Report on Energy Production Prediction using LSTM

Preprocessing:

- Handling of missing data with forward fill.
- Feature engineering to extract useful temporal features.

Exploratory Data Analysis (EDA):

- Visualizations of yearly and monthly energy production.
- Identification of seasonal patterns and trends in energy production.

Modeling:

- Selection of LSTM architecture for time series prediction.
- Configuration of layers, including LSTM, dense, and dropout layers.
- Dataset preparation for LSTM input.

Evaluation:

- Use of Mean Absolute Error (MAE) and Mean Squared Error (MSE) for model performance assessment.
- Hyperparameter tuning for optimal model performance.
- Logging of losses during training for monitoring.

Results and Conclusion:

- Successful prediction of solar and wind energy production.
- Insights from EDA guided model design and feature selection.
- Future work suggested for refinement and enhancement of model accuracy.

Results

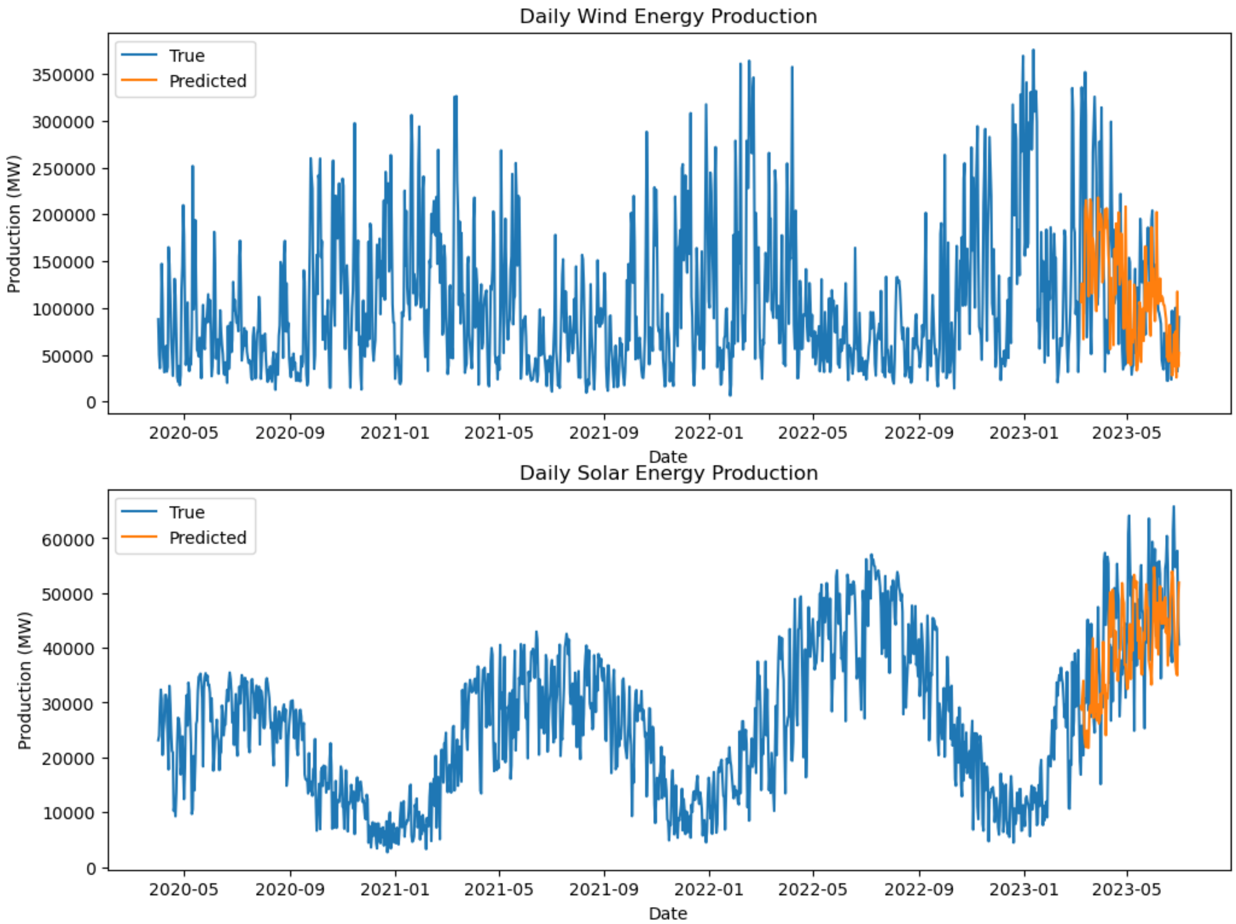

Fig: Predicted vs Actual Energy production.

The model successfully predicted solar and wind energy production, demonstrated by visual comparisons between actual and predicted values. During model training, experiments were conducted with batch sizes of 8 and 32, and models were trained over 50 and 300 epochs, respectively. These variations helped fine-tune the model for more accurate forecasting.

To optimize the model's hyperparameters, **Keras Tuner** was employed. This method tested multiple configurations to identify the best-performing hyperparameters, including the number of units, dense layer sizes, dropout rates, and learning rate. The final results from Keras Tuner are as follows:

- **Best validation loss**: 0.0107
- **Elapsed time**: 25 minutes and 9 seconds
- **Best hyperparameters**:
    - Units: 352

    - Dense Units 1: 384
    - Dropout 1: 0.2
    - Dense Units 2: 256
    - Dropout 2: 0.4
    - Learning Rate: 0.00179

This tuning helped significantly reduce validation loss while maintaining accuracy. For example, in one of the key trials:

- **Epoch 0**: Loss = 0.04197 | Accuracy = 25.42%
- **Epoch 50**: Loss = 0.02379 | Accuracy = 36.99%
- **Epoch 100**: Loss = 0.00789 | Accuracy = 54.54%
- **Epoch 150**: Loss = 0.00365 | Accuracy = 68.89%

The model's performance continually improved with more epochs, and a balance between overfitting and accuracy was struck using regularization techniques such as dropout layers.