its potential audience includes but is not limited to the following:

DEnergy Management &Smart Grid Operators:Real-time solar potential prediction models ffer accurate data for power distribution,helping optimiz e grid resources based on weather conditions and solar radiation levels

□Solar Power System Designers and Maintenance Personnel:Accurate predictions aid in optimizing PV system layout during design and commisionin gand adjusting power generation plans to enhance system efficiency and stability.

DMeteorological and Environmental Scientists:The study provides valuable data on cloud dynamics,weather patterns,and radiation levels,serving as a reference for other weather-sensitive research areas.

DPolicymakers and Renewable Energy Agencies:Solar forecasts support clean energy adoption,strategy development,and optimized renewable ener gy management,contributing to sustainable development goas.

Chapter 2Background Review

The application of deep learning in solar radiation predictionis becoming more and more extensive,and several research teams have proposed difer ent model structures to improve the accuracy and timeliness of prediction.Feng and Zhang T9]proposed the SolarNet,a 20-ayer deep CNN,specificllyd esigned for hourly prediction of global horizontaliradiance (GHD.Alani eta.2)further researched the application of CNNs by developing a hybrid CNN- Multi-Layer Perceptron (MLP)model,which are used to extract spatial features from images,and MLP networks are used to explore complex relationships between image information,GHI,and different weather variables.Papatheofanous et al.[10]introduced a CNN-based Image Regression Module (IRM)for estimating short-term solar radiation from sky images.

In adition to CNN structures,more and more studies are trying to introduce time series information into predictive models to capture the dynamicc hanges in cloud cover and radiation.Paletta etal[11 compared the effects of four deep learning models,CNN,CNN-Long short-term memory (LSTM),3D

-CNN,and ConvLSTM,and the experimental results showed that recurent neural networks containing time series information (LSTM,3D-CNN,and ConvL STM)outperformed traditional CNN models in prediction accuracy,especilly3D-CNN and ConvLSTM performed well in short-term predictionsill indicat ors.Zhang et al.[12]also evaluated three deep learning models,MLP,CNN,and LSTM,for photovoltaic nowcasting using sky images,finding that the LST M-based model significantly outperformed others,achieving a 21%improvement in RMSE skill score over the persistence baseline in predicting one-minu te-ahead solar power output.

In this section,three main approaches to daylight forecasting are presented:traditional methods,machine learning methods,and deep learning meth ods.Among the deep learning methods,this section describes the application of CNNs and attention mechanisms,which have shown great potential to i mprove the accuracy and efficiency of daylight forecasting in particular.

2.1Traditional Method of Solar Radiation Prediction

Traditional solar radiation prediction methods mainly rely on empirical models,statistical methods,and physical simulations,and since the 80s of the 20th centuries,time series methods have become the early focus of PV forecasting research,with countries such as Europe,the United States,and Japan le ading the development of PV technology.Sidrach-de-Cardona and Lopez [13]of the University of Malaga,Spain,were among the first scholars to apply m ultiple linear regression models to predic the energy output of independent photovoltaic systems;Chowdhury and Salfur [14]used autoregressive movin g averages(ARMA)and autoregressive moving averages(ARMA)to predict the energy outputof photovoltaic systems.ARMA)and Autoregressive Integra I Moving Average (ARIMA)models to study the energy output of photovoltaic systems,further developing this field.Subsequenty.Hassanzadeh et al.[15] proposed an ARMA model for houdy PV generation forecasting in collaboration with NV Energy.Besides,to adresslarge-scale solar forecasting.Numeric al Weather Prediction (NWP)systems solvefuid dynamics and radiative transfer equations,though their computational complexity limits temporal resolut ion.Jimenez et al[16]researched a WRF-Solar model,which is an operational NWP model optimized for solar forecasting,integrating aerosal-radiation fe edbacks and high-temporal-resolution outputs to address industry needswhich is shown in Figure 3.

**202118020205\_Final\_Report.docx\_ 第4部分**

**原文内容**

Figure 3:Suncast solar power forecasting system [16]

2.2Machine Leaning Method of Solar Radiation Prediction

Machine learning has greatly improved the ability to predict solar radiation,which solves the limitation tha it is dificult for traditional power systems to accurately predict unconventional power generation [17.Machine learning models enable accurate predictions by using historical solar data to identify and exploit complex relationships between inputs and outputs.This process begins with preprocessing of large datasets to ensure that the model is traine d on relevant,high-quality data.Machine learning models in this field typically employ one of three approaches:models based on meteorological and geo graphic parameters,time-series models using historical solar irradiance data,and hybrid models with exogenous variables [18].

Figure 4:ML Solar PV Power[17]

Figure 4ilustrates a comprehensive framework for forecasting PV generation using machine learning techniques,emphasizing the integration of data collection,data preparation,model training,and preditive validation.The most commonly used machine algorithms for solar iradiance prediction indud e K-nearest neighbor(KNN),support vector machine (SVM),decision tree(DT),and random forest (RF).However,despite its advantages,machine learning models also have thei limitations,such as relying on large amounts of high-quality training data,being prone to overfiting,and requiring large amounts of computational resources [19].These challenges need to befurther explored,especiall as the use of photovoltaic power generation systems continuest

o increase,and the need for advanced data preprocessing techniques to manage large and complex data sets increases.

2.3Deep Learning Method of Solar Radiation Prediction

It has been proven that deep learning methods,especilly convolutional neural networks (CNNs),caneffectively extract spatial features from sky imag es for solarirradiance prediction.

2.3.1CNN Models

As shown in Figure 5,a convolutional neural network consists of a convolutional layer,an aggregation layer,and afuly connected layer.The convoluti onal layer uses adaptivefiters to extract spatial features,the aggregation layer reduces feature sampling to improve effcency,and theflly connected lay er maps features to output.During training,the kernel parameters were optimized using backpropagation and gradient descent,which allowed the CNNt

o learn patterns from low-level to high-level structures hierarchiclly [20].This adaptability makes CNNs very effective forimage-based tasks,such as sun prediction by analyzing sky images.

Researchers are actively working on neural networks,with a particularfocus on CNNs and their hybrid models.In integrated systemsthese models of ten improve prediction accuracy,especially in the case of short-term forecasts [21].While researchers have made important contributions to the developm ent of solar irradiance prediction,CNNs are inherently incapable of processing temporal information.Because of this limitation,further research is needed on how to combine CNNs with other models and methods that can process temporal data,so that forecasts can be based on both temporal variation and spatial analysis.

2.3.2Attention Mechanism

The integration ofattention mechanisms into deep learning models has significantly enhanced the accuracy of solar radiation prediction by enabling models to selectively focus on critical input data.Wang and Zhang [22]proposed a CNN-Attention model for solariradiance prediction,which standardiz es and normalizes input features before processing them through a convolutional layer with ReLU activation and L2 regularization,which depicted in the F igure 6.

Figure 5:Convolutional Neural Network Overview by Yamashita et al.[20]

The atention mechanism integrates feature maps,ensuring vital features are considered,followed by another convolutional layer for enhanced featur e extraction.The model outputs solar irradiance predictions via a linear activation Conv2D layer,trained on a comprehensive dataset from 48 scenarios for accurate estimation.

Figure 6:Architecture of CNN-Attention model by Wang and Zhang [22]

Jonathan et al.[23]introduced an Attention-embedded ConvolutionalNeural Network(ATT\_CNN)model for solar irradiance forecasting using sky ima ge sequences,achieving superior accuracy.Qu et al.[24]proposed integrating attention into CNN-LSTM models to capture both short-term and long-term temporal changes in time series data,further improving prediction accuracy.This capabilit is crucial for optimizing photovoltaic system performance bye nhancing responsiveness to changing weather conditions.While attention mechanisms improve model interpretability and prediction precision,they alsoi ntroduce complexity and increase computational demands.Despite these chllenges,their benefits in solar radiation forecasting make them a valuable ad dition to predictive tools for managing and optimizing solarr energy resources.Table 1 summarizes the datasets used and the results obtained for the diffe rent studies:

Table 1:Summary of Related Works

Author Datasets Methods &Models Limitations Results

Feng and Zhang [9]SRRL CNN Weather impact and single input nRMSE:8.85%FSS:25.14%

Alani et al.[2]GEP CNN-MLP Limited to single time and site RMSE:13.05W/m²-49.16W/m²

Papatheofanous et al.[10]CA CNN Need real-time irradiance forecasting application RMSE:10.44W/m²

Paletta etal[11]SRTA CNN,CNN-LSTM,3D-CNN,ConvLSTM Limited effectiveness of past image sequence training 10-min ahead forecast skill204% Zhang et aL[12]Hemispherical HDR sky images MLP,CNN,and LSTM Single site,single camera and single photovoltaic panel RMSE:21%

Jonathan et al.[23]SRRL Attention-embedded CNN Rely solely on sky image sequences RMSE:62.75W/m²MBE:2.71W/m²FSS:38.81%

Qu et al.[24]Alice Springs photovoltaic power system Attention-based CNN-LSTM Long prediction range is limited nRMSE:6.34%

Chapter 3Methodology

3.1Approach

This chapter introduces the core methods of solar forecasting,indluding the following key aspects:proposedattention-based CNN architecture desig n,sky image data collection,and data prepossessing steps.The approach aims to adressthe challenges of short-term solar forecasting by establishing a systematic workflow from data processing to predictive modeling.

3.2Proposed Model Structure

This section introduces the proposed deep learning model,which focuses on improving the accuracy of solar energy prediction through attention-en hanced feature extraction.The development of the model begins with the construction of a basic CNN for sky image processing,and then use separatelyt wo attention mechanisms,extruded excitation(SE)attention and spatial attention,to improve weather feature learning.Finally,a comparative analysis is c arried out to optimize the prediction performance and interpretability of the proposed model in solar forecasting applications.

1.1.1CNN Model

The CNNs are the backbone of this study's deep learning architecture.CNNs are highly effective in processing grid-structured datalike images,thanks to their convolutional layers,which extract spatal features through kernel operations.A kernel K,represented as a small matrix of weights,slides over the i nput image l to compute feature maps F:

F(x,y)=i=0m-1j=On-1K(i,y)-I(x+i,y+i)(1)

Here,m and n represent the kernel dimensions,and (xy)denote the spatial coordinates o the output feature map.CNNs are particularly adept at cap turing local patterns such as edges,textures,and shapes,making them ideal for extracting cloud and radiation-related features from sky images.

1.1.2Attention CNN Model

Attention mechanisms are incorporated into the CNN framework to enhance its ability to focus on the most critical regions of the input.This project e mploys Squeeze-and-Excitation (SE)Atention,neverthelessfor a bete justification why we have focused on SE-Atention,the project did an ablation stu dy on the other type of attention mechanism called spatial attention

**202118020205\_Final\_Report.docx\_** **第5部分**

**原文内容**

Spatial Attention focuses on"where"the model should look in the image by emphasizing spatially important regions.The attention map is computed as:

A8=sigmoid(Conv2D([Favg,Fmax]))(2)

Where and represent the average-pooling and max-pooling operations applied along the channel dimension of feature maps F.Although this mechan ism is effective in identifying important spatial regions,it i sil inuficient for solar forecasting.For example,it tratsall channel in the same way,ignori

ng their unique spectral signatures that are essential to distinguish between cloud types and solar features.In addition,the clustering operations it perfor ms magnify local artifacts,causing larger weather patterns that span multiple regions to be ignored.These limitations prompted this study to focus more on SE-Attention mechanism in order to better capture the channel relationships that are critical for accurate solar forecasting.

With the limitation of spatal attention mechanism,this project has focus on squeeze and excitation (SE)attention.SE Attention focuses on"what"feat ures to emphasize by adaptively recalibrating channel-wise feature responses.This involves a two-step process:

-Squeeze:Global average pooling reduces each feature map to a single value.

-Excitation:Fully connected layers apply non-linear transformations to model inter-dependencies between channels:

S=0(W2·ReLU(W1·z))(3)

Here,is the squeezed vector,and are trainable weightsand o denotes the sigmoid activation.

The architecture of the proposed model,ilustrated in Figure 7,combines CNN with Attention mechanisms to predict solar energy potental from radia nce sky images.The input is a 64×64×3 image representing the radiance distribution of the sky. The model consists of two convolutional blocks,each com prising a convolutional layer, batch normalization,an Attention module,and max pooling.These blocks progressively etract and refine spatial features,fo cusing on the most relevant regions through Attention mechanisms.The extracted features aefattened and passed through two fully connected layers,e ach with 1024 neurons and dropout regularization.The final output layer predicts the solar energy potental as a single numerical value,making this mode I suitable for regression tasks.

The model is trained with the Mean Squared Eror (MSE)loss function and the Adam optimizer,with a learning rate of 3×10-6,to ensure efficient par ameter updating and stable convergence.To avoid overfiting,a dropout rate of 0.4 was used in the fully connected layers,while batch normalization stabi lized the learning of the convolutional layer.In adition,the experiment used 10-fold cross-validation to verify performance to create a robust evaluation f ramework that improves the generalization ability of the model.

Figure 7:The proposed model architecture

3.3Dataset Collection

The first dataset,called Sky Images and Photovoltatic Power Generation Dataset (SKIPPD),was developed by Stanford University's Environment Asess ment and Optimization(EAO)Group.The SKIPPD dataset includes sky imagery and photovoltaic data,making it suitable for short-term solar forecasting. The sky image was recorded by a 6MP 360-degree fisheye camera at video resolution at 2048x2048 pixels,running at 20 frames per second.The recorde d video then generates an image in JPG format at a 1-minute sample rate.Figure 8 shows examples of sky images in different weather conditions.In addit ion,raw photovoltaic (PV)data was recorded for a photovoltaic installation located approximately 125 meters away from the camera.These PV data are al so recorded at one-minute intervals,which coincides with the frequency at which sky images are captured,allowing for accurate corelation between visua I data and output power [25].

The second dataset,also cllcted on the 6Stanford campus,contains 2048×2048 pixels ultra-high-resolution video images of the sky recorded at 20 frames per second and every 60 seconds using photographic images and solar measurements of the same resolution.This continuou imaging method pr eserves complete spatial details and records changing cloud covers,allowing for a detailed study of the effects of the atmosphere on solar energy product ion [26].

(a)sunny(b)Cloudy

Figure 8:Sample of the sky images in different weather conditions,(ais sunny day and(b)is cloudy day

In this study,the benchmark dataset used has undergone necessary image preprocessing steps,which include resizing the image frames and filtering out duplicate images caused by sporadic anomalies in the OpenCV video capture functionality.Additionally,the sky photos and PV power generation data in the dataset are organized into aligned pairs to ensure consistency and alignment of the data.Figure 9 illustrates the distribution of photovoltaic power generation in both the development and test sets,and a detailed profile of PV power generation over 20 specific days in the test set.

Figure 9:The PV power generation data distribution:A is the development set data distribution,B is the test set data distribution,Cis PV profile for ea ch test day [25]

3.4Data Preprocessing

The data preprocessing phase establishes a robust foundation for model training by systematiclly transforming raw sky images into standardized inp uts while ensuring representative data partitioning.This stage addresses two critical requirements for solar forecasting models:consistent input dimensio ns and temporally coherent evaluation splits that reflect real-world operational conditions.

1.1.3Data Resizing

Sky images undergo spatial and numerical standardization to meet modeliput specifications.Original images are rescaled to a uniform resolution of 64×64 pixels through aspect ratio-preserving transformations,followed by pixel value normalization to the [0,1]range using linear scaling.This standardiz ed processing offers two advantages:the ability to batch image data in different weather conditions,and the ability to reduce brightnessdifferences due t

o changes in solar altitude and weather fluctuations.During the pre-processing process,we paid special attention to maintaining the color fidelity of the R GB three-channel,which is essential for the subsequent attention mechanism to effectively identify the texture features of the clouds.

1.1.4Data Partitioning

In the data partitioning section,the observations are cdustered into daly chunks of the full olar cycle,which are randomly shufled while preserving t he intra-day chronological order.The hierarchical k-fold cross-validation scheme allocates the entire day block into different folds,ensuring that each valid ation set contains unique weather states that are proportional to the weather conditions that ocu in the entire data set.The above steps can be used to maintain time consistency during the performance evaluation process,so that the model can be exposed to different cloud mobilityscenarios during the t raining iteration process.The partitioning logic used in the study combined with index remapping capabilitie allows for both ful-resolution datasets and computationally optimized subsets without compromising the consistency of the evaluation.

3.4.1Evaluation Metrics

The evaluation metrics of the proposed model are designed to rigorously assessits performance in predicting solar energy potential from radiance sk y images.The eva|uation process involves the use of a separrate test dataset,appropriate preprocessing,performance metrics,and visual analysis to validat e the model's effectiveness and generalizability.The test dataset consists of 14,003 samples,including images and corresponding PV output values.These samples are preprocessed by normalizing image data to the range [0,1]and ensuring consistency in data types.To analyze the model's performance unde r varying weather conditions,the test data is categorized into sunny and cloudy days based on known dates.This allows fora more granular evaluation of the model's behavior in different scenarios.

**202118020205\_Final\_Report.docx\_** **第6部分**

**原文内容**

The testing process begins by evaluating the performance of each of the 10 models trained during cross-validation on the test dataset.For each mod el,predictions are generated and compared against the ground truth PV outputs to calculate key evaluation metrics.The ensemble approach is applied by averaging the predictions of all models,resulting in a final prediction thatleverages the strengths of multiple modelsto enhance robustness.To quantify t he models performance,several metrics are employed,including Root RMSE,MAE,R2,and EVS.RMSE measures the average magnitude of the prediction error and is computed as follows,where n is the number of data,is the predicted value and is the measured value:

RMSE=1ni=1n(yi-yi)2(4)

MAE calculates the average absolute error between predictions and ground truth values,expressed as:

MAE=1ni=1nyi-yi(5)

The coefficient of determination(R2)evaluates how well the predictions explain the variance in the ground truth data:

R2=1-i=1n(yi-yi)2i=1n(yi-y)2(6)

Finallythe Explained Variance Score(EVS)measures the proportion of variance captured by the model:

EVS=1-Var(y-y)Var(y)(7)

3.5Experimental Setup and Technology

To ensure theffective development and evaluation of our deep learning models for solar energy prediction,the project has carefullyselected a robus t technology stack that balances computational efficency,development lexiblity and reproducilit.The chosen tools and hardware components are sp ecificlly optimized for handling image-based deep learning tasks,particularly the processing of high-resolution sky images and the implementation of at tention mechanisms.Table 2 below outlines the complete technology stack that wil be utilized in this projec,including both software frameworks and har dware specifications.

Table 2:Summary of Technology for the project

Software Framework TensorFlow

Language Python

Libraries Numpy,Keras,Matplolib,itertools,h5py

Hardware Central processing unit(CPU)Gen Intel(R)Core(TM)i7-11800H @2.30GHz 2.30 GHz

Graphic Processing Unit(GPU)NVIDIA GeForce RTX 3050

3.6Project Version Management

The details is shown in Table 3:

Table 3:Version Control Progress

Version Number Code Name Content Results

1 Baseline Model Basic CNN model implementation,initial design structure,and h5 modelfiles Initial training results,and baseline performance metri cs for RMSE,MAE,R2

2 Attention Integration Codes for integrating Spatial Attention and SE-Aention modules into CNN Comparison of performance for CNN,CNN+Spat ial Attention,and CNN+SE-Attention;

3 Testing on Alternative Datasets Testing the final CNN+SE-Attention model on alternative datasets Evaluation results on new datasets,including RM SE,MAE,R²,and EVS metrics

Chapter 4Implementation and Result Analysis

This chapter presents the practical development and outcomes of the solar energy prediction system.It covers three main aspects:the design and im plementation of the deep learning models,the explainability analysis of model decisions,and the deployment of an interactive Graphical User Interface(G UI)for real-world application.Together,these components demonstrate the project's technical execution,interpretability,and practical usability.

4.1Design and Implementation

This section details the design,development,and implementation of a solar potential prediction model.Three model variants,benchmark CNN,CNN with spatial attention,and CNN with SE attention,were evaluated to find the best performing model.In addition,we also visually analyzed the prediction r esults of the best model to verify its practical application value.

To ensure fair comparison,all models were trained and evaluated under the same experimental conditions.Each architecture uses 10-fold cross-valida tion,combined with the division of time-series block data,which not only retains the time dependence,but also ensures the balanced distribution of the d ata at each fold.The parameters were reinitiaized at the start of training,using the Adam optimizer,with the mean square error(MSE)as the optimization target.To prevent overitting,we employ an early stop mechanism with a 5-epoch patience window and automatically save the optimal model weights ba sed on validation losses.During training,training and validation losses for each iteration are recorded for detailed convergence analysis.

The architectural iferences between the three models are mainly in the attention mechanism,while maintaining the same underlying convolutionall ayer.The baseline CNN is used as a reference model without any attention module,while the spatial attention variant dynamically weights the characterist ics of a specific region through the spatial importance map of learning.In contrast,the SE attention model uses channel-level feature recalibration to enha nce discriminative feature learning by squeezing and excitation.

Performance evaluation was conducted through a multi-dimensional assessment framework,including convergence behavior analysis via training/vali dation loss,optimal model selection per fold based on validation performance, with comprehensive resuts across both training and test sets presented in Table 4.

Table 4:The overall results

Train loss validation loss RMSE MAE R2EVS

Dataset 1 CNN 2.202.002.4821.5240.8950.902

CNN+Spatial-Attention 1.461.502.3471.3900.9060.912

CNN+SE-Attention 1.701.722.2311.3110.9080.912

Dataset 2 CNN+SE-Attention 4.054.013.9272.7920.6550.655

As shown in Table 4,the baseline CNN shows higher training loss than validation oss,sugesting mild underfiting.In contrast,attention models dem onstrate closely matched losses,with SE at 1.70 versus 1.72 and Spatial at 1.46 versus 1.50,indicating strong generalization.The SE-Attention's smallerg

ap highlights its stability,likely due to effective channel-wise feature weighting.Moreover,the CNN+SE-Attention model outperforms both the baseline CNN and the CNN+Spatial Attention variants acros all metrics including RMSE,MAE,R2.The improvement in RMSE and MAE highlights theffectivenes s of SE-Aention in enhancing prediction accuracy,particularly under dynamic weather conditions.Furthermore,the and EVS metrics demonstrate the SE- Attention model's superior ability to explain and capture variance in the data.

While SE-Attention achieved the best results on Dataset 1,RMSE 2.231 and MAE:1.311,its performance degraded significantly when applied to Datase t2,RMSE 3.029 and MAE 1.709,despite maintaining similar R²and EVS scores.This suggests that while SE-Attention generalizes well within Dataset 1's dis tribution,it struggles with Dataset 2's characteristics,likely due to domain differences in the video-extracted images.The performance metrics of first data set incuding sunny and cloudy conditions are summarized in Table 5.

Table 5:The Dataset 1 results including sunny and cloudy days

RMSE MAE R²EVS

Sunny CNN 0.7510.610.9990.993

CNN+spatial-Attention 0.6750.5470.9920.996

CNN+SE-Attention 0.5110.4140.9950.997

Cloudy CNN 3.4252.4340.7930.805

CNN+spatial-Attention 3.2462.2290.8140.823

CNN+SE-Attention 3.2382.2040.8150.822

To further validate the best performance CNN+SE-Attention model in the first Datasetits predictions were visualized for representative sunny and cl oudy days.Figure 10 illustrates the predicted versus actual PV outputs under these two distinct weather conditions.In sunny scenarios,the model consiste ntly achieves high accuracy in sunny conditions.Acrossall ten repetitions,the RMSE values for sunny days range from 0.23 in Sunny\_5 to 0.76 in Sunny\_3, with a mean of 0.49 and standard deviation of 0.19.Similarly,MAE spans from 0.17 in Sunny\_5 to 0.71 in Sunny\_3,averaging 043 with a standard deviatio n of 0.19.Notably,Sunny\_5 yields the lowest errors,RMSE 0.23 and MAE 0.17,whereas Sunny\_3 in Repetition 3 shows slightly elevated values,RMSE 0.76 and MAE 0.71.Despite minor fluctuations all retitions maintain RMSE below 0.76 and MAE below 0.71,demonstrating robust performance under stable atmospheric conditions.

**202118020205\_Final\_Report.docx\_** **第7部分**

**原文内容**

In contrast,for cloudy scenarios,the model reveals higher variability,reflecting the complexity of dynamic doud cover.RMSE spans from 1.44 in Cloud y\_8 to 4.70 in Cloudy\_4,with a mean of3.15 and standard deviation of 1.18.MAE ranges from 1.17 in Cloudy\_8 to 3.31 in Cloudy\_4,averaging 2.26 with a standard deviation of 0.85.Early repetitions,like Cloudy2 with RMSE 4.64 and MAE 3.10,exkhibit significant errors,but later iterations show progressive st abilization.For instance,Cloudy\_8 achieves the lowest errors,RMSE 1.44 and MAE 1.17,and Cloudy\_10 maintains RMSE 2.23 and MAE 1.50.

The dual visualization in Figures 10 shows that sunny predictions remain stable with minimal variablity,confirming the model s reliability in ideal con ditions.Besides,cloudy predictions initilly fluctuate but gradually stabilize,with RMSE decreasing by 52%from Repetition 4 to Repetition 10and MAE im proving by 55%.While short-term variability exists in challenging conditions,aggregated performance across repetitions ensures reliable generalization fo r real-world applications.

ORepetition

ORepetition

(Repetition

ORepetition

(Repetition

(Repetition

ORepetition

ORepetition

ORepetition

ORepetition

1 model

2 model

3 model

4 model

5 model

6 model

7 model

8 model

9 model

10 model

Figure 10:Visualization of nowcast predictions of CNN+SE-Attention model,(a)-(j)shows 10 repetitions

This study quantifies the uncertainty during the training process and verifies the reliability of the practical application of the model in Figure 11.The le ft figure reveals the sensitvity of model training to data division through the RMSE distribution of each fold in ten cross-validations,while the right figure proves the stability of model performance through the mean distribution of ten full cross-validations.Random fluctuations in a single training are quantifi

ed through dual visual design and provide a key basis for evaluating the robustnessof the model to cope with changes in data distribution in real scenar os.

4.2Model Explainability

To interpret the decision-making process of the best performance CNN+SE-Attention model in the first dataset,the project employs Gradient-weight ed Class Activation Mapping(Grad-CAM),a visualization technique that highlights the regions of input images most influential for the model's prediction s.To improve the efficiency of model interpretability analysis,the project strategically reduced the size of the first dataset to 20%of its original capacity.T he implementation incorporates robust eror handling to ensure reliable heatmap generation even when gradient vanishing issues occu,while introducin g elliptical sky masking to better align with the physical imaging characteristics.Moreover,the analysis compares model attention patterns incuding sunn y and cloudy conditions by examining four representative sample categories:best-performing cases,median-error cases,worst-performing cases,and ran domly selected samples.

Figure 11:Model performance evaluation:Left panel shows the RMSE distribution across all 10 fold cross validation runs,demonstrating the variability in individual fold performance,right panel displays the distribution of mean RMSE values for each complete 10 fold CV repetition

The visualization results,as shown in Figure 12,reveal a strong correlation between prediction accuracy and attention localization precision.For both s unny and cloudy conditions,the best-performing samples,error=0.00,demonstrate optimal attention focusing within the elliptical sky region.And for me dian-eror samples,the sunny sample,eror=0.62,maintains relatively concentrated attention in the central sky area,though with slight radial dispersion, while the cloudy sample,error=1.72,shows spiral-shaped attention distribution that extends beyond key meteorological features.This structural differenc e in attention patterns corresponds to the nearly threefold increase in prediction error for cloudy conditions.However,the worst-performing samples reve

al catastrophicattention misalignment.The sunny case with eror=3.15 displays fragmented attention clusters in non-sky regions,while the cloudy sample with error=22.12 exhibits completely scatered activation patterns with no discerniblefocus on cloud structures.The magnitude oferror escalation sugges ts an abrupt breakdown in feature extraction rather than gradual performance decay.Random samples demonstrate intermediate characteristics,with atte ntion maps showing partial sky-region coverage combined with erratic activation.

These observations collectively indicate that prediction accuracy is highly sensitive to the geometric organization of attention.Optimal performance r equires tight spatial dustering of attention within physically relevant regions,while even minor dispersion correlates with measurable error increases.The most severe errors occur when attention loses its spatial coherence entirely,suggesting the model's decision-making process depends fundamentally on maintaining proper attention localization.

(a)Best sunny and best cloudy samples

(b)Median sunny and cloudy samples

(c)Worst sunny and cloudy samples

(d)Random sunny and cloudy samples

Figure 12:The visualization of four categories samples,(a)-(d)shows best,median,worst and random samples

Building upon Grad-CAM's localized explanations,we systematically analyze attention patterns through a multi-stage comparative approach.The anal ysis includes aggregate heatmaps for sunny and cdoudy conditions,pixel-wise statistical testing to identify significant differences,and regional compariso ns through partitioned image analysis,which displayed in Figure 13.

The RegionalAtention Intensity Comparison reveals three key findings.First,all fieregions demonstrate extreme statistical significance of p<0.001,c onfirming fundamental differences in how the model processes sunny versus cloudy conditions.Second,sunny conditions consistently show near-zero att ention in peripheral regions from Top-Left or Top-Right ≈=0.0,while maintaining moderate focus on central areas In contrast,cloudy conditions exhibit su bstantally heightened attention acrossall regions,particularly in the Bottom-Right quadrant where scattering effects are most pronounced.

Most notably,the Center region maintains stable attention llevels regardless of weather conditions,serving as an invariant reference point for the mod el's decision-making.This spatial patern reflects meteorologically sound reasoning,which suppress noise in clear skies while actively monitoring cloud for mations during overcast conaditions.The Bottom-Right quadrant's particularly strong response to cloudy conditions suggests the model has learned to pri oritize regions where atmospheric scattering signatures are typically most visible.

OSunny mean attention(b)Cloudy mean attention

(c)Attention Difference(d)Significance map

(e)Regional Attention intensity comparison

Figure 13:The comparison of attention patern heatmaps,a)-(e)shows sunny and cloudy days meanattention heatmaps,atention difference (Cloudy

-Sunny),significance map and regional attention intensity comparison

4.3Model Visualization -GUI Design

The developed web application integrates the trained model through a Flask+TensorFlow backend with Bootstrap+jQuery (V1.11.1)frontend,featur ing three core functional modules:

4.3.1Main Pages

To enhance the usability and accessibility of the solar energy prediction system,the project developed an interactive web-based GUl that enables real- time forecasting and model explainability.The platform consists of three main pages,which shown in Figure 14,15,166:Home Page,providing an overview of the project and navigation;Dataset Display Page,allowing users to explore the sky image datasets used for training;and Solar Prediction Model Page, which offers core functionalities including solar irradiance prediction and model explainability visualization using Grad-CAM.This GUI bridges the gap bet

ween deep learning research and practical solar energy applications,making the CNN+Attention model accessible to both technical and non-technical u sers.

**202118020205\_Final\_Report.docx\_ 第8部分**

**原文内容**

4.3.2Core functionality test

The predictive model was first validated by testing its ability to sucesfully generate corect evaluation metrics (RMSE,MAE,R²,EVS)and Grad-CAMe xplainability visualizations.As demonstrated in Figure 17 and Figure 18,the system properly processed uploaded test datasets including times\_test.npy ti me series filesdisplaying allrequired prediction results and attention heatmaps in the web inteface.

Figure 14:Home Page

Figure 15Dataset Display Page

Figure 16:Solar Prediction Model Page

Figure 17Solar Prediction Merics result in GUI

Figure 18:Model Explainability result in GUI

Chapter 5Professional lssues

5.1Project Management

In order to ensure the achievement of project objectives,this section illsystematically elaborate on the project management part,covering the key a spects of project activity planning,schedule control,data management and results delivery.Through a structured process and a standardized approach,th is project management solution aims to optimize resource allocation,reduce risk,and ensure that projects move forward efficiently and on schedule.

5.1.1Activities

Table 6 below illustrates the details of the project process:

Table 6:Details of phrase and objectives

Phase Objectives

Preparation Review related literature:Literature review on solar energy potential prediction,deep learning models,and sky image processing.

ldentify and narrow down issues:ldentify challenges and limitations in existing methods.Define the scope and objectives of the project.

Explore potential solutions to address the identified issues.

Learn relevant deep learning knowledge Study deep learning concepts

Learn about different deep learning models

Familiarize yourself with deep learning libraries and frameworks

Data collection Gather 2-3 datasets or online resources.

Clean and normalize the collected data.

Model Construction Develop and implement different model architectures,inluding CNN,CNN with Spatial Attention,and CNN with SE-Attention. Train,evaluate,and compare model performance based on predefined metrics.

Optimize model parameters to achieve improved prediction accuracy.

Testing and Report Use different datasets to evaluate themodel performance andanalyze the results and identify areas for improvement.

Write a comprehensive project report documenting and prepare a presentation to showcase the project findings.

Reflect on the project expeience and identify areas for future research and development.

5.1.2Schedule

The project schedule is shown as Figure 19.

Figure 19:Gantt Chart about project schedule

5.1.3Project Data Management

In Table 7,to ensureficient data management and version control,resources such as Ali Drive and Gitee wereutlized.These platforms facilitated th e storage,sharing,and organization of datasets,model codes,performance logs,and reports throughout the project ifecycle.The folowing table summar izes the key resources and their uses.

5.1.4Project Deliverables

.The project proposal:A detailed document outlining the objectives,methodology,and expected outcomes of the project.

.Weekly report:A weekly summary of the activities,progress,and any issues encountered during the project.

.Progress Report:A periodic report detailing the milestones achieved and the overallprogress towards the project goals.

.Final Project Report:A comprehensive document summarizing the entire project,including methodology,results,discusions,and conclusions specifi c to the CNN-Attention model.

.Project codes:The complete set of source codes developed for the CNN-Attention solar energy prediction model.

.Project presentation slides:A set of PowerPoint slides or equivalent presentation materials to be used for final project presentations,highlighting the CNN-Attention model's features and performance.

Project presentation:An oral presentation of the project findings,outcomes,and any recommendations for future work,with a focus on the CNN-Att ention model's effectiveness and potential applications

Table 7Data Management Plan

Resource Purpose

Ali Drive Storage of datasets(original and processed),literature,intermediate results,and backups.

Gitee Version control for code implementationincluding different model variants and logs.

Local Server Execution of experiments,storing temporary results,and ensuring fast access to large files.

5.2Risk Analysis

Risk analysis has been conducted throughout the projec to identify potential challenges and ensure effective mitigation.The key risks,mitigation stra tegiesand impacts on the project are summarized below in

Table 8:Table 8:Risk Analysis

Potential Risks Potential Causes Severity Likelihood Risk Mitigation

Limited dataset diversity Geographic constraints and

Limited temporal coverage 435-Augment with synthetic data-Collaborate for multi-location datasets

Dataset version mismatch Online source updates 624-Dataset fingerprinting-Frozen snapshots

Local hardware limitations Insufficient GPU memory for image batches 847-Use cloud-based development environments-Implement memory-efficie nt data loading

Code/result loss Single-point storage failure 7312-Automated version control (Git)-Cloud backup every 4 hours

Computational botlenecks High-res images+attention mechanisms 649-Progressive image resizing-Gradient accumulation

Attention mechanism flaws SE blocks overiting to artifacts 537-Attention dropout (20%rate)-Attention consistency checks

Training instability Loss divergence with spatial attention 436-Learning rate warmup-Gradient clipping

5.3Professional lssues

This solar forecasting project has been developed in strict accordance with professional standards and ethical computing practices,following the BCS Code of Conduct and the ACM Code of Ethics.This project carefully considers the legal,social,ethical,and environmental issues of Al applications in rene wable energy forecasting.

5.3.1Legal lssues

The project strictly adheres to the law by using only publicdy available sky imagery datasets from authorized meteorological sources and properly citin g relevant literature to ensure that copyright or privacy is not violated.All oftware components,including PyTorch,OpenCV,and other libraries,are used under their open soure licenses.The research methodology avoids the use of any proprietary data or constrained computing resources and relies slely o n academically recognized tools and platforms available to undergraduates.

5.3.2 Social lssues

In terms of technology acceptance related to social issues,small PV operators,such as household users and rural cooperatives,may have bariers to u nderstanding and misgivings about predictions based on deep learning due to the lack of technical expertise,and this technology gap will reduce the act ual adoption rate of the model.Therefore,there is a need to introduce the development of user-friendly visual interfaces to lower the barier to entry,wor k with local governments to conduct technology popularization training,and promote the open sharing of regional meteorological data to ensure equitab le access to forecasting services for operators ofall szes.

5.3.2Ethical lssues

In terms ofethical issues,this study focuses on the potentialimpact that over-reliance on predictive models may have on the capabilities of traditional meteorological analysis.Athough the solar prediction model developed in this project shows good predition performance under specific conditions,it m ust be clearly aware that the model is only trained on conventional weather patterns,and its prediction reliability for extreme climate events is limited.Ov

er-reliance on automated forecasting may lead energy managers to neglect the training of basic skil such as traditionalweather map interpretation and f ield observations.Therefore,this study suggests that while developing in-depth study of solar energy forecasting,researchers should maintain continuous learning of traditional analysis methods,so as to promote users'decison-making habits of building comprehensive model prediction and manual judgme nt.

**202118020205\_Final\_Report.docx\_ 第9部分**

**原文内容**

5.3.3Environmental lssues

While requiring computational resources for model training,the project actively minimizes its carbon footprint through techniques like mixed-precisio n training and batch optimization.The resulting solar forecasting system itself promotes environmental sustainability by enabling better integration of cle an energy into power grids.By improving prediction accuracy,the model helps reduce reliance on fosifuel backups,creating a net positive environment al impact that outweighs its development footprint.

Chapter 6Conclusion

This study investigates the prediction of solar energy potential from radiance sky images using deep learning,systematiclly evaluating three convolut ional architectures,CNN,CNN+SE-Attention,and CNN+Spatial-Attention,on two sky image datasets.Experimental results demonstrated that the CNN+ SE-Atention model achieved optimal performance,with the performance ofirst dataset better compared to the second,highlighting its suitability for sol ar irradiance mapping under varying sky conditions.For the best SE-attention model in the first dataset with the best performance,the study further uses Grad-CAM visualization to verify the interpretability of the model,revealing different attention patterns in sunny and dloudy scenarios,and proritizing key sky regions in the predition proces.By integrating tese findings into an interactive GUI the research bridges theoretical advancements in atention mec hanisms with practical applications,offering a deployable tool or solar energy forecasting.This work establishes a framework for sky image-based renewa ble energy prediction,emphasizing model transparencymeteorological relevance,and user accessibility.

However,there are stillimitations to the curent research.Model performancei stillimited by the diversity of datasets,especiallyfor rainy weather a nd rapidly changing cloud cover scenarios.The current training data is mainly from a single weather station at a fixed location,lacking a balanced distribu tion of different seasons and weather patterns.In adition,due to the limitation of experimental equipment,the captured sky images have low resolution and are greaty affected by lighting conditions,so exposure anomalies are prone to occur during sunrise and sunset.The model is slow to respond to sud den weather changes,and there is a delay in prediction results.In terms of hardware deployment,the existing model requires GPU support with high com puting power,which is difficult to drectly apply to the embedded monitoring system of solar power plants.

Future research will adress these limitations by optimizing data acquisition schemes to obtain more comprehensive images of the sky using multi-an gle camera arrays.Secondly,a lightweight model based on mobile devices is developed,and knowledge distillation and quantization techniques are used to reduce the computational requirements.The timeliness of short-term forecasts can also be improved by introducing time seies analysis methods,and a more reliable corection mechanism can be established by combining historical power generation data.In adition,a complete test platform will be buil t to evaluate the long-term performance of the model in the actual solar power plant,and the adaptation of the model to different weather conditions wil be enhanced through transfer learning technology.These improvements illsignificanty increase the utlity of the forecasting system in tefield of renew able energy.

References

[1JPérez-Rodriguez,S.A.et al,"Metaheuristic Algorithms for Solar Radiation Prediction:A Systematic Analysis,"IEE Access,vol.12,pp.100134-10014 8,Jul.2024,doi:10.1109/ACCESS.2024.3429073.

[2]EI Alani,O.et al.,"Short term solar irradiance forecasting using sky images hybrid CNN-MLP"Energy Reports,vol.7,pp.888-900,doi:[https://doi.](https://doi.org/10.1016/j.egyr.2021.07.053) [org/10.1016/j.egyr.2021.07.053](https://doi.org/10.1016/j.egyr.2021.07.053)

[3]Martinez Lopez V.A.etal.,"Using sky-classification to improve the short-term prediction of iradiance with sky images and convolutional neural ne tworks,"Solar Energy,vol.269,pp.112320,Jan.2024,doi:10.1016/j.solener.2024.112320.

[4]Paletta.Qet al,"Advances in solar forecasting:Computer vision with deep learning,"Advances in Applied Energy,vol 11,100150,Aug.2023,doi:1 0.1016/j.adapen.2023.100150.

[5]Ajith.M and Martínez-Ramón.M,"Deep learning algorithms for very short-term solar iradiance forecasting:A survey"Renewable and Sustainable Energy Reviews,vol.182,113362,2023,doi:10.1016/j.rser.2023.113362.

[61Wang.Y.et al,"The cost of day-ahead solar forecasting errors in the United States,"Solar Energy,vol.231,pp.846-856,Jan.2022,doi:10.1016/jis olener.2021.12.012

[7]Nie.Y.et al,"Open-source sky image datasets for solar forecasting with deep learning:A comprehensive survey."Renewable and Sustainable Energ y Reviews,vol.189,113977,2024do:10.1016/j.rser.2023.113977.

[8Gao.H and Liu.M."Short-Term Solar Iradiance Prediction From Sky Images With a Clear Sky Model.'Australian National University,Canberra,Aus tralia,2024.

[9JFeng.C and Zhang.J,"SsolarNet:A sky image-based deep convolutional neural network for intra-hour solar forecasting,"Solar Energy,vol.204,pp.

71-78,Apr.2020,doi:10.1016/j.solener.2020.03.083.

[10]Papatheofanous.E.A.etal,"Deep Learning-Based Image Regression for Short-Term Solar Irradiance Forecasting on the Edge,"Electronics,vol.11, no.22,3794,Nov.2022,doi:10.3390/electronics11223794.

[11Paleta.Q et al.,"Benchmarking of deep learning irradiance forecasting models from sky images:An in-depth analysis,"Solar Energy,vol.224,p.

855-867,2021,doi:10.1016/j.solener.2021.05.056.

[12]Zhang.J.et al.,"Deep photovoltaic nowcasting,"Solar Energy,vol.176,pp.267-276,Oct.2018,doi:10.1016/j.solener.2018.10.024.

[13]Sidrach-de-Cardona.Mand Lopez.L.M.,"A simple model for sizing stand alone photovoltaic systems,"Solar Energy Materials and Solar Cell,p p.199-214,1997.

[14]Chowdhury.B.H.and Salfur.R,"Forecasting sub-hourly solar iradiance for prediction of photovoltaic output,"IEE,pp.171-176,1987.

[15]Hassanzadeh.M.et al,"Practical Approach for Sub-Hourly and Hourly Prediction of PV Power Output,"North American Power Symposium,201 0.

[16Jimenez.PA.e al.,"WR-SOLAR Description and Clear-Sky Assessment of an Augmented NWP Model for Solar Power Prediction,"AMERICAN METEOROLOGICAL SOCIETY,Sep.2015,doi:10.1175/BAMS-D-14-00279.1

[17]Rachna and Singh.A.K.,"Prediction of Photovoltaic Power Generation using Machine Learning-A Review,"IEEE,2023.

[18]Voyant.C.et al,"Machine Learning methods for solar radiation forecasting:a review,"Renewable Energy,2016,doi:10.1016/j.renene.2016.12.09 5.

[19]Gaboitaolelwe.J.et al.,"Machine Learning Based Solar Photovoltaic Power Forecasting:A Review and Comparison,"IEE,vol 11,Apr.2023.

[20JYamashita.R.et al,”Convolutional neural networks:an overview and aplication in radiology"Insight into lmaging,vol.9,no.611-629,2018,d

oi:10.1007/s13244-018-0639-9.

[21]Ahmed.R.et al,“A review and evaluation of the state-of-the-art in PV solar power forecasting:Techniques and optimization,”Renewable and Su stainable Enegy Reviews,vol.124,no.109792,2020doi:10.1016/jrser.2020.109792.

**202118020205\_Final\_Report.docx\_** **第10部分**

**原文内容**

[22]Jonathan A.L,“.A radiant shift:Attention-embedded CNNsfor accurate solar iradiance forecasting and prediction from sky images,Renewabl e Energy,Vol234,121133,2024,doi:10.1016/j.renene.2024.121133.

[23]Wang.S.and Zhang.Y,"An attention-based CNN model integrating observational and simulation data for high-resolution spatial estimation of urban air quality,"Atmospheric Environment,Vol.340,120921,2025,doi:10.1016/j.atmosenv.2024.120921.

[24]Qu.J.etal.,"Day-ahead hourly photovoltaic power forecasting using attentionbased CNN-LSTM neural network embedded with multiple relevan t and target variables prediction pattern,"Energy,vol.232,no.120996,2021,doi:10.1016/j.energy.2021.120996.

[25]Nie.Y.et al,"SKIPP'D:A SKy Images and Photovoltaic Power Generation Dataset for short-term solar forecasting."Solar Energy,vol.255,p.17 1-179,2023,doi:10.1016/j.solene.2023.03.043.

[26JSun.Y.et al.”Solar PV output prediction from video streams using convolutional neural networks,"Energy &Environmental science,11,pp.1811 -1818,2018,doi:10.1039/c7ee03420b.

说明：1.指标是由系统根据《学术论文不端行为的界定标准》自动生成的

2.本报告单仅对您所选择比对资源范围内检测结果负责

**写作辅助工具**

选题分析

帮您选择合适的论文题目

资料搜集

提供最全最好的参考文章

**提纲推荐**

**辅助生成文章大纲**

**在线写作**

规范写作，提供灵感

**参考文献**

规范参考文献，查漏补缺

版权所有：笔杆[www.bigan.net](https://www.bigan.net) 分享到：