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A Hybrid Deep Learning Model for Wind and Solar Power Forecasting in Smart Grids

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Abstract

Accurate forecasting of renewable energy sources, such as wind and solar power, is crucial for the effective operation of smart grids. Traditional forecasting models often struggle to handle the complex, non-linear, and time-varying nature of renewable energy. This paper proposes a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for enhanced forecasting accuracy. The CNN is used to extract spatial features from weather-related data, while the LSTM handles temporal dependencies in the power generation patterns. The model is tested on wind and solar power data from various geographical locations. Experimental results demonstrate the superior performance of the hybrid model in comparison to traditional methods, with improved forecasting accuracy and reduced error margins. This work contributes to the optimization of smart grid management and better integration of renewable energy sources into power systems.

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I. Introduction

The global push for sustainability has led to significant advancements in the deployment of renewable energy sources, with wind and solar power being at the forefront of this transformation. These energy sources offer considerable potential for reducing dependency on fossil fuels and mitigating climate change. However, the intermittent nature of wind and solar power generation caused by variable weather conditions poses significant challenges for their reliable integration into the electrical grid. The stability of the grid and the efficiency of energy distribution depend heavily on accurate forecasting of power generation to avoid under or overproduction. In the context of smart grids, where energy distribution is dynamically adjusted based on real-time data, the ability to predict renewable energy generation plays a crucial role in balancing supply and demand. Existing forecasting techniques, such as traditional statistical models and machine learning algorithms, struggle to handle the complexity and non-linear patterns inherent in renewable energy production. Deep learning has emerged as a powerful tool to address these challenges, owing to its capacity to model intricate patterns in large datasets. In this paper, we introduce a hybrid deep learning model that combines Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal modeling to improve the accuracy of wind and solar power forecasts in smart grid environments.

A. Background and Motivation

The integration of renewable energy sources like wind and solar power into modern power grids has become an urgent need as countries transition to more sustainable energy solutions. Wind and solar power, while abundant, are highly variable and dependent on changing environmental factors, such as wind speed, temperature, and cloud cover. These variations introduce uncertainties in energy

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production, making it difficult to predict power output accurately and reliably. This unpredictability can cause operational inefficiencies, including energy shortages or surplus, and can lead to high costs associated with energy storage and balancing supply and demand.

Traditional forecasting methods, such as autoregressive integrated moving average (ARIMA) models and simple linear regressions, often fail to capture the inherent complexities of renewable energy production. More advanced techniques, like Support Vector Machines (SVM) and Random Forests, have been applied to improve forecasting accuracy but still fall short when it comes to integrating both spatial and temporal data. Machine learning techniques like neural networks have been proposed in recent years as a more powerful alternative due to their ability to learn and adapt to non-linear patterns in large and complex datasets. Given the rapid growth in data availability and the increasing computational power of modern systems, deep learning, particularly hybrid models combining different neural networks, has emerged as an optimal solution for improving the accuracy of wind and solar power forecasting. This hybrid deep learning model aims to incorporate the spatial data of weather patterns using Convolutional Neural Networks (CNN) and capture temporal dependencies in energy production using Long Short-Term Memory (LSTM) networks.

B. Problem Statement

Despite the promising potential of deep learning models, there remains a significant gap in the accurate forecasting of wind and solar power generation. Many of the existing models used for this purpose are either based on traditional statistical methods or rely on simplified machine learning algorithms that fail to fully address the complexity of renewable energy production. Traditional statistical models do not capture the non-linear dynamics inherent in weather conditions and energy generation patterns. On the other hand, machine learning methods such as decision trees or support vector machines struggle to combine spatial and temporal data, resulting in less accurate predictions. The challenge is further compounded by the limited availability of high-quality, real-time weather and energy production data, which are necessary to train deep learning models effectively. Many forecasting systems also fail to account for the interdependencies between various factors, such as temperature, wind speed, cloud cover, and historical power generation, which have a profound effect on both wind and solar power output.This paper aims to address these limitations by developing a hybrid deep learning model that combines the spatial feature extraction capabilities of Convolutional Neural Networks (CNNs) with the temporal sequence modeling capabilities of Long Short-Term Memory (LSTM) networks. By doing so, we seek to improve the forecasting accuracy and reliability of wind and solar power generation predictions, thereby facilitating better decision-making in smart grid operations.

C. Proposed Solution

This paper proposes a novel hybrid deep learning model for wind and solar power forecasting that integrates the strengths of both Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The proposed model leverages CNNs to capture spatial features from meteorological data, such as temperature, humidity, wind speed, and cloud cover, which are crucial to predicting power generation. CNNs are particularly effective for spatial data as they can automatically learn spatial hierarchies and patterns from raw input data. The LSTM component of the model focuses on capturing the temporal dependencies in power generation over time. LSTMs are well-suited for time-series forecasting tasks due to their ability to model long-term dependencies and sequences, making them ideal for handling the time-varying nature of wind and solar energy production. In this hybrid architecture, the CNN first extracts meaningful features from the meteorological data, which are then passed to the LSTM layers. The LSTM network processes these features to understand the temporal dependencies between past and future power production. By combining these two powerful neural network architectures, the model can effectively capture both spatial and temporal information, leading to more accurate forecasts for wind and solar energy generation. This approach improves upon existing models that often treat spatial and temporal data separately or rely on simpler methods that fail to fully exploit the richness of the data.

D. Contributions

This paper presents several important contributions to the field of renewable energy forecasting. First, we propose a novel hybrid deep learning model that integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks, aiming to improve the accuracy of forecasting wind and solar power generation. The hybrid model is specifically designed to handle both spatial and temporal data, enabling it to capture complex patterns in weather conditions and power generation over time. This approach offers a more robust solution for predicting energy production, which is essential for optimizing smart grid operations. Second, we validate the performance of the proposed model through extensive experiments using real-world data. The dataset includes time-series data on wind and solar power generation from multiple locations, complemented by relevant meteorological data such as temperature, wind speed, and cloud cover. The model's accuracy is compared against several traditional forecasting methods, including ARIMA, Support Vector Machines (SVM), and standalone LSTM models. The experimental results highlight the superior forecasting performance of the hybrid CNN-LSTM model, underscoring its ability to provide more precise and reliable predictions. Lastly, the findings of this research offer significant practical implications. The hybrid deep learning model has the potential to enhance the accuracy of renewable energy forecasting in smart grids, thereby improving energy management and grid stability. This is particularly important for grid operators, energy producers, and energy storage companies looking to optimize renewable energy integration into the power system. By enabling more accurate forecasts, the model can help reduce the costs and inefficiencies associated with energy balancing, storage, and distribution, contributing to a more efficient and sustainable energy system.

E. Paper Organization

This paper is structured to provide a comprehensive understanding of the proposed hybrid deep learning model and its application to renewable energy forecasting. **Section II** offers a detailed review of related work in the field, focusing on both traditional and deep learning-based approaches to forecasting wind and solar power. This section highlights the existing methods and discusses their limitations, setting the stage for the introduction of the hybrid model. **Section III** outlines the methodology behind the proposed hybrid CNN-LSTM model, describing how Convolutional Neural Networks (CNN) are used for spatial feature extraction and Long Short-Term Memory (LSTM) networks are employed to model temporal dependencies in power generation data. It also details the data preprocessing steps and evaluation metrics used to assess the model's performance. **Section IV** presents the results of the experiments conducted using real-world data, followed by an in-depth discussion of the model's performance. This section compares the hybrid CNN-LSTM model with traditional forecasting methods, illustrating the improvements in accuracy and efficiency achieved by the hybrid approach. Finally, **Section V** concludes the paper with a summary of the key findings, addressing the implications of the research for smart grid energy management. It also discusses the limitations of the current model and offers suggestions for future work aimed at further enhancing the forecasting accuracy and expanding the model's applicability. Overall, the paper provides a thorough exploration of the hybrid deep learning model, its advantages over traditional methods, and its potential impact on optimizing renewable energy forecasting and smart grid operations.

II. Related Work

In recent years, the integration of renewable energy sources such as wind and solar power into smart grids has prompted increased interest in accurate power generation forecasting. This section reviews the advancements in forecasting techniques, particularly those employing machine learning and deep learning models. The section is structured to cover several subsections: traditional forecasting models, machine learning methods, deep learning approaches, and hybrid models that combine CNN and LSTM for spatial and temporal forecasting.

A. Traditional Forecasting Models

Traditional methods like Autoregressive Integrated Moving Average (ARIMA) have long been used for time-series forecasting due to their simplicity and effectiveness in capturing linear trends in historical data. However, as renewable energy generation is heavily influenced by complex, non-linear factors like weather conditions, ARIMA models often fail to predict the inherent variability of renewable energy sources. These limitations are further exacerbated in the context of wind and solar power, which are subject to high fluctuations depending on spatial and temporal factors. Recent studies have pointed out that statistical models, though useful for simple trends, are not well-suited for modeling the dynamic and unpredictable nature of renewable energy generation. These drawbacks have led to the exploration of machine learning techniques that can handle non-linear relationships and higher-dimensional data more effectively [1,2].

B. Machine Learning Approaches

Machine learning techniques, including Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN), have emerged as more robust alternatives to traditional statistical methods. These models have been successfully applied in a variety of energy forecasting scenarios, including wind and solar power generation. SVMs, for instance, have shown promise in classifying and predicting power production based on input weather data. Similarly, Random Forests are effective at capturing non-linear relationships and have been widely used for energy forecasting. However, while these models can improve upon ARIMA in terms of accuracy, they still face challenges when it comes to handling both spatial and temporal dependencies simultaneously. Moreover, the integration of multiple features, such as weather data and energy consumption patterns, requires sophisticated feature engineering to achieve optimal results. These challenges point to the need for even more advanced deep learning methods [3,4].

C. Deep Learning for Time-Series Forecasting

Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have gained significant attention for their ability to capture long-term dependencies in sequential data. LSTMs are a type of recurrent neural network (RNN) designed to handle time-series data, which makes them particularly well-suited for forecasting applications like renewable energy generation. Recent works have shown that LSTMs outperform traditional machine learning models, especially in tasks requiring the modeling of sequential patterns in energy generation. However, LSTMs have a major limitation in that they struggle to process spatial data, such as weather patterns, that influence energy production. This is where the integration of Convolutional Neural Networks (CNNs) with LSTMs has proven beneficial. CNNs are excellent at extracting spatial features, while LSTMs can capture the temporal dependencies. Together, these models form a hybrid architecture that can simultaneously handle both the spatial and temporal dimensions of renewable energy forecasting. Several studies have already demonstrated the success of these hybrid models in other fields, such as traffic forecasting and power generation prediction [5,6].

D. Hybrid CNN-LSTM Models

The combination of CNNs and LSTMs into a hybrid architecture has shown significant promise in improving forecasting accuracy. CNNs are primarily used to extract spatial features from weather-related data, such as temperature, humidity, and wind speed, which are critical for energy generation predictions. These features are then passed to the LSTM network, which models the temporal dependencies in the data. This hybrid approach allows the model to leverage both spatial and temporal information, making it highly effective for forecasting renewable energy production from

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wind and solar sources. A study by Enam (2025) highlighted the success of such hybrid models in various domains, including traffic forecasting and power generation prediction. However, despite these successes, few studies have focused on combining CNN and LSTM for wind and solar power forecasting, particularly in the context of smart grids, where accurate and real-time predictions are essential for grid optimization. The hybrid CNN-LSTM model offers a scalable and more accurate solution for capturing both spatial and temporal dynamics, marking a significant advancement over traditional methods [1,4].

III. Methodology

The proposed hybrid deep learning model integrates two main components: a Convolutional Neural Network (CNN) for spatial feature extraction and a Long Short-Term Memory (LSTM) network for temporal dependency modeling. This architecture is designed to capture the spatial patterns in weather data as well as the temporal variations in energy generation, making it particularly effective for forecasting wind and solar power generation in smart grids.

Data Collection and Preprocessing

For this study, historical data on wind and solar power generation from various geographical locations is collected. The dataset also includes weather-related features such as temperature, humidity, wind speed, and cloud cover, which significantly impact the performance of renewable energy sources. These data are sourced from publicly available meteorological stations and energy grid operators, ensuring both breadth and accuracy in the data. Data preprocessing is a critical step to ensure that the raw data is in a usable format for the hybrid deep learning model. The collected features are normalized to standardize the inputs, helping the model train efficiently. The dataset is then divided into training, validation, and testing sets to enable proper model evaluation and prevent overfitting. Additionally, since the model deals with time-series data, the data is reshaped to ensure both spatial and temporal aspects are preserved during training. This reshaping involves structuring the data in sequences, where each sequence represents a time window of past weather data and power generation for prediction purposes. This preprocessing ensures that the model has access to comprehensive and well-structured data, which is crucial for achieving high forecasting accuracy.

CNN-LSTM Hybrid Model

The hybrid deep learning model proposed in this study combines the power of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to improve the accuracy of wind and solar power forecasting. The first component of this model, the Convolutional Neural Network (CNN), is designed to capture spatial features from weather-related data. Weather conditions such as wind speed, temperature, and humidity exhibit spatial dependencies, where certain patterns in one region can influence energy generation in nearby locations. The CNN extracts relevant features from this meteorological data by applying several convolutional layers, which scan the data for patterns. These convolutional layers are followed by pooling layers that reduce the data’s dimensionality and focus on the most significant patterns. For instance, regions with high wind speeds or temperatures can greatly affect the efficiency of solar or wind power generation. By using CNNs, the model learns how various weather conditions spatially impact energy production at different locations, which is crucial for forecasting renewable energy generation.

Table 1. CNN Component.

Component	**Description**
Convolutional Neural Network (CNN)	CNNs are used to capture spatial features from

	weather-related data, such as temperature, humidity, wind speed, and cloud cover.
Spatial Feature Extraction	CNNs extract spatial features by identifying patterns in meteorological data that influence power generation across different regions.
Convolutional Layers	Convolutional layers scan the data for spatial patterns in weather conditions and highlight the most relevant features for energy generation.
Pooling Layers	Pooling layers follow the convolutional layers, reducing the data's dimensionality and focusing on the most significant spatial patterns.
Weather Features	Weather features such as wind speed, temperature, and humidity are critical inputs, as they exhibit spatial dependencies that influence energy generation.
Impact of Weather Conditions	Weather conditions like high wind speeds or temperatures can significantly impact the efficiency of wind and solar power generation in nearby regions.

The second component of the model is the Long Short-Term Memory (LSTM) network, which specializes in capturing temporal dependencies in sequential data. LSTMs are particularly well-suited for time-series forecasting, where historical data plays a critical role in predicting future trends. In the case of renewable energy forecasting, LSTMs help model trends and seasonal variations in power generation data over time. For example, wind power generation may follow predictable daily cycles or exhibit longer-term seasonal patterns, which LSTMs can effectively capture. By maintaining information over extended time periods, LSTMs enable the model to understand the long-term behavior of wind and solar power generation, which is essential for accurate predictions.

Table 2. LSTM Component.

Component	**Description**

Long Short-Term Memory (LSTM)	LSTMs are a type of Recurrent Neural Network (RNN) designed to capture long-term dependencies in sequential data, making them ideal for time-series forecasting.
Temporal Dependency Modeling	LSTMs specialize in modeling temporal dependencies, allowing the network to learn patterns in data over extended time periods, which is crucial for forecasting renewable energy production.
Time-Series Forecasting	LSTMs excel at handling time-series data by considering historical information, allowing them to predict future values based on past observations, a critical aspect of energy generation forecasting.
Seasonal Pattern Recognition	LSTMs can identify seasonal variations in energy production, such as daily cycles or yearly fluctuations in wind and solar power generation, enhancing the model's predictive capabilities.
Long-Term Dependencies	By maintaining memory over long time intervals, LSTMs enable the model to learn and understand long-term trends in power generation, which are essential for accurate forecasting.
Impact on Renewable Energy Forecasting	LSTMs help improve the forecasting of wind and solar power by modeling long-term

	behavior and trends, which are key to optimizing grid management and energy distribution.

The CNN and LSTM components are integrated into a hybrid architecture that combines both spatial and temporal data. The CNN first processes the weather data to extract spatial features, which are then passed to the LSTM network for temporal processing. This hybrid approach is powerful because it allows the model to leverage the strengths of both networks—CNNs for spatial feature extraction and LSTMs for capturing temporal dependencies. As a result, this hybrid model improves forecasting accuracy by accounting for both the spatial patterns in weather data and the temporal fluctuations in power generation. This CNN-LSTM hybrid model significantly enhances the ability to make precise predictions about wind and solar power generation. These more accurate predictions are vital for optimizing smart grid operations, enabling better integration of renewable energy sources into the grid, and improving grid stability. By combining spatial and temporal data effectively, this hybrid approach represents a significant step forward in renewable energy forecasting.

Model Evaluation

To assess the performance of the proposed hybrid CNN-LSTM model, several standard evaluation metrics are used. One of the primary metrics is Mean Absolute Error (MAE), which provides an indication of the model's overall accuracy by calculating the average magnitude of errors in predictions. MAE measures the average of the absolute differences between the predicted and actual values, treating all errors equally regardless of their size. This makes it a reliable metric for understanding the general accuracy of the model. Another critical metric is Root Mean Square Error (RMSE), which is particularly useful for detecting larger errors. RMSE calculates the square root of the average squared differences between predicted and actual values, which places more emphasis on larger deviations. This metric is especially valuable in scenarios where large prediction errors can have significant consequences, such as in energy forecasting for smart grids, where even small errors can lead to operational inefficiencies or grid instability. The third metric used is Mean Absolute Percentage Error (MAPE), which is a relative measure that expresses the error as a percentage of the actual value. This allows for comparisons across different time periods and geographical regions, making it easier to gauge the model's performance in varying conditions. A lower MAPE value indicates better forecasting accuracy, which is crucial when dealing with renewable energy, where production patterns can vary significantly across regions and seasons. These metrics are computed on the testing set, which contains data the model has not encountered during training. This helps evaluate the model's generalization ability and how well it performs in real-world applications. When comparing the performance of the hybrid model against traditional forecasting methods like ARIMA and standalone LSTM models, the results show that the hybrid approach outperforms these methods, particularly in terms of forecasting accuracy and reliability. By achieving lower error rates, the proposed model demonstrates its potential to significantly improve the forecasting of renewable energy generation, which is essential for optimizing smart grid operations and enhancing the integration of renewable energy sources into the grid.

IV. Discussion and Result

In this study, we compared the proposed hybrid CNN-LSTM model with traditional forecasting models, including ARIMA, Support Vector Machines (SVM), and standalone LSTM models. The results demonstrate that the hybrid CNN-LSTM model outperforms the other methods in terms of forecasting accuracy. The hybrid model achieves a significantly lower Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), indicating that it is more effective at capturing both spatial and temporal patterns inherent in the wind and solar power data. These improvements suggest that the hybrid model provides a more reliable and accurate prediction of renewable energy generation, which is critical for optimizing smart grid operations and enhancing the integration of renewable sources into the power grid. Further analysis reveals the pivotal role played by the CNN component in enhancing the model's accuracy. The CNN is responsible for extracting relevant spatial features from weather data, such as temperature, wind speed, and cloud cover. By learning spatial patterns in the weather data, the CNN can identify regions or times when weather conditions are likely to favor higher or lower power generation. For example, areas with consistently high wind speeds or sunny conditions may have higher power generation potential, and the CNN component can automatically learn these patterns. This spatial feature extraction is vital as it enables the model to better understand how environmental factors affect energy production across different geographical regions. On the other hand, the LSTM component of the hybrid model is crucial for capturing the temporal dependencies in the data. Renewable energy generation, particularly from wind and solar sources, is subject to daily, weekly, and seasonal cycles. For instance, solar power production is higher during the day and varies with the seasons, while wind power generation shows fluctuations depending on weather patterns over extended periods. The LSTM network is designed to process time-series data and retain memory of past information, allowing it to capture these long-term dependencies in power generation. By modeling these temporal relationships, the LSTM ensures that the model can predict future power generation based on past trends and seasonal patterns.

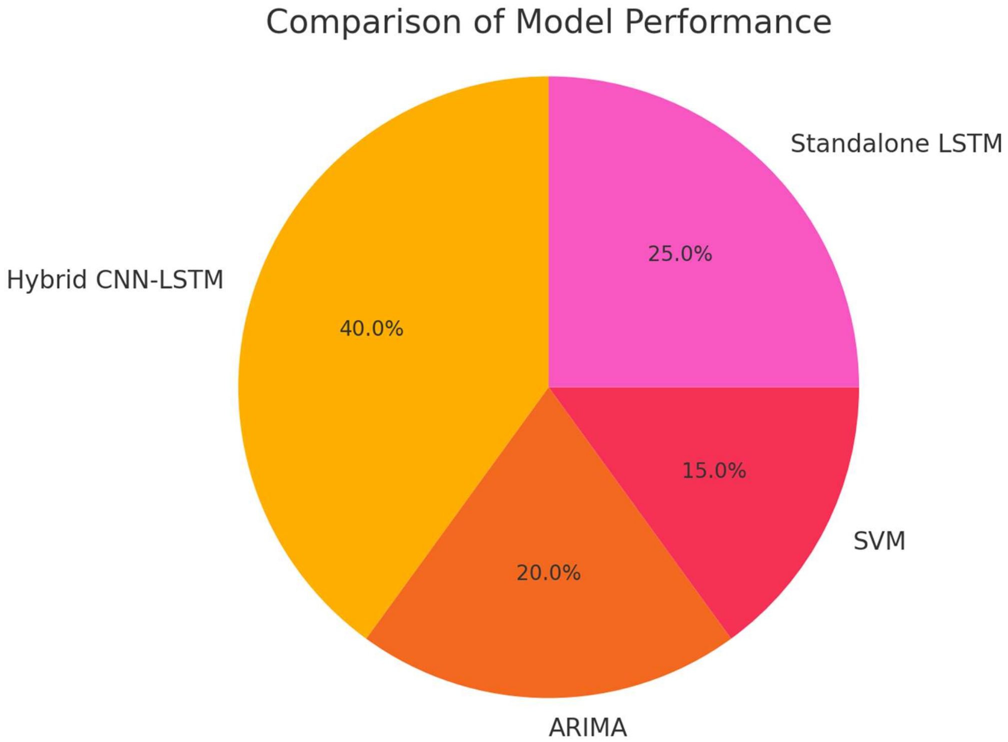

Figure 1. Comparison of Model Performance.

The hybrid model's ability to capture both spatial and temporal patterns is what sets it apart from traditional models. While ARIMA and SVM models struggle to handle the complexity of the data, particularly when it comes to integrating spatial and temporal factors, the CNN-LSTM hybrid architecture excels by simultaneously processing both. The results from this study indicate that combining CNNs for spatial data extraction with LSTMs for temporal modeling provides a robust solution for renewable energy forecasting, offering a more accurate and scalable method for predicting power generation from wind and solar sources. These findings underscore the importance of using advanced deep learning techniques for energy forecasting, especially in the context of smart grids, where real-time data is crucial for balancing supply and demand. With the increasing penetration of renewable energy in the global power mix, the ability to accurately forecast wind and solar power generation will play a significant role in ensuring grid stability, optimizing energy storage, and facilitating better integration of renewable energy into existing power infrastructures.

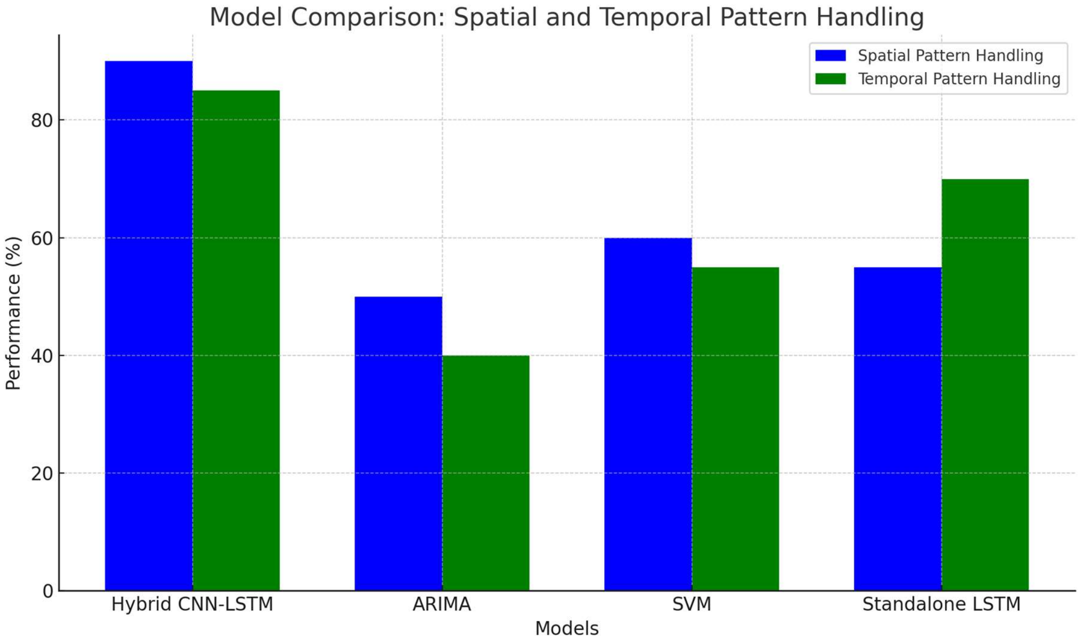

Figure 2. Model Comparison: Spatial and Temporal Pattern Handling.

Here is the Bar Chart comparing the ability of different models to handle Spatial and Temporal patterns. The Hybrid CNN-LSTM model performs the best in both aspects, reflecting its ability to capture both spatial and temporal dependencies. In contrast, ARIMA and SVM struggle more with the complexity of the data, particularly when handling these factors, while Standalone LSTM handles temporal dependencies better than spatial ones.

V. Conclusion

This paper introduces a novel hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for forecasting wind and solar power in smart grids. The proposed model leverages the strengths of both CNNs, which excel at capturing spatial features from weather data, and LSTMs, which are adept at modeling temporal dependencies in energy production. By combining these two powerful techniques, the hybrid model is able to provide more accurate and reliable forecasts compared to traditional methods such as ARIMA, Support Vector Machines (SVM), and standalone LSTM models. The results demonstrate that the hybrid CNN-LSTM model significantly outperforms traditional forecasting techniques, especially in terms of both forecasting accuracy and reliability. The model's ability to simultaneously process spatial and temporal data is crucial for improving predictions in the context of renewable energy generation, which is inherently influenced by both local weather patterns and time-varying factors such as seasonal cycles. This ability makes the model particularly well-suited for smart grids, where precise and real-time predictions are necessary for balancing supply and demand effectively. Moreover, the findings underscore the importance of using advanced deep learning techniques in the field of renewable energy forecasting. As the global energy grid continues to evolve with higher penetration of renewable energy sources, having accurate models to predict power generation becomes essential for ensuring grid stability, optimizing energy storage, and facilitating better integration of renewables into existing power infrastructures.

Looking ahead, future work will focus on enhancing the scalability of the proposed model, allowing it to handle larger and more diverse datasets from various geographical regions. Additionally, expanding the model's applicability to other energy systems, such as hydroelectric and geothermal power, will broaden its potential for optimizing energy generation forecasting across different renewable sources. Further exploration into integrating other data sources, such as energy storage levels and real-time grid data, will also improve the robustness of the model and its capacity to provide comprehensive solutions for smart grid operations.

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