Solar-Net: Leveraging Transformers for Enhanced Solar Power Prediction

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When Dataset is Splitted into 80:20 Ratio

Step 1: Import Libraries

In [ ]:
```
# Import necessary libraries
import numpy as np
import pandas as pd
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
import plotly.graph_objects as go
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegresso
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_erro
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.models import Model,Sequential
from tensorflow.keras.layers import Input, LSTM, Dense, Dropout, LayerNormal
from sklearn.preprocessing import MinMaxScaler
from keras_tuner import HyperModel, RandomSearch
from scikeras.wrappers import KerasRegressor
from scipy import stats

# Set random seed for reproducibility
np.random.seed(42)
tf.random.set_seed(42)

import warnings
warnings.filterwarnings('ignore')
```

Step 2: Load and Explore the Data

Dataset Link: https://www.kaggle.com/datasets/stucom/solar-energy-power-generation-dataset

In [ ]:
```
# Load the dataset
data = pd.read_csv('solar_power_data.csv')
```

In [ ]:
```
# Display the First Few Attributes
data.head(10)
```

Out[ ]:

	temperature_2_m_above_gnd	relative_humidity_2_m_above_gnd	mean_sea_l
0	2.17	31	
1	2.31	27	
2	3.65	33	
3	5.82	30	
4	7.73	27	
5	8.69	29	
6	9.72	27	
7	10.07	28	
8	9.38	32	
9	6.54	47	

10 rows × 21 columns

Here's the description of the columns of Solar Power Generation Dataset:

Column	Description
`temperature_2_m_above_gnd`	Air temperature at 2 meters above ground level (°C or °F), affecting solar panel efficiency.
`relative_humidity_2_m_above_gnd`	Relative humidity percentage at 2 meters above ground level, indicating moisture in the air.
`mean_sea_level_pressure_MSL`	Average atmospheric pressure at mean sea level (hPa or mmHg), influencing weather conditions.
`total_precipitation_sfc`	Total precipitation at the surface (mm), which can reduce solar radiation reaching panels.
`snowfall_amount_sfc`	Amount of snowfall at the surface (mm), potentially covering solar panels and decreasing output.
`total_cloud_cover_sfc`	Total cloud cover at the surface (tenths), indicating sky obscurity affecting solar radiation.
`high_cloud_cover_high_cld_lay`	Amount of high-altitude cloud cover (tenths), affecting solar radiation differently.
`medium_cloud_cover_mid_cld_lay`	Amount of mid-altitude cloud cover (tenths), influencing solar radiation levels.
`low_cloud_cover_low_cld_lay`	Amount of low-altitude cloud cover (tenths), impacting solar generation.

Column	Description
`shortwave_radiation_backwards_sfc`	Amount of shortwave radiation reflected back from the surface (W/m^2), useful for energy absorption.
`wind_speed_10_m_above_gnd`	Wind speed at 10 meters above ground level (m/s), influencing cooling and solar efficiency.
`wind_direction_10_m_above_gnd`	Wind direction at 10 meters above ground level (degrees), indicating prevailing winds.
`wind_speed_80_m_above_gnd`	Wind speed at 80 meters above ground level, relevant for understanding high-altitude conditions.
`wind_direction_80_m_above_gnd`	Wind direction at 80 meters above ground level (degrees), providing data on higher-altitude winds.
`wind_speed_900_mb`	Wind speed at a pressure level of 900 mb, typically around 800-1000 meters above ground.
`wind_direction_900_mb`	Wind direction at a pressure level of 900 mb (degrees), affecting weather patterns and radiation.
`wind_gust_10_m_above_gnd`	Maximum wind gusts at 10 meters above ground level (m/s), impacting solar panel structures.
`angle_of_incidence`	Angle at which sunlight strikes the solar panels (degrees), affecting energy capture.
`zenith`	Angle between the sun and the vertical (degrees), important for solar energy availability.
`azimuth`	Angle of the sun's position relative to true north (degrees), helping determine panel orientation.
`generated_power_kw`	Electrical power generated by the solar panels (kW), the primary output of interest in the dataset.

In [ ]:
```
# Display basic information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4213 entries, 0 to 4212
Data columns (total 21 columns):
 #   Column                             Non-Null Count  Dtype  
---  ------                             --------------  -----  
 0   temperature_2_m_above_gnd          4213 non-null   float64
 1   relative_humidity_2_m_above_gnd    4213 non-null   int64  
 2   mean_sea_level_pressure_MSL        4213 non-null   float64
 3   total_precipitation_sfc            4213 non-null   float64
 4   snowfall_amount_sfc                4213 non-null   float64
 5   total_cloud_cover_sfc              4213 non-null   float64
 6   high_cloud_cover_high_cld_lay      4213 non-null   int64  
 7   medium_cloud_cover_mid_cld_lay     4213 non-null   int64  
 8   low_cloud_cover_low_cld_lay        4213 non-null   int64  
 9   shortwave_radiation_backwards_sfc  4213 non-null   float64
 10  wind_speed_10_m_above_gnd          4213 non-null   float64
 11  wind_direction_10_m_above_gnd      4213 non-null   float64
 12  wind_speed_80_m_above_gnd          4213 non-null   float64
 13  wind_direction_80_m_above_gnd      4213 non-null   float64
 14  wind_speed_900_mb                  4213 non-null   float64
 15  wind_direction_900_mb              4213 non-null   float64
 16  wind_gust_10_m_above_gnd           4213 non-null   float64
 17  angle_of_incidence                 4213 non-null   float64
 18  zenith                             4213 non-null   float64
 19  azimuth                            4213 non-null   float64
 20  generated_power_kw                 4213 non-null   float64
dtypes: float64(17), int64(4)
memory usage: 691.3 KB
```

In [ ]:
```python
# Basic Description of Dataset
data.describe()
```

Out[ ]:

	temperature_2_m_above_gnd	relative_humidity_2_m_above_gnd	mean_s
count	4213.000000	4213.000000	
mean	15.068111	51.361025	
std	8.853677	23.525864	
min	-5.350000	7.000000	
25%	8.390000	32.000000	
50%	14.750000	48.000000	
75%	21.290000	70.000000	
max	34.900000	100.000000	

8 rows × 21 columns

In [ ]:
```python
# Check for the Null Values Column Wise
print(data.isnull().sum())
```

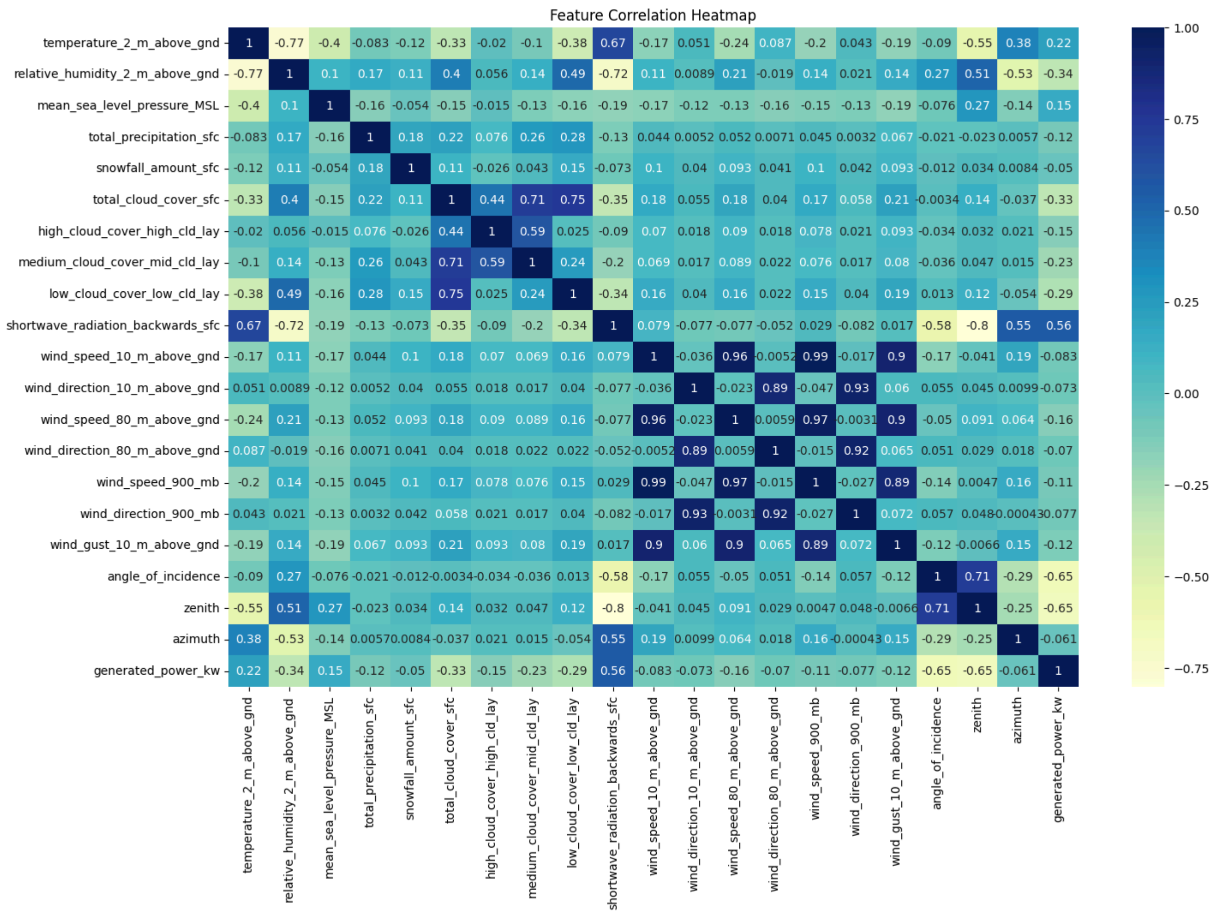
```
temperature_2_m_above_gnd            0
relative_humidity_2_m_above_gnd      0
mean_sea_level_pressure_MSL          0
total_precipitation_sfc              0
snowfall_amount_sfc                  0
total_cloud_cover_sfc                0
high_cloud_cover_high_cld_lay        0
medium_cloud_cover_mid_cld_lay       0
low_cloud_cover_low_cld_lay          0
shortwave_radiation_backwards_sfc    0
wind_speed_10_m_above_gnd            0
wind_direction_10_m_above_gnd        0
wind_speed_80_m_above_gnd            0
wind_direction_80_m_above_gnd        0
wind_speed_900_mb                    0
wind_direction_900_mb                0
wind_gust_10_m_above_gnd             0
angle_of_incidence                   0
zenith                               0
azimuth                              0
generated_power_kw                   0
dtype: int64
```

In [ ]:

```
# Check for missing values
if data.isnull().sum().any():
    data = data.fillna(data.mean())  # Simple imputation for missing values
```

In [ ]:

```
# Target and feature correlation heatmap
plt.figure(figsize=(16, 10))
sns.heatmap(data.corr(), annot = True, cmap="YlGnBu")
plt.title("Feature Correlation Heatmap")
plt.show()
```

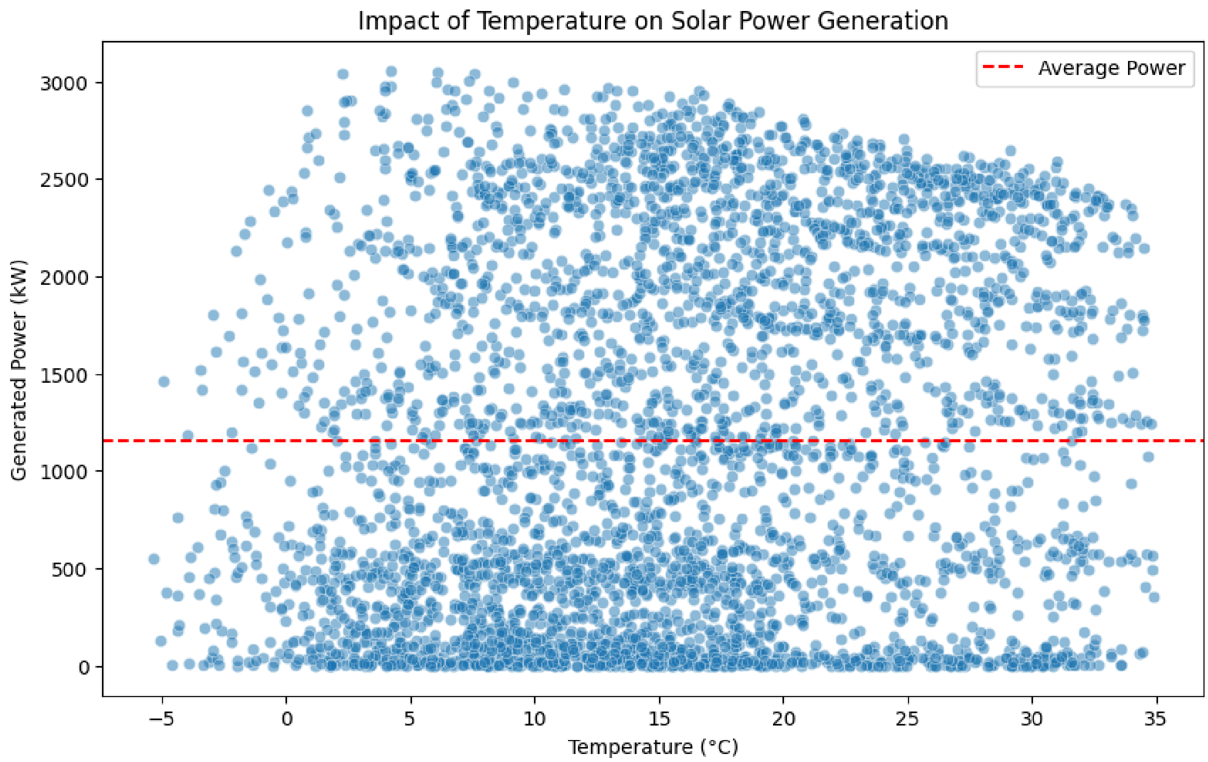


Step 3: Data Preprocessing & Exploratory Data Analysis (EDA)

Remove Outliers

In [ ]:
```python
# Detect and remove outliers using Z-score
z_scores = np.abs(stats.zscore(data.select_dtypes(include=[np.number])))
filtered_entries = (z_scores < 3).all(axis=1)
data = data[filtered_entries]
```

In [ ]:
```python
# Scatter plot for Solar Power Genrated vs Temperature
plt.figure(figsize=(10, 6))
sns.scatterplot(data=data, x='temperature_2_m_above_gnd', y='generated_power
plt.title('Impact of Temperature on Solar Power Generation')
plt.xlabel('Temperature (°C)')
plt.ylabel('Generated Power (kW)')
plt.axhline(y=data['generated_power_kw'].mean(), color='r', linestyle='--',
plt.legend()
plt.show()
```



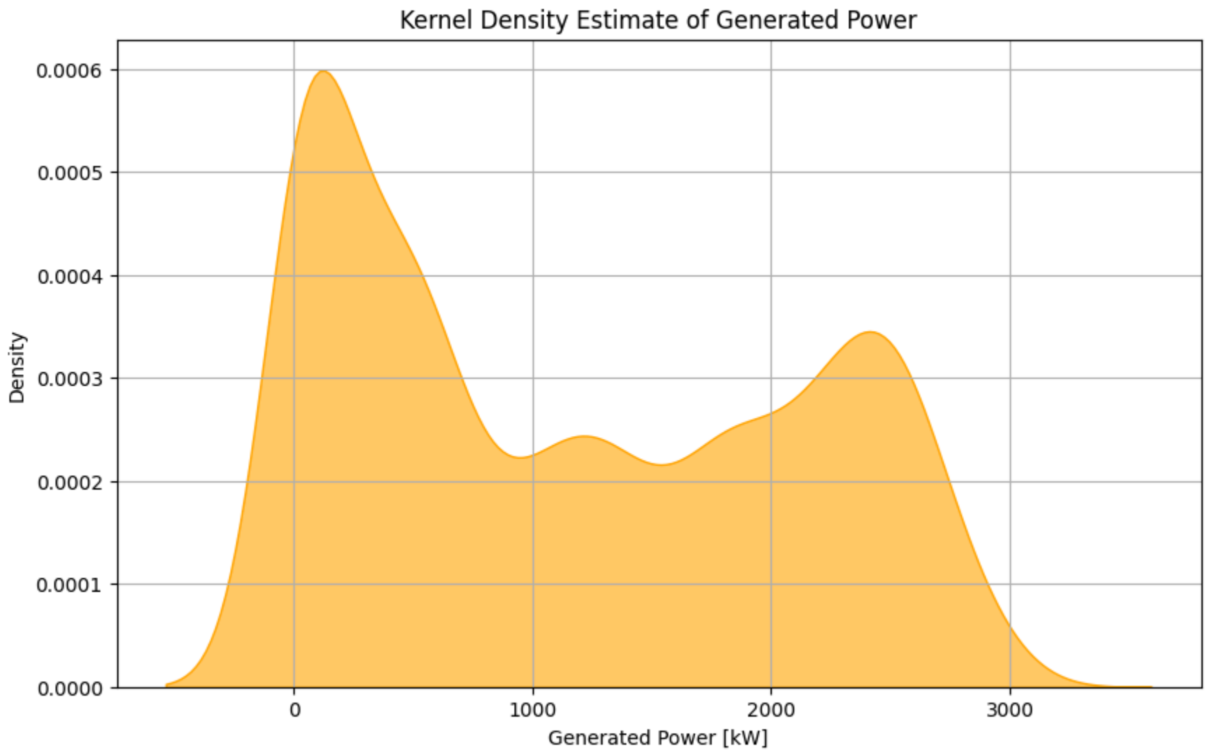
In [ ]:
```python
# Create a figure with a histogram
fig = px.histogram(data_frame=data, x='generated_power_kw', nbins=20,
                   title='Frequency of Solar Power Generation Values',
                   labels={'generated_power_kw': 'Generated Power [kW]',
                           'count': 'Frequency'},
                   template='plotly_dark')
fig.update_xaxes(title_text='Generated Power [kW]')
fig.update_yaxes(title_text='Frequency')
fig.update_layout(width=800, height=500, margin=dict(l=50, r=20, t=50, b=50)
fig.update_traces(histnorm='probability density', marker=dict(color='green')
fig.show()
```

In [ ]:
```python
fig = px.scatter(data, x='shortwave_radiation_backwards_sfc', y='generated_p
                 title='Shortwave Radiation vs. Generated Power',
                 labels={'shortwave_radiation_backwards_sfc': 'Shortwave Rad
                         'generated_power_kw': 'Generated Power [kW]'},
                 template='plotly_dark')
fig.update_traces(marker=dict(size=5, opacity=0.6))
fig.update_layout(width=800, height=500)
fig.show()
```

In [ ]:
```python
fig = px.scatter(data, x='temperature_2_m_above_gnd', y='generated_power_kw'
                 color='total_cloud_cover_sfc',
                 title='Generated Power by Temperature and Cloud Cover',
                 labels={'temperature_2_m_above_gnd': 'Temperature [°C]',
                         'generated_power_kw': 'Generated Power [kW]'},
                 template='plotly_dark')
fig.update_traces(marker=dict(size=5, opacity=0.6))
fig.update_layout(width=800, height=500)
fig.show()
```

In [ ]:

```
plt.figure(figsize=(10, 6))
sns.kdeplot(data['generated_power_kw'], fill=True, color='orange', alpha=0.6
plt.title('Kernel Density Estimate of Generated Power')
plt.xlabel('Generated Power [kW]')
plt.ylabel('Density')
plt.grid()
plt.show()
```



In [ ]:

```
# Assuming wind_direction is in degrees
fig = px.scatter_polar(data, r='generated_power_kw', theta='wind_direction_1
                       title='Generated Power vs. Wind Direction',
                       labels={'wind_direction_10_m_above_gnd': 'Wind Direc
                               'generated_power_kw': 'Generated Power [kW]'
                       template='plotly_dark')
fig.update_traces(marker=dict(size=5, opacity=0.6))
fig.update_layout(width=800, height=500)
fig.show()
```

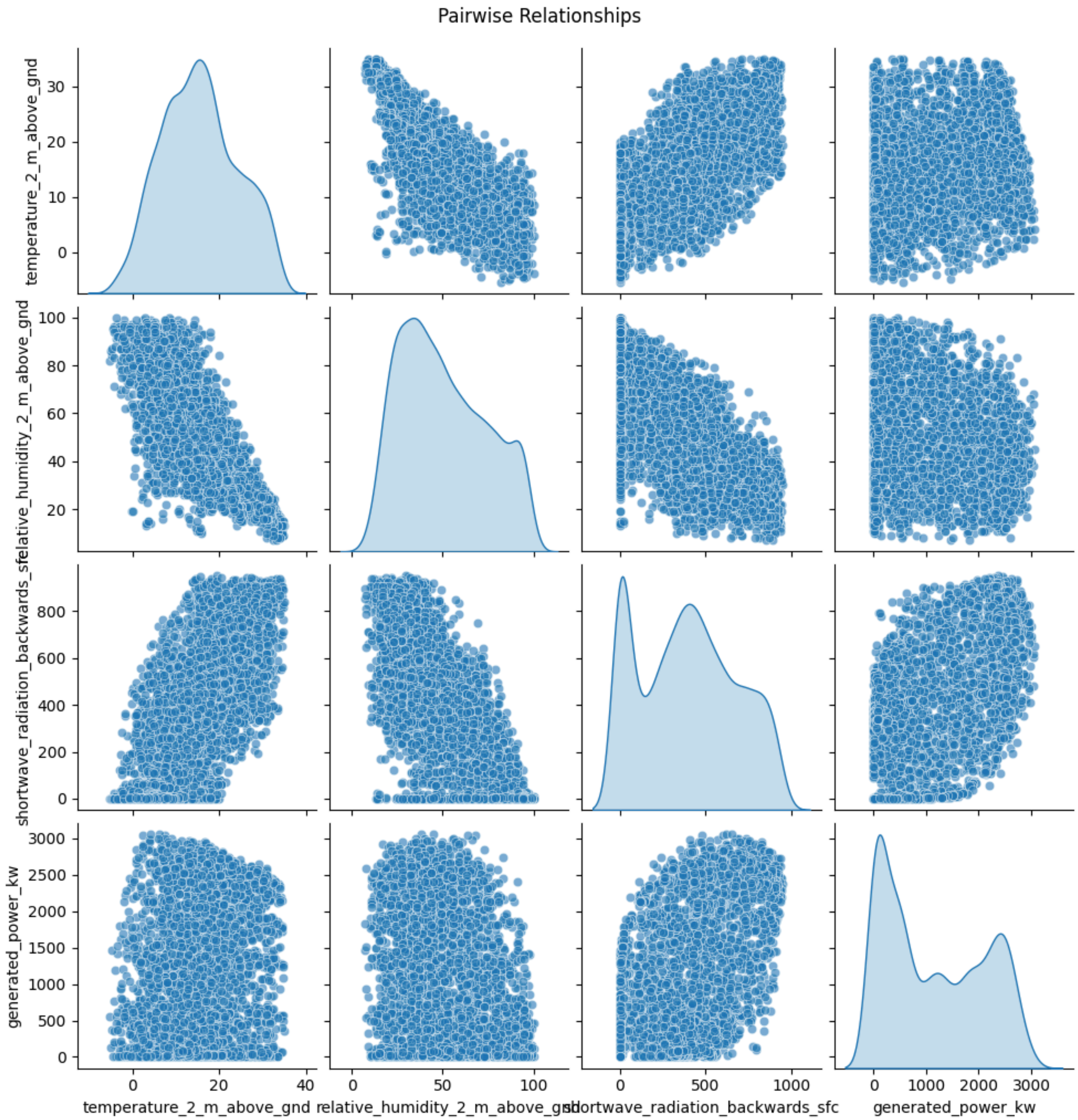
In [ ]:

```
fig = px.scatter_3d(data, x='temperature_2_m_above_gnd', y='relative_humidit
                    z='generated_power_kw', color='generated_power_kw',
                    title='3D Scatter Plot: Temperature, Humidity, and Gener
                    labels={'temperature_2_m_above_gnd': 'Temperature [°C]',
                            'relative_humidity_2_m_above_gnd': 'Relative Hum
                            'generated_power_kw': 'Generated Power [kW]'},
                    template='plotly_dark')
fig.update_traces(marker=dict(size=5, opacity=0.7))
fig.update_layout(width=800, height=600)
fig.show()
```

In [ ]:

```
# Select relevant columns for the pair plot
subset = data[['temperature_2_m_above_gnd', 'relative_humidity_2_m_above_gnd
```

```
                'shortwave_radiation_backwards_sfc', 'generated_power_kw']]

sns.pairplot(subset, diag_kind='kde', plot_kws={'alpha': 0.6})
plt.suptitle("Pairwise Relationships", y=1.02)
plt.show()
```



In [ ]:
```
# Prepare data for radar chart
summary_data = {
    'Factor': ['Temperature [°C]', 'Humidity [%]', 'Cloud Cover [tenths]', '
    'Value': [data['temperature_2_m_above_gnd'].mean(),
              data['relative_humidity_2_m_above_gnd'].mean(),
              data['total_cloud_cover_sfc'].mean(),
              data['wind_speed_10_m_above_gnd'].mean()]
}
summary_df = pd.DataFrame(summary_data)

fig = px.line_polar(summary_df, r='Value', theta='Factor', line_close=True,
                    title='Average Weather Factors Affecting Generated Powe
```

```
                     template='plotly_dark')
fig.update_traces(fill='toself')
fig.update_layout(width=800, height=500)
fig.show()
```

Visualize Data Distributions

In [ ]:

```
# Plot distributions of features and target variable
data.hist(bins=20, figsize=(20, 18), edgecolor='black')
plt.suptitle("Feature Distributions")
plt.show()
```

Step 4: Feature Engineering

Feature Creation

In [ ]:

```
#check the datatypes
data.dtypes
```

```
Out[ ]: temperature_2_m_above_gnd            float64
relative_humidity_2_m_above_gnd        int64
mean_sea_level_pressure_MSL          float64
total_precipitation_sfc              float64
snowfall_amount_sfc                  float64
total_cloud_cover_sfc                float64
high_cloud_cover_high_cld_lay          int64
medium_cloud_cover_mid_cld_lay         int64
low_cloud_cover_low_cld_lay            int64
shortwave_radiation_backwards_sfc    float64
wind_speed_10_m_above_gnd            float64
wind_direction_10_m_above_gnd        float64
wind_speed_80_m_above_gnd            float64
wind_direction_80_m_above_gnd        float64
wind_speed_900_mb                    float64
wind_direction_900_mb                float64
wind_gust_10_m_above_gnd             float64
angle_of_incidence                   float64
zenith                               float64
azimuth                              float64
generated_power_kw                   float64
dtype: object
```

Feature Scaling

```
In [ ]: # Standardize the data
scaler=StandardScaler()
for col in data.select_dtypes(include=np.number).columns:
    data[col]=scaler.fit_transform(data[[col]])
```

```
In [ ]: # Separate features and target
X = data.drop('generated_power_kw', axis=1)
y = data['generated_power_kw']
```

```
In [ ]: # Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rar
```

Step 5: Machine Model Training

Support Vector Regression (SVR)

```
In [ ]: # SVR model with hyperparameter tuning
svr = SVR(max_iter=280)
param_grid_svr = {'kernel': ['linear', 'rbf', 'poly'], 'C': [0.1, 1, 10], 'e
grid_search_svr = GridSearchCV(svr, param_grid_svr, cv=5, scoring='neg_mean_
grid_search_svr.fit(X_train, y_train)

# Best SVR model
best_svr = grid_search_svr.best_estimator_
y_pred_svr = best_svr.predict(X_test)

# Create a DataFrame to store the metrics
metrics_df = pd.DataFrame(columns=["Model", "R2 Score (%)", "Mean Squared Er
```

```
#Evalute the Support Vector Machine Model
r2_score_svr = round(r2_score(y_test,y_pred_svr) * 100, 2)
mean_sq_svr = mean_squared_error(y_test,y_pred_svr)
mean_ab_svr = mean_absolute_error(y_test,y_pred_svr)
metrics_df.loc[len(metrics_df)] = ["Support Vector Machine", r2_score_svr, m
print("R2 Score for Support Vector Machine Model: ",r2_score_svr,"%")
print("Mean Square Error of Support Vector Machine Model: ",mean_sq_svr)
print("Mean Absolute Error of Support Vector Machine Model: ",mean_ab_svr)
```

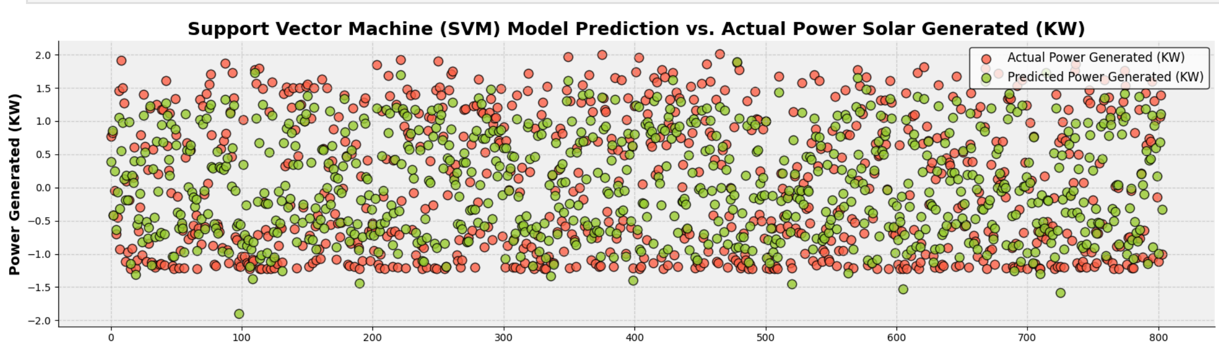
```
R2 Score for Support Vector Machine Model:  74.77 %
Mean Square Error of Support Vector Machine Model:  0.26052699614422364
Mean Absolute Error of Support Vector Machine Model:  0.406757259232767
```

In [ ]:

```
# Create traces for Actual and Predicted values for Support Vector Machine (
actual_trace = go.Scatter(x=list(range(100)), y=y_test.values[:100], mode='l
predicted_trace = go.Scatter(x=list(range(100)), y=y_pred_svr[:100], mode='l
# Create layout
layout = go.Layout(
    title='Actual vs Predicted Values for Support Vector Machine (SVM)',
    xaxis=dict(title='Frequency Days'),
    yaxis=dict(title='Generated Power (KW)'),
    legend=dict(x=0, y=1),
    hovermode='closest')
# Create figure
fig = go.Figure(data=[actual_trace, predicted_trace], layout=layout)
# Show the plot
fig.show()
```

In [ ]:

```
# Scatter plot for actual and predicted data for Support Vector Machine (SVM
plt.figure(figsize=(17, 5))
array = np.arange(len(y_test))
plt.scatter(array, y_test, color='#FF6347', label='Actual Power Generated (K
plt.scatter(array, y_pred_svr, color='#9ACD32', label='Predicted Power Gener
plt.title('Support Vector Machine (SVM) Model Prediction vs. Actual Power Sc
plt.xlabel('Predictions', fontsize=14, fontweight='bold')
plt.ylabel('Power Generated (KW)', fontsize=14, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.5)
legend = plt.legend(loc='upper right', fontsize=12, fancybox=True, framealph
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().set_facecolor('#F0F0F0')
plt.tight_layout()
plt.show()
```



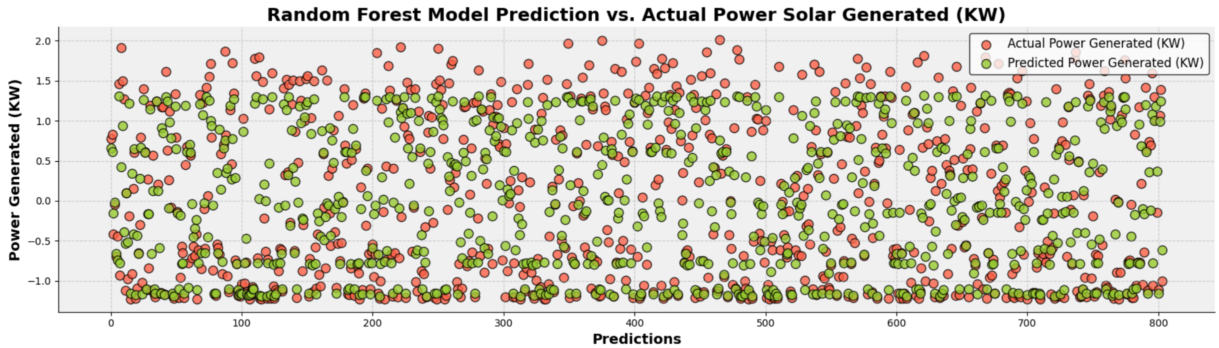
Random Forest Regression

In [ ]:
```
# Random Forest model with hyperparameter tuning
rf = RandomForestRegressor(max_depth = 5,random_state=42)
param_grid_rf = {'n_estimators': [50, 100, 200], 'min_samples_split': [2, 5,
grid_search_rf = GridSearchCV(rf, param_grid_rf, cv=5, scoring='neg_mean_squ
grid_search_rf.fit(X_train, y_train)

# Best Random Forest model
best_rf = grid_search_rf.best_estimator_
y_pred_rf = best_rf.predict(X_test)

#Evalute the Random Forest Model
r2_score_rf = round(r2_score(y_test,y_pred_rf) * 100, 2)
mean_sq_rf = mean_squared_error(y_test,y_pred_rf)
mean_ab_rf = mean_absolute_error(y_test,y_pred_rf)
metrics_df.loc[len(metrics_df)] = ["Random Forest", r2_score_rf, mean_sq_rf,
print("R2 Score for Random Forest Model: ",r2_score_rf,"%")
print("Mean Square Error of Random Forest Model: ",mean_sq_rf)
print("Mean Absolute Error of Random Forest Model: ",mean_ab_rf)
```

```
R2 Score for Random Forest Model:  77.65 %
Mean Square Error of Random Forest Model:  0.23074408344443378
Mean Absolute Error of Random Forest Model:  0.32603066566352806
```

In [ ]:
```
# Create traces for Actual and Predicted values for Random Forest
actual_trace = go.Scatter(x=list(range(100)), y=y_test.values[:100], mode='l
predicted_trace = go.Scatter(x=list(range(100)), y=y_pred_rf[:100], mode='li
# Create layout
layout = go.Layout(
    title='Actual vs Predicted Values for Random Forest',
    xaxis=dict(title='Frequency Days'),
    yaxis=dict(title='Generated Power (KW)'),
    legend=dict(x=0, y=1),
    hovermode='closest')
# Create figure
fig = go.Figure(data=[actual_trace, predicted_trace], layout=layout)
# Show the plot
fig.show()
```

In [ ]:
```
# Scatter plot for actual and predicted data for Random Forest
plt.figure(figsize=(17, 5))
array = np.arange(len(y_test))
plt.scatter(array, y_test, color='#FF6347', label='Actual Power Generated (K
plt.scatter(array, y_pred_rf, color='#9ACD32', label='Predicted Power Genera
plt.title('Random Forest Model Prediction vs. Actual Power Solar Generated (
plt.xlabel('Predictions', fontsize=14, fontweight='bold')
plt.ylabel('Power Generated (KW)', fontsize=14, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.5)
legend = plt.legend(loc='upper right', fontsize=12, fancybox=True, framealph
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().set_facecolor('#F0F0F0')
plt.tight_layout()
plt.show()
```



Gradient Boosting Machine (GBM)

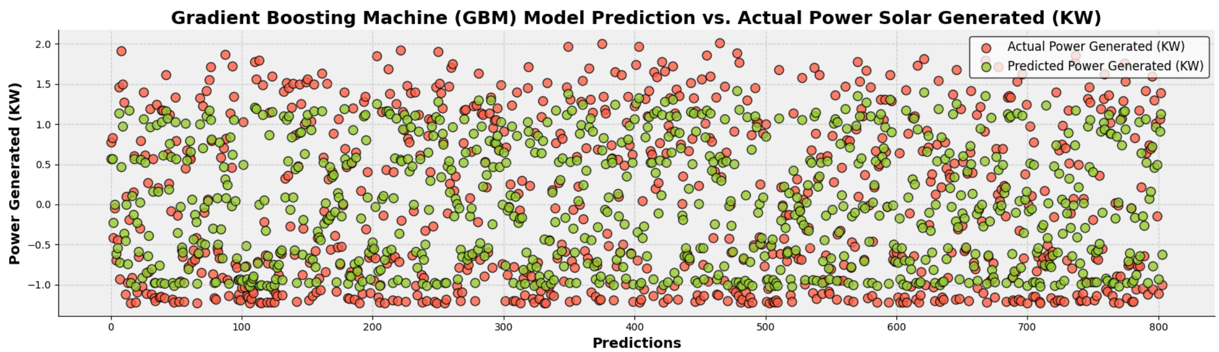
In [ ]:
```
# Gradient Boosting model with hyperparameter tuning
gbm = GradientBoostingRegressor(n_estimators = 8,random_state=42)
param_grid_gbm = {'learning_rate': [0.01, 0.1, 0.2], 'max_depth': [3, 5, 7]}
grid_search_gbm = GridSearchCV(gbm, param_grid_gbm, cv=5, scoring='neg_mean_
grid_search_gbm.fit(X_train, y_train)

# Best GBM model
best_gbm = grid_search_gbm.best_estimator_
y_pred_gbm = best_gbm.predict(X_test)

#Evalute the Gradient Boosting Model
r2_score_gbm = round(r2_score(y_test,y_pred_gbm) * 100, 2)
mean_sq_gbm = mean_squared_error(y_test,y_pred_gbm)
mean_ab_gbm = mean_absolute_error(y_test,y_pred_gbm)
metrics_df.loc[len(metrics_df)] = ["Gradient Boosting", r2_score_gbm, mean_s
print("R2 Score for Gradient Boosting Model: ",r2_score_gbm,"%")
print("Mean Square Error of Gradient Boosting Model: ",mean_sq_gbm)
print("Mean Absolute Error of Gradient Boosting Model: ",mean_ab_gbm)
```

```
R2 Score for Gradient Boosting Model:  76.79 %
Mean Square Error of Gradient Boosting Model:  0.23963099462335988
Mean Absolute Error of Gradient Boosting Model:  0.3644358121616285
```

In [ ]:
```
# Create traces for Actual and Predicted values for Gradient Boosting Machin
actual_trace = go.Scatter(x=list(range(100)), y=y_test.values[:100], mode='l
predicted_trace = go.Scatter(x=list(range(100)), y=y_pred_gbm[:100], mode='l
# Create layout
layout = go.Layout(
    title='Actual vs Predicted Values for Gradient Boosting Machine (GBM)',
    xaxis=dict(title='Frequency Days'),
    yaxis=dict(title='Generated Power (KW)'),
    legend=dict(x=0, y=1),
    hovermode='closest')
# Create figure
fig = go.Figure(data=[actual_trace, predicted_trace], layout=layout)
# Show the plot
fig.show()
```

In [ ]:
```
# Scatter plot for actual and predicted data for Gradient Boosting Machine (
plt.figure(figsize=(17, 5))
array = np.arange(len(y_test))
plt.scatter(array, y_test, color='#FF6347', label='Actual Power Generated (K
```

```
plt.scatter(array, y_pred_gbm, color='#9ACD32', label='Predicted Power Gener
plt.title('Gradient Boosting Machine (GBM) Model Prediction vs. Actual Power
plt.xlabel('Predictions', fontsize=14, fontweight='bold')
plt.ylabel('Power Generated (KW)', fontsize=14, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.5)
legend = plt.legend(loc='upper right', fontsize=12, fancybox=True, framealph
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().set_facecolor('#F0F0F0')
plt.tight_layout()
plt.show()
```



Step 6: Deep Learning Models

LSTM for Time Series

In [ ]:
```
# Reshape data for LSTM (samples, timesteps, features)
timesteps = 1

# Reshape data for LSTM input
x_train_lstm = X_train.values.reshape((X_train.shape[0], timesteps, X_train.
x_test_lstm = X_test.values.reshape((X_test.shape[0], timesteps, X_test.shap

# Scale the target variable to a range between 0 and 1
scaler_y = MinMaxScaler()  # Initialize the scaler
y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1, 1))
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1, 1))
```

In [ ]:
```
# Build the LSTM model
model = Sequential()  # Initialize a sequential model
# Add the first LSTM layer with 100 units and return sequences for the next
model.add(LSTM(units=50, return_sequences=True, input_shape=(x_train_lstm.sh
# Add the second LSTM layer without returning sequences
model.add(LSTM(units=50))
# Add a Dropout layer to reduce overfitting
model.add(Dropout(rate=0.2))
# Add a Dense layer with a single output unit for regression
model.add(Dense(units=1))

# Compile the model with Adam optimizer and mean squared error loss functior
model.compile(optimizer='adam', loss='mean_squared_error')
```

In [ ]:

```
# Train the model on the training data
model.fit(x_train_lstm, y_train_scaled, epochs=50, batch_size=128)
```

```
Epoch 1/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.2111
Epoch 2/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0830
Epoch 3/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0336
Epoch 4/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0285
Epoch 5/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0262
Epoch 6/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0252
Epoch 7/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0249
Epoch 8/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0241
Epoch 9/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0232
Epoch 10/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0232
Epoch 11/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0233
Epoch 12/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0223
Epoch 13/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0223
Epoch 14/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0223
Epoch 15/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0215
Epoch 16/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0214
Epoch 17/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0219
Epoch 18/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0210
Epoch 19/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0211
Epoch 20/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0212
Epoch 21/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0209
Epoch 22/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0205
Epoch 23/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0201
Epoch 24/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0200
Epoch 25/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0197
Epoch 26/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0201
Epoch 27/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0198
Epoch 28/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0198
```

```
Epoch 29/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0196
Epoch 30/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0196
Epoch 31/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0189
Epoch 32/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0189
Epoch 33/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0189
Epoch 34/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0186
Epoch 35/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0184
Epoch 36/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0185
Epoch 37/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0180
Epoch 38/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0180
Epoch 39/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0179
Epoch 40/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0179
Epoch 41/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0175
Epoch 42/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0177
Epoch 43/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0175
Epoch 44/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0177
Epoch 45/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0173
Epoch 46/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0170
Epoch 47/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0170
Epoch 48/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0171
Epoch 49/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0170
Epoch 50/50
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step - loss: 0.0169
```

Out[ ]: <keras.src.callbacks.history.History at 0x1de97771940>

In [ ]:

```
# Make predictions on the test data
y_pred_lstm_scaled = model.predict(x_test_lstm)
y_pred_lstm = scaler_y.inverse_transform(y_pred_lstm_scaled)
```

```
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 10ms/step
```

In [ ]:

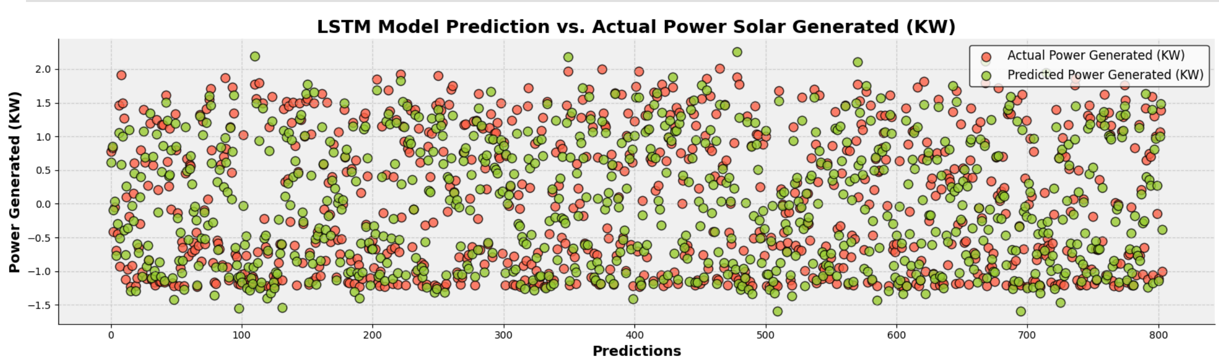
```
#Evalute the LSTM model's performance
r2_score_lstm = round(r2_score(y_test,y_pred_lstm) * 100, 2)
mean_sq_lstm = mean_squared_error(y_test,y_pred_lstm)
mean_ab_lstm = mean_absolute_error(y_test,y_pred_lstm)
```

```
metrics_df.loc[len(metrics_df)] = ["LSTM", r2_score_lstm, mean_sq_lstm, mear
print("R2 Score for LSTM Model: ",r2_score_lstm,"%")
print("Mean Square Error of LSTM Model: ",mean_sq_lstm)
print("Mean Absolute Error of LSTM Model: ",mean_ab_lstm)
```

```
R2 Score for LSTM Model:  80.24 %
Mean Square Error of LSTM Model:  0.20402779226884776
Mean Absolute Error of LSTM Model:  0.312377688764255
```

In [ ]:
```
# Create traces for Actual and Predicted values for CNN model
actual_trace = go.Scatter(x=list(range(100)), y=y_test.values[:100], mode='l
predicted_trace = go.Scatter(x=list(range(100)), y=y_pred_lstm[:100].flatter
# Create layout
layout = go.Layout(
    title='Actual vs Predicted Values for LSTM model',
    xaxis=dict(title='Frequency Days'),
    yaxis=dict(title='Generated Power (KW)'),
    legend=dict(x=0, y=1),
    hovermode='closest')
# Create figure
fig = go.Figure(data=[actual_trace, predicted_trace], layout=layout)
# Show the plot
fig.show()
```

In [ ]:
```
# Scatter plot for actual and predicted data for LSTM model
plt.figure(figsize=(17, 5))
array = np.arange(len(y_test))
plt.scatter(array, y_test, color='#FF6347', label='Actual Power Generated (K
plt.scatter(array, y_pred_lstm, color='#9ACD32', label='Predicted Power Gene
plt.title('LSTM Model Prediction vs. Actual Power Solar Generated (KW)', for
plt.xlabel('Predictions', fontsize=14, fontweight='bold')
plt.ylabel('Power Generated (KW)', fontsize=14, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.5)
legend = plt.legend(loc='upper right', fontsize=12, fancybox=True, framealph
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().set_facecolor('#F0F0F0')
plt.tight_layout()
plt.show()
```



Transformer Model (Solar-Net)

In [ ]:
```
# Reshape data for transformer
timesteps = 1
```

```
x_train_trans = X_train.values.reshape((X_train.shape[0], timesteps, X_train
x_test_trans = X_test.values.reshape((X_test.shape[0], timesteps, X_test.sha

# Scale the target variable
scaler_y = MinMaxScaler()
y_train_scaled = scaler_y.fit_transform(y_train.values.reshape(-1, 1))
y_test_scaled = scaler_y.transform(y_test.values.reshape(-1, 1))
```

In [ ]:
```
# Define the Transformer Model (Solar-Net) HyperModel
class TransformerHyperModel(HyperModel):
    def build(self, hp):
        inputs = Input(shape=(x_train_trans.shape[1], x_train_trans.shape[2]

        # Hyperparameters
        num_heads = hp.Int('num_heads', min_value=2, max_value=8, step=2)
        ff_dim = hp.Int('ff_dim', min_value=16, max_value=128, step=16)
        dropout_rate = hp.Float('dropout_rate', 0.1, 0.5, step=0.1)

        # Build transformer block
        x = self.transformer_block(inputs, num_heads, ff_dim, dropout_rate)
        x = GlobalAveragePooling1D()(x)
        x = Dropout(0.3)(x)
        outputs = Dense(1)(x)

        model = Model(inputs, outputs)
        model.compile(optimizer='adam', loss='mean_squared_error', metrics=[
        return model

    def transformer_block(self, inputs, num_heads, ff_dim, dropout):
        # Multi-head attention layer
        attention_output = MultiHeadAttention(num_heads=num_heads, key_dim=i
        attention_output = Dropout(dropout)(attention_output)
        out1 = LayerNormalization(epsilon=1e-6)(inputs + attention_output)

        # Feed-forward network
        ffn_output = Dense(ff_dim, activation='relu')(out1)
        ffn_output = Dropout(dropout)(ffn_output)

        # Ensure dimensions match for addition
        if out1.shape[-1] != ffn_output.shape[-1]:
            ffn_output = Dense(out1.shape[-1])(ffn_output)

        return LayerNormalization(epsilon=1e-6)(out1 + ffn_output)
```

In [ ]:
```
# Create the tuner
tuner = RandomSearch(
    TransformerHyperModel(),
    objective='val_mae',
    max_trials=10,
    executions_per_trial=1,
    directory='my_dir',
    project_name='transformer_tuning'
)
```

```
Reloading Tuner from my_dir\transformer_tuning\tuner0.json
```

In [ ]:
```
# Split the training data for validation
x_train_split, x_val_split = x_train_trans[:int(len(x_train_trans)*0.8)], x_
y_train_split, y_val_split = y_train_scaled[:int(len(y_train_scaled)*0.8)],
```

In [ ]:
```
# Start the tuning process
tuner.search(x_train_split, y_train_split, epochs=100, validation_data=(x_va

# Get the best model and hyperparameters
best_model = tuner.get_best_models(num_models=1)[0]
best_hyperparameters = tuner.get_best_hyperparameters(num_trials=1)[0]

# Train the best model on the full training data
best_model.fit(x_train_trans, y_train_scaled, epochs=100, batch_size=32)
```

```
WARNING:tensorflow:From d:\new\assignment_left\Thesis Sept - Dec\Solar Power
\Code Implementation\env\Lib\site-packages\keras\src\backend\common\global_s
tate.py:82: The name tf.reset_default_graph is deprecated. Please use tf.com
pat.v1.reset_default_graph instead.

Epoch 1/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - loss: 0.0211 - mae: 0.1090
Epoch 2/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0215 - mae: 0.1084
Epoch 3/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0209 - mae: 0.1063
Epoch 4/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0206 - mae: 0.1061
Epoch 5/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0214 - mae: 0.1081
Epoch 6/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0206 - mae: 0.1053
Epoch 7/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0208 - mae: 0.1057
Epoch 8/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0200 - mae: 0.1041
Epoch 9/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0203 - mae: 0.1043
Epoch 10/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0200 - mae: 0.1048
Epoch 11/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0204 - mae: 0.1036
Epoch 12/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0199 - mae: 0.1032
Epoch 13/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0194 - mae: 0.1023
Epoch 14/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0201 - mae: 0.1034
Epoch 15/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0196 - mae: 0.1005
Epoch 16/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0198 - mae: 0.1021
Epoch 17/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0193 - mae: 0.1016
Epoch 18/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0195 - mae: 0.1020
Epoch 19/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0193 - mae: 0.1019
Epoch 20/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0195 - mae: 0.1021
Epoch 21/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0194 - mae: 0.1010
Epoch 22/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0191 - mae: 0.1014
Epoch 23/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0190 - mae: 0.1007
Epoch 24/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0192 - mae: 0.1007
Epoch 25/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0187 - mae: 0.0997
Epoch 26/100
```

```
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0189 - mae: 0.0996
Epoch 27/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0189 - mae: 0.0996
Epoch 28/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0188 - mae: 0.0995
Epoch 29/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0183 - mae: 0.0981
Epoch 30/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0190 - mae: 0.1015
Epoch 31/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0191 - mae: 0.1010
Epoch 32/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0180 - mae: 0.0976
Epoch 33/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0182 - mae: 0.0992
Epoch 34/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0184 - mae: 0.0975
Epoch 35/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0186 - mae: 0.0994
Epoch 36/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0186 - mae: 0.0998
Epoch 37/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0190 - mae: 0.1000
Epoch 38/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0183 - mae: 0.0990
Epoch 39/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0189 - mae: 0.0989
Epoch 40/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0178 - mae: 0.0972
Epoch 41/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0178 - mae: 0.0971
Epoch 42/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0178 - mae: 0.0965
Epoch 43/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0181 - mae: 0.0980
Epoch 44/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0180 - mae: 0.0964
Epoch 45/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0179 - mae: 0.0970
Epoch 46/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0179 - mae: 0.0983
Epoch 47/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0176 - mae: 0.0963
Epoch 48/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0179 - mae: 0.0976
Epoch 49/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0175 - mae: 0.0956
Epoch 50/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0178 - mae: 0.0972
Epoch 51/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0171 - mae: 0.0960
Epoch 52/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0173 - mae: 0.0955
Epoch 53/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0177 - mae: 0.0958
Epoch 54/100
```

```
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0175 - mae: 0.0959
Epoch 55/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0170 - mae: 0.0949
Epoch 56/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0167 - mae: 0.0942
Epoch 57/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0170 - mae: 0.0948
Epoch 58/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0171 - mae: 0.0959
Epoch 59/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0168 - mae: 0.0953
Epoch 60/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0172 - mae: 0.0959
Epoch 61/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0161 - mae: 0.0931
Epoch 62/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0169 - mae: 0.0950
Epoch 63/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0168 - mae: 0.0941
Epoch 64/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0170 - mae: 0.0939
Epoch 65/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0161 - mae: 0.0928
Epoch 66/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0165 - mae: 0.0944
Epoch 67/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0170 - mae: 0.0956
Epoch 68/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0165 - mae: 0.0945
Epoch 69/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0162 - mae: 0.0935
Epoch 70/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0162 - mae: 0.0932
Epoch 71/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0162 - mae: 0.0937
Epoch 72/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0167 - mae: 0.0942
Epoch 73/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0166 - mae: 0.0940
Epoch 74/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0164 - mae: 0.0932
Epoch 75/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0159 - mae: 0.0924
Epoch 76/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0171 - mae: 0.0964
Epoch 77/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0159 - mae: 0.0932
Epoch 78/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0167 - mae: 0.0951
Epoch 79/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0157 - mae: 0.0920
Epoch 80/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0158 - mae: 0.0928
Epoch 81/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0924
Epoch 82/100
```

```
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0911
Epoch 83/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0157 - mae: 0.0932
Epoch 84/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0158 - mae: 0.0922
Epoch 85/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0925
Epoch 86/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0159 - mae: 0.0925
Epoch 87/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0166 - mae: 0.0945
Epoch 88/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0156 - mae: 0.0918
Epoch 89/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0157 - mae: 0.0922
Epoch 90/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0917
Epoch 91/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0922
Epoch 92/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0158 - mae: 0.0923
Epoch 93/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0153 - mae: 0.0901
Epoch 94/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0160 - mae: 0.0927
Epoch 95/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0153 - mae: 0.0907
Epoch 96/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0152 - mae: 0.0903
Epoch 97/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0158 - mae: 0.0945
Epoch 98/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0154 - mae: 0.0912
Epoch 99/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - loss: 0.0150 - mae: 0.0907
Epoch 100/100
101/101 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 0.0152 - mae: 0.0898
```

Out[ ]: <keras.src.callbacks.history.History at 0x1de976f1370>

In [ ]:

```python
# Make predictions
y_pred_trans_scaled = best_model.predict(x_test_trans)
y_pred_trans = scaler_y.inverse_transform(y_pred_trans_scaled)
```

```
26/26 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
```

In [ ]:

```python
# Evaluate the model
mse_trans = mean_squared_error(y_test, y_pred_trans)
rmse_trans = np.sqrt(mean_squared_error(y_test, y_pred_trans))
r2_trans = r2_score(y_test, y_pred_trans)

print("Best Hyperparameters:")
print("Num Heads:", best_hyperparameters['num_heads'])
print("Feed-Forward Dim:", best_hyperparameters['ff_dim'])
print("Dropout Rate:", best_hyperparameters['dropout_rate'])
```

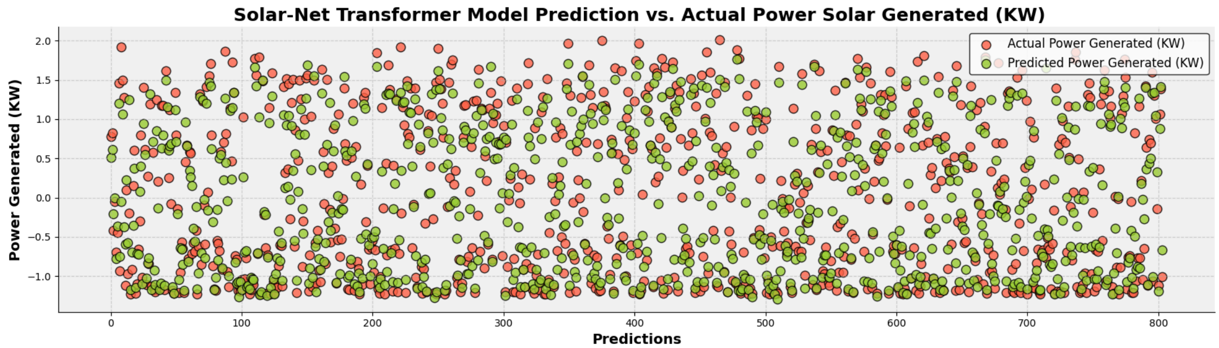
```
Best Hyperparameters:
Num Heads: 6
Feed-Forward Dim: 128
Dropout Rate: 0.1
```

In [ ]:
```python
#Evalute the Solar-Net Transformer model's performance
r2_score_solar = round(r2_score(y_test,y_pred_trans) * 100, 2)
mean_sq_solar = mean_squared_error(y_test,y_pred_trans)
mean_ab_solar = mean_absolute_error(y_test,y_pred_trans)
metrics_df.loc[len(metrics_df)] = ["Solar-Net Transformer", r2_score_solar,
print("R2 Score for Solar-Net Transformer Model: ",r2_score_solar,"%")
print("Mean Square Error of Solar-Net Transformer Model: ",mean_sq_solar)
print("Mean Absolute Error of Solar-Net Transformer Model: ",mean_ab_solar)
```

```
R2 Score for Solar-Net Transformer Model:  81.54 %
Mean Square Error of Solar-Net Transformer Model:  0.19061348215622076
Mean Absolute Error of Solar-Net Transformer Model:  0.2898884608017335
```

In [ ]:
```python
# Create traces for Actual and Predicted values for Solar-Net Transformer mo
actual_trace = go.Scatter(x=list(range(100)), y=y_test.values[:100], mode='l
predicted_trace = go.Scatter(x=list(range(100)), y=y_pred_trans[:100].flatte
# Create layout
layout = go.Layout(
    title='Actual vs Predicted Values for Solar-Net Transformer model',
    xaxis=dict(title='Frequency Days'),
    yaxis=dict(title='Generated Power (KW)'),
    legend=dict(x=0, y=1),
    hovermode='closest')
# Create figure
fig = go.Figure(data=[actual_trace, predicted_trace], layout=layout)
# Show the plot
fig.show()
```

In [ ]:
```python
# Scatter plot for actual and predicted data for Solar-Net Transformer model
plt.figure(figsize=(17, 5))
array = np.arange(len(y_test))
plt.scatter(array, y_test, color='#FF6347', label='Actual Power Generated (K
plt.scatter(array, y_pred_trans, color='#9ACD32', label='Predicted Power Ger
plt.title(' Solar-Net Transformer Model Prediction vs. Actual Power Solar Ge
plt.xlabel('Predictions', fontsize=14, fontweight='bold')
plt.ylabel('Power Generated (KW)', fontsize=14, fontweight='bold')
plt.grid(True, linestyle='--', alpha=0.5)
legend = plt.legend(loc='upper right', fontsize=12, fancybox=True, framealph
plt.gca().spines['top'].set_visible(False)
plt.gca().spines['right'].set_visible(False)
plt.gca().set_facecolor('#F0F0F0')
plt.tight_layout()
plt.show()
```



Step 7: Compare the Machine Learning Models

In [ ]:
```
# Display the metrics DataFrame
metrics_df
```

Out[ ]:

	Model	R2 Score (%)	Mean Squared Error	Mean Absolute Error
0	Support Vector Machine	74.77	0.260527	0.406757
1	Random Forest	77.65	0.230744	0.326031
2	Gradient Boosting	76.79	0.239631	0.364436
3	LSTM	80.24	0.204028	0.312378
4	Solar-Net Transformer	81.54	0.190613	0.289888

In [ ]:
```
# Create a horizontal bar chart
fig = px.bar(metrics_df,
             x='R2 Score (%)',
             y='Model',
             orientation='h',
             title='Comparison of Models by R-Squared Score',
             labels={'R2 Score (%)': 'R-Squared Score (%)', 'Model': 'Algori
             color='R2 Score (%)',  # Color bars by R2 Score
             color_continuous_scale='Viridis')  # Use a nice color scale

# Update layout for better aesthetics
fig.update_layout(
    xaxis_title='R-Squared Score (%)',
    yaxis_title='Algorithm',
    title_font_size=14,
    xaxis_tickfont_size=10,
    yaxis_tickfont_size=10,
    margin=dict(l=50, r=50, t=50, b=50)  # Adjust margins
)

# Show the plot
fig.show()
```