Solar Index Prediction using Machine Learning

A Comprehensive Mini Project Report

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1. Problem Statement

Title: Solar Index Prediction using Machine Learning Models by Time Series Analysis for Renewable Energy Optimization

Objective: To develop and compare multiple machine learning models for predicting solar index in Ghatkopar, Mumbai, using historical weather data from NASA POWER API. The project aims to create an accurate forecasting system that can assist in solar energy planning and optimization.

Key Challenges:

- Handling time-series data with seasonal variations Dealing with
- multiple meteorological features Comparing different ML
- approaches for optimal accuracy Creating reliable 30-day future
- predictions

Expected Outcomes:

- Accurate solar index prediction models Comparative analysis of
- different ML algorithms
- Practical forecasting tool for renewable energy planning

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2. Group Members

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3. Introduction

3.1 Background

Solar energy is one of the most promising renewable energy sources for addressing climate change and energy security challenges. Accurate prediction of solar index is crucial for:

- Grid integration of solar power systems Energy storage
- optimization
- Solar farm site selection Economic
- feasibility analysis

3.2 Solar Index

Solar Index is a standardized measure representing the amount of solar energy available at a specific location and time, typically derived from solar irradiance measurements and expressed in kWh/m²/day. It serves as a practical indicator for solar energy potential and varies based on:

- Geographic location and time
- Atmospheric conditions Seasonal
- patterns
- Weather parameters

3.3 Machine Learning in Solar Prediction

Traditional statistical methods often fail to capture complex patterns in solar data. Machine learning approaches offer:

- Better handling of non-linear relationships Ability to
- incorporate multiple features Adaptive learning from
- historical patterns Improved prediction accuracy
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3.4 Study Area

Location: Ghatkopar, Mumbai, India

- **Latitude:** 19.0860°N
- **Longitude:** 72.9081°E
- **Climate:** Tropical monsoon climate
- **Data Period:** October 2022 - October 2025 (3 years)

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4. Methodology and Block Diagram

4.1 Data Collection

- **Source:** NASA POWER API (Prediction of Worldwide Energy Resources)
- **Parameters:** Solar index, temperature, humidity, wind speed, precipitation
- **Frequency:** Daily measurements
- **Duration:** 3 years (1,096 records)

4.2 Data Preprocessing

1. **Missing Value Treatment:** Forward fill and backward fill
2. **Feature Engineering:**
   - Temporal features (Month, Day of Year, Season) ∘ Lag features (1-day, 7-day historical values)

- Rolling statistics (7-day moving average and standard deviation)

3. **Data Cleaning:** Removal of negative index values
4. **Normalization:** Min-Max scaling for ML models

4.3 Model Development

Four different approaches were implemented:

4.3.1 ARIMA (Auto Regressive Integrated Moving Average) Type:

- Time series statistical model
- **Parameters:** (5,1,2) - AR (5), I (1), MA (2)
- **Use Case:** Capturing temporal dependencies

4.3.2 Random Forest

- **Type:** Ensemble learning method
- **Parameters:** 100 estimators, max depth 15
- **Use Case:** Handling non-linear relationships

4.3.3 XGBoost (Extreme Gradient Boosting)

- **Type:** Gradient boosting framework
- **Parameters:** 100 estimators, max depth 7, learning rate 0.1
- **Use Case:** Optimized gradient boosting

4.3.4 Prophet

- **Type:** Time series forecasting
- **Parameters:** Yearly and weekly seasonality
- **Use Case:** Seasonal pattern detection

4.4 Block Diagram

```
[NASA POWER API] → [Data Collection] → [Data Preprocessing]
                                              ↓
[Feature Engineering] ← [Missing Value Treatment] ← [Data Cleaning]
         ↓
[Train-Test Split (80-20)]
         ↓
    [Model Training]
    ├── ARIMA
    ├── Random Forest
    ├── XGBoost
    └── Prophet
         ↓
[Model Evaluation] → [Performance Comparison] → [Best Model Selection]
         ↓
[Future Predictions (30 days)] → [Visualization] → [Results Analysis]
```

4.5 Evaluation Metrics

- **MAE (Mean Absolute Error):** Average absolute difference
- **RMSE (Root Mean Square Error):** Square root of average squared differences
- **R^2 Score:** Coefficient of determination (explained variance)

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5. Pseudo Code and Flow Chart

5.1 Main Algorithm Pseudo Code

```
PROJECT: Solar_Index_Prediction_Mumbai
OBJECTIVE: Predict daily solar index for renewable energy planning
TIMEFRAME: 3 years historical data + 30 days forecast
LOCATION: Mumbai, India (Ghatkopar: 19.0860°N, 72.9081°E)


BEGIN DATA_COLLECTION
    // Connect to NASA POWER API
    API_ENDPOINT = "https://power.larc.nasa.gov/api/temporal/daily/point"

    PARAMETERS = {
        'ALLSKY_SFC_SW_DWN': 'Solar Index (kWh/m²/day)',
        'T2M': 'Temperature (°C)',
        'RH2M': 'Humidity (%)',
        'WS2M': 'Wind Speed (m/s)',
        'PRECTOTCORR': 'Precipitation (mm/day)'
    }

    // Fetch 3 years of daily data
    DATA = FETCH_FROM_NASA_API(
        latitude = 19.0860,
        longitude = 72.9081,
        start_date = CURRENT_DATE - 3_YEARS,
        end_date = CURRENT_DATE
    )

    // Create structured dataset
    SOLAR_DATASET = CREATE_DATA_FRAME({
        'Date': datetime_series,
        'Solar_Index': radiation_values,
        'Temperature': temp_values,
        'Humidity': humidity_values,
        'Wind_Speed': wind_values,
        'Precipitation': rain_values
    })

    SAVE_RAW_DATA('solar_index_raw_data.csv')
END DATA_COLLECTION

BEGIN DATA_PREPROCESSING
    // Data Quality Checks
    CHECK_FOR_MISSING_VALUES(SOLAR_DATASET)
    REMOVE_INVALID_ENTRIES(Solar_Index < 0)
    APPLY_FILL_METHODS(forward_fill → backward_fill)

    // Feature Engineering
    TEMPORAL_FEATURES = EXTRACT_FROM_DATE({
        'Year', 'Month', 'Day', 'DayOfWeek',
        'DayOfYear', 'Week', 'Quarter'
    })

    // Seasonal Classification
    FUNCTION GET_SEASON(month):
        IF month IN [12,1,2]: RETURN 'Winter'
        IF month IN [3,4,5,6]: RETURN 'Summer'
        IF month IN [7,8,9]: RETURN 'Monsoon'
        ELSE: RETURN 'Post-Monsoon'

    // Lag Features Creation
    FOR lag IN [1, 2, 3, 7, 14, 30]:
        CREATE_FEATURE(f'Solar_Lag_{lag}' = SHIFT(Solar_Index, lag))

    // Rolling Statistics
    FOR window IN [3, 7, 14, 30]:
        CREATE_FEATURE(f'Rolling_Mean_{window}' = ROLLING_MEAN(Solar_Index, window))
        CREATE_FEATURE(f'Rolling_Std_{window}' = ROLLING_STD(Solar_Index, window))
        CREATE_FEATURE(f'Rolling_Min_{window}' = ROLLING_MIN(Solar_Index, window))
        CREATE_FEATURE(f'Rolling_Max_{window}' = ROLLING_MAX(Solar_Index, window))

    // Advanced Features
    CREATE_FEATURE('Temp_Humidity_Interaction' = Temperature * Humidity)
    CREATE_FEATURE('Wind_Precip_Interaction' = Wind_Speed * Precipitation)
    CREATE_FEATURE('Solar_EWMA_7' = EXPONENTIAL_WEIGHTED_MEAN(Solar_Index, 7))
    CREATE_FEATURE('Solar_EWMA_30' = EXPONENTIAL_WEIGHTED_MEAN(Solar_Index, 30))

    // Final Cleaning
    REMOVE_ROWS_WITH_NULL_VALUES()
```

```
    SAVE_PROCESSED_DATA('solar_index_processed_data.csv')
END DATA_PREPROCESSING

BEGIN EXPLORATORY_ANALYSIS
    // Statistical Summary
    PRINT_DESCRIPTIVE_STATISTICS(Solar_Index)

    // Visualization Suite
    PLOT_TIME_SERIES(
        title = "Solar Index Time Series - Mumbai",
        y_label = "Solar Index (kWh/m²/day)",
        show_moving_average = True
    )

    PLOT_SEASONAL_ANALYSIS(
        subplot1 = "Monthly Average Solar Index",
        subplot2 = "Seasonal Distribution",
        subplot3 = "Histogram with Normal Curve",
        subplot4 = "Box Plots by Season"
    )

    PLOT_CORRELATION_MATRIX(
        features = ['Solar_Index', 'Temperature', 'Humidity',
                   'Wind_Speed', 'Precipitation', 'Solar_Lag_1', 'Solar_Lag_7']
    )

    PLOT_YEAR_OVER_YEAR_COMPARISON(
        colors = ['blue', 'orange', 'green', 'red']
    )

    PLOT_WEATHER_IMPACT_SCATTERS(
        subplot1 = "Solar Index vs Temperature",
        subplot2 = "Solar Index vs Humidity",
        subplot3 = "Solar Index vs Wind Speed",
        subplot4 = "Solar Index vs Precipitation"
    )

    PLOT_MONTHLY_HEATMAP(
        x_axis = "Year",
        y_axis = "Month",
        values = "Solar_Index"
    )
END EXPLORATORY_ANALYSIS

BEGIN TIME_SERIES_ANALYSIS
    // Prepare time series data
    TIME_SERIES = SET_INDEX(Date, Solar_Index)

    // Seasonal Decomposition
    DECOMPOSITION = SEASONAL_DECOMPOSE(
        TIME_SERIES,
        model = 'additive',
        period = 365
    )

    COMPONENTS = {
        'Observed': DECOMPOSITION.observed,
        'Trend': DECOMPOSITION.trend,
        'Seasonal': DECOMPOSITION.seasonal,
        'Residual': DECOMPOSITION.resid
    }

    PLOT_DECOMPOSITION(COMPONENTS)

    // Stationarity Testing
    ADF_TEST = AUGMENTED_DICKEY_FULLER(TIME_SERIES)
    PRINT_STATIONARITY_RESULTS(ADF_TEST)

    IF ADF_TEST.p_value >= 0.05:
        PRINT("Series is non-stationary - applying differencing")
        STATIONARY_SERIES = DIFFERENCE(TIME_SERIES)
    ELSE:
        PRINT("Series is stationary - proceeding directly")
        STATIONARY_SERIES = TIME_SERIES
END TIME_SERIES_ANALYSIS

BEGIN MODEL_TRAINING
    // Feature Selection
    SELECTED_FEATURES = [
        'Temperature', 'Humidity', 'Wind_Speed', 'Precipitation',
```

```
        'Month', 'DayOfYear', 'DayOfWeek',
        'Solar_Lag_1', 'Solar_Lag_2', 'Solar_Lag_3', 'Solar_Lag_7',
        'Solar_Rolling_Mean_3', 'Solar_Rolling_Mean_7', 'Solar_Rolling_Mean_14',
        'Solar_Rolling_Std_7', 'Solar_EWMA_7'
    ]

    X = DATASET[SELECTED_FEATURES]
    y = DATASET['Solar_Index']

    // Train-Test Split (80-20)
    SPLIT_INDEX = 0.8 * LENGTH(DATASET)
    X_train, X_test = SPLIT(X, SPLIT_INDEX)
    y_train, y_test = SPLIT(y, SPLIT_INDEX)

    // Feature Scaling
    SCALER = MIN_MAX_SCALER()
    X_train_scaled = SCALER.FIT_TRANSFORM(X_train)
    X_test_scaled = SCALER.TRANSFORM(X_test)

    // Model 1: ARIMA
    BEGIN ARIMA_TRAINING
        MODEL_ARIMA = ARIMA(
            order = (5, 1, 2),  // (p, d, q)
            seasonal_order = (0, 0, 0, 0)
        )
        FIT_ARIMA = MODEL_ARIMA.FIT(y_train)
        PREDICTIONS_ARIMA = FIT_ARIMA.FORECAST(LENGTH(y_test))
    END ARIMA_TRAINING

    // Model 2: Random Forest
    BEGIN RANDOM_FOREST_TRAINING
        MODEL_RF = RANDOM_FOREST_REGRESSOR(
            n_estimators = 100,
            max_depth = 15,
            min_samples_split = 5,
            min_samples_leaf = 2,
            random_state = 42
        )
        MODEL_RF.FIT(X_train_scaled, y_train)
        PREDICTIONS_RF = MODEL_RF.PREDICT(X_test_scaled)
    END RANDOM_FOREST_TRAINING

    // Model 3: XGBoost
    BEGIN XGBOOST_TRAINING
        MODEL_XGB = XGB_REGRESSOR(
            n_estimators = 100,
            max_depth = 7,
            learning_rate = 0.1,
            subsample = 0.8,
            colsample_bytree = 0.8,
            random_state = 42
        )
        MODEL_XGB.FIT(X_train_scaled, y_train)
        PREDICTIONS_XGB = MODEL_XGB.PREDICT(X_test_scaled)
    END XGBOOST_TRAINING

    // Model 4: Prophet
    BEGIN PROPHET_TRAINING
        PROPHET_DATA = CREATE_PROPHET_FORMAT(
            ds = DATASET['Date'],
            y = DATASET['Solar_Index']
        )

        MODEL_PROPHET = PROPHET(
            yearly_seasonality = True,
            weekly_seasonality = True,
            daily_seasonality = False,
            seasonality_mode = 'multiplicative'
        )
        MODEL_PROPHET.FIT(PROPHET_DATA[:SPLIT_INDEX])

        FUTURE_DATES = MODEL_PROPHET.MAKE_FUTURE_DATAFRAME(
            periods = LENGTH(y_test)
        )
        FORECAST_PROPHET = MODEL_PROPHET.PREDICT(FUTURE_DATES)
        PREDICTIONS_PROPHET = EXTRACT_TEST_PREDICTIONS(FORECAST_PROPHET)
    END PROPHET_TRAINING
END MODEL_TRAINING

BEGIN MODEL_EVALUATION
```

```
    // Initialize results storage
    MODEL_RESULTS = {}

    FOR EACH model IN [ARIMA, RANDOM_FOREST, XGBOOST, PROPHET]:
        PREDICTIONS = GET_PREDICTIONS(model)

        METRICS = CALCULATE_PERFORMANCE_METRICS(
            actual = y_test,
            predicted = PREDICTIONS
        )

        MODEL_RESULTS[model] = {
            'MAE': METRICS.mean_absolute_error,
            'RMSE': METRICS.root_mean_squared_error,
            'R2': METRICS.r_squared,
            'Predictions': PREDICTIONS
        }

    // Performance Comparison
    CREATE_COMPARISON_TABLE(MODEL_RESULTS)
    SORT_BY_METRIC('MAE', ascending=True)

    // Identify Best Model
    BEST_MODEL = FIND_BEST_MODEL(
        primary_metric = 'MAE',
        secondary_metric = 'R2'
    )

    PRINT("BEST PERFORMING MODEL: " + BEST_MODEL.name)
    PRINT_PERFORMANCE_METRICS(BEST_MODEL.metrics)

    // Visualization of Results
    PLOT_MODEL_COMPARISON_BAR_CHARTS(
        metrics = ['MAE', 'RMSE', 'R2'],
        models = ['ARIMA', 'Random Forest', 'XGBoost', 'Prophet']
    )

    PLOT_ACTUAL_VS_PREDICTED_ALL_MODELS(
        test_dates = dates_test,
        actual_values = y_test,
        predictions = MODEL_RESULTS
    )

    PLOT_FEATURE_IMPORTANCE(
        model = BEST_MODEL,
        features = SELECTED_FEATURES
    )
END MODEL_EVALUATION

BEGIN FUTURE_PREDICTIONS
    // Generate 30-day forecast
    FORECAST_PERIOD = 30
    LAST_DATE = MAX(DATASET['Date'])
    FUTURE_DATES = GENERATE_DATE_RANGE(
        start = LAST_DATE + 1_DAY,
        periods = FORECAST_PERIOD
    )

    IF BEST_MODEL.TYPE IN ['Random_Forest', 'XGBoost']:
        FUTURE_PREDICTIONS = []

        FOR i IN RANGE(FORECAST_PERIOD):
            CURRENT_DATE = FUTURE_DATES[i]

            // Prepare features for current day
            FEATURES = CREATE_FUTURE_FEATURES(
                date = CURRENT_DATE,
                recent_data = LAST_30_DAYS,
                previous_predictions = FUTURE_PREDICTIONS,
                current_index = i
            )

            // Scale features
            SCALED_FEATURES = SCALER.TRANSFORM([FEATURES])

            // Make prediction
            PREDICTION = BEST_MODEL.PREDICT(SCALED_FEATURES)[0]
            FUTURE_PREDICTIONS.APPEND(PREDICTION)

    ELIF BEST_MODEL.TYPE == 'Prophet':
```

```
        FUTURE = BEST_MODEL.MAKE_FUTURE_DATAFRAME(
            periods = FORECAST_PERIOD
        )
        FORECAST = BEST_MODEL.PREDICT(FUTURE)
        FUTURE_PREDICTIONS = EXTRACT_FUTURE_VALUES(FORECAST)

    // Create forecast dataframe
    FORECAST_DF = CREATE_FORECAST_TABLE({
        'Date': FUTURE_DATES,
        'Predicted_Solar_Index': FUTURE_PREDICTIONS,
        'Lower_Bound': CALCULATE_LOWER_BOUND(FUTURE_PREDICTIONS, BEST_MODEL.rmse),
        'Upper_Bound': CALCULATE_UPPER_BOUND(FUTURE_PREDICTIONS, BEST_MODEL.rmse),
        'Day_of_Week': EXTRACT_DAY_NAMES(FUTURE_DATES),
        'Season': CLASSIFY_SEASONS(FUTURE_DATES)
    })

    // Save results
    SAVE_FORECAST('solar_index_30day_forecast.csv', FORECAST_DF)

    // Visualize forecast
    PLOT_FORECAST_VISUALIZATION(
        historical_data = LAST_90_DAYS,
        forecast_data = FORECAST_DF,
        confidence_interval = True
    )
END FUTURE_PREDICTIONS

PROJECT Solar_Index_Prediction_Mumbai

// 1. DATA COLLECTION
DATA = FETCH_FROM_NASA_API(
    location: [19.0860, 72.9081],
    parameters: [ALLSKY_SFC_SW_DWN, T2M, RH2M, WS2M, PRECTOTCORR],
    period: 3_years
)

// 2. DATA PREPROCESSING
CLEAN_DATA = REMOVE_MISSING_VALUES(DATA)
ENGINEER_FEATURES:
    temporal = [Year, Month, DayOfYear, Season]
    lags = [Lag_1, Lag_7, Lag_30]
    rolling = [Mean_7, Std_7, EWMA_7]
    weather = [Temp*Humidity, Wind*Precipitation]

// 3. EXPLORATORY ANALYSIS
PLOT time_series WITH moving_average
ANALYZE seasonal_patterns BY month AND season
COMPUTE correlation_matrix WITH weather_variables
CREATE monthly_heatmap FOR pattern_analysis

// 4. TIME SERIES DECOMPOSITION
DECOMPOSE Solar_Index INTO [Trend, Seasonal, Residual]
TEST stationarity USING Augmented_Dickey_Fuller
IF p_value >= 0.05: APPLY differencing

// 5. MODEL TRAINING
SPLIT data: 80% training, 20% testing
SCALE features USING MinMaxScaler

TRAIN_MODELS:
    ARIMA = FIT(5,1,2) ON training_data
    Random_Forest = FIT(100_trees, max_depth=15)
    XGBoost = FIT(100_estimators, learning_rate=0.1)
    Prophet = FIT(yearly+weekly_seasonality)

// 6. MODEL EVALUATION
FOR EACH model:
    predictions = PREDICT(test_data)
    CALCULATE [MAE, RMSE, R²]
SELECT best_model BASED ON lowest_MAE
ANALYZE residuals FOR best_model

// 7. FUTURE PREDICTIONS
GENERATE 30_day_forecast USING best_model
FOR i IN range(30):
    features = CREATE_FEATURES(
        date = future_dates[i],
        recent_data = last_30_days,
        previous_predictions = future_predictions[0:i]
    )
```

prediction = PREDICT(features)
future_predictions.APPEND(prediction)

ADD confidence_intervals = prediction ± 2*RMSE
SAVE forecast_table WITH daily_predictions

// 8. BUSINESS INSIGHTS
CALCULATE:
best_season = MAX(seasonal_averages)
worst_season = MIN(seasonal_averages)
annual_potential = daily_average * 365
seasonal_variation = (season_avg/annual_avg - 1)*100

GENERATE_RECOMMENDATIONS:
install_timing = BEFORE best_season
maintenance = DURING worst_season
backup_plan = FOR monsoon_period

// 9. OUTPUT GENERATION
SAVE_FILES:
raw_data.csv
processed_data.csv
model_comparison.csv
30_day_forecast.csv
12_visualization_plots.png

PRINT_PROJECT_SUMMARY:
location: Mumbai
best_model: [name]
accuracy: R²_score
avg_solar_index: daily_value
forecast_period: 30_days

END PROJECT

5.2 Flow Chart

```
                [START]
                   ↓
         [Initialize Parameters]
             (Location, Dates)
                   ↓
         [Fetch Data from NASA API]
                   ↓
          [Data Preprocessing]
        ├─ Handle Missing Values
        ├─ Feature Engineering
        ├─ Remove Invalid Data
        └─ Scale Features
                   ↓
        [Split Data (80% Train, 20% Test)]
                   ↓
          [Train Multiple Models]
        ├─ ARIMA (5,1,2)
        ├─ Random Forest (100 trees)
        ├─ XGBoost (100 estimators)
        └─ Prophet (seasonal)
                   ↓
         [Evaluate All Models]
        ├─ Calculate MAE
        ├─ Calculate RMSE
        └─ Calculate R² Score
                   ↓
          [Compare Performance]
                   ↓
        [Select Best Model] → [Random Forest: Lowest MAE]
```

```
                  ↓
      [Generate Future Predictions]
            (30 days ahead)
                  ↓
        [Create Visualizations]
      ├─ Time Series Plots
      ├─ Model Comparison Charts
      ├─ Feature Importance
      └─ Seasonal Analysis
                  ↓
        [Save Results & Report]
                  ↓
                [END]
```

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6. Results and Analysis

6.1 Dataset Overview

- **Total Records:** 1,096 daily observations
- **Date Range:** October 25, 2022 - October 18, 2025
- **Location:** Ghatkopar, Mumbai (19.0860°N, 72.9081°E)
- **Features:** 6 meteorological parameters + 8 engineered features

Key Statistics:

- **Mean Solar Index:** 4.89 kWh/m²/day
- **Maximum Solar Index:** 7.32 kWh/m²/day **Minimum**
- **Solar Index:** 0.94 kWh/m²/day **Standard Deviation:**
- 1.45 kWh/m²/day

6.2 Model Performance Comparison

Model	MAE	RMSE	R^2 Score	Rank
Random Forest	**23.643**	**151.852**	**-0.021**	**1**
XGBoost	23.725	151.956	-0.023	2
Prophet	24.176	152.072	-0.024	3
ARIMA	25.042	152.293	-0.027	4

Key Findings:

1. **Best Model:** Random Forest achieved the lowest MAE (23.643)
2. **Performance Gap:** Small differences between tree-based models
3. **R^2 Scores:** All models show negative R^2, indicating challenges with the prediction task
4. **RMSE Values:** All models have similar RMSE around 152

6.3 Seasonal Analysis

- **Summer (Mar-Jun):** Highest index (avg. 5.8 kWh/m²/day) **Winter**
- **(Dec-Feb):** Lowest index (avg. 4.2 kWh/m²/day) **Monsoon (Jul-**
- **Sep):** Variable index (avg. 4.1 kWh/m²/day)
- **Post-Monsoon (Oct-Nov):** Moderate index (avg. 5.1 kWh/m²/day)

6.4 Feature Importance Analysis

Random Forest Top Features:

1. Solar_Rolling_Mean_7 (28.5%) - 7-day moving average
2. Solar_Lag_1 (24.8%) - Previous day's index
3. Temperature (18.3%) - Daily temperature
4. Day Of Year (12.1%) - Seasonal patterns
5. Solar_Lag_7 (8.7%) - Weekly patterns

XGBoost Top Features:

1. Solar_Lag_1 (31.2%) - Previous day's index
2. Solar_Rolling_Mean_7 (26.9%) - 7-day moving average
3. Temperature (15.4%) - Daily temperature
4. Day Of Year (11.8%) - Seasonal patterns
5. Month (7.2%) - Monthly patterns

6.5 30-Day Future Predictions

- **Prediction Period:** October 19 - November 17, 2025
- **Average Predicted Index:** 4.65 kWh/m²/day **Prediction**
- **Range:** 4.30 - 4.95 kWh/m²/day
- **Seasonal Trend:** Slight decline expected (autumn transition)

6.6 Model Limitations

1. **Negative R^2 Scores:** Indicates models perform worse than simple mean prediction
2. **High MAE Values:** Suggests significant prediction errors
3. **Limited Feature Set:** Only basic meteorological parameters used
4. **Data Quality:** Potential noise in NASA POWER data

6.7 Visualization Results

Generated 8 comprehensive visualizations:

1. **Time Series Plot:** Shows historical index patterns
2. **Seasonal Analysis:** Monthly and seasonal variations
3. **Correlation Matrix:** Feature relationships
4. **Year-over-Year Comparison:** Multi-year trends
5. **Box Plot by Season:** Distribution analysis
6. **Monthly Heatmap:** Calendar view of index
7. **Statistical Summary:** Comprehensive statistics
8. **Data Quality Overview:** Dataset characteristics

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7. Conclusion

7.1 Key Achievements

1. **Successful Data Integration:** Retrieved and processed 3 years of NASA POWER data
2. **Comprehensive Model Comparison:** Implemented and evaluated 4 different ML approaches
3. **Feature Engineering:** Created meaningful temporal and lag features
4. **Automated Pipeline:** Developed end-to-end prediction system
5. **Rich Visualizations:** Generated insightful plots for analysis

7.2 Performance Analysis

- **Best Model:** Random Forest with MAE of 23.643
- **Model Consistency:** Small performance differences between top models
- **Prediction Challenges:** Negative R^2 scores indicate room for improvement
- **Feature Importance:** Historical values and temperature are key predictors

7.3 Practical Implications

1. **Solar Energy Planning:** Models can assist in preliminary capacity planning
2. **Seasonal Insights:** Clear seasonal patterns identified for Mumbai region
3. **Weather Dependencies:** Strong correlation with temperature confirmed
4. **Forecasting Capability:** 30-day predictions available for operational planning

7.4 Limitations and Challenges

1. **Model Accuracy:** Higher prediction errors than desired for critical applications
2. **Data Dependencies:** Reliance on external API for real-time predictions
3. **Feature Limitations:** Additional parameters like cloud cover could improve accuracy
4. **Generalization:** Models trained specifically for Ghatkopar location

7.5 Future Work

1. **Enhanced Features:** Include satellite imagery, cloud cover data
2. **Deep Learning:** Implement LSTM/CNN models for time series
3. **Ensemble Methods:** Combine multiple models for better accuracy
4. **Real-time Updates:** Develop streaming prediction system
5. **Multi-location:** Extend to other geographic regions
6. **Weather Integration:** Include detailed meteorological forecasts

7.6 Recommendations

1. **For Solar Installers:** Use seasonal insights for optimal installation timing
2. **For Grid Operators:** Consider prediction uncertainties in planning
3. **For Researchers:** Focus on advanced feature engineering and deep learning
4. **For Policy Makers:** Support data collection initiatives for better modeling

The project successfully demonstrates the application of machine learning to solar index prediction, providing a foundation for renewable energy forecasting systems while highlighting areas for continued research and development.

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8. References

1. NASA POWER Project. "Prediction of Worldwide Energy Resources." Available: https://power.larc.nasa.gov/
2. Voyant, C., et al. (2017). "Machine learning methods for solar radiation forecasting: A review." Renewable Energy, 105, 569-582.
3. Sharma, N., et al. (2011). "Predicting solar generation from weather forecasts using machine learning." IEEE International Conference on Smart Grid Communications.
4. Chen, T., & Guestrin, C. (2016). "XGBoost: A scalable tree boosting system." Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

5. Taylor, S. J., & Letham, B. (2018). "Forecasting at scale." The American Statistician, 72(1), 37-45.

6. Breiman, L. (2001). "Random forests." Machine Learning, 45(1), 5-32.

7. Box, G. E., et al. (2015). "Time series analysis: forecasting and control." John Wiley & Sons.

8. Pedregosa, F., et al. (2011). "Scikit-learn: Machine learning in Python." Journal of Machine Learning Research, 12, 2825-2830.

9. McKinney, W. (2010). "Data structures for statistical computing in Python." Proceedings of the 9th Python in Science Conference.

10. Hunter, J. D. (2007). "Matplotlib: A 2D graphics environment." Computing in Science & Engineering, 9(3), 90-95.

11. Waskom, M. L. (2021). "Seaborn: statistical data visualization." Journal of Open Source Software, 6(60), 3021.

12. National Renewable Energy Laboratory. (2021). "Solar Resource Assessment and Forecasting." Technical Report NREL/TP-5D00-78583.