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| **Algorithm Name** | **Algorithm Category** | **Advantages** | **Disadvantages** | **References** |
| Artificial Neural Network (ANN) | Supervised Learning | - Can handle non-linear relationships  - High prediction accuracy | - Long training time  - Requires a large amount of training data | [1], [2], [3], [4], [5] |
| Support Vector Machine (SVM) | Supervised Learning | - Can handle high-dimensional data  - Strong robustness against noise and outliers | - Sensitive to parameter selection  - Long training time | [6], [7], [8], [9] |
| Decision Tree (DT) | Supervised Learning | - Easy to understand and interpret | - Prone to overfitting - Sensitive to noise | [10], [11] |
| Random Forest (RF) | Ensemble Learning | - High prediction accuracy  - Strong robustness against noise and outliers | - Long training time  - Complex model | [3], [12], [13], [14] |
| XGBoost | Ensemble Learning | - High prediction accuracy  - Fast training speed | - Complex model - Sensitive to parameter selection | [3], [8], [15] |
| Convolutional Neural Network (CNN) | Deep Learning | - Excels at extracting spatial features from data  - Suitable for image, video, etc. | - Long training time  - Requires a large amount of training data | [11], [16] |
| Long Short-Term Memory (LSTM) | Deep Learning | - Excels at handling time series data  - Can predict solar power generation for future periods | - Long training time  - Complex model | [10], [11], [14], [16] |

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