

CS F407 AI Project

Group Number 17

Aditya Seth	2020A8PS2151H	f20202151@hyderabad.bits-pilani.ac.in
Anmol Goyal	2020A3PS2139H	f20202139@hyderabad.bits-pilani.ac.in
Ayush Mishra	2020A3PS2130H	f20202130@hyderabad.bits-pilani.ac.in
Aditya Kumar	2020A3PS0624H	f20200624@hyderabad.bits-pilani.ac.in

Solar Power Prediction using Genetic Algorithm and Gradient Boosting and Artificial Neural Networks

→ We reviewed a number of research papers and they have been presented in the mid sem report submitted earlier. It has a brief literature review of all the papers studied which are mentioned in the references.

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Algorithms Used

We have used the following algorithms in our project:

- 1) **Genetic algorithm for Gradient Boosting using single point crossover:**
A crossover point on the parent organism string is selected. All data beyond that point in the organism string is swapped between the two parent organisms. Strings are characterized by Positional Bias.
- 2) **Genetic algorithm for Gradient Boosting using n (n = 3) point crossover:** In this crossover n random combination points on the both parents are selected and each pair of them are swapped with each other along the both chromosomes
- 3) **Genetic algorithm for Gradient Boosting using uniform crossover:**
Each gene (bit) is selected randomly from one of the corresponding genes of the parent chromosomes.
- 4) **Genetic algorithm for Artificial Neural Networks using single point crossover:**
For finding a set of optimal values that will give a specific output from a neural network, the answer is easy. When applying GAs to other problems, defining an appropriate

fitness function can make all the difference between success and an unexpectedly random result.

Dataset

We used a “Solar energy power generation dataset” from Kaggle to train and test our models. It gives the maximum instantaneous power generated by the solar power plant on each particular day. It has 20 input parameters for the one target variable - “generated_power_kw”.

Link to dataset:

<https://www.kaggle.com/datasets/stucom/solar-energy-power-generation-dataset>

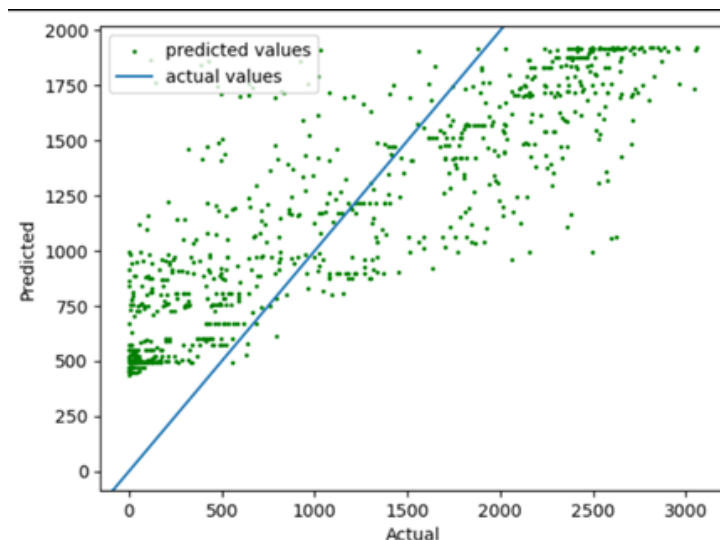
Analysis and Comparative Study

Gradient Boosting Results

1) Generic Parameters :

n_estimators: 100, max_depth: 4,min_samples_split: 3, learning_rate: 0.01, loss: 'squared_error'

MAE	RMSE	R2 SCORE
497.473469841029	571.5507228799847	0.6423829377080243

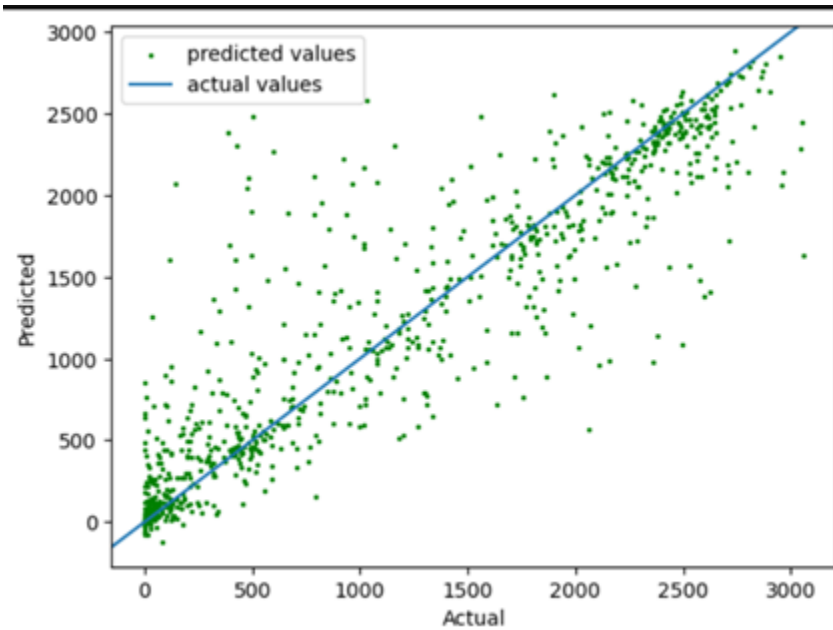


2) Parameters we got using GA

a) Single Point Crossover

n_estimators : 287, max_depth : 6, min_samples_split : 15, learning_rate : 0.06997182991301101, loss : 'huber'

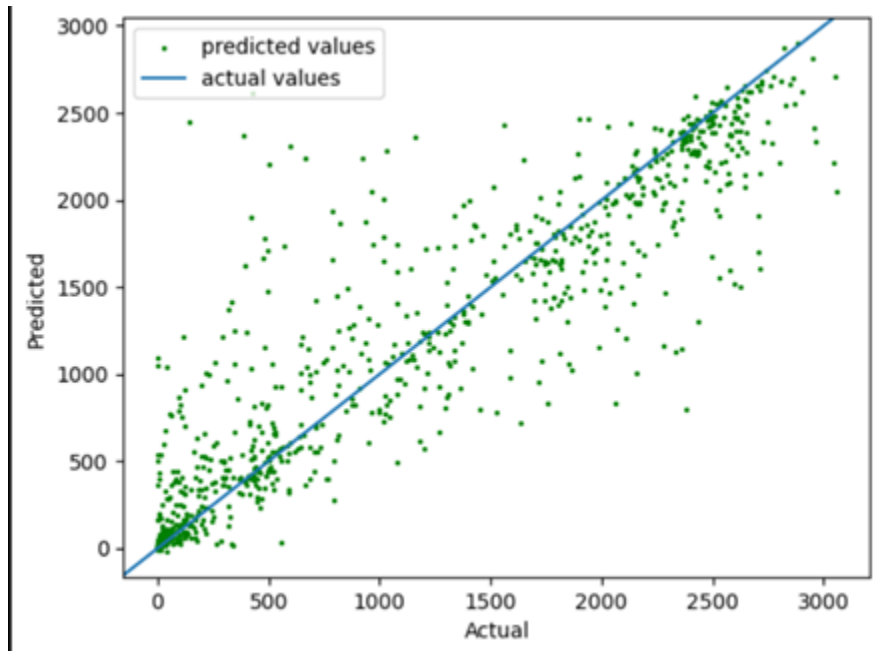
MAE	RMSE	R2 SCORE
244.2287226542215	400.888541979373	0.8240634944526923



b) N Point Crossover

N_estimators : 905, max_depth : 16, min_samples_split : 11, learning_rate : 0.01394445686878295, loss : 'absolute_error'

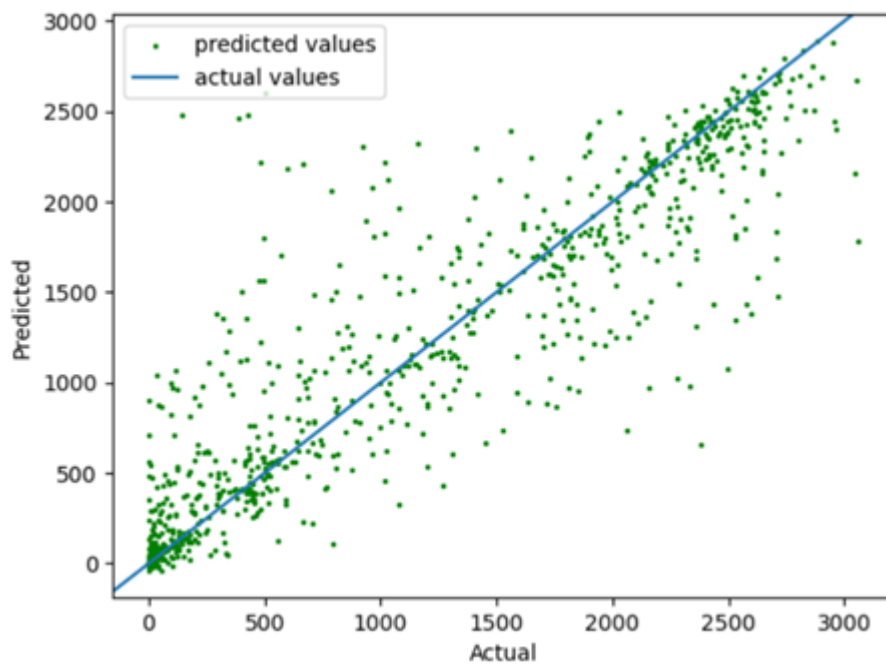
MAE	RMSE	R2 SCORE
242.07723411542645	395.9650176666561	0.8283584955428379



c) Uniform Crossover

n_estimators : 464, max_depth : 12, min_samples_split : 20, learning_rate : 0.12666669356005764, loss : 'absolute_error'

MAE	RMSE	R2 SCORE
249.257771512771	410.13988505125803	0.8158495920610587



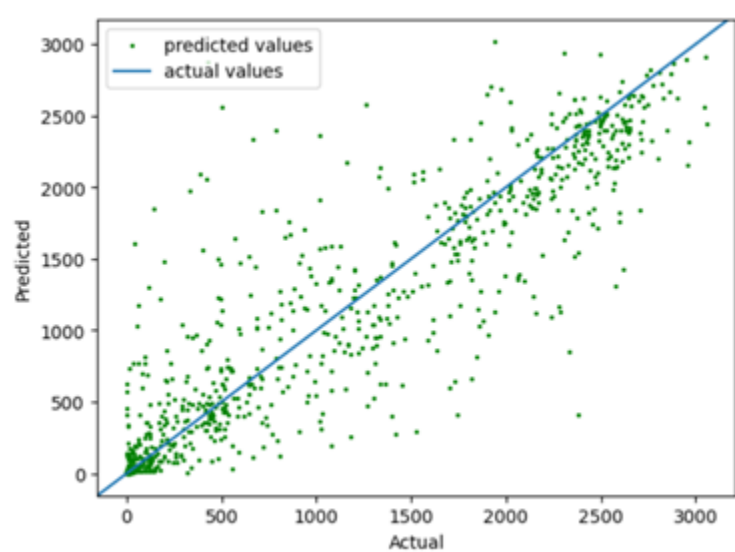
ANN Results

1) Generic Parameters for an ANN

Layer (type)	Output Shape	Param #
dense_209 (Dense)	(None, 64)	1344
dense_210 (Dense)	(None, 128)	8320
dense_211 (Dense)	(None, 256)	33024
dense_212 (Dense)	(None, 512)	131584
dense_213 (Dense)	(None, 256)	131328
dense_214 (Dense)	(None, 128)	32896
dense_215 (Dense)	(None, 64)	8256
dense_216 (Dense)	(None, 1)	65

Loss : Mean Squared Error, Optimizer : Adam, Activation Function : Relu

MAE	RMSE	R2 SCORE
268.6700589762128	421.6882478706812	0.8053332985521076

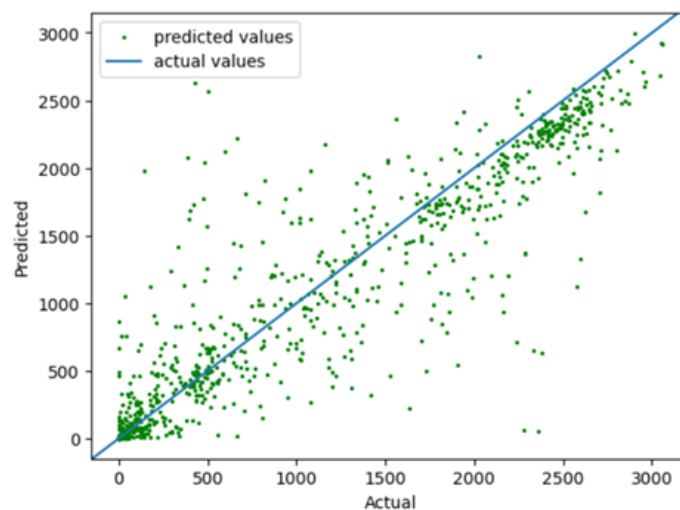


2) Parameters using a single point crossover genetic algorithm

Layer (type)	Output Shape	Param #
dense_217 (Dense)	(None, 512)	10752
dropout_62 (Dropout)	(None, 512)	0
dense_218 (Dense)	(None, 512)	262656
dense_219 (Dense)	(None, 512)	262656
dense_220 (Dense)	(None, 512)	262656
dense_221 (Dense)	(None, 512)	262656
dense_222 (Dense)	(None, 512)	262656
dropout_63 (Dropout)	(None, 512)	0
dense_223 (Dense)	(None, 1)	513

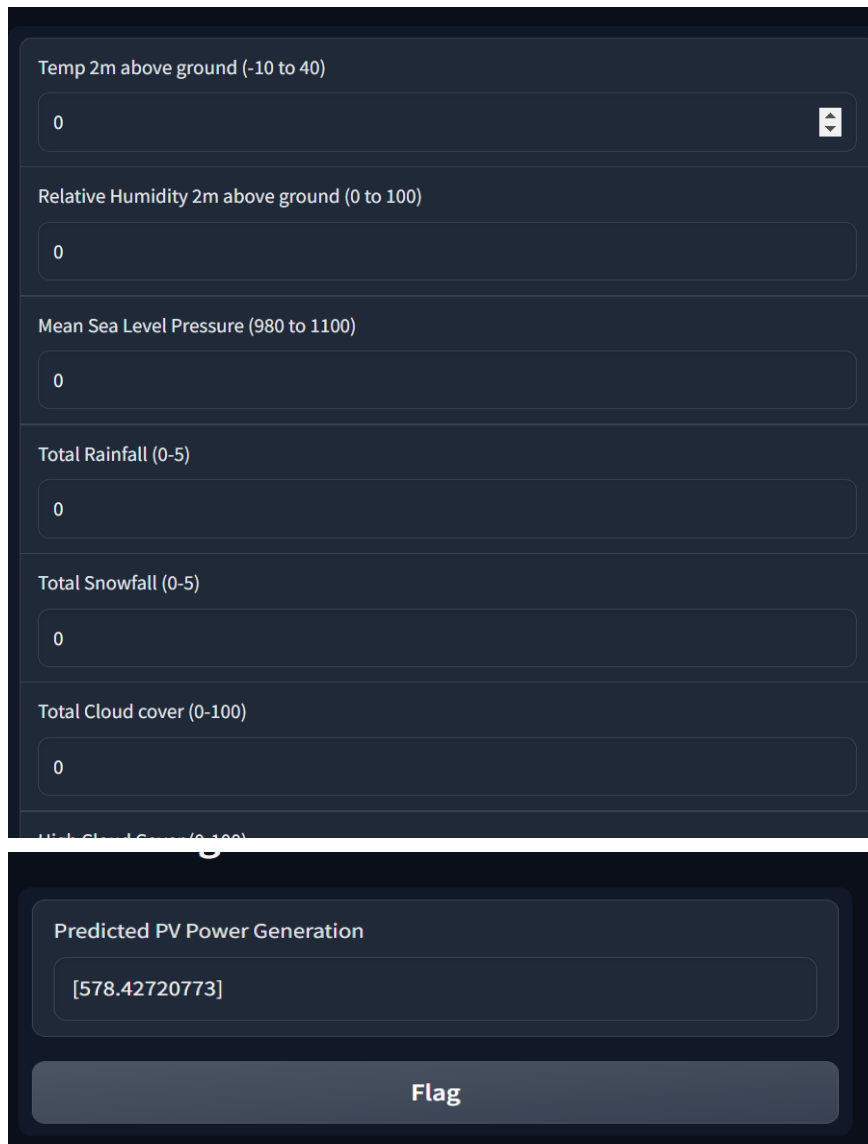
Learning Rate : 0.01, Number of Neurons : 512, Activation Function : 'relu', Dropout Range : 0.1, loss : 'mae', number of hidden layers : 6, optimizer : 'adam'

MAE	RMSE	R2 SCORE
244.38931711361622	402.99660110284805	0.8222083169716261



GUI for Using the Algorithm

We used the Gradio application to create an interface for the prediction model of solar power. It takes the 20 input parameters as the basis for prediction, and it uses the best function found using the code to find the predicted Solar Power.



The image shows a Gradio interface for a solar power prediction model. It consists of two main panels. The top panel contains six input fields, each with a label and a range in parentheses: 'Temp 2m above ground (-10 to 40)', 'Relative Humidity 2m above ground (0 to 100)', 'Mean Sea Level Pressure (980 to 1100)', 'Total Rainfall (0-5)', 'Total Snowfall (0-5)', and 'Total Cloud cover (0-100)'. Each field has a value of '0' and a small up/down arrow icon. The bottom panel contains a single output field labeled 'Predicted PV Power Generation' with the value '[578.42720773]'. Below the output field is a button labeled 'Flag'.

Input Parameter	Value
Temp 2m above ground (-10 to 40)	0
Relative Humidity 2m above ground (0 to 100)	0
Mean Sea Level Pressure (980 to 1100)	0
Total Rainfall (0-5)	0
Total Snowfall (0-5)	0
Total Cloud cover (0-100)	0

Output
Predicted PV Power Generation
[578.42720773]

Flag