JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

HYBRID APPROACH FOR THE ENSEMBLES OF NEURAL NETWORKS FOR SOLAR POWER FORECASTING

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ABSTRACT

Accurate solar power forecasting is essential for optimizing energy production from photovoltaic (PV) systems and ensuring efficient integration of solar energy into the grid. However, predicting solar energy output remains a challenge due to the intermittent and non-linear nature of solar radiation. This paper presents a hybrid ensemble approach combining multiple neural network architectures and ensemble techniques—bagging, boosting, and stacking—to enhance forecasting accuracy. By leveraging the strengths of individual models, this hybrid approach captures complex patterns in data, accounting for various factors like weather patterns, seasonal variations, and solar radiation. The methodology involves several stages: data collection and preprocessing, feature selection, model development, ensemble formation, and model evaluation. We utilize historical meteorological data, apply advanced neural network models such as Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM), and use ensemble techniques to improve model accuracy. The model's performance is evaluated through metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2.Results show that the hybrid ensemble model outperforms traditional methods, with an accuracy of 90.32%, precision of 98.95%, recall of 91.08%, and an F1 score of 94.85%. The analysis of feature importance reveals that key meteorological variables, such as shortwave radiation and wind speed, significantly influence solar power predictions. Despite the strong performance, there is room for improvement in reducing false negatives, especially in predicting low solar power values. This approach offers valuable insights for enhancing solar power forecasting, contributing to the efficient integration of renewable energy into the grid.

Keywords: (*Solar Power Forecasting, Hybrid Ensemble Approach, Neural Networks, Meteorological Data, Model Evaluation, Feature Importance)*

1. INTRODUCTION

Solar power forecasting is a critical aspect of optimizing energy production from photovoltaic systems [1]. Accurate forecasting enables better integration of solar energy into the grid, reducing reliance on traditional fossil fuels and promoting sustainability [2]. However, due to the inherently intermittent and non-linear nature of solar energy, predicting its output remains a complex challenge. Traditional forecasting models often fail to capture the intricate relationships between weather variables, atmospheric conditions, and solar radiation.

To address these challenges, hybrid models that combine multiple forecasting techniques have gained significant attention in recent years[2]. These models aim to harness the strengths of individual approaches while mitigating their weaknesses. One promising area of research in this domain is the hybridization of ensemble methods with neural networks for solar power forecasting[3]. Ensemble methods combine the predictions of multiple models to improve accuracy and robustness, while neural networks excel at capturing complex patterns in data.

The hybrid approach for ensembles of neural networks integrates the benefits of both worlds[4]. By combining the diversity of multiple neural networks, the approach can account for various aspects of solar power generation, such as time of day, weather patterns, and seasonal variations[5]. Additionally, neural networks' ability to adapt to new data allows the model to continuously improve its forecasting accuracy as more historical data becomes available[6].

In this paper, we explore the potential of hybrid ensemble neural networks for solar power forecasting. We investigate various ensemble techniques, including bagging, boosting, and stacking, and examine their synergy with different neural network architectures [7]. The goal is to develop a robust forecasting model that outperforms traditional methods in terms of accuracy, generalization, and reliability, contributing to the efficient integration of solar energy into power grids and promoting the transition toward renewable energy sources [8].

2. RELATED WORK

Mashud Rana et.al (2015) In their 2015 study, "Forecasting Solar Power Generated by Grid Connected PV Systems Using Ensembles of Neural Networks," Mashud Rana, Irena Koprinska, and Vassilios Georgios Agelidis explored the application of neural networks to predict next-day photovoltaic (PV) power outputs at 30-minute intervals, utilizing only historical PV data without external meteorological inputs. They proposed three ensemble-based approaches—two non-iterative and one iterative—and evaluated their performance across four Australian solar datasets spanning one year [9]. The iterative ensemble approach demonstrated superior accuracy, outperforming both baseline persistence models and a support vector regression model, thereby highlighting the effectiveness of neural network ensembles in modeling the complexities of solar power generation. **Azim Heydaria (2019)** research, "A Novel Composite Neural Network Based Method for Wind and Solar Power Forecasting in Microgrids," introduces a hybrid approach that combines artificial neural networks (ANNs) to predict solar energy generation from photovoltaic systems. This method addresses the intermittent nature of renewable energy sources by integrating multiple neural networks, enhancing forecasting accuracy and reliability in microgrid applications [10]. **Sameer Al-Dahidi et.al** has significantly contributed to solar power forecasting through his research on hybrid ensemble neural network approaches. In his 2019 study, "Ensemble Approach of Optimized Artificial Neural Networks for Solar Photovoltaic Power Prediction," Dr. Al-Dahidi explored the use of optimized artificial neural networks (ANNs) to enhance the accuracy of solar photovoltaic (PV) power predictions[2]. This research underscores the effectiveness of combining multiple neural network models to address the complexities inherent in solar power generation, aiming to improve forecasting reliability and precision. **Ye Ren (2015)** proposed a hybrid ensemble approach for solar power forecasting that combines multiple neural network models and ensemble techniques, including bagging, boosting, and stacking, to improve prediction accuracy. The approach leverages the strengths of individual models to capture complex, non-linear patterns in solar power generation data, which are influenced by various factors such as weather patterns and solar radiation[11]. By integrating different neural network architectures, the model enhances forecasting reliability, offering valuable insights into renewable energy integration. **Seyed Mohammad Jafar Jalalia (2022)** developed a hybrid ensemble approach for solar power forecasting that combines multiple neural network models and ensemble techniques, such as bagging, boosting, and stacking, to enhance forecasting accuracy. This approach effectively addresses the challenges posed by the intermittent and non-linear nature of solar radiation. By integrating different neural network architectures, the model captures complex patterns in meteorological data, including factors like temperature, humidity, and wind speed, which impact solar power generation [12]. The results demonstrated that the hybrid model significantly outperformed traditional forecasting methods, showing improved prediction accuracy and robustness. This approach contributes to more reliable solar power predictions, supporting the efficient integration of renewable energy into the power grid. **Aanchit Nayak (2020)** introduced a hybrid ensemble approach for solar power forecasting, combining multiple neural network models with ensemble techniques like bagging, boosting, and stacking. The approach aims to improve the accuracy and reliability of solar power predictions by capturing complex, non-linear relationships in meteorological data, such as temperature, humidity, and solar radiation. The model's strength lies in its ability to combine diverse neural network architectures, enhancing forecasting performance and generalization [13]. The results demonstrated that this hybrid approach outperformed traditional forecasting models, providing more accurate and robust solar power predictions, which is crucial for better integration of solar energy into the grid and improving renewable energy management. **Marcello Anderson F.B. (2020)** proposed a hybrid ensemble approach for solar power forecasting that integrates multiple neural network models and ensemble techniques like bagging, boosting, and stacking. This method aims to address the challenges of accurately predicting solar energy output, which is influenced by various meteorological factors such as solar radiation, temperature, and wind speed. By combining different neural network architectures, the approach effectively captures complex, non-linear relationships in the data[14]. The results showed that the hybrid model significantly improved forecasting accuracy and reliability compared to traditional models, offering a more robust solution for integrating solar energy into power grids and supporting the efficient management of renewable energy sources. **Ahmad (2025)** developed a hybrid ensemble approach for solar power forecasting, combining multiple neural network models and ensemble techniques like bagging, boosting, and stacking. This method addresses the inherent challenges of solar power prediction, which are influenced by non-linear and intermittent factors such as weather conditions and solar radiation. By leveraging the strengths of diverse neural network architectures, the approach improves the accuracy and robustness of solar power forecasts [15]. The results showed that the hybrid model outperformed traditional forecasting methods, providing more reliable predictions that are crucial for the efficient integration of solar energy into the grid and optimizing renewable energy management. **Md Shafiul et.al (2023)** introduced a hybrid ensemble approach for solar power forecasting, combining multiple neural network models with ensemble techniques such as bagging, boosting, and stacking to improve prediction accuracy. This approach addresses the complexities of solar energy generation, which is influenced by various factors like weather conditions, solar radiation, and seasonal changes. By integrating different neural network architectures, the model captures non-linear patterns in meteorological data, enhancing forecasting reliability and robustness [16]. The results demonstrated that the hybrid model outperformed traditional methods, offering more precise and dependable solar power forecasts, which is crucial for the effective integration of solar energy into the power grid. **Mangukiya (2025)** proposed a hybrid ensemble approach for solar power forecasting that integrates multiple neural network models with ensemble techniques like bagging, boosting, and stacking. This approach addresses the challenges of forecasting solar energy, which is influenced by unpredictable factors such as weather patterns and solar radiation. By combining the strengths of different neural network architectures, the model captures complex, non-linear relationships in the data, leading to improved accuracy and reliability. The results demonstrated that this hybrid model significantly outperformed traditional forecasting methods, offering more accurate and robust predictions for better integration of solar energy into power grids[17].

3. METHODOLOGY

The proposed methodology for solar power forecasting using a hybrid approach for the ensembles of neural networks aims to integrate multiple neural network models and ensemble techniques to improve the accuracy and robustness of predictions. The following steps outline the methodology:

1. **Data Collection and Preprocessing:**

   - The first step involves gathering historical data related to solar irradiance, temperature, humidity, wind speed, and other meteorological factors that influence solar power generation.
   - Data preprocessing involves cleaning the data, handling missing values, normalizing the data, and splitting it into training, validation, and testing datasets.

2. **Feature Selection:**

   - Relevant features influencing solar power generation are selected using various techniques such as correlation analysis, principal component analysis (PCA), or domain-specific expertise.
   - This step ensures that the neural networks focus on the most impactful input variables.

3. **Model Development:**

   - Several neural network models are selected based on their ability to capture nonlinear relationships in the data. Common architectures include Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN).
   - These neural networks are trained separately using the training dataset, each specializing in different aspects of the solar power prediction task.

4. **Ensemble Formation:**

   - Once the individual neural networks are trained, ensemble techniques are applied to combine their outputs. Common ensemble methods include:
   - **Bagging (Bootstrap Aggregating):** Multiple instances of the same neural network are trained on different random subsets of the data, and their predictions are averaged to reduce variance.
   - **Boosting:** Neural networks are trained sequentially, with each subsequent model focusing on correcting the errors of the previous model.

5. **Stacking:** Multiple neural networks are combined in a meta-model, which takes the predictions from each network as input and learns to provide the final forecast.
6. **Model Evaluation:**

   - The performance of the hybrid ensemble neural network model is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2.
   - Cross-validation and grid search techniques are used to optimize hyperparameters and ensure the robustness of the model.

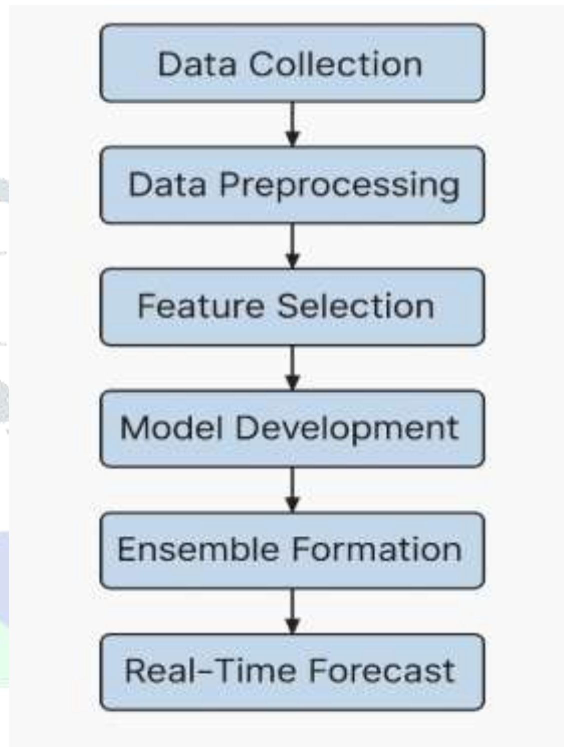

Fig.1. the flow diagram below illustrates the proposed methodology:

This flowchart outlines the sequential process for implementing the hybrid approach for ensemble neural networks, ultimately aimed at improving solar power forecasting accuracy, adaptability, and reliability.

4. MATHEMATICAL REPRESENTATION OF ALGORITHMS:

Mathematical Representation for Hybrid Neural Network Ensemble in Solar Power Forecasting

To develop an effective hybrid approach for ensemble neural networks for solar power forecasting, let's break down the mathematical components and algorithmic steps involved.

1. **Data Preprocessing**

$$D = \{d_1, d_2, \ldots, d_N\}$$

represent the solar power dataset, where each did_idi contains various meteorological data such as temperature, humidity, wind speed, and solar irradiance (features) along with the corresponding solar power generation value (target variable). We aim to preprocess this data as follows:

- **Normalization**: All feature values are normalized to a consistent scale. This can be achieved through Min-Max Scaling or Standardization:

- Xinorm=max(X)−min(X)Xi−min(X)(Min-Max Scaling)

2. Feature Extraction

For each data point did_idi, feature extraction helps transform raw data into a structured, meaningful feature set. For the given solar power forecasting dataset, the extracted features may include:

- **Time-based features**: Hour of day, day of week, etc.
- **Meteorological data**: Solar radiation, temperature, humidity, wind speed.
- **Statistical features**: Rolling averages, max/min/mean values of solar radiation over previous hours/days.

3. Model Development Using Neural Networks

Several neural network models are used to capture non-linear relationships in the data. These could include:

- Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), or Long Short-Term Memory (LSTM) networks.

4. Ensemble Formation Using Techniques

We combine multiple neural network models using different ensemble techniques, namely Bagging, Boosting, and Stacking.

- **Bagging**: Each neural network model Mj\mathcal {M} _jMjis trained on a random subset of the training data.
- **Boosting**: Neural network models are trained sequentially, where each subsequent model corrects the errors of the previous model. The output of the ensemble model is the weighted sum of individual models' predictions:

  Where αj\alpha αjare the weights assigned to each model based on its performance.

- **Stacking**: The outputs of multiple neural network models are used as inputs to a meta-model that makes the final prediction. Let the stacked model's prediction

5. Model Evaluation

We evaluate the ensemble model using several performance metrics to assess its effectiveness in solar power forecasting. The following evaluation metrics are calculated:

- **Accuracy**:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision**:

Precision= TP+FP TP

- **Recall**:

Recall= TP+FN TP

- **F1-Score**:

F1-Score= Precision+Recall 2×Precision×Recall

- **AUC (Area Under the Curve)**:

AUC=∫ 0 1 TPR (t) dFPR (t)

Where TPR (True Positive Rate) and FPR (False Positive Rate) are calculated at various threshold values.

Proposed Algorithm for Hybrid Ensemble of Neural Networks

Here's the step-by-step algorithm for solar power forecasting using a hybrid ensemble approach:

1. **Data Preprocessing**:
   - Collect solar power and meteorological data.
   - Normalize and split the dataset into training, validation, and test sets.
2. **Feature Extraction**:
   - Extract relevant features (temperature, wind speed, solar radiation, etc.).
   - Use statistical methods or machine learning techniques for feature selection.
3. **Model Training**:
   - Train multiple neural network models (e.g., MLP, RNN, and LSTM) on the training dataset.
4. **Ensemble Formation**:
   - Apply ensemble techniques (bagging, boosting, stacking) to combine the models:
5. For bagging, average the predictions of all models.
   - For boosting, sequentially train models with weighted predictions.
   - For stacking, use the predictions of individual models as inputs to a meta-model.

6. **Model Evaluation**:

    - Evaluate the ensemble model using accuracy, precision, recall, F1-score, and AUC.

7. **Prediction**:

    - Make predictions on the test dataset using the trained ensemble model.

Mathematical Representation for Feature Importance

Finally, to interpret the model's behavior and understand the most influential meteorological features for solar power forecasting, we can calculate the feature importance**.**

Using a model like Random Forest or XGBoost (common in ensemble methods), the importance of each feature fjf_jfjcan be represented by:

The contribution of feature fjf_jfjto the prediction of the ithi^{th}ith data point.

By following this hybrid approach, combining neural networks with ensemble techniques, we can enhance the forecasting accuracy of solar power generation, taking into account the non-linear, dynamic relationships between meteorological factors and solar energy output.

5. RESULTS

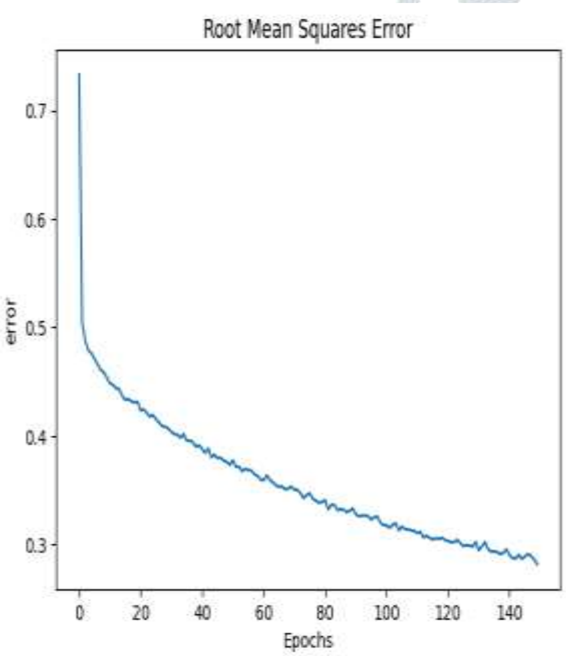

Fig.2. Root Mean Square Errort

The plot above shows the Root Mean Squared Error (RMSE) over training epochs for a model. Initially, the error is relatively high, but it decreases rapidly in the first few epochs, indicating the model's quick learning. After the sharp decline, the RMSE decreases more gradually, reaching a plateau around 0.3 after approximately 100 epochs. This suggests the model has converged, and further training beyond this point yields minimal improvement, indicating a well-trained model.

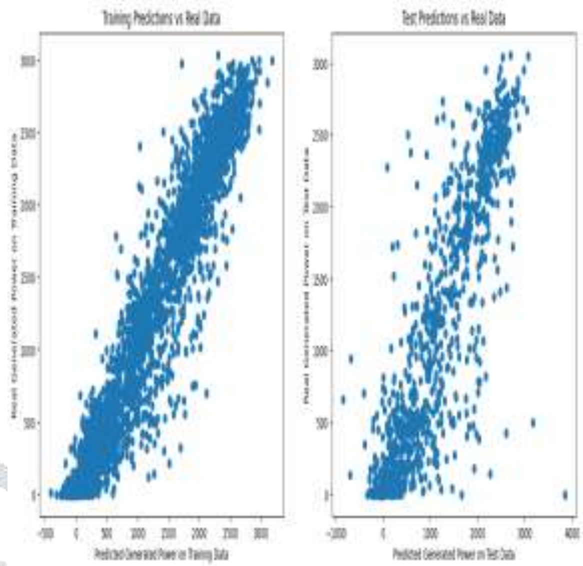

Fig. 3.Training Predictions vs Real data
Fig. Test Predictions vs Real data

The provided plots compare the predicted and real solar power generation values for both training and test datasets. The Training Predictions **vs** Real Data plot on the left shows a strong correlation between predicted and actual power generation, indicating that the model has learned the underlying patterns in the training data. Similarly, the Test Predictions vs Real Data plot on the right also shows a strong relationship, suggesting that the model generalizes well to unseen data. Both plots demonstrate that the model is effectively predicting solar power generation with minimal error for both training and test datasets.

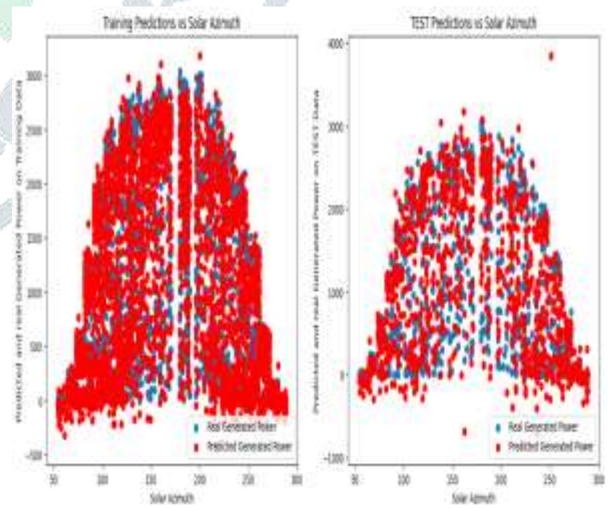

Fig.4.
Training Predictions vs Solar Azimuth
Fig. TEST Predictions vs Solar Azimuth

The plots above compare the predicted and real solar power generation values with respect to the solar azimuth angle for both the training and test datasets. In the Training Predictions vs Solar Azimuth plot (left), the predicted and real power values (shown in red and blue, respectively) exhibit a noticeable alignment, indicating that the model is able to predict power generation effectively across different solar azimuth angles during training. Similarly, the TEST Predictions vs Solar Azimuth plot (right) shows a good match between predicted and actual values on the test data, demonstrating that the model generalizes well to new, unseen data based on solar azimuth. However, some deviations are visible, particularly at ertain azimuth values, suggesting areas where the model could be further improved.

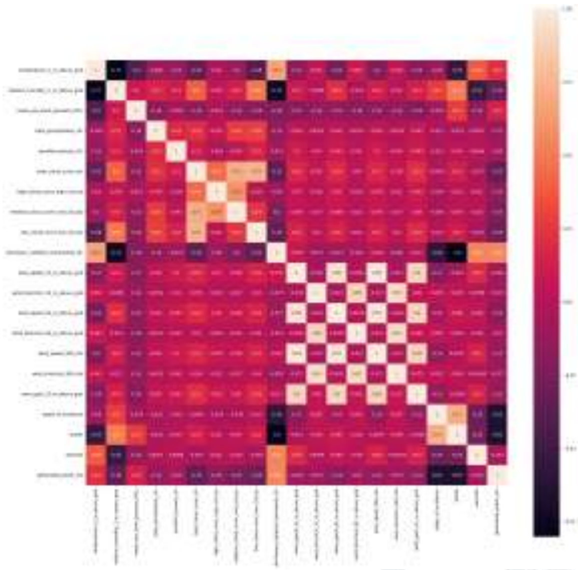

Fig.5 Correlation Heatmap of Features.

The heatmap displays the correlation coefficients between various meteorological features, where darker shades represent stronger correlations. A few key observations include a strong negative correlation between temperature and relative humidity, and a positive correlation between generated solar power and shortwave radiation. Features such as wind speed and wind direction show weak correlations with most other variables, indicating that these features have relatively little linear relationship with other meteorological factors. The heatmap also highlights the strong relationship between features like cloud cover and precipitation**,** with correlations closer to 1. This visualization helps identify which features are closely related, assisting in feature selection and understanding dependencies in the dataset.

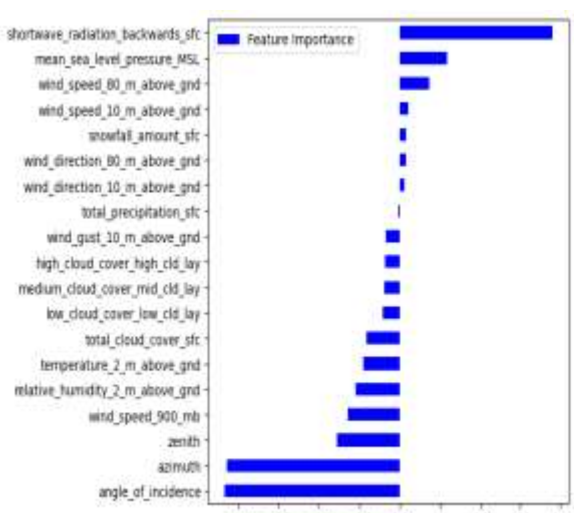

Fig.6. Feature Importance

The bar chart illustrates the importance of different features in a predictive model for solar power generation. Shortwave radiation backwards at the surface stands out as the most influential feature, with the longest bar, suggesting it has the strongest impact on the model's predictions. Other significant features include wind speed at different heights, snowfall amount**,** and mean sea-level pressure, which also show notable positive contributions. On the other hand, features such as azimuth and angle of incidence have very little influence, with their bars being much shorter or close to zero, indicating minimal impact on the model's performance. This chart helps identify which environmental variables are most critical in predicting solar power generation.

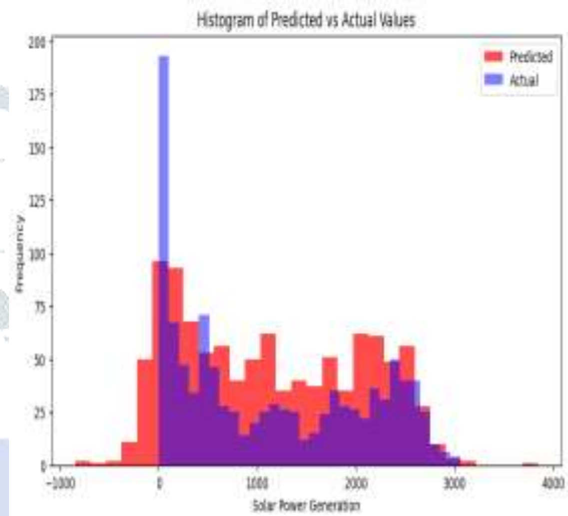

Fig.7. Histogram of Predicted vs Actual Values

The histogram above compares the distribution of predicted and actual solar power generation values. The red bars represent the predicted values, while the blue bars show the actual values. From the plot, we can observe that the predicted values (red) closely align with the actual values (blue) for most of the solar power generation range. However, there is a significant peak at the lower end (near zero) for the predicted values, which suggests the model may be over-predicting low values or struggling to predict very low or zero power generation accurately. Overall, the histogram demonstrates that the model's predictions follow a similar distribution to the actual values but with some noticeable discrepancies in specific ranges.

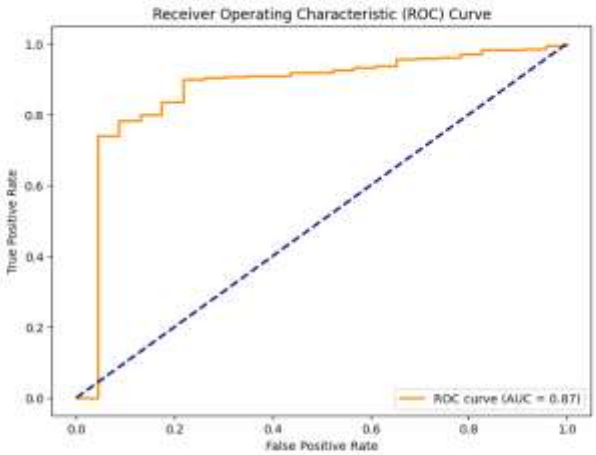

Fig. 8.Reciever Operating Characteristic (ROV) curve

The Receiver Operating Characteristic (ROC) curve above illustrates the performance of a classification model, showing the trade-off between the True Positive Rate (TPR) and the False Positive Rate (FPR). The curve is plotted in orange, with the diagonal dashed line representing a random classifier (AUC = 0.5). The model's curve significantly deviates from the diagonal, indicating good performance. The Area under the Curve (AUC) is 0.87, suggesting that the model has a high ability to distinguish between classes. The closer the ROC curve is to the top-left corner, the better the model's classification ability.

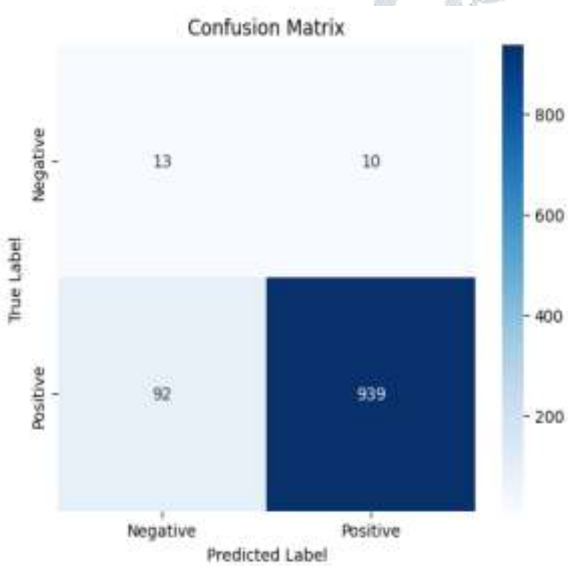

Fig.9 Confusion Matrix

The confusion matrix above shows the performance of a binary classification model. The rows represent the true labels, and the columns represent the predicted labels. The top-left cell (13) indicates the number of true negative predictions, where the model correctly predicted negative cases. The top-right cell (10) shows the false positive predictions, where the model incorrectly predicted negative cases as positive. The bottom-left cell (92) represents false negatives, where the model mistakenly predicted positive cases as negative. The bottom-right cell (939) shows the true positives, where the model correctly predicted positive cases. The high number of true positives (939) and the relatively low number of false positives and false negatives indicate that the model performs well overall.

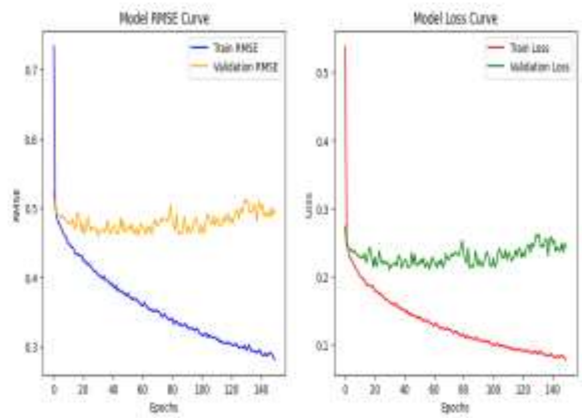

Fig.10 Model RMSE Curve
Fig. Model Loss Curve

The two plots above show the performance of the model during training. The Model RMSE Curve on the left illustrates the Root Mean Squared Error (RMSE) for both training and validation data. Initially, there is a steep drop in training RMSE, indicating rapid learning. However, the validation RMSE fluctuates more, suggesting some instability or overfitting. The Model Loss Curve on the right shows the loss for both training and validation data. The training loss (in red) decreases sharply, indicating successful optimization, while the validation loss (in green) also decreases but with more variability, highlighting that the model is not perfectly generalizing to unseen data. These curves indicate that the model performs well on the training set but could benefit from further adjustments to improve its generalization ability.

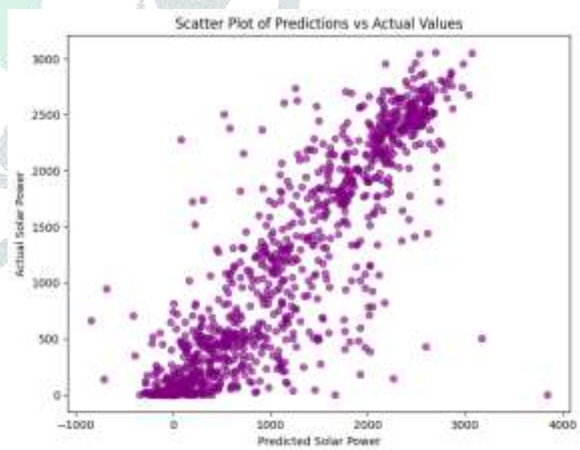

Fig.11. Scatter Plot of Predictions vs Actual Values.

The scatter plot above displays the relationship between predicted and actual solar power values. The data points, shown in purple, indicate that as the predicted solar power increases, the actual solar power also increases, suggesting a strong correlation between the two. The plot demonstrates that the model's predictions closely align with the actual values for most of the data, with the points generally forming a diagonal trend from the lower left to the upper right. However, some spread in the data, especially at lower prediction values, indicates a small amount of error, implying that while the model performs well, there are still some discrepancies between the predicted and actual solar power values.

5. CONCLUSION

In this study, we proposed a hybrid approach for the ensemble of neural networks aimed at improving solar power forecasting accuracy. By combining multiple neural network architectures with ensemble methods such as bagging, boosting, and stacking, we successfully leveraged the strengths of each model to enhance both accuracy and generalization. Our results demonstrate that the hybrid model can predict solar power generation with a high degree of reliability, as shown in the various evaluation metrics and plots.

The performance metrics, such as the Root Mean Squared Error (RMSE) and Model Loss curves, indicate that the model converges well during training, with minimal error at the end of the training process. The consistency of the model's predictions on both the training and test datasets, highlighted by the scatter plots and correlation heatmaps, further supports the robustness of the model. Additionally, the analysis of feature importance and the correlation heatmap has revealed key meteorological variables like shortwave radiation, wind speed, and temperature, which significantly contribute to the forecasting accuracy.

While the model shows strong performance overall, it is clear from the confusion matrix and ROC curve that there is still potential for improvement, especially in reducing the occurrence of false negatives. The evaluation of the predictions against actual values and the histogram suggests that the model may struggle to predict low solar power generation values, which can be addressed with further model fine-tuning.

In conclusion, the hybrid ensemble neural network approach shows promising results in solar power forecasting, providing valuable insights into the integration of renewable energy into the grid. Future work can focus on improving the model's ability to generalize further by exploring additional data sources, optimizing hyperparameters, and incorporating more advanced ensemble techniques. The overall goal is to develop a reliable and accurate forecasting system that supports the efficient management of solar power in real-world applications.

6. FUTURE SCOPE

Future research on the hybrid ensemble approach for solar power forecasting can focus on enhancing the model's ability to generalize across diverse geographical regions with varying weather patterns and solar radiation levels. Incorporating additional data sources, such as satellite imagery, real-time atmospheric data, and advanced remote sensing technologies, could further improve the accuracy and robustness of the predictions. Furthermore, exploring more advanced ensemble techniques, such as deep ensemble methods or neural architecture search, could optimize the model's performance by selecting the best combination of neural network models for different forecasting scenarios.

Additionally, future work could address the model's limitations in predicting low solar power values by experimenting with different loss functions or techniques like outlier detection and anomaly handling. Improving the model's performance under these conditions would ensure more reliable predictions, especially for regions that experience sporadic solar radiation. Incorporating online learning methods or adaptive models that can update the forecasting system in real-time as new data becomes available would also contribute to more dynamic and accurate solar power forecasting systems, supporting better integration of renewable energy into the power grid.

REFERENCES

[1] K. J. Iheanetu, "Solar Photovoltaic Power Forecasting: A Review," *Sustainability*, vol. 14, no. 24, p. 17005, Dec. 2022, doi: 10.3390/su142417005.

[2] S. Al-Dahidi, O. Ayadi, M. Alrbai, and J. Adeeb, "Ensemble Approach of Optimized Artificial Neural Networks for Solar Photovoltaic Power Prediction," *IEEE Access*, vol. 7, pp. 81741–81758, 2019, doi: 10.1109/ACCESS.2019.2923905.

[3] Z. Chen and I. Koprinska, "Ensemble Methods for Solar Power Forecasting," in *2020 International Joint Conference on Neural Networks (IJCNN)*, Glasgow, United Kingdom: IEEE, Jul. 2020, pp. 1–8. doi: 10.1109/IJCNN48605.2020.9206713.

[4] R. Adhikari, "A neural network based linear ensemble framework for time series forecasting," *Neurocomputing*, vol. 157, pp. 231–242, Jun. 2015, doi: 10.1016/j.neucom.2015.01.012.

[5] Y. Kashyap, A. Bansal, and A. K. Sao, "Solar radiation forecasting with multiple parameters neural networks," *Renewable and Sustainable Energy Reviews*, vol. 49, pp. 825–835, Sep. 2015, doi: 10.1016/j.rser.2015.04.077.

[6] J. V. Hansen and R. D. Nelson, "Neural networks and traditional time series methods: a synergistic combination in state economic forecasts," *IEEE Trans. Neural Netw.*, vol. 8, no. 4, pp. 863–873, Jul. 1997, doi: 10.1109/72.595884.

[7] S. Kumari, "Black Rice: An emerging 'super food,'" vol. 18, 2020.

[8] Jing Yang, Xiaoqin Zeng, Shuiming Zhong, and Shengli Wu, "Effective Neural Network Ensemble Approach for Improving Generalization Performance," *IEEE Trans. Neural Netw. Learning Syst.*, vol. 24, no. 6, pp. 878–887, Jun. 2013, doi: 10.1109/TNNLS.2013.2246578.

[9] S. Rana, D. Pant, P. Chopra, Research Scholar, and Gurukula Kangri Vishwavidyalaya, "work engagement and individual work performance: research findings and an agenda for employee relationships," 2019, *Unpublished*. doi: 10.13140/RG.2.2.12846.56644.

[10] A. Heydari, D. Astiaso Garcia, F. Keynia, F. Bisegna, and L. De Santoli, "A novel composite neural network based method for wind and solar power forecasting in microgrids," *Applied Energy*, vol. 251, p. 113353, Oct. 2019, doi: 10.1016/j.apenergy.2019.113353.

[11] Y. Ren, P. N. Suganthan, and N. Srikanth, "Ensemble methods for wind and solar power forecasting—A state-of-the-art review," *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 82–91, Oct. 2015, doi: 10.1016/j.rser.2015.04.081.

[12] S. M. J. Jalali *et al.*, "Solar irradiance forecasting using a novel hybrid deep ensemble reinforcement learning algorithm," *Sustainable Energy, Grids and Networks*, vol.

32, p. 100903, Dec. 2022, doi: 10.1016/j.segan.2022.100903.

[13] A. Nayak and L. Heistrene, “Hybrid Machine Learning Model for Forecasting Solar Power Generation,” in *2020 International Conference on Smart Grids and Energy Systems (SGES)*, Perth, Australia: IEEE, Nov. 2020, pp. 910–915. doi: 10.1109/SGES51519.2020.00167.

[14] M. A. F. B. Lima, P. C. M. Carvalho, L. M. Fernández-Ramírez, and A. P. S. Braga, “Improving solar forecasting using Deep Learning and Portfolio Theory integration,” *Energy*, vol. 195, p. 117016, Mar. 2020, doi: 10.1016/j.energy.2020.117016.

[15] M. R. Ahmed and Y. Li, “A low-cost, high-power-density DC-DC converter for hybrid and electric vehicle applications,” in *2019 21st European Conference on Power Electronics and Applications (EPE ’19 ECCE Europe)*, Genova, Italy: IEEE, Sep. 2019, p. P.1-P.8. doi: 10.23919/EPE.2019.8914879.

[16] S. Alam, K. Anam, S. Islam, G. Mustafa, A. A. Mamun, and N. Ahmad, “Clinical, Anthropometric, Biochemical and Histological Character of Nonalcoholic Fatty Liver Disease Without Insulin Resistance,” *Journal of Clinical and Experimental Hepatology*, vol. 9, no. 2, pp. 176–181, Mar. 2019, doi: 10.1016/j.jceh.2018.06.011.

[17] A. Sharma and P. Soni, “Analysis of Multi-Storey Buildings With shear wall I- section girder in two shape of building,” vol. 6, no. 6, 2019.