

Deep Learning-Based Prediction System of Energy Load from Solar and Wind Energy

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Abstract—Considering an ongoing global boost in interest in renewable energy solutions, it is evident that improving the accuracy and performance of prediction models is crucial for optimizing the renewable energy production process. The objective of this project is to create a very efficient deep learning-based prediction system that can determine the amount of energy produced by wind and solar power in various geographic areas. This model makes use of large data, including historical energy demands, meteorological data, and performance indicators of wind and solar power plants. Deep learning methods are used to harness the complex nature of the data. This model's methodology enables it to forecast energy generation with an extremely high level of accuracy. This predictive capacity is vital for regulating rising energy demands as well as to address the inherent risk involved in renewable resources. In the end, it provides a reliable and scalable technological solution that enables the smooth integration of renewable resources into modern power networks, encouraging the creation of sustainable energy infrastructure in line with international environmental goals.

Index Terms—Renewable energy, energy prediction, deep learning, solar energy generation, wind energy generation, data analysis, grid management, resource optimization, sustainable energy systems, energy forecasting.

I. INTRODUCTION

As the needs of our modern civilization continue to rise, the global shift to renewable energy sources like solar and wind is necessitating the development of accurate and effective predictive models to improve energy generation. Predicting energy output from these highly variable sources, such as solar and wind, is made more difficult by the growing demand for renewable energy sources. The production of renewable energy is heavily reliant on environmental variables, which can change greatly. This further complicates energy management by making the generation unpredictable. To address these complications, new prediction models are being created that use deep learning techniques to analyse large information, such as historical energy consumption, meteorological data, and operational metrics from solar and wind installations. Using precise energy output predictions, these models provide improved opportunities for dependable and effective renewable energy management. The main objective of this project is to develop a deep learning-based, reliable system for forecasting solar and wind energy production in different geographic locations. Renewable energy is less successful in real-world applications because traditional models are unable to reflect the non-linear correlations that exist inside complex patterns. In contrast, ResNet is the suggested architecture. ResNet was specifically created to handle the unpredictability and uncertainty associated with renewable energy sources. This type of

network may learn deep and complex patterns that lead to residual connections in the ResNet design, which fixes the vanishing gradient problems and increases the precision and resilience of the model. ResNet offers a significant advance over current models because of its exceptional ability to detect intricate connections in renewable energy datasets. Deep learning is an instance of machine learning that uses multiple-layer neural networks to autonomously generate complex patterns from massive data streams. In order to anticipate solar and wind power, deep learning models for the current study process comprehensive information, such as meteorological conditions, facility-specific metrics, and patterns of past consumption. High-dimensional, heterogeneous data that could otherwise need a lot of work in human feature engineering can be processed effectively by this system because of ResNet's special characteristics. This made the model in question more scalable and enhanced energy forecast accuracy, which made it a great fit for handling the enormous and constantly expanding datasets related to renewable energy. In particular, the ResNet-based model incorporates inputted connections, which helps the ResNet model address non-linear dynamics and temporal dependencies in renewable energy generation. This gives the proposed system a significant advantage over conventional models that lack the depth necessary to represent the full complexity of nuances in renewable energy data. This feature enables it to accurately depict the chaotic character of solar and wind energy, whose outputs can fluctuate wildly depending on the surrounding conditions. Furthermore, the model is in a much better position than other, more straightforward models might anticipate because it learns spatial relationships across various regional domains and incorporates them into the integration. This is because there may not be an account to take into account all of these intricate and fine-tuned relationships of interplays. Finally, a high-precision forecast model of solar and wind energy generation based on various locations will be developed in this study. We will create a ResNet-based model that can produce estimates of energy output under historical demand, weather, and facility-specific conditions with a reasonable degree of accuracy. In the end, this study advances the field of renewable energy forecasting and establishes a sustainable energy framework that is more equipped for the future driven by renewable energy.

A. Related Work

Deep learning research on renewable energy prediction reveals sophisticated techniques that use massive datasets, such as historical energy use and meteorological data, to provide precise forecasts. Low-cost sensors are integrated into IoT systems to collect real-time data, which is subsequently analyzed using machine learning models including neural networks, regression approaches, and hybrid architectures. Research places a strong emphasis on spatiotemporal analysis to better understand regional connections and trends and increase forecast accuracy. By facilitating the smooth integration of renewable resources into smart grids, these strategies help to ensure effective administration and policymaking. These models are essential for maximizing energy output, coordinating with sustainable energy objectives, and guaranteeing a steady power supply in the face of renewable energy sources' unpredictability.

B. Problem Statement

Since renewable energy sources like solar and wind are becoming more and more popular worldwide, researchers have focused a lot of attention on the consequences of renewable energy variability for grid management and energy forecasting. To ascertain their prognostic importance, researchers have looked at a number of variables, including past energy statistics, patterns of energy consumption, and weather conditions. This overview of the literature offers insights into the nonlinear dynamics of renewable energy generation and provides a basis for developing precise forecasting models. Predicting the energy production of solar and wind power was made possible by the integration of IoT devices with real-time data gathering capabilities to build a special dataset designed for the study. By giving decision-makers practical insights to maximize energy distribution and reduce grid instability, this research has the potential to revolutionize renewable energy management. The study increases the possibility for efficient and sustainable energy systems by utilizing machine learning and Internet of Things technology.

II. METHODOLOGY AND SOLUTION APPROACH

This section aims to describe the procedure for gathering the data and configuring the settings required for training and testing the prediction models. To ensure that the models have the necessary data to predict energy loads accurately.

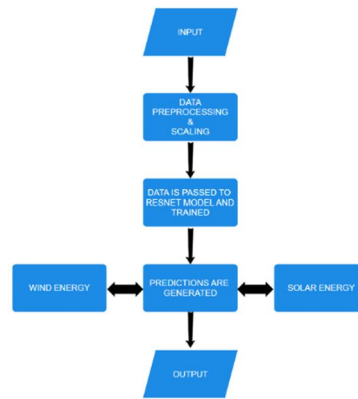


Figure 1. Flow Chart on Methodology

A. Model Description

A kind of deep neural network called ResNet (Residual Network) uses residual learning to make it possible to train extremely deep networks. ResNet addresses the problem of disappearing gradients by incorporating skip connections or shortcut connections, in contrast to standard networks. If adding more layers does not increase performance, these connections enable the network bypass one or more levels, allowing the model to learn the identity function.

Residual Block

A collection of convolutional layers before an identity mapping in which the block's input is appended to its output makes up each ResNet block. By using this technique, the network is able to "skip" levels and get around the issue of deeper networks experiencing performance degradation. The residual function formula is as follows:

$$y = F(x) + x$$

where $F(x)$ is learned transformation and x is the input. The addition of x ensures that the gradient can flow directly through the network.

Depth of the Network

ResNet is appropriate for difficult applications such as energy load prediction since it may include a large number of layers (for example, 50, 101, or more). A ResNet-50 architecture, with 50 layers including convolutional, pooling, and fully connected layers, is employed for this model.

Activation and Optimization

Rectified Linear Unit (ReLU) activation functions are used in the hidden layers of the model to create non-linearity and enable the network to learn intricate patterns. Dropout is used to stop overfitting and batch normalization is utilized to normalize the learning process during training. The Adam optimizer is used to optimize the model, and mean squared error (MSE) is used to minimize the loss.

B. Model Preparation

ResNet (Residual Neural Network)

The vanishing gradient issue in deep neural networks is explicitly addressed by the deep learning architecture ResNet. Even in very deep networks, the model's residual connections, also known as skip connections, permit gradients to pass straight through them without disappearing. This makes it possible for ResNet to effectively discover intricate patterns and connections within the data. In order to preserve information across layers, ResNet's structure stacks residual blocks, each of which consists of many layers with nonlinear activations. The block's input is then added to its output. The model is especially well-suited for jobs like renewable energy projection that need huge datasets with complex feature interactions.

Min Max Scaler for Feature Scaling

A preprocessing method called Min Max Scaler is used to normalize data within a certain range, usually 0 to 1. To guarantee constant scaling, it is applied independently to the target variables and the input features in this project. Better convergence during training is made possible by normalizing the data, which prevents the model from being biased toward features with wider ranges. This is especially crucial to make sure the ResNet model correctly identifies trends across a variety of characteristics, such as historical load data and solar and wind generating capacity.

Residual Block

The residual block is the fundamental component of ResNet. A skip connection that adds the block's input to its output comes after two Dense layers with ReLU activations make up each residual block in the design. This facilitates optimization and enhances the model's generalizability by enabling the network to learn residual mappings rather than immediately mapping the input to the output. To capture the nonlinear relationships between features and the targets, this project stacks numerous residual blocks.

Training with Early Stopping

The Early Stopping strategy is used to train the model in order to increase training efficiency and avoid overfitting. Early Stopping keeps track of the validation loss throughout training and halts the process after a certain number of epochs in which the loss no longer improves. This guarantees that the model performs at its best without overfitting to the training set, improving generalization to new data.

Predicting Solar and Wind Energy Generation

Normalized input variables from various geographic regions, including as capacity, load measurements, and statistics on solar and wind power, are fed into the ResNet model. It forecasts two outputs: the production of wind and solar energy. The inverse transformation of MinMaxScaler is used to scale these projections back to their initial range, producing forecasts that are accurate and comprehensible.

Performance Metrics

Metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) are used to assess the model's performance. In order to examine binary performance for situations such as high or low energy generation, a classification threshold is also used. The model exhibits its capacity to perform intricate, multi-target forecasts and offers practical insights into the management of renewable energy.

C. Model Evaluation

MSE (MSE (Mean Square Error))

The Mean Squared Error (MSE) metric measures the average of the squared variances between the estimated and actual values. A lower mean square error (MSE) in noise pollution prediction models indicates a higher level of accuracy, as the model's predictions closely align with the actual values.

MAE (Mean Absolute Error)

On MAE measures the average magnitude of errors between the predicted and actual values. It is calculated as the average of the absolute differences between the predicted and true values.

Interpretation: A lower MAE indicates that the model is capable of making predictions closer to the true values, providing an intuitive measure of the model's prediction accuracy.

R-SQUARE

The R-squared (R^2) value measures the extent to which the independent variable(s) in a regression model explain the variance in the dependent variable. It is also referred to as the coefficient of determination. In noise pollution prediction models, a higher R-squared value indicates a stronger agreement between the model and the observed data, suggesting a higher level of correlation between the variables under study.

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$
$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Where: y_i - true values of y
 $\hat{y}_i$ - predicted values of y
 $\bar{y}$ - average value of y

TABLE I: MODEL EVALUATION

	Precision	Recall	F1-Score	Support
0	1	0.95	0.97	20
1	0.97	1	1	147
Accuracy			0.97	167
Micro avg	1	0.97	0.99	167
Weighted avg	0.99	0.99	0.99	167

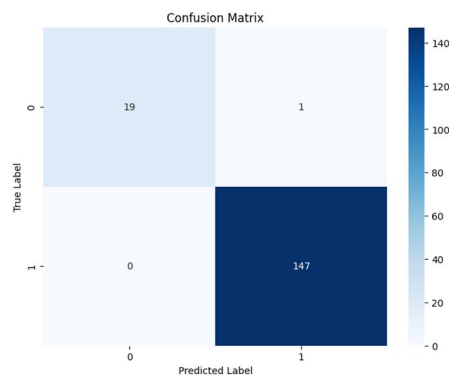


Figure 4. Confusion Matrix of ResNet

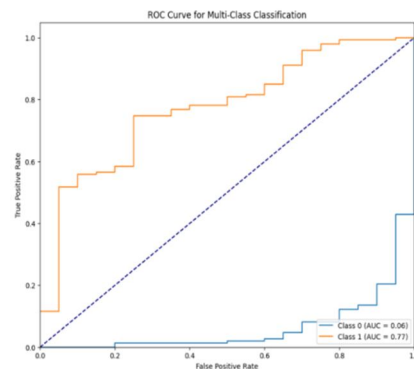


Figure 5. ROC Curve

III. CONCLUSIONS

The research used residual connections to overcome the vanishing gradient problem and facilitate efficient learning of complicated patterns in a deep learning model based on ResNet for forecasting solar and wind energy output. For both forms of energy generation, the model showed good predicting ability, with an overall accuracy of 99%. The confusion matrix verified that the predictions were accurate, and the scatter plot of the expected vs. actual values revealed little inaccuracy. The model struggled with lower output situations, as seen by the lower AUC of 0.06 for Class 0, but it performed well for larger energy generation instances, as shown by an AUC of 0.77 for Class 1.

Reduced Mean Absolute Error and a consistent fall in training and validation loss indicated strong generalization to previously encountered data. ResNet demonstrated efficacy in capturing the intricate relationships present in the data; nevertheless, next advancements may concentrate on optimizing low energy output performance via enhanced loss functions, dataset balance, or data supplementation. More varied characteristics or hybrid modelling may further increase the model's accuracy and range of practical applications, enabling more precise forecasting of renewable energy for sustainable energy management.

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