

SOLAR POWER GERNERATION PREDICTION USING MACHINE LEARNING

Submitted in partial fulfilment of the requirements for the
award of Bachelor of Engineering degree in Computer
Science and Engineering
by

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SATHYABAMA

**INSTITUTE OF SCIENCE AND
TECHNOLOGY (DEEMED TO BE
UNIVERSITY)**
Accredited with Grade "A" by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **BILL GATES.V (38110084), MOHAN RAJ.P(38110322)** who carried out the project entitled "**SOLAR POWER GENERATION PREDICTION USING MACHINE LEARNING**" under my supervision from **November 2021 to March 2022**.

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BILL GATES.V(38110084), MOHAN RAJ.P(381100322) hereby declare that the Project Report entitled “**SOLAR POWER GENERATION PREDICTION USING MACHINE LEARNING**” done by me under the guidance of Dr.A. Mary Posonia., is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering.

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ABSTRACT

The precise minute time scale forecasting of an individual PV power station output relies on accurate prediction of cloud distribution, which can lead to dramatic fluctuation of PV power generation. Precise cloud distribution information is mainly achieved by ground-based total sky imager, then the future cloud distribution can also be achieved by sky image prediction. In previous studies, traditional digital image processing technology (DIPT) has been widely used in predicting sky images. However, DIPT has two deficiencies: relatively limited input spatiotemporal information and linear extrapolation of images. The first deficiency makes the input spatiotemporal information not rich enough, while the second creates the prediction error from the beginning. To avoid these two deficiencies, convolutional auto-encoder (CAE) based sky image prediction models are proposed due to the spatiotemporal feature extraction ability of 2D CAEs and 3D CAEs. For 2D CAEs and 3D CAEs, 4 architectures are given respectively. To verify the effectiveness of the proposed models, two typical DIPT methods, including particle image velocimetry (PIV) and Fourier phase correlation theory (FPCT) are introduced to build the benchmark models. Besides, 5 different scenarios are also set and the results show that the proposed models outperform the benchmark models in all scenarios.

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LIST OF ABBREVIATIONS

ABBREVIATION

DIPT

CAE

PIV

FPCT

EXPANSION

Digital Image processing technology

Convolutional auto-encoder

Particle image velocimetry

Fourier phase correlation theory

CHAPTER 1

INTRODUCTION

1. OUTLINE

With the increase of solar PV integrated capacity [1] and wind power integrated capacity [2], the difficulty of stable operation of the power system is also increasing. The reason behind this is that renewable energy is aggressively promoted by governments due to its clean, low-cost, and inexhaustible characteristics [3]. However, both solar PV power and wind power have inherent and prominent uncertainty caused by weather conditions and meteorological factors, which makes a big difference between their fluctuation random process and the usual load curve of consumers [4]. Thus, when it comes to large-scale solar PV power integrated into power grids, to reduce the operation difficulty generated by the difference, the key lies in weakening the uncertainty of solar PV power, one kind of effective methods is solar PV power forecasting [5]. Besides, accurate solar PV power forecasting under some cases is important to electricity price forecasting, even though the latter is more difficult than the former. The output of a single PV power plant is mainly influenced by the surface irradiance [7], while the surface irradiance is dominantly impacted by the clouds with complex distribution over the plant [8]. When the clouds change drastically on the minute time scale, the surface irradiance will show significant nonlinear fluctuation [9]. The larger the capacity of a single station, the more serious the adverse effect of this fluctuation on power grids. Accurate minute time scale solar PV power forecasting is propitious to the stability of power system operation, the consumption of solar PV power, and electricity market operation [10]. Such methods use ground-based sky images commonly

DATASET PROCESSING

The sky images used in this paper are from the PV power station in Alamosa, Colorado, which are available on the National Oceanic and Atmospheric Administration (NOAA) website [24]. Their UTC time span is from May 22 2015 to May 31 2015. For each image, the time resolution is 0.5 min and the size is 352×288 . After data cleansing, the processing of an image is shown as Fig. 1, with the image resolution marked below each image.

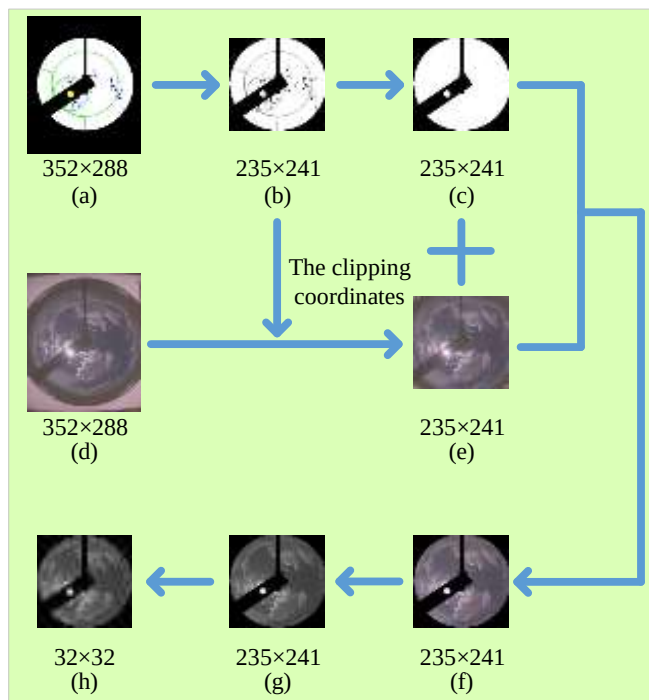


Fig. 1. Sky image processing.

CHAPTER 2

LITERATURE REVIEW

In addition to DIPT, sky image prediction can also draw lessons from the video prediction models based on deep learning. The common between sky image prediction and video prediction is that they have the same modeling idea, that is, using historical image sequences to predict future image sequences. The difference between them lies in spatiotemporal resolutions of image sequences, due to their different data sources. The temporal resolution of image sequences used in video prediction is very high, such as usually 24 frames per second. Dynamic information in videos often focuses on people or objects in real life, so the spatial resolution of the image is very high, and the people or objects in a video sequence usually do not undergo violent movement and change. The temporal resolution of image sequences used for sky image prediction is usually up to the second level at most, and the observed target is cloud. However, because the spatial scale of sky images is significantly larger than that of video prediction, cloud distributions in two adjacent sky images with longer time interval than video prediction is usually close. For that reason, sky image sequences can also achieve the smooth and continuous vision effect like video frame sequences, so sky image prediction can learn from video prediction methods.

Video prediction models are usually complex and deep convolutional auto-encoders (CAEs) in which convolutions include 2D convolution and 3D convolution. Specifically, over 20 computational layers are used in prediction CAEs at most in reference [19]. In reference [20], 5 computational layers are used in prediction CAEs at most. In reference [21], over 10 computational layers are used in prediction CAEs.

Convolutional neural network is a deep learning model widely used in the field of computer science [22]. An auto-encoder is an unsupervised deep learning model. For video prediction models, their input and output are image sequences and can be flexibly set lengths according to the need, which means that models can easily input more than two images.

Thus, more abundant spatiotemporal information can be input and then prediction performance of models can be improved.

First, the first kind of models, CAE based sky image prediction models, are first established. Furthermore, convolutions have 2D and 3D forms, and CAE models have 4 structures. As controls, then the second kind of models, DIPT based sky image prediction models, are established using PIV and FPCT. Finally, 5 different prediction time resolutions are considered on the practical dataset, and the performance of CAEs and DIPT are compared under each scenario. The results under 5 scenarios indicate the performance of CAEs is superior to that of DIPT models. To sum up, the main contributions in this paper include:

1. CAE based sky image prediction models are proposed to overcome the deficiencies of DIPT based sky image prediction models, including limited input image sequence length and linear image extrapolation.

To obtain accurate CAE based sky image prediction models, 2D convolution and 3D convolution are used regarding computation layers, and 4 different architectures are set regarding model structures

The comparison between CAE based sky image prediction models and two widely used DIPT based methods (PIV and FPCT) is simulated under 5 different prediction scenarios. The superiority of the proposed models can be verified by the results

The rest of this paper is organized as follows. Section II introduces data processing. Section III shows the methodology of the above two kinds of models

CHAPTER 3 METHODOLOGY

PURPOSE

The proposed CAEs consist of convolutional layers and transposed convolutional layers. The two types of layers are the same in the calculation theory, the main difference between them is generally that a convolutional layer generates a down-sampled feature map while a transposed convolutional layer generates an up-sampled one

SCOPE

The scope of this paper is to implement and investigate how different supervised regression methods impact default prediction. The main scope of the project is to find the accuracy and getting result from the flask framework deployment

EXISTING SYSTEM

The precise minute time scale forecasting of an individual PV power station output relies on accurate prediction of cloud distribution, which can lead to dramatic fluctuation of PV power generation. Precise cloud distribution information is mainly achieved by ground-based total sky imager, then the future cloud distribution can also be achieved by sky image prediction. In previous studies, traditional digital image processing technology (DIPT) has been widely used in predicting sky images. However, DIPT has two deficiencies: relatively limited input spatiotemporal information and linear extrapolation of images.

PROPOSED SYSTEM

Solar power generations datasets from different sources would be combined to form a generalized dataset, and then different machine learning algorithms would be applied to extract patterns and to obtain results with maximum accuracy.

CAE

Convolution operations including 2D convolution and 3D convolution is depicted as Fig. 2 [26]. A 2D convolution kernel has two directions to move, so 2D convolution applied on multiple frames stacked together generates a feature map. A 3D convolution kernel has three directions to move, so 3D convolution applied on multiple frames generates an output volume [26]. Under the same conditions, 3D convolution is finer than 2D convolution in terms of spatiotemporal feature extraction, but which means longer computation time

$$\mathbf{Y}_j = (f \circ \sum_i \mathbf{X}_i \mathbf{W}_{ij} + \mathbf{B}_j) \quad (1)$$

where $\mathbf{W}_{ij}$ denotes the i -th weight kernel in the j -th layer, $\mathbf{X}_i$ represents the input corresponding to $\mathbf{W}_{ij}$, $\mathbf{B}_j$ is the bias of the j -th layer, $\mathbf{Y}_j$ is the output feature map of the j -th layer and $f(\cdot)$ is an activation function.

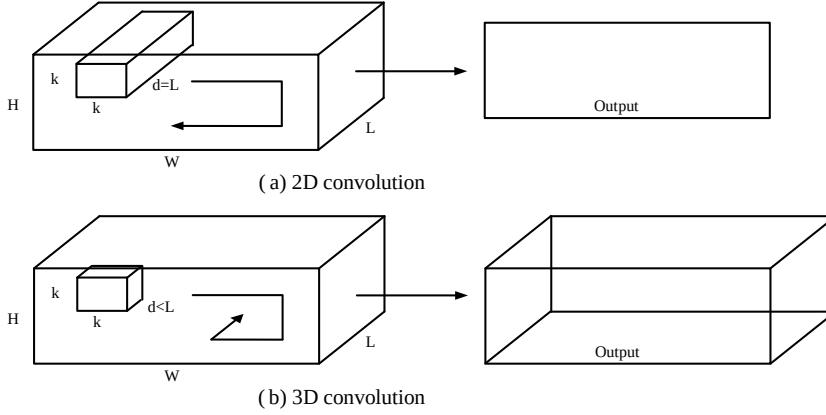
In CAE based sky image prediction models, an input image sequence information is processed when passing through an encoder and a bottleneck layer successively. Then the processed information is used by a decoder to predict a future frame. This process can be described as follows:

$$\mathbf{f}_{BL} = f_{CE}(\mathbf{X}) \quad (2)$$

$$\hat{\mathbf{X}} = f_{CDBL}(\mathbf{f}_{BL}) \quad (3)$$

where $\mathbf{X}$ is a sky image sequence; $f_{CE}(\cdot)$ represents a convolutional encoder; $\mathbf{f}_{BL}(\cdot)$ represents the features generated by a bottleneck layer; $f_{CD}(\cdot)$ represents a convolutional decoder; $\hat{\mathbf{X}}$ is a predicted image

The flowchart of a CAE based sky image prediction model is demonstrated as Fig. 4. And for CAEs, their input images, from $SI_{t0}^{-(n-1) \times t}in$ to SI_{t0} , are the same as Fig. 1(h).



H: Height, d: Height of a kernel,
L: Height of input frames, W: Width,
k: Side length of a kernel

Fig. 2.Convolution operation

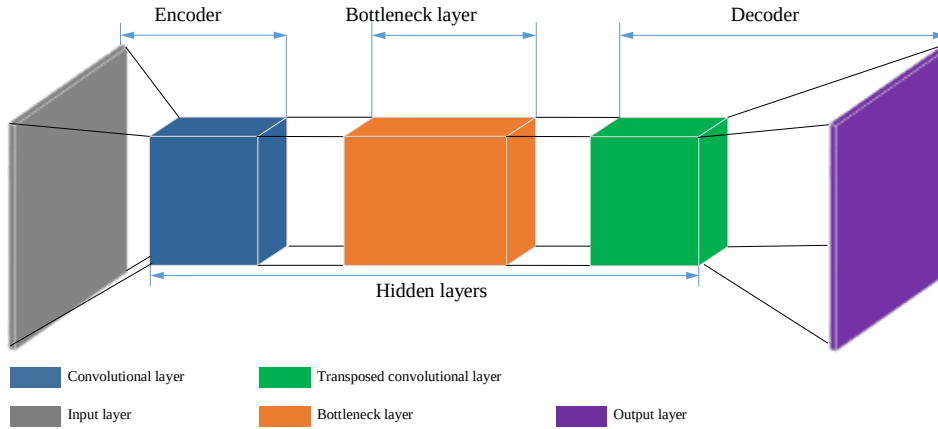


Fig. 3.The architecture of a convolutional auto-encoder

DIPT

PIV first divides both input images into small block regions, and then computes the cloud displacement vector by matching these blocks [15]. For FPCT, it uses Fast Fourier Transform to realize the interconversion between image space domain and frequency domain [17]. Fourier Transform of two input images is calculated and then used to calculate the crosspower spectrum. Finally, the cloud

displacement vector is obtained by the inverse Fourier Transform of the cross power spectrum.

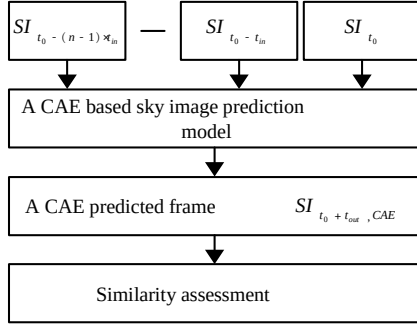


Fig. 4.The flowchart of a CAE based sky image prediction model

PIV and FPCT are used to construct two determined models which generate a predictive image by linear extrapolation of the image at t_0 . The type of models can be described as follows:

$$SI_{t_0+t_{out}}, DIPT = f_{DIPT}([SI_{t_0-t_{in}}, SI_{t_0}]) \quad (5)$$

where $SI_{t_0+t_{out}}, DIPT$ is the predicted sky image generated by a DIPT based method; $f_{DIPT}()$ is a DIPT based sky image prediction model; besides, $n=2$, $t_{out} = t_{in}$.

SIMULATION

Structural similarity (SSIM) and mean square error (MSE) are introduced to evaluate the performances of sky image prediction models

If x and y are two images with same resolution of $M \times N$, their SSIM is the product of luminance comparison $l(x, y)$, the contrast comparison $c(x, y)$ and the structure comparison $s(x, y)$, the three comparisons are expressed as Equation (6)(8): For two images, SSIM whose value range is $[0, 1]$ [29] is used to measure the similarity of structural information; while MSE is used to measure the similarity of gray values. The larger SSIM of two images means that their structures are more similar; the smaller MSE means that their pixels values are more similar.

$$l(x, y) = \frac{xy}{\frac{x^2}{2} + \frac{y^2}{2} + 1} \quad (6)$$

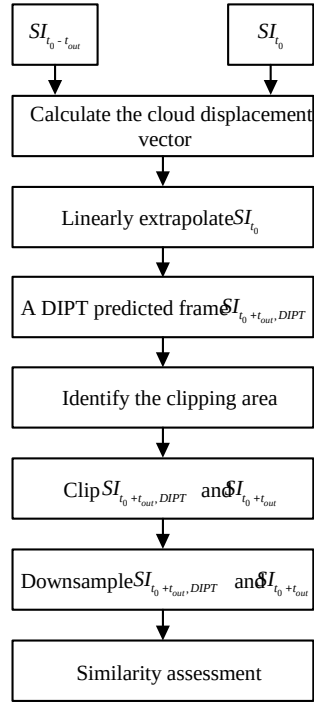


Fig. 5. The flowchart of a DIPT based sky image prediction model

C_2 and C_3 are three constants to avoid denominator very close to zero, and they can be respectively described as follows: $C_1 = (KL_1)^2$, $C_2 = (KL_2)^2$ and $C_3 = 1/2$. In general, $K_1 = 0.01$, $K_2 = 0.03$ and $L=255$. Finally, SSIM is described below:

$$SSIM(x, y) = l(x, y) \times c(x, y) \times s(x, y) \quad (9)$$

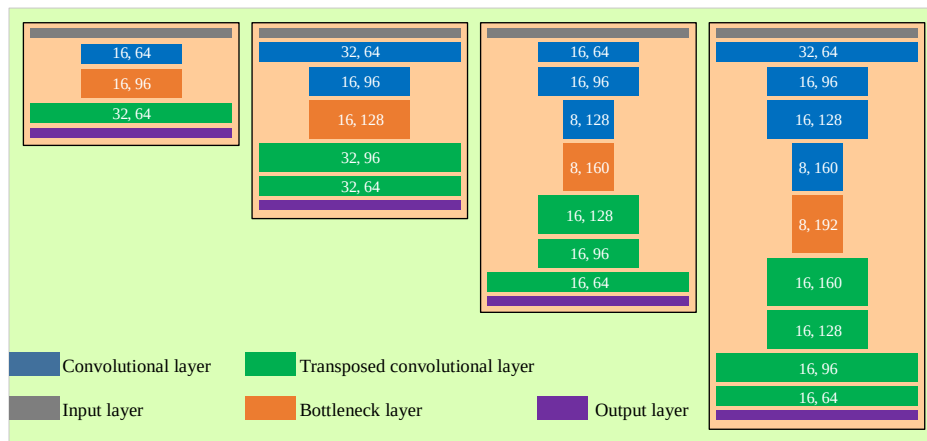
For x and y , MSE is described as follows:

$$MSE(x, y) = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [(x_{ij}) - y_{ij}]^2 \quad (10)$$

where x_{ij} and y_{ij} represent the pixel values of coordinate (i, j) in x and y respectively

All CAE models were built by Spyder and Keras, and they were run on a computer equipped with the Linux operating system, i7 CPU, 16 GB RAM, and a NVIDIA GeForce GTX 1080Ti GPU. All DIPT models were built by Spyder, OpenCV and OpenPIV, and they were run on a computer equipped with the Window10 operating system, i5 CPU, and 12 GB RAM

Fig. 6. Forexample, in the first hidden layer of a 3-layer 2D CAE



For a sky image prediction model, the mean value on the test set will be used as its performance evaluation. Since Adam optimizer performing a random gradient descent is used during the training process [30], each evaluation of a CAE is slightly different. To mitigate this randomness, each CAE is evaluated 10 times in each situation, the median of 10 evaluation values is taken as the performance evaluation value. Furthermore, each PIV based or FPCT based sky image prediction model is evaluated only once in each situation due to its determination.

Random Forest Regression

Random Forest Regression is a supervised learning algorithm that uses ensemble learning method for regression. Ensemble learning method is a technique that combines predictions from multiple machine learning algorithms to make a more accurate prediction than a single model.

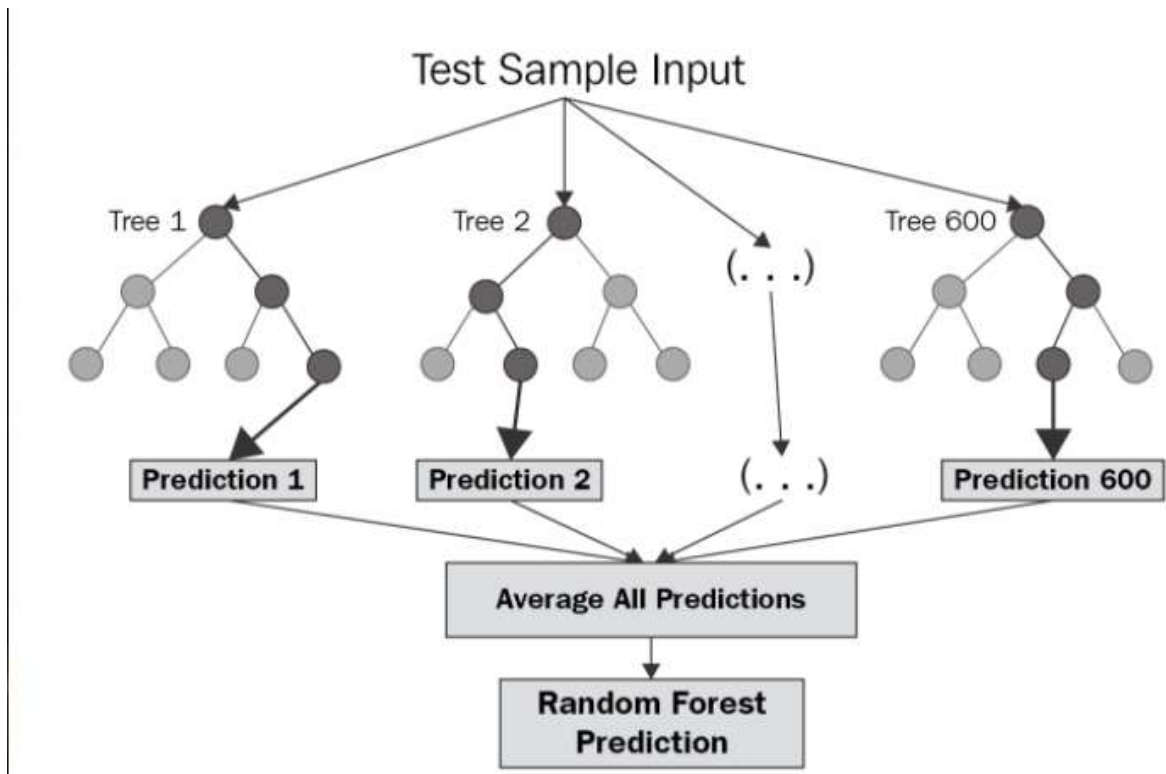
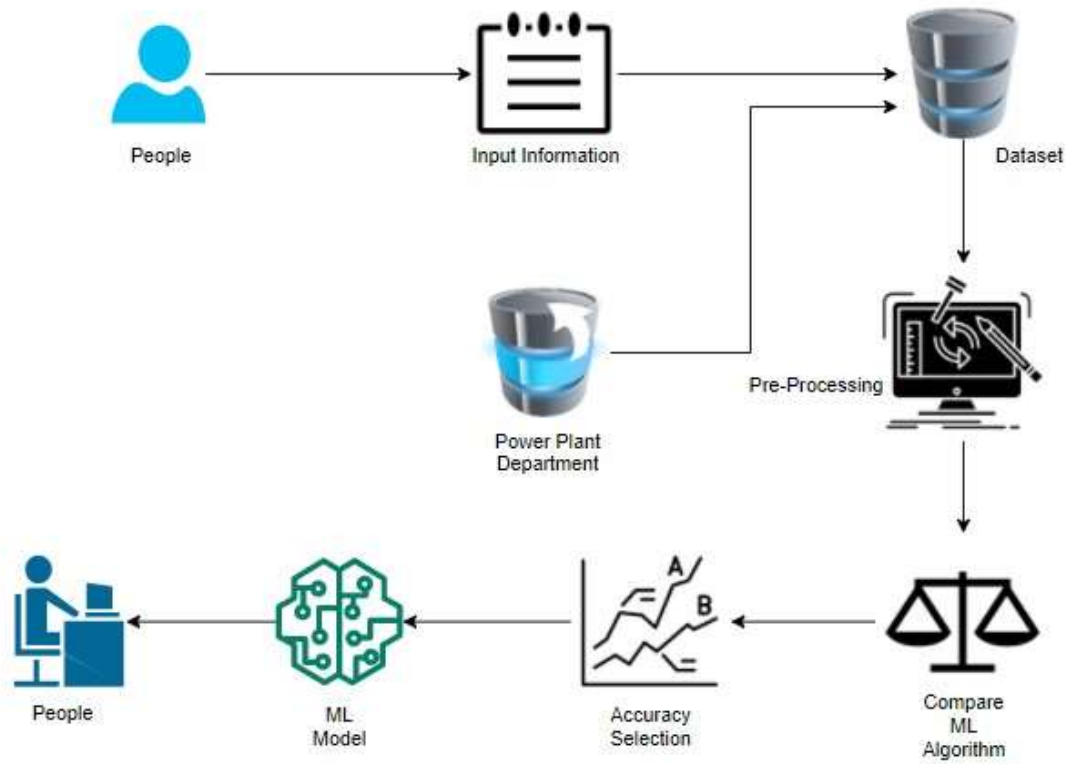


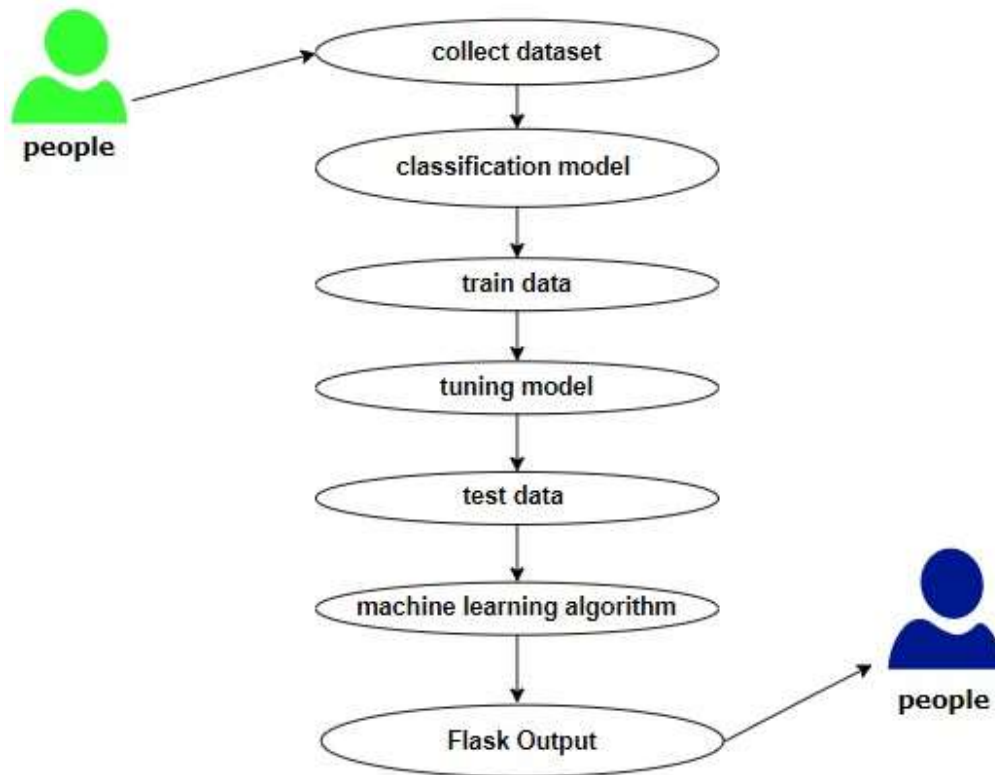
Figure 7 – structure of a Random Forest

The diagram above shows the structure of a Random Forest. You can notice that the trees run in parallel with no interaction amongst them. A Random Forest operates by constructing several decision trees during training time and outputting the mean of the classes as the prediction of all the trees

SYSTEM ARCHITECTURE



USE CASE DIAGRAM



MODULES

- Data Pre-processing
- Data Analysis of Visualization
- Comparing Algorithm with prediction in the form of best accuracy result
- Deployment Using Flask

CHAPTER 4 RESULTS AND DISCUSSION

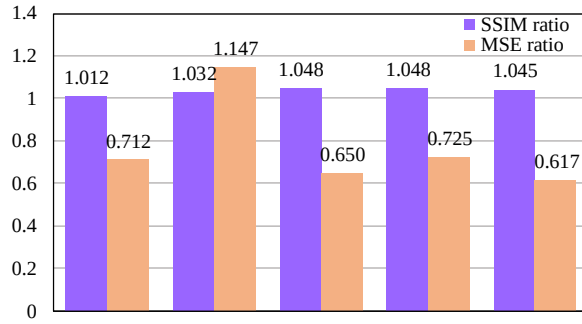


FIG 9-The ratios of optimal evaluations between two types of models

TABLE I. INPUT AND OUTPUT SETTINGS OF THE TWO TYPES OF MODELS

Scenario Number	CAE based models ($n=10$)		DIPT based models ($n=2$)	
	t/min_{in}	t_{out}/min	t/min_{in}	t_{out}/min
1	0.5	0.5	0.5	0.5
2	0.5	1	1	1
3	0.5	2	2	2
4	0.5	3	3	3
5	0.5	4	4	4

TABLE II. SSIMVALUES OF TWO TYPES OF MODELS

t_{out}/min	Best 2D CAEs		Best 3D CAEs		PIV	FPCT
	NHL		Values		NHL	Values
	Values		Values		Values	Values
0.5	0.9953	5	0.9953	5	0.9830	0.9831
1	0.9889	5	0.9890	5	0.9584	0.9586
2	0.9692	5	0.9678	5	0.9244	0.9245
3	0.9475	5	0.9444	5	0.9039	0.9038
4	0.9291	3	0.9259	5	0.8895	0.8895

TABLE III. MSEVALUES OF TWO TYPES OF MODELS

t_{out}/min	Best 2D CAEs		Best 3D CAEs		PIV	FPCT
	NHL		Values		NHL	Values
	Values		Values		Values	Values
0.5	5.12	5	5.22	5	7.19	7.18
1	14.14	3	15.24	3	12.32	12.30
2	11.84	3	12.12	3	18.23	18.24
3	15.90	3	15.88	3	21.91	21.83
4	15.07	3	15.17	3	24.41	24.39

Fig 10

CHAPTER 5

CONCLUSION AND FUTURE WORK

As the dynamic cloud distribution can cause significant generation fluctuation in a very short time, it is very important to achieve accurate sky image prediction for the minute time scale output forecasting of PV power station. Recently, most related works use DIPT to achieve cloud distribution prediction.

However, DIPT uses relatively limited spatiotemporal information and linear image extrapolation, which may lead to inaccurate prediction result of cloud. To avoid these shortages of DIPT based sky image prediction methods, 2D CAE based and 3D CAE based sky image prediction models are proposed. In this paper, 4 structures are designed for CAE based models, and the benchmark models are built by using two typical DIPT methods: PIV and FPCT. Besides, 5 different output time resolutions are considered

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APPENDICES