LIST OF FIGURES

2.1	Ensemble learning architecture using Bagging to generate final predictions by averaging the outputs of Random Forest, AdaBoost, and XGBoost models.	11
2.2	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	12
	prediction	13
2.4	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	15
		10
3.1 3.2	Flowchart of research methodology	17
	September	18
3.3	Signal Reconstruction of Active Power Data Using Variational Mode Decomposit (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	ion
	the original signal into various frequency components	21

3.4	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)
3.5	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).
4.1	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
A.1	Performance Metrics of Solar Power Prediction Models Using Ensemble Learning Bagging with Selected Weather Variables using Spearman Correlation for Various K-values
A.2	K-values=7
A.3	K-values=8
A.4	K-values=14
A.5	Performance Metrics of Solar Power Prediction Models Using Ensemble
	Learning Bagging with Selected Weather Variables using Pearson Correlation
A 6	for Various K-values
A.6 A.7	K-values=7
A.7 A.8	K-values=0
A.9	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
A.10) K-values=7
A.1	1 K-values=8
A 1	2 K-values=14

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
∆ 16 K-values—14	46