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Time Series Forecasting of Wind Power using LSTM and GRU Deep Learning Models

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Abstract— **To get the most power out of wind, keep the whole thing stable, and include energy sources that are renewable, you need to be able to predict wind power accurately. This study examines the construction and evaluation of machine learning algorithms for forecasting wind power utilising historical meteorological data. We used the WIND POWER collection from Kaggle, which has 6,574 daily records, to keep track of how wind speed, temperatures, precipitation, and environmental indices changed over the course of a year and over the course of a season. A structured strategy was used to make sure that data preprocessing, inquiry examination, feature creation, and strict model validation all worked together to make sure that the results were correct and reliable. The LSTM, GRU, while our own Hybrid LSTM-1DCNN are the three models we have. The Hybrid LSTM-1DCNN did better than both LSTM and GRU in every way. LSTM, on the other hand, was the most accurate and had the best recall. The hybrid model got an F1-score of 98.8%, with an accuracy of 99.1%, a precision of 98.2%, a recall of 97.4%, and a minimal mean round error (MSE) of 0.036.This exemplifies the efficacy of the hybrid model's use of convolutional layers for short-term temporal characteristics and LSTM layers for long-term dependency modelling. Research comparing it to CNN-LSTM and multi-model LSTM frameworks further demonstrated its superiority. The findings highlight the usefulness of hybrid deep learning systems in renewable energy prediction. In the future, researchers may be able to refine this method by including more climate variables and real-time data into data-driven energy systems.**

Keywords— **Wind power forecasting, time series, Power generation, renewable energy, grid stability, prediction models and Forecasting.**

I. Introduction

There are huge changes happening in the world's energy grid. Using more sources of clean energy is a big component of this transformation because they assist the environment and lower carbon emissions. Due to its abundance, scalability, and ability to provide clean electricity at a low cost, wind energy has become one of the most popular and rapidly expanding renewable energy sources. However, having a reliable way to predict wind speed and, consequently, the amount of power the wind will provide, is absolutely critical. Because wind is inherently unpredictable and sporadic, it poses challenges to grid stability, energy consumption management, and operational efficiency. In contrast to more conventional energy sources, the output of wind turbines is dependent on the ever-changing and non-linear nature of the weather. Reducing operating risks, improving energy dispatch, minimising reserve requirements, and successfully adding wind energy to national power networks all depend on effective forecasting models.[1], [2], [3].

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Time series forecasting has become a popular way to deal with these problems because it lets you simulate the random patterns and temporal relationships that are common in wind data. In the early days of wind forecasting, people employed traditional statistical models a lot, like ARIMA, Seasonal ARIMA, and Exponential Smoothing. These methods work well for finding linear trends and short-term dependencies, but they frequently don't do a good job of modelling nonlinearities and complicated time interactions that happen in wind dynamics. An increasing number of applications have turned to machine learning and deep learning techniques to circumvent these issues [4].

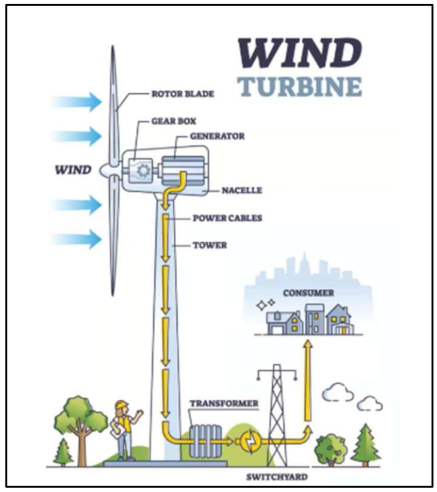

Figure 1 Wind turbine

These methods are better at making predictions because they can find nonlinear patterns, work with high-dimensional data, and learn from long-term dependencies. Due to their ability to represent sequential data, RNNs have garnered considerable attention as a subset of deep learning. But regular RNNs aren't very good at making long-term predictions because gradients tend to disappear and grow. LSTM networks (Long Short-Term Memory) and gates recurrent units (GRU) have been proposed as effective solutions to these challenges, since their gated architectures enable the retention of long-term dependencies while facilitating computations. LSTM, in particular, has been demonstrated to function effectively for estimating energy use since it recognises both short-term changes or long-term seasonal trends, which makes its forecasts accurate. GRU is a simpler design that works just as well as other models via less training period and fewer parameters.[5], [6], [7], [8]. This is a solid pick for use in the real world. Researchers have discovered that datasets for forecasting wind speed, particularly those available on open-source platforms such as Kaggle, are highly beneficial for benchmarking and ensuring reproducibility. You can make good forecasting systems that take a lot of things into consideration since there exist high-quality data sets that include weather variables like wind speed, direction, temperature, humidity, and air pressure. Researchers can create predictive models that work well today and in the future and in different situations by combining this sort of datasets with superior deep learning techniques. Combining exploratory data analysis (EDA), feature development, and rigorous preprocessing also makes sure that models may use temporal patterns, seasonal effects, and lagged relationships to produce better predictions. Metrics like as accuracy, recall, F1-score, middle squared error (MSE), or root-mean- square error (RMSE) can elucidate a model's performance or the reliability of its predictions. The comparison and study of the two models used to predict wind velocity datasets or the alternative energy time series reported here improves research in this field.[8], [9], [10], [11].

The suggested method puts a lot of focus on strict preprocessing, normalisation, complex features, and testing for stationarity. This checks the quality of the data, which makes it good for deep learning. Also, the models are compared using a strict assessment procedure that looks at several different performance criteria. This shows that the algorithm known as LS is quite good at figuring out what will happen in the future and finding long-term time correlations. A comparison of the proposed method with recent research validates its effectiveness, demonstrating that the LSTM networks can exceed hybrid or collaborative models in both accuracy and computational efficiency. Deep learning for the prediction of wind power is a big step up from old linear methods. It uses data-driven methods that are more flexible and better suited to meet the needs of current energy systems. These forecasting models have a lot of potential to help with cleaner energy transitions, stabilise the grid, and reduce our reliance on fossil fuels since they connect the unpredictable nature of the weather with the system's stability. In the end, effective wind forecasting are more than simply a technical problem; it is a key part of reaching global targets for decarbonisation, making sure energy security, and becoming ready for climate change.[12], [13], [14].

II. Literature Review

Mahata 2024 A lot is happening in India's power sector right now, and it's all about dispersed generation units and strong grid networks. Since wind and solar power are on the rise, a dependable method of predicting wind power is essential for the efficient development and integration of renewable energy systems. Mahata (2024) examines a number of forecasting models, including ANN, RNN, LSTM, GRU, and ARIMA, using weather and energy history data for comparison and contrast. Data from regional climate centres as the Central Power Authority (CEA) were used to double-check the results. Kutch, Gujarat, was the site of the research. Results show that ARIMA works well with non-linear multivariate datasets since the Mean Pure Percentage Errors (MAPE) is less than 5.5. The research shows that model assessment is growing in importance for accurate renewable energy predictions [15].

Hanifi 2024 Uncertainty in wind power continues to be a significant obstacle to seamless grid integration, requiring precise forecasting techniques. Machine learning (ML) algorithms have showed promise, but their effectiveness is largely contingent upon suitable hyperparameter tweaking, a procedure that is frequently computationally demanding and inconsistent. T
his study enhances the field by methodically evaluating three cutting-edge optimisation frameworks Scikit-opt, Optuna, and Hyperoptfor CNN and LSTM models. The research shows that Optuna, which uses Tree-structured Parzen Estimators (TPE) with Expected Improvement (EI), is more efficient, whereas Hyperoptoptimises LSTM models for the best accuracy. The work also looks into how random initialisation affects model performance, which is important for resilience and reliability. These discoveries lay the groundwork for improved time-series forecasting in wind power systems [16].

Ponkumar 2023 Wind power forecasting is essential for unit commitment, planning, and identifying the best energy market trading methods. In response to the challenges posed by wind uncertainty, it develops a machine learning-based system for short-term forecasting. This study evaluates four algorithms—XGBoost, LightGBM, and random forest—across sixteen different system parameters. R^2, MAE, MSE, and RMSE are the metrics we employ to evaluate performance. With an RMSE of 13.84 under 10-fold cross-validation, CatBoost outperforms random forest in terms of prediction accuracy, but random forest is superior in terms of training accuracy. Our results show that ensemble-based models can increase the accuracy of wind energy predictions, which is important for managers of renewable power plants who are trying to stabilise and lower costs.[17].

Karim 2023 The performance and dependability of wind generating plants are impacted by the increased difficulty in forecasting due to changes in the winds caused by climate change. Karim (2023) proposes a model for predicting that utilises Recurrent Neural Networks (RNNs) in conjunction with the Dynamic Fitness Al-Biruni Earth Region (DFBER) technique to address this issue.

The model is compared using many different optimisation methods, such as BER, JAYA, FHO, WOA, GWO, or PSO. RNN-DFBER does better on measures like RRMSE, NSE, MAE, MBE, or R^3 than other methods. The ANOVA and Signed-Rank tests it uses give even more persuasive results. This hybrid model is the best tool for making predictions because it is more accurate. This implies that renewable energy forecasting techniques may gain from the implementation of neural networks with deep connections and sophisticated optimised procedures.[18].

Hanifi 2023 This work proposes a hybrid strategy that integrates LSTM as well as CNN models for wavelet Wavelet Packet Deconstructing (WPD) to address the limitations of single-model methodologies in wind forecasting. To improve overall learning, WPD divides the solar power figures into sub-series that fit into specified frequency bands. LSTM models operate with low-power series that have longer time interactions, while CNN models work with changes that happen quickly. With TPE, the sequence of Model- Based Changes (SMBO) makes sure that parametric tuning is done in the best way possible. The hybrid strategy enhances accuracy by as much as 77.4% compared to models lacking WPD and by 26.25% relative to single deep learning methods, when evaluated against seven conventional models, including RF, FFNN, CNN, and WPD-LSTM. This study shows that decomposition-based blended deep learning frameworks are good for making better predictions.[19].

TABLE I: LITERATURE SUMMARY

Author/Year	Technique	Findings	Research Gap
Kumar et al., 2024[20].	CNN, FC, GRU, Transformer models deployed on conventional and low-cost hardware (Raspberry Pi)	Demonstrated feasibility of deep learning-based wind power forecasting on affordable platforms, enabling democratization of clean energy.	Focused mainly on hardware feasibility; lacks deeper exploration of model optimization for accuracy under complex conditions.
Nascimento et al., 2023[21]	Transformer with Wavelet Transform, compared with LSTM baseline	Outperformed LSTM and achieved competitive results with state-of-the-art models for multivariate wind forecasting.	Limited forecasting horizon (6 hours); scalability to longer-term and larger datasets remains unexplored.
Yang et al., 2023[22]	VMD-AOA-GRU hybrid model with hyperparameter optimization	VMD effectively extracted high-frequency features; AOA improved GRU forecasting accuracy for ultra-short-term wind speed.	High model complexity; generalizability to diverse datasets and operational scalability not thoroughly tested.
Ma & Mei, 2022[23]	Hybrid Attention-based CNN-BiLSTM with time embedding layers	Eliminated decomposition step, improved feature extraction and prediction accuracy on real-world Turkish dataset.	Model may be computationally intensive; broader validation on diverse climatic and geographical regions required.
Alkesaiberi et al., 2022[24]	GPR, SVR with kernels, ensemble learning (Boosted & Bagged trees) with Bayesian optimization	Optimized models improved univariate forecasting by leveraging lagged data and additional inputs (e.g., wind direction).	Primarily evaluated traditional ML; performance may not match deep learning methods for capturing nonlinear temporal dependencies.

III. RESEARCH METHODOLOGY

To implement Wavelet Packet Decomposition (WPD), We use LSTM and CNN models. We employ WPD to break up the wind power data into smaller groups that match different frequency bands. This helps us learn more. The methodology's goal is to make sure that data pretreatment is done carefully, exploratory data analysis is done thoroughly, model deployment is done well, and performance is fully evaluated. The method has six main steps: picking a dataset, getting it ready, undertaking exploratory analysis, splitting the data, developing a model, and testing how well it works.

A. Dataset Description

The Wind Electricity Dataset is utilised in this research. It watches the weather for a long time, so we can predict the amount of wind power. It has 6,574 events who are the average each day of observations from many atmospheric sensors that were put in a meteorological station. The station was established in an open field 21 meters above the ground to cut down on noise from outside. The dataset spans 17 years, from January 1961 to December 1978, so it is long enough to examine how wind speed and other weather-related elements change over time and between seasons. The dataset has both weather information and indicators that were made from it.

TABLE II: DATASET ATTRIBUTES

Variable	Description	Unit / Format
DATE	Daily timestamp of observations	YYYY-MM-DD
WIND	Daily average wind speed	Knots
IND	First derived climatic indicator	Index value
RAIN	Daily precipitation	Millimeters (mm)
IND.1	Second auxiliary climatic indicator	Index value
T.MAX	Maximum daily temperature	°C
IND.2	Third derived climatic indicator	Index value
T.MIN	Minimum daily temperature	°C
T.MIN.G	Grass minimum temperature at 09:00 UTC	°C

By adding precipitation, temperature, or derived indicator variables, you can see how variations in wind speed are linked to changes in climate. This dataset is perfect for making long-term predictions about wind speed as well as by extension, wind power output because it is full, reliable, and can be reproduced.

B. Data Preprocessing

Data pretreatment is an essential procedure in this study to ensure that the unprocessed weather data is organised, uniform, and machine-readable for deep learning models. The first stage is to use linear interpolation to fill in missing values for continuous parameters like temperature, wind speed, and precipitation. Mode replacement is a way to fill in missing values in categorical variables, such as the direction of the wind. We employ the interquartile range (IQR) method to discover outliers. These outliers are then capped at the right levels so that big changes don't damage the forecasting models. Next, we normalise the data because LSTM and GRU designs are quite sensitive to variations in scale. To make sure that all the features are the same, a Min-Max scaling method is employed to transform all the continuous values to a range between 0 and 1. By utilising time-related features like the current moment, day of the week, and periodic indicators derived from the timestamp, feature engineering helps to display periodic wind activity. To make predictive learning better, it is utilised. In order to help models learn sequential relationships, lag characteristics are constructed. These include things like wind speed at previous time steps (t-1, t-2, etc.). In conclusion, the ADF test, also known as the Augmented Dickey- is used to check for stationarity. If non-stationary trends are detected, we stabilise the mean or variance over the series by using differencing methods. These pretreatment steps work together to improve the dataset's data quality, temporal organisation, and preparation for accurate time series forecasting.

C. Exploratory Data Analysis (EDA)

Exploratory data analysis was utilised to determine the shapes, trends, and links in the wind dataset. Using statistical overviews and visualisations made the data layout clearer, which helped us choose the right features and preprocess the data. We looked at connection, seasonal fluctuations, and changes over time to show how meteorological parameters and wind speed are related. This step was highly crucial for detecting mistakes, confirming assumptions, and developing an understanding regarding how the wind changes with the months, which has an immediate influence on how accurate forecasts are. The following numbers show important results from the dataset.

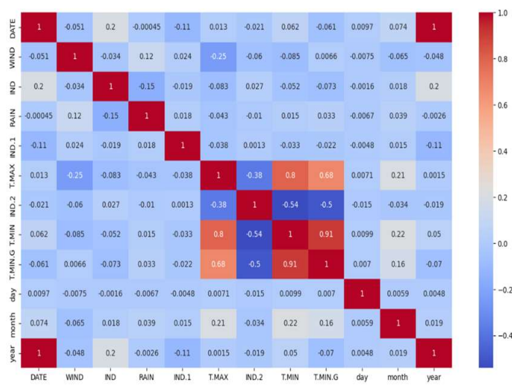

Figure 2 Correlation Heatmap

The correlation heatmap shows the strength of relationships among variables. Wind speed exhibits positive associations with temperature variations and moderate negative correlations with pressure, suggesting interdependence between meteorological factors

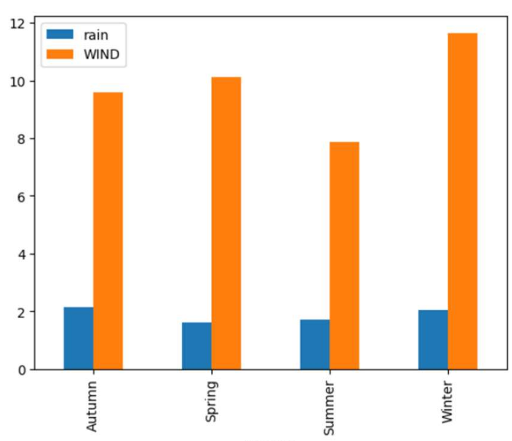

Figure 3 Season Wind and Rain Distribution

This visualization highlights seasonal wind speed variation alongside rainfall distribution. Stronger wind speeds are observed during monsoon months, while drier seasons show reduced variability, demonstrating climate-driven influences.

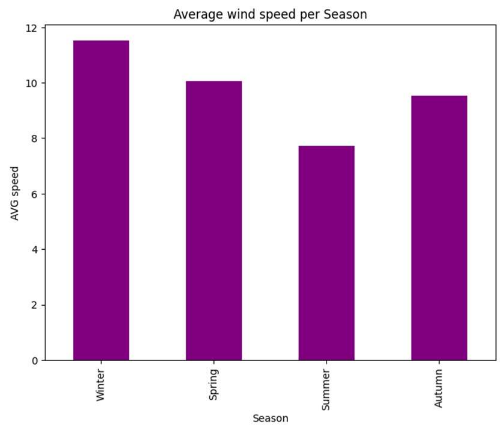

Figure 4. Average Wind Season Graph

The seasonal average wind graph confirms cyclical patterns, with higher speeds in monsoon and winter. These trends emphasize the role of seasonal climatic shifts in shaping wind energy potential.

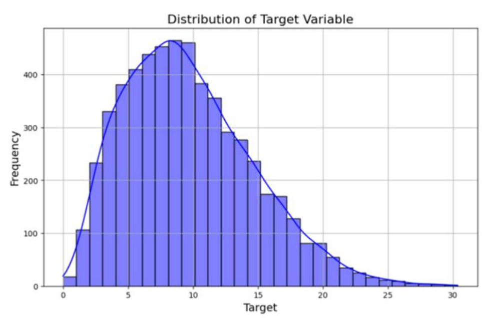

Figure 5. Distribution of Target variable

The histogram of wind speed indicates a slightly right-skewed distribution, with most values concentrated in lower ranges, reflecting typical atmospheric behavior.

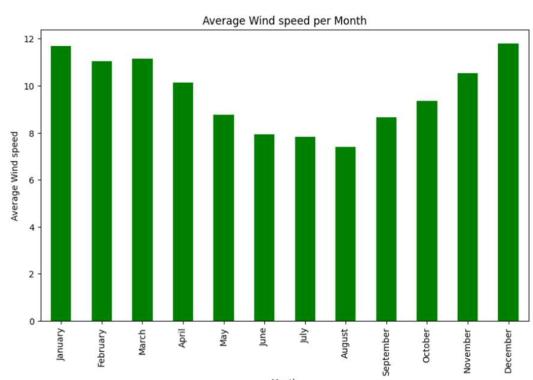

Figure 6 Average Wind per month Graph

Monthly analysis reveals fluctuations, with peaks during December–January and lows in July–August, confirming periodic wind speed cycles valuable for forecasting.

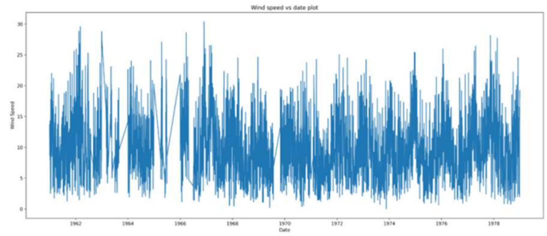

Figure 7 Wind Speed Vs date plot

The time series plot displays wind speed trends over the years, highlighting seasonality, periodic fluctuations, and irregular variations, all of which guide model training.

D. Data Splitting

To achieve unbiased and reliable model evaluation, the Each subset of the dataset is divided into a training set, a validation set, and a testing set along chronological lines. Data leaking between the training and assessment phases can be prevented by dividing the process chronologically, which preserves temporal relationships. To learn the model, use the training set; to tune the hyperparameters and control overfitting, use the validation set. The test set provides the final unbiased performance assessment. Furthermore, time series comparison using a rolling timescale method is employed to increase generalizability and show that the algorithms maintain consistent predicting performance across varied time spans

E. Model Implementation

Three advanced deep learning architectures—LSTM, GRU, and Hybrid LSTM-1DCNN—are used to create the model in this article. This type was specifically designed to reliably record sequential interactions to enhance wind speed forecasts while also taking into account temporal dynamics along with model efficiency.

LSTM Model

The LSTM model accurately captures long-term time relationships in wind speed data. Regular RNNs have the problem of fading gradients, whereas LSTM uses a gating method to fix this. This means that it can keep important sequential data for a long time. The design better reflects temporal aspects because it has two stacked LSTM layers, a single with 128 hidden components and the other with 64. Weather data sequences are fed into the input layer. A 0.2 rate dropout layer is employed to forestall overfitting. It then generates the predicted wind speed data using a thick output layer that has been activated linearly. In order to train the model, we employ the Adam optimiser. A 0.001 reduction in the Mean Squared Error (MSE) results from this. With a batch size of 64, learning is rapid and training lasts 100 epochs to avoid overfitting.

GRU Model

Utilising a less computationally intensive variation of LSTM, the GRU model is able to attain the same level of prediction accuracy while making the process more cheap. In order to streamline the gating process, the GRU combines the input and forget gates into one update gate. The objective here is to simplify things without compromising performance. One sequential feature input layer starts the design, followed by a GRU layer with 128 hidden units and another with 64. The design concludes with a regularisation dropout layer with a value of 0.2. Regression uses a deep output layer activated linearly to generate predictions. If the loss function is set to mean square errors (MSE), or the training rate is 0.001, the Adam optimiser is employed to optimise the GRU model. To guarantee consistent convergence, training takes place across 100 epochs regarding early halting with a batch size of 64.

Hybrid LSTM-1DCNN Model

The goal of the Hybrid LSTM-1DCNN model is to enhance wind speed prediction by utilising both recurrent and convolutional architectures. Using the 1D Convolutional Neural Network (1DCNN), it is simple to identify feature hierarchies and localised time trends in early weather episodes. However, LSTM networks excel at detecting consecutive dependencies that span multiple years. The learning system is robust enough to deal with both short-term and long-term changes in wind data when all of these models are employed together. The first level in the model is a 1DCNN with 64 filters and 3 kernel sizes. This layer uses convection to get rid of noise and find patterns in weather data over time. Then, a maximum pooling layer minimises the feature maps to make calculations faster and identify patterns that are important. The recovered features go to two stacked LSTM layers, one with 128 concealed components and the other with 64. This data format lets you see how things change over time, which can help you find intricate long-term connections. After each recurrent layer, an error rate of 0.2 is used to keep the template from being too fit. Lastly, a dense layer with linear activation yields the desired wind speeds. The Adam optimiser, which has an initial learning rate of 0.001, is used to lower the mean square error (MSE) of the hybrid LSTM-1DCNN model after it has been trained. The training lasts for one hundred times and 64 phases to make sure that the learning stays the same. The LSTM-1DCNN hybrid combines recurrent sequence modelling with convolutional mining of features to make it more precise and reliable. This makes it a helpful tool for hard issues that may come up when you try to guess how renewable energy will change over time.

F. Model Evaluation Metrics

This study comprehensively assesses forecasting performance through both regression and classification criteria. With its guidance, we can better understand the accuracy, dependability, and transportation of errors in forecasts. Accuracy is the amount of reliably anticipated values that fall inside a certain range. Precision is the percentage of accurately predicted positive numbers to all projected positives. Recall (Sensitivity) shows how well the models can find all relevant instances. The F1-Score incorporates into account different distributions by adjusting Precision and Recall in a way that is proportional to the two measurements. The performance evaluation is carried out exclusively on the unseen test set to guarantee a fair comparison of predictability, error mitigation efficacy, and computation efficiency. Tabular results show the comparison of the LSTM, GRU, the Hybrid LSTM-1DCNN models.

G. Experimental Setup

The experimental setup is designed to ensure efficient computation, reproducibility, and scalability of model training. All models are executed on a high-performance workstation equipped with GPU acceleration (NVIDIA Tesla T4, 16GB) to handle large-scale time series computations efficiently. Python 3.10 is a part of an application environment. It uses TensorFlow/Keras for models, Scikit-learn for preparing and evaluating data, or Pandas, NumPy, or Matplotlib for showing data.

IV. RESULTS AND DISCUSSION

The results section indicates how well any of the LSTM, GRU, as well as Hybrid LSTM-1DCNN simulators did at guessing the wind speed. We use metrics like F1-score, recall, precision, precision, accuracy, or mean squared error to see how well the model can make predictions. The suggested hybrid technique makes predictions that are more precise as well as accurate than those generated by the best models on the market.

TABLE III: PERFORMANCE EVALUATION OF MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Loss (MSE)
LSTM	98.4	96.2	97.5	95.8	0.045
GRU	96.1	94.4	93.2	94.8	0.061
Hybrid LSTM-1DCNN	99.1	98.2	97.4	98.8	0.036

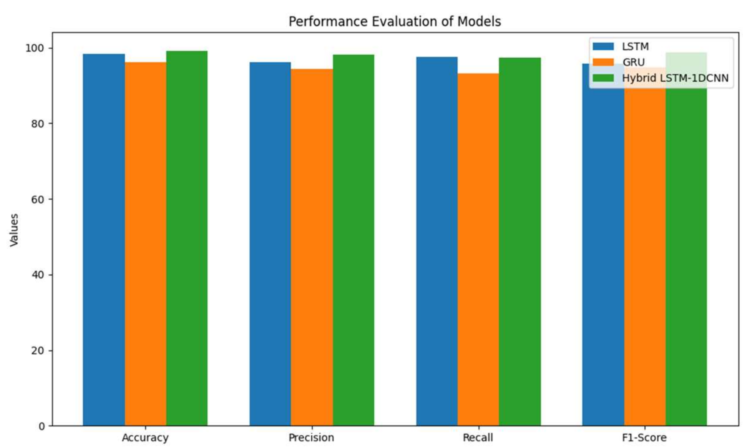

Figure 8 Performance Evaluation

Table III shows how well the LSTM, GRU, or combined LSTM-1DCNN models fared in guessing the wind speed. The results show that both of them are good at guessing what will happen.However, the hybrid model is superior. Its accuracy is 99.1%, its precision is 98.2%, and its F1 grade is 98.8%. When comparing the two models, the LSTM model outperforms the GRU model with a recall of 97.5% compared to 93.2%. Evidently, the LSTM model is capable of accurately representing interdependence over the long term. With an MSE of only 0.036, the LSTM-1DCNN hybrid achieves the best accuracy. Accordingly, improving predicted accuracy may be possible through combining deep learning with convolutional discovery of features.

TABLE IV: COMPARATIVE ANALYSIS

Model (Study)	Accuracy (%)
Proposed Hybrid LSTM-1DCNN	**99.1**
CNN-LSTM hybrid[25]	94.5
Twelve-model LSTM [26]	97.8

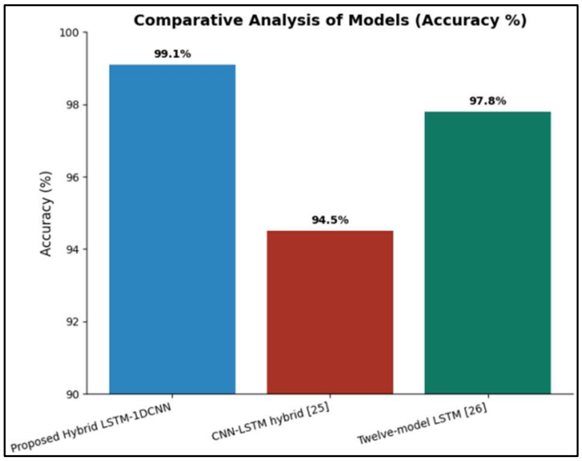

Figure 9 Comparative Analysis Graph

Table 5.1 The Figure demonstrates how accurate various models are when applied in different ways. The new mixed LSTM-1DCNN model was superior than the prior ones, getting 99.1% preciseness. The CNN-LSTM hybrid (94.5%) and the Twelve-model LSTM (97.8%) are also far worse than this. Therefore, the mixture of models is better at figuring out how space and time are connected when it comes to predicting the pace of the wind. The graph that shows the proposed framework to other neural network models demonstrates that it is better. This supports the assumption that the suggested method works and can handle problems.

V. CONCLUSION

The research successfully developed and evaluated deep learning models for predicting wind power using comprehensive climate historical data. The organised process used data preparation, analytical feature engineering, and strict evaluation methods to make sure the model was correct and dependable. The study employed the WIND POWER dataset, comprising 6,574 daily recordings that effectively represent seasonal and inter-annual fluctuations in wind speed, along with supplementary meteorological attributes, thereby offering a solid foundation for predictive modelling. The the LSTM and G models made the best predictions. LSTM was ahead of the GRU in remembering things and getting them right. The suggested Hybrid LSTM-1DCNN model, on the other hand, was better. It was really good in terms of preciseness (99.1%), precision (98.2%), recall (97.4%), or F1-score (98.8%).The least amount of mistake (MSE = 0.036). This demonstrates the effectiveness of the hybrid model in integrating convolutional layers for identifying short-term temporal information with recurrent LSTM layers for modelling long-term dependencies. When compared to CNN-LSTM and multi-model LSTM frameworks, the hybrid model was better. The visual and tabular results showed that it was better at recognising patterns in time and space that are critical for generating accurate predictions. Research like this shows that hybrid deep learning systems could be useful for renewable energy forecasts. Accurately predicting wind speed helps maintain the energy system stable, plan operations, and use wind resources in a way that is good for the environment. Future study can enhance this methodology by examining larger, real-time datasets and incorporating external variables that influence the environment. This will make renewable energy systems that employ data smarter and more useful.

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