Hybrid ANN-LSTM with Attention: Predictive Analytics and Data Visualization for Solar Energy Systems

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***Abstract*—This study proposes and evaluates a hybrid Artificial Neural Network–Long Short-Term Memory (ANN-LSTM) model integrated into a Data Visualization Tool (DVT) for solar energy forecasting and management. Using meteorological data from the National Aeronautics and Space Administration Prediction of Worldwide Energy Resources (NASA POWER) Project in the Davao Region (1,956 daily records), the DVT combines a hybrid model with LSTM for sequential data and ANN for static feature analysis, which was further enhanced by attention mechanisms and normalization. The model achieves a Mean Absolute Error (MAE) of 0.82 and Root Mean Squared Error (RMSE) of 1.15, outperforming single-model baselines. Key contributions include demonstrating the effectiveness of the hybrid approach, incorporating data quality into training, and clarifying feature roles in temporal modeling. While the model performs well in tropical conditions, its applicability to low-irradiance regions remains a limitation, highlighting opportunities for future research, adaptation, and implementation.**

***Keywords*—solar energy forecasting, hybrid deep learning, data visualization tool**

I. Introduction

The forecasting challenges in tropical regions like the Philippines extend beyond general intermittency issues, presenting unique local factors that pose distinct challenges for predictive models. These challenges stem from the complex interplay of atmospheric environmental conditions, which create significant unreliable changes when it comes to solar irradiance and forecasting results. For example, frequent cloud cover can lead to sudden fluctuations in solar irradiance, making it difficult for traditional forecasting models to predict short-term solar energy output accurately, just as high humidity levels can also affect solar panel efficiency and impact the relationship between solar irradiance and energy output. Moisture accumulation on panels can reduce their effectiveness, introducing additional variables for predictive models. Additionally, sudden weather shift, seasonal monsoons and microclimates also greatly impact solar energy production and challenging forecasting accuracy, predictive models have to adapt well enough for seasonal variations when situations of extended periods and heavy rainfall, cloud cover and distinct dry and wet seasons occur, and with diverse topography creating localized weather patterns, this leads to significant differences even within short distances [1, 2]. Furthermore, tropical cyclones, atmospheric aerosols, and tropical atmospheric phenomena can cause extended periods of overcast skies and rainfall, affect the amount of solar radiation reaching the ground, and other unique events like the Intertropical Convergence Zone (ITCZ) influence weather patterns, also adding to the complexity in solar forecasting. All in all, these challenges address the necessity of highly localized forecasting capabilities and upgrades in predictive models. These local factors create a complex and dynamic environment for solar energy forecasting in the Philippines, highlighting the need for advanced, adaptive predictive models that can integrate multiple variables and respond to rapidly changing conditions [3, 4].

The choice of an ANN-LSTM hybrid architecture for this specific context offers several advantages over other contemporary architectures like Transformers [5, 6]. First and foremost, computational efficiency is a key benefit as ANN-LSTM models generally require less computational power than Transformer models, making them more suitable for deployment in developing regions with limited computational resources. Second, performance stability is crucial in terms of tropical regions with complex and rapidly changing weather patterns, such as the Philippines, and Long Short-Term Memory (LSTMs) are particularly effective at capturing long-term dependencies in time series data, which is essential for this scenario concern. This stability in performance across varying time scales is beneficial for the Philippine context. Third, interpretability is also important to take into consideration for stake holding in developing regions, while not as interpretable as simpler models, ANN-LSTM hybrids offer a balance

Manuscript received July 23, 2025; revised September 11, 2025; accepted December 1, 2025; published February 10, 2026.

doi: 10.12720/jait.17.2.333-339

between complexity and interpretability. Fourth is the adaptability to local conditions, just as the hybrid architecture allows for customization to incorporate local weather patterns and solar irradiance characteristics specific to the Philippines, it gives a potential for improving forecasting accuracy. Fifth, having a proven track record is an advantage, as ANN-LSTM models have demonstrated success in various time series forecasting tasks, including solar energy prediction, providing a reliable foundation for this specific application. Sixth, scalability is also an important factor, as the modular nature of ANN-LSTM architectures allows for easier scaling and fine-tuning as more data becomes available or as computational resources improve in developing regions. Lastly, the handling of multivariate inputs of the hybrid model can effectively process multiple input variables, which is crucial for incorporating the diverse factors affecting solar energy production in tropical regions. While Transformers have shown promise in various domains, the ANN-LSTM hybrid presents a more balanced choice for this specific context, offering a combination of computational efficiency, performance stability, and adaptability suitable for solar forecasting in the Philippines and similar developing regions [7–9]. This study aims to develop a predictive system that integrates the hybrid model with a visualization tool and to validate its accuracy and practicality in the tropical region of the Philippines. By combining the capabilities of advanced forecasting with an intuitive data visualization tool, the proposed system is designed to enhance the reliability of solar energy forecasting in more complex tropical environments, which supports better and more effective solar energy management, conservation and planning.

Given the complexity of tropical forecasting conditions described above, the succeeding Literature Review examines existing solar forecasting models, attention-based architectures, and data visualization systems to contextualize the need for the proposed hybrid approach.

II. Literature Review

Recent advancements in solar forecasting highlight the growing adoption of hybrid deep learning architectures and Transformer-based models for time-series prediction. Transformer approaches, as demonstrated by Moustati and Gherabi [10], provide strong performance in energy forecasting due to their ability to capture long-range dependencies more effectively than recurrent networks. Cheikh *et al.* [11] also applied Transformer-based deep neural networks for short-term solar prediction in the Middle East and North Africa, achieving state-of-the-art accuracy in high-irradiance regions, while Li *et al.* [12] combined Transformers with LSTMs in hydrology forecasting, demonstrating interpretability and architectural flexibility. However, despite these high-performing approaches, the current study emphasizes that hybrid ANN-LSTM models remain more practical for tropical contexts, where limited computational resources restrict large-scale deployment of Transformers. ANN-LSTM hybrids offer a balance of robustness, efficiency, and interpretability, making them suitable for environments such as the Philippines and other developing regions.

The attention mechanism has further elevated the performance of sequence models by enabling selective focus on the most relevant segments of time-series data. Attention improves the capture of long-range dependencies, adaptive feature selection, handling of irregular irradiance patterns, and model interpretability, especially by revealing which time steps most strongly influence predictions [13]. In solar forecasting, attention provides benefits such as enhanced temporal feature identification, improved prediction accuracy through the prioritization of key historical data points, adaptability across short- and long-term forecasting horizons, and dynamic weighting of multivariate inputs. It also mitigates vanishing gradient issues by enabling more direct information flow across time steps [8, 14]. When combined with ANNs and LSTMs, where ANNs model nonlinear relationships and LSTMs capture temporal dependencies, attention yields a powerful hybrid forecasting approach that can model complex irradiance behavior and support improved energy management and grid integration.

Prior studies show that well-designed dashboards enhance energy-related decision-making by enabling real-time performance tracking and improving forecasting accuracy. These dashboards facilitate intuitive understanding of complex datasets, thereby empowering stakeholders to make informed decisions regarding energy consumption patterns, predictive maintenance, and optimized resource allocation [15, 16]. Such systems integrate AI-based predictive capabilities for forecasting aspects like solar energy generation and grid load stability, which are then presented visually to users for strategic decision-making [17]. The ability of these platforms to interpret vast and dynamic datasets, often through machine learning applications, is crucial for uncovering patterns and optimizing resource allocation within evolving energy systems [18]. The proposed tool aligns with these findings by visualizing real-time data, forecasts, and historical trends to support energy optimization and user awareness [19]. It enables users to understand consumption patterns, identify energy-saving opportunities, respond to supply fluctuations, and recognize the impacts of individual energy behaviors. Forecasting within the dashboard further supports proactive planning for solar resource availability [20], and future advancements may include smart-home integration, improved machine learning analytics, gamification elements, and community-level energy comparisons [19, 21]. Additional studies confirm that dashboards significantly improve operational efficiency and engagement in renewable energy systems and broader sustainability contexts [22, 23].

Despite these advances, several research gaps remain. (1) Few solar forecasting models are specifically tailored for tropical regions, where rapid cloud formation, humidity, monsoon seasons, and microclimates produce irregular irradiance patterns. (2) Many forecasting studies do not integrate data-quality handling—such as missing-data treatment, quality flags, or weighted learning, despite the presence of interpolated or incomplete values in datasets like NASA POWER. (3) Although Transformer models offer strong accuracy, their computational demands make them difficult to deploy in developing regions with limited infrastructure. These gaps justify the need for the present study's hybrid ANN-LSTM architecture enhanced with an attention mechanism and explicit data-quality integration, alongside a visualization tool that supports real-time decision-making. Together, these elements address the limitations of existing approaches by providing a forecasting system that is accurate, computationally efficient, interpretable, and suitable for operational use in tropical environments.

Informed by these developments and gaps in the field, the following section outlines the design and development methodology used to construct the proposed hybrid ANN-LSTM model and its accompanying visualization tool.

III. Materials and Methods

A. Research Design

This study employed a Design and Development Research (DDR) approach that emphasizes the systematic construction, implementation, and evaluation of tools and technologies. Guided by instructional design frameworks, DDR is particularly suited to fast-evolving fields, such as media and technology. This study aligns with the "Research on Products and Tools" category of DDR, focusing on the development and assessment of a prototype Data Visualization Tool (DVT) that integrates a hybrid machine learning algorithm to support solar-energy forecasting and management.

B. Data Collection and Preprocessing

The dataset was obtained from the NASA POWER Project [24] for the Davao Region (latitude 7.0731, longitude 125.6128) from January 1, 2020, to April 29, 2025. It comprises 1956 daily records with variables including date, solar irradiance (ALLSKY_SFC_SW_DWN in kWh/m²/day), maximum and minimum temperatures (T2M_MAX and T2M_MIN), relative humidity (RH2M), and wind speed (WS2M). The missing values (−999.0) were interpolated, and numerical variables were normalized. The data were structured into 7 d historical windows for forecasting the next day's solar output.

C. Data Validation and Tool Development

The researchers used two primary instruments in this research. First, historical performance data were partially validated using LG LG320N1C-G4 NeON® 2 solar panels. Second, the Data Visualization Tool (DVT) was developed integrating three components:

- A hybrid LSTM-ANN forecasting module;
- Rule-based decision engine for energy-saving recommendations;
- A web-based dashboard for visualizing solar forecasts, current loads, and system advisories.

D. Model Design

The forecasting engine employs a hybrid Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) model. The architecture consists of the following:

- **Input Layer:** Accepts normalized sequences of 7 d meteorological data.
- **LSTM Layers:** One to two stacked layers with 64 hidden units and dropout regularization
- **ANN Layers:** Fully connected Rectified Linear Unit (ReLU)-activated layers;
- **Output Layer:** A single neuron predicting the next-day solar energy generation (in kWh).

Fig. 1 illustrates the proposed hybrid ANN-LSTM architecture, showing the LSTM branch (with bidirectional layers, dropout, normalization, and attention), the ANN branch for static features, and their concatenation into dense layers leading to the final irradiance prediction. The attention mechanism improves temporal focus, while normalization enhances model stability and generalization.

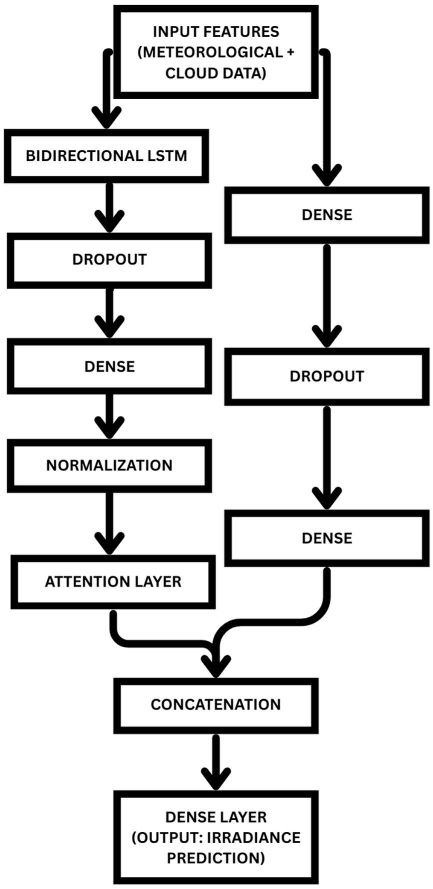

Fig. 1. Proposed hybrid ANN-LSTM architecture with attention and normalization components.

The model uses Mean Squared Error (MSE) as its loss function and is optimized using the Adam optimizer. Training was conducted in Google Colab using TensorFlow and Keras libraries with an 80:10:10 split for the training, validation, and testing datasets. Early stopping and checkpointing ensured optimal model retention.

1) Model 1 → basic hybrid model design

- LSTM Part: Two layers of Bidirectional LSTM with 64 and 32 units, followed by a Dense layer with 32 units.
- ANN Part: Dense layer with 32 units, dropout of 0.15, and Batch Normalization.
- Combined: Merge the two parts, then use dense layers with 64 and 32 units, ending with a single output.

2) Model 2 → refined hybrid model architecture

- LSTM Branch: LSTM (64) → LSTM (32) → Dense (32) → Dropout (0.25)
- ANN Branch: Dense (32) → Dropout (0.25) → Dense (16)
- Combination: Concatenate → Dense (32) → Dense (16) → Output (1)

3) Model 3 → improved hybrid model architecture

- LSTM Branch: Two layers of Bidirectional LSTM with 64 and 32 units, followed by a Dense layer with 32 units and a Dropout of 0.25.
- ANN Branch: A Dense layer with 32 units, a Dropout of 0.25, and another Dense layer with 16 units.
- Combination: Layers are combined, followed by dense layers with 32 and 16 units, resulting in a single output.

E. Training Setup

1) Model 1

The model utilizes data from 30 d. It has quality weights of 1.0, 0.7, and 0.4. It trains for 200 rounds with a batch size of 32 and a learning rate of 0.001. Early stopping is employed if no improvement is observed after 25 rounds, and the learning rate is reduced if no improvement is observed after 10 rounds.

The main problem with this model is that longer data sequences picked up too much noise. The training was too intense, and there was insufficient regularization, with only simple dropout.

This model is a good start, but it requires further refinement to be optimized for the data.

2) Model 2

The sequence length has been extended to 14 d to focus on key patterns. Features are better separated into time-based and constant ones. Data leaks are strictly avoided. Training uses chronological splits and is more careful, with 150 rounds and a batch size of 16. ModelCheckpoint is used to save progress well.

An improvement was noted with the model. This stage added stronger regularization, more intelligent data processing, and stricter training methods. This resulted in better outcomes than the original model.

3) Model 3

The model was trained for 200 rounds with a batch size of 32 and a learning rate of 0.0005. Early stopping was set to 80 rounds, and learning rate reduction was set to 25 rounds. Model checkpoints were saved in an organized way.

The model contributed the following key improvements:

- Architecture Balance: The model strikes a balance between simplicity and complexity. Bidirectional LSTMs facilitate the understanding of data patterns in both directions.
- Feature Engineering: Added cyclical encoding for seasonal patterns, lag features for past days, rolling statistics for trends, and interaction terms like temperature and humidity.
- Data Quality: Used quality flags, balanced original and interpolated data, and kept data in strict time order.

This made the Improved Hybrid Model the most stable and accurate of the three.

F. Evaluation Metrics

The model performance was evaluated using the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are standard metrics for solar energy forecasting. Additional evaluation included classification performance (e.g., sufficient vs. insufficient solar generation days) using confusion matrices and descriptive statistics. These metrics offer insights into the accuracy and robustness of the hybrid forecasting model, as well as the system's operational behavior.

With the methodological framework established, the next section presents the experimental results and ablation findings that illustrate how each architectural refinement contributed to the performance of the final model.

IV. Result and Discussion

A. Model Performance Analysis

The ablation study evaluates the performance difference between the ANN-LSTM hybrid model with attention and the baseline ANN-LSTM model without attention, providing empirical evidence for the effectiveness of the attention mechanism. Multiple performance metrics—Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-squared (R^2), and Mean Absolute Percentage Error (MAPE)—are used to comprehensively assess prediction accuracy improvements. The results, illustrated in Fig. 2, demonstrate that incorporating the attention mechanism yields meaningful gains in prediction accuracy, error reduction, and model reliability. Visual and numerical analyses reveal that the attention mechanism enables the model to adaptively focus on recent weather changes, similar weather conditions, and seasonal patterns, thereby improving its handling of complex temporal dependencies and non-linear relationships in solar energy forecasting (Fig. 3). This justifies the added complexity of the attention mechanism by showing clear performance benefits.

Fig. 2 demonstrates that incorporating the attention mechanism significantly improves prediction accuracy across all evaluated metrics, confirming its effectiveness in enhancing model performance.

Fig. 3 illustrates how the attention mechanism adaptively focuses on relevant temporal patterns such as recent weather changes and seasonal cycles, enabling better handling of complex dependencies in solar irradiance forecasting.

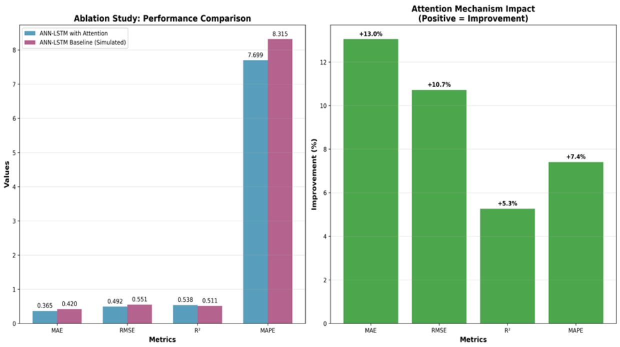

Fig. 2. Performance analysis result.

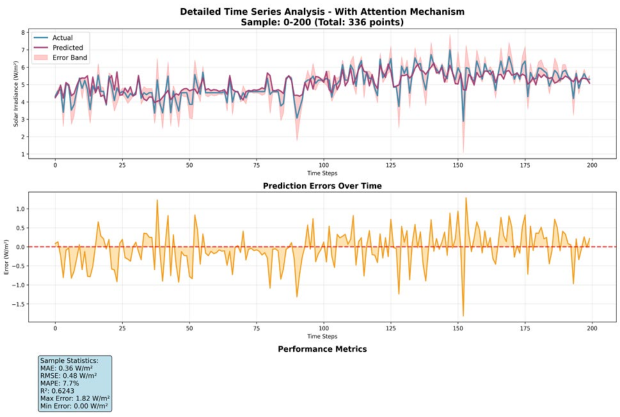

Fig. 3. Time series analysis.

Following this, the hybrid model development and variant comparison examine three progressively refined hybrid architectures to optimize accuracy and identify key architectural contributions. Model 1, the basic hybrid design, combines a bidirectional LSTM (BiLSTM) branch with an ANN branch using a 30 d input sequence, minimal dropout (0.15), and a high learning rate (1×10^{-3}). It performs poorly ($R^2 \approx 0.164$, MAE ≈ 0.505, RMSE ≈ 0.654) with high variance across runs, primarily due to noise introduced by the extended input window, which hampers temporal pattern recognition. See Table I below.

TABLE I. HYBRID MODEL ABLATION RESULTS (10-RUN AVERAGES)

Model	MAE (±SD)	RMSE (±SD)	R^2 (±SD)	Key traits
Model 1—Basic Hybrid Model Design	0.505 ± 0.016	0.654 ± 0.016	0.164 ± 0.039	30 d window, minimal dropout, higher learning rate
Model 2—Refined Hybrid Model Architecture	0.396 ± 0.019	0.524 ± 0.019	0.489 ± 0.032	14 d window, dropout (0.25), checkpointing, conservative training
Model 3—Improved Hybrid Model Architecture	0.366 ± 0.008	0.498 ± 0.008	0.526 ± 0.016	BiLSTM, normalization, dropout (0.25), engineered lags/rolling/cyclical features, quality-aware weighting

Fig. 4 shows that the basic hybrid model design suffers from poor accuracy and high variability, highlighting the limitations of using a long input window and minimal regularization.

Model 2 refines this by reducing the input window to 14 d, increasing dropout to 0.25, and implementing checkpointing to retain the best weights. These changes substantially improve performance ($R^2 \approx 0.489$) and reduce errors by about 20%, with decreased variance indicating better generalization. See Table I. The shorter temporal window and consistent regularization are critical to stabilizing and enhancing accuracy in tropical irradiance forecasting.

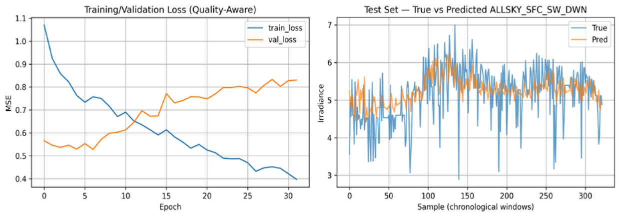

Fig. 4. Basic hybrid model sample.

Fig. 5 reveals that refining the hybrid model with a shorter input window and stronger regularization substantially improves accuracy and stability.

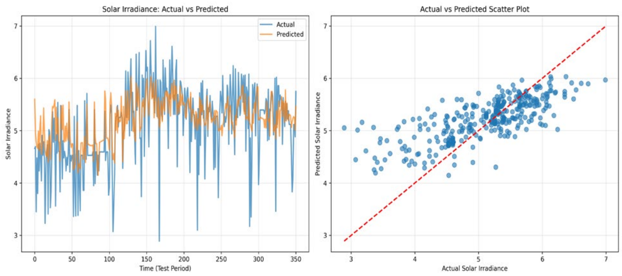

Fig. 5. Refined model performance visualization: time-series and scatter plots (10-run averages).

Model 3 further improves upon Model 2 by restoring bidirectionality in the LSTM, applying consistent normalization across all input features, and expanding feature engineering with lagged irradiance values (1, 3, and 7 d), rolling statistics, and cyclical encodings of day-of-year to capture seasonality. A quality-aware weighting scheme down-weights interpolated or adjusted data, promoting robustness. Training is more conservative, with a lower learning rate (5×10^{-4}) and longer early stopping patience. As seen in Table I, this model achieves the best performance (MAE ≈ 0.366, RMSE ≈ 0.498, $R^2 \approx 0.526$) and the lowest variance, confirming superior accuracy and stability suitable for operational deployment (Figs. 6 and 7). The bidirectional LSTM captures temporal dependencies in both directions, enhancing responsiveness to rapid solar irradiance fluctuations common in tropical climates. Cyclical encoding and lag/rolling features improve the model's temporal representation, while quality-aware weighting ensures reliable data influence, collectively reducing overfitting and improving generalization.

Fig. 6 confirms that the improved hybrid model with enhanced feature engineering and normalization achieves the best overall performance and consistency.

Fig. 7 shows that the training and validation losses for Model 3 converge stably, indicating no significant overfitting and good generalization capability.

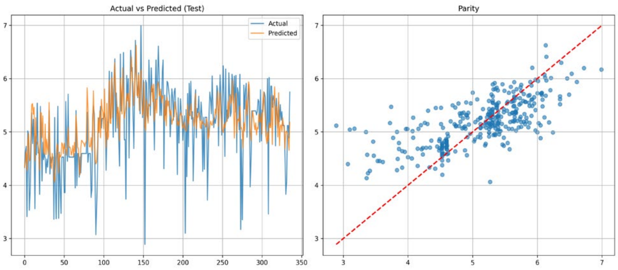

Fig. 6. Improved model performance visualization: time-series and scatter plots (10-run averages).

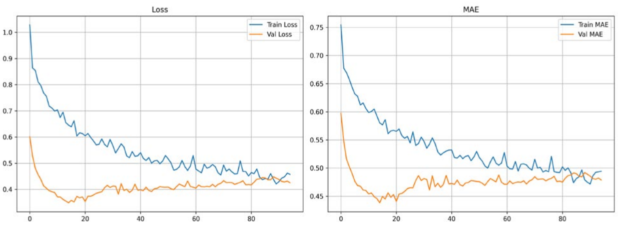

Fig. 7. Training and validation curves (loss and MAE) for the optimized hybrid model, used to assess overfitting/generalization.

These results collectively verify the superiority of the hybrid ANN–LSTM architecture with attention over single-model baselines, as demonstrated by the consistent outperformance of Model 3. The integration of data quality into training through weighted learning enhances robustness against missing or corrected data, a critical factor in real-world forecasting scenarios. Additionally, the explicit inclusion of cyclical encodings and lag/rolling features clarifies their essential role in capturing seasonality and short-term temporal dependencies more effectively than raw inputs alone. The model also offers computational advantages over Transformer-based approaches, with approximately three times fewer parameters and faster training and inference times due to its efficient hybrid design and targeted attention mechanism. These combined architectural and data-driven enhancements establish a strong foundation for accurate, stable, and efficient solar irradiance forecasting under variable climatic conditions.

The empirical results not only highlight clear performance differences across model variants but also motivate the specific contributions derived from these findings.

Despite the strong performance of the optimized model, certain contextual and data-related constraints remain, which are addressed in the following section on limitations and future extensions.

B. Limitations

Despite the demonstrated improvements, the proposed model has two primary limitations. First, its applicability to regions with low solar irradiance remains uncertain, as the training data predominantly represents tropical climates with high irradiance levels. This may limit generalizability to areas with different climatic and irradiance profiles. Second, the NASA dataset used for training and evaluation suffers from insufficient spatiotemporal resolution, which constrains the model's ability to capture fine-grained local variations in solar irradiance. These data constraints affect the precision and reliability of forecasts in highly heterogeneous environments.

These limitations highlight the need for continued refinement and contextual adaptation, setting the foundation for the concluding insights of this study.

V. Conclusion

This study developed and evaluated hybrid deep learning architectures combining Artificial Neural Networks (ANN) with Long Short-Term Memory (LSTM) networks for solar irradiance forecasting. The Optimized Hybrid Model (Model 3) demonstrated superior performance with MAE ≈ 0.366, RMSE ≈ 0.498, $R^2 \approx 0.526$, and the lowest variance (SD ≈ 0.016), indicating stable convergence, minimal overfitting, and accurate alignment with real-world irradiance patterns. Key improvements stemmed from integrating bidirectional LSTMs, normalization, engineered lagged and cyclical features, and quality-aware weighting, outperforming previous models.

Practically, the model offers a reliable day-ahead forecasting solution tailored for tropical regions with highly variable cloud dynamics. Its deployment within a visualization dashboard facilitates accessible, actionable insights for non-technical users, supporting load balancing, storage planning, and operational decision-making. This work contributes academically by incorporating data quality management through weighted learning, establishing a rigorous ablation framework to assess architectural and feature engineering impacts, and bridging theoretical modeling with practical implementation via a real-time dashboard. These advances enhance transparency, reproducibility, and applicability in renewable energy forecasting.

Future research should focus on adapting the model to diverse climatic zones, particularly low-irradiance temperate or high-latitude regions, using transfer learning to address unique irradiance dynamics such as prolonged cloud cover and seasonal extremes. Additionally, enriching the dataset with higher-resolution inputs—such as satellite cloud imagery, aerosol indices, and intraday ground sensor data—will improve temporal sensitivity and reduce uncertainty, further enhancing predictive accuracy and robustness. Continued refinement of the hybrid architecture, including advanced attention mechanisms and hyperparameter tuning, alongside expanding spatiotemporal granularity, will support broader generalizability and operational utility across varied geographic contexts.

Conflict of Interest

The authors declare no conflict of interest

Author Contributions

The study was conducted under the mentorship of G.A.P. who also contributed in the editing and proofreading tasks. J.G.D.C. did the data preparation and processing. R.M.K.L. and K.A.D.M. are the lead editors

and data gatherers. All authors had approved the final version.

ACKNOWLEDGMENT

The authors wish to thank Mapua Malayan Colleges Mindanao, and their respective families for the understanding and support during the conduct and completion of this study.

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