

## LIST OF FIGURES

2.1	<i>Ensemble learning architecture using Bagging to generate final predictions by averaging the outputs of Random Forest, AdaBoost, and XGBoost models. . . . .</i>	11
2.2	<i>The Architecture of ensemble learning stacking in predictive modelling. The first layer, Base Learning, applies various base models, including Random Forest, AdaBoost, and XGBoost, to the input data to create an optimal training dataset. The second layer, Meta Learning, uses this optimal dataset to generate final predictions, leveraging the combined strengths of the different base models for improved accuracy. . . . .</i>	12
2.3	<i>Ensemble Learning Process using Bagging with Decision Trees (e.g., Random Forest): The diagram illustrates how a dataset trains multiple decision trees independently. Each tree produces an individual result, aggregated (by averaging or majority voting) to produce a final, more accurate and robust prediction. . . . .</i>	13
2.4	<i>Architecture of the AdaBoost Algorithm: The diagram illustrates how AdaBoost sequentially trains multiple weak learners (e.g., decision stumps) using a weighted dataset. The process starts with the initial dataset, and each weak learner is trained one after another. After each weak learner makes a prediction, the data is reweighted to emphasize the misclassified samples, ensuring that the next weak learner focuses on the harder cases. The predictions from all weak learners are then combined in a weighted sum to produce a final, strong prediction result. . . . .</i>	15
2.5	<i>XGBoost Prediction Process: The diagram illustrates how XGBoost uses input variables to train multiple decision trees sequentially (Tree 1, Tree 2, ..., Tree N). Each tree produces a prediction function <math>f_i(x)</math>, which is then combined using the average to generate the final prediction result. This process allows XGBoost to refine predictions, reduce errors, and improve model accuracy iteratively. . . . .</i>	16
3.1	<i>Flowchart of research methodology. . . . .</i>	17
3.2	<i>Daily Characteristics of Solar Power Plants Based on Sampling Data from September. . . . .</i>	18
3.3	<i>Signal Reconstruction of Active Power Data Using Variational Mode Decomposition (VMD) into Eight Intrinsic Mode Functions (IMFs): Each subplot represents one of the IMFs (IMF 1 to IMF 8) over time, showing the decomposition of the original signal into various frequency components. . . . .</i>	21

3.4	<i>Time Series of Active Energy (kWh) Compared with Surface Radiation Downward (ssrd) and Wind Speed Using Spearman Correlation: The top graph shows a strong positive correlation between active energy and surface radiation downward (CC: 0.838), while the bottom graph illustrates a weaker and less consistent correlation between active energy and wind speed (CC: 0.838).</i>	23
3.5	<i>Relationship Between Active Power and Weather Variables with Pearson Correlation Coefficients: (a). Surface Temperature (tsurf, CC: 0.532), (b). Surface Radiation Downward Clear Sky (ssrdc, CC: 0.746), (c). Surface Radiation Downward (ssrd, CC: 0.731), and (d). Relative Humidity (rh, CC: -0.455).</i>	24
4.1	<i>Comparison of Actual Solar Power Output with Predicted Values Using Different Models in Scenario 2: The plots show the predicted solar power output versus the actual data for the month of August 2022. (a) Model 1 - Ensemble Learning Bagging, (b) Model 2 - Ensemble Learning Stacking with Adaboost as the Meta-Model, (c) Model 3 - Ensemble Learning Stacking with Random Forest as the Meta-Model, and (d) Model 4 - Ensemble Learning Stacking with XGBoost as the Meta-Model. The figures illustrate the models' performance in capturing the daily solar power generation patterns.</i>	32
A.1	<i>Performance Metrics of Solar Power Prediction Models Using Ensemble Learning Bagging with Selected Weather Variables using Spearman Correlation for Various K-values</i>	42
A.2	K-values=7	42
A.3	K-values=8	42
A.4	K-values=14	42
A.5	<i>Performance Metrics of Solar Power Prediction Models Using Ensemble Learning Bagging with Selected Weather Variables using Pearson Correlation for Various K-values</i>	43
A.6	K-values=7	43
A.7	K-values=8	43
A.8	K-values=14	43
A.9	<i>Performance Metrics of Solar Power Prediction Models Using Ensemble Learning Stacking:Adaboost as meta-model with Selected Weather Variables Spearman Correlation for Various K-values</i>	44
A.10	K-values=7	44
A.11	K-values=8	44
A.12	K-values=14	44

---

A.13 *Performance Metrics of Solar Power Prediction Models Using Ensemble Learning Stacking: Adaboost as meta-model with Selected Variables and Pearson Correlation for Various K-values* . . . . . 46

A.14 K-values=7 . . . . . 46

A.15 K-values=8 . . . . . 46

A.16 K-values=14 . . . . . 46