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MACHINE LEARNING-BASED WIND SPEED ESTIMATION FOR RENEWABLE ENERGY OPTIMIZATION IN URBAN ENVIRONMENTS: A CASE STUDY IN KANO STATE, NIGERIA

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ABSTRACT: *Climate change always had a massive effect on worldwide cities. which can only be decreased through considering renewable energy sources (wind energy, solar energy). However, the need to focus on wind energy prediction will be the best solution to the world electricity petition. Wind power (WP) estimating techniques have been used for diverse literature studies for many decades. The hardest way to improve WP is its nature of differences that make it a tough undertaking to forecast. In line with the outdated ways of predicting wind speed (WS), employing machine learning methods (ML) has become an essential tool for studying such a problem. The methodology used for this study focuses on sanitizing efficient models to precisely predict WP regimens. Two ML models were employed "Gaussian Process Regression (GPR), and Feed Forward Neural Network (FFNN)" for WS estimation. The experimental methods were used to focus the WS prediction. The prophecy models were trained using a 24-hour' time-series data driven from Kano state Region, one of the biggest cities in Nigeria. Thus, investigating the (ML) forecast performance was done in terms of coefficient of determination (R^2), linear correlation coefficient (R), Mean Square Error (MSE), and Root Mean square error (RMSE). Were. The predicted result shows that the FFNN produces superior outcomes compared to GPR. With R^2= 1, R = 1, MSE = 6.62E-20, and RMSE = 2.57E-10*

KEYWORDS: Machine learning, Gaussian process regression, Feed forward neural network, Wind speed prediction.

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INTRODUCTION

In the recent economic and public situation, the intersection of weather estimating and wind energy, (WE) emphasize the paramount role of Wind power (WP) in meeting energy demand, (ED) while addressing environmental apprehension. Renewable energy, particularly wind power (WP), has taken out some important portion of global electrical power production. Precise wind speed (WS) forecasting of the power output of wind farms is such a crucial constituent for energy supply (Ba & Muzy, 2021). An estimate has been made by the International Energy Agency, (IEA). that lack of electricity brings massive trouble to developing countries around the globe and mostly plights Africa and Asian regions. Thus, this electricity demand has regulated the advancement of these countries for both urban and rural areas i.e., dating back to 2017; Nigeria recorded generation plants from 28 grids, 5074 as generation peak to almost 190 million people, and their peak load demand of 17,700 MW. However, the national electrification of the country was just 59% with a disparity of 78% for the urban and 39% for the rural area therefore postponement of the grid to the rural areas cannot be done successfully for some reasons, such as lack of good road maintenance, dense areas, and super as high energy costs, among others. Moreover, to get rid of environmental fear over climate change, Nigerian power companies need to turn over to renewable energy sources for standard electricity (Abba et al., 2021).

WP extenuation is among the valuable dimensional and multi-step series time expectation problems. But, controlling and optimization are some of the challenges for the perception of WP. Even to generate electricity using wind turbines (WT) is quite expensive and can only be settled in specific areas (Kent et al., 2018). There are various obstacles that wind speed estimation for renewable energy optimization must overcome, which might affect the wind energy systems' dependability and efficiency. The intrinsic complexity and diversity of wind patterns, which are impacted by local topography, terrain, and atmospheric conditions, is one of the main challenges (Wang et al., 2020). Precise assessment is especially difficult in urban or topographically complex areas where obstructions and buildings cause turbulence, which modifies wind patterns. Another major obstacle is the lack of high-quality, localized wind data. Accurate machine learning models require reliable historical wind data, but locating such data can be challenging, particularly in underdeveloped nations or places with inadequate monitoring infrastructure (Yang et al., 2016). Overcoming these obstacles is essential to improving wind speed estimation models' accuracy, which will ultimately support the integration of renewable energy sources into sustainable energy landscapes and aid in the efficient optimization of renewable energy systems (Lo Brano et al., 2011). WP is among the fastest growing energy sources for its benefit and good to the environment, abundant resources with inexpensive prices. Also, combustion of non-renewable sources such as fossil fuels is inviting serious environmental hazards. Henceforth advancing renewable energy is one of the vital gears of today’s world in the ways of suggesting the best technique to address the variability bags that are attached to wind power generation (Jiao et al., 2023). At this stage at which energy needs are globally advancing, greenhouse gasses capture for higher feasting of energy produced by red-hot fossil fuels; those sources should be reduced by renewable energy sources. Wind energy WE are a plentiful energy source for the environment (Rahman et al., 2022).

The assessment of wind speed for the purpose of optimizing renewable energy was a difficult task with limitations in accuracy and efficiency before the development of artificial intelligence (Gualtieri & Secci, 2011). Conventional techniques mostly depended on meteorological data

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gathered from weather stations, which was frequently insufficient and unable to offer precise, localized information. Even if they were helpful, numerical weather prediction models have trouble capturing the complex dynamics of wind flow in particular urban and geographic settings. The inability to derive significant insights from the existing data was further hampered by the lack of advanced data processing technologies (Bañuelos-Ruedas et al., 2010). These restrictions led to inaccurate estimates of wind speed, which decreased the efficiency of renewable energy installations. Since then, artificial intelligence has transformed this industry by providing the ability to process large datasets, simulate intricate wind patterns, and produce more accurate predictions. As a result, optimization of renewable energy solutions has been greatly enhanced (Palutikof et al., 1999).

Many difficulties arise when estimating wind speed in Kano State, Nigeria, in order to optimize renewable energy. Accurately evaluating wind patterns is complicated by Kano State's distinct urban environment. Because of the numerous buildings, infrastructure, and other impediments found in urban settings, turbulent wind flows are common, making it difficult to accurately forecast and predict wind speeds. Another major challenge is the dearth of detailed and regional wind data in Kano State. Precise wind speed measurements are essential to the performance of renewable ES, and robust ML models cannot be developed in the absence of trustworthy local data. In order to successfully execute renewable energy solutions in Kano State and guarantee the sustainability of sustainable energy practices in urban settings, it is imperative that these problems be addressed.

Accurate WS prediction is essential for a wide-scale wind power cohort as it can reduce the effect of the wind power system. WP has now taken over a hopeful way of renewable energy, to bring a balanced supply and smart grid demand (Alkesaiberi & Harrou, 2022). With the growth of the wind turbine system across the globe the common vision in the present power network. Studies have now gone AI and ML for the prediction system in science and engineering (Aliyu et al., 2021; Asnake Metekia et al., 2022; Ibrahim et al., 2022; Manzar et al., 2022; Nourani et al., 2018; Sammen et al., 2021; Usman et al., 2022; Yassin et al., 2022; Farrar & Ali, 2023). Development in wind estimating will be a welcoming tool; when it comes to the electricity square, there will be a need for accurate WS predictions that will always fascinate for a different intention. It will attract market prices that offer energy inequity charges based on the market price (Soman et al., 2010). During COVID-19, a lot of challenges were faced to predict higher quality air which became a difficult task for seasonal and temporal air pollution. However, new techniques need to be explored to be accurately expected (Lei et al., 2022).

In a reflected shallow with deep learning models for wind speed estimation at location in the Bay of Bengal (BOB) and Arabian sea (AS) basins of India, Biswas and Sinha (2021) employed three estimation models compared to see the one with highest fit. A shallow learning model was the first, consisting of FFNN model with the following LSTM, BiLSTM networks. However, the independent validation set is selected in contrast to 2018 wind speed data to check for precision. Thus, the LSTM gives the accurate result with the highest value of the fit. To study the ability of advanced metrological predicting models, ANN methods were employed by Biswas and Sinha (2021) to estimate the hourly solar radiation with wind speed data. The predicted data are the world indirect irradiation (WIR), the direct radiation (DR) and diffuse or scattered irradiance (DSR). The need for precise wind speed predicting is paramount for different business and management sectors. Trebing (2020) presented a new model based on convolutional neural network (CNN) for wind speed estimation. In advanced, the model is

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compared to the classical Neural Network (NN) model. Nonetheless the models are able to categorize the spatiotemporal evolution of the data by noticing the basic complex of the input and output relation from different dimensions of the wind speed data. The models exhibit the spatial-temporal multivariate past weather data for learning new illustrations to estimate wind speed in Denmark city.

In order to advance generalization ability, input data has to be pre-processed by splitting the input so that the estimating approach is planned for each subclass and the standard deviation function, mean, variance, slope calculated for the model (Baig et al., 2023; Abba et al., 2023; Salami et al., 2023; Yassin et al., 2024). This technique of pre-processing will redefine the way of indecision in the data set (Santhosh, 2020). Numerical weather estimation methods usually used for modeling are not solely less, cost-effective but also deplorable in estimating a short time horizon. Tao et al. (2020) precise WS modeling is essential for optimal minimizing of wind energy. Therefore, Novel WS estimation based on the multivariate empirical mode decomposition (MEMD), Random Forest Algorithm (RF) and Kernel Ridged Regression (KRR) apply for better wind speed prediction. Yet the particle swamp optimization algorithm (PSO) was also used to optimize the limits of the MEMD model with the RF and KRR models applied to Iraq, Bagdad station and Mosul study from the time 1977 to 2013. Result shows that the MEMD, PSO and RF models have the outstanding presentation in the estimation of the wind speed. A new chance distribution model was tested to implement WS at several locations in Jordan (Al-quraan et al., 2023). The result indicates that there is large computability among the model and wind resources. Yet this model was used to predict the values of the wind energy and the removed energy of wind turbines received from the Weibull PDF. Different AI models were used including GA, SA, BFOA. The indecision and nonlinearity matters are addressed mostly using deep learning-based Bi-LSTM (Subbiah et al., 2023).

Despite that many studies have been carry out to estimate WS using different machine learning models, there is a need to explore the capability and correctness of other ML based model, therefore this study employed Feedforward Neural Network (FFNN) and Gaussian Process Regression (GPR) in order to anticipate the WS of Kano State, Nigeria. However, the feature scope of this work is to achieve a safe WS forecasting in a region for having less access to electricity. This research can provide an excellent vision to strategy makers and government interventions for the development of regulations and guidelines for wind speed estimates which can provide more chances of clearing electricity issues in Kano state Nigeria.

The Study Region

Kano state is one of the biggest cities among the 36 states in Nigeria, located in the northern part of the country. The state was ranked as number 21^{st} among the states of the country, with a land area of about 20,131 km^2 (7,773 sq. mil); the GDP of the state is almost $27.17 billion. It is the second most populated city in Nigeria after Lagos with a population of almost 9,383,682. The state has borders to the northwest, southwest, and northeast of the country i.e. Jigawa which is located to the northeast, and Bauchi to the southwest region. however, Kaduna state to the southwest (Hadi et al., 2019). Kano state was located in the GPS harmonizes of 12^0 00.0000 N and 8^0 31 0.0012 E corresponds to Scope of 12.000000 and longitudes of 8.51666 with. The study map of the location is shown in Figure 1. The state temperature of this state diverges mostly at the bottom of about 15.8^0C with main off 33^0C; Kano state has different seasons with midway rain and long dry periods of nearly 5 pt. 6 months. The state city has a yearly mean of rainwater of virtually 800mm (Mustapha 2014).

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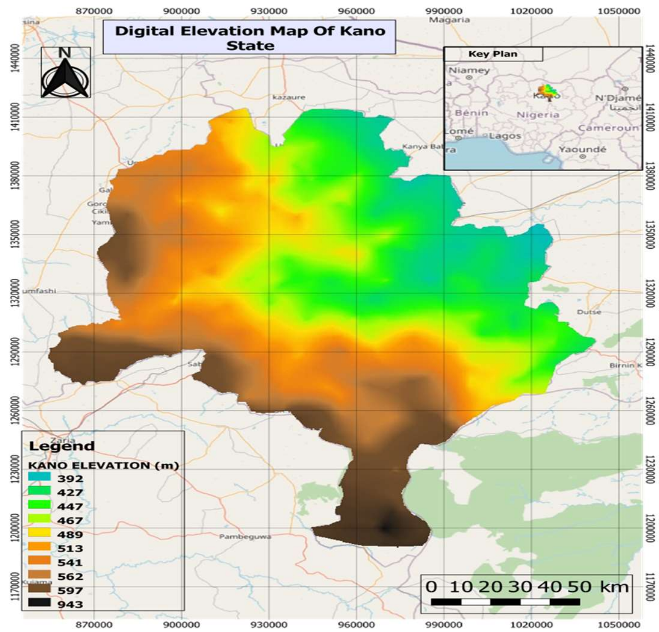

Fig 1**:** The study map of the location

Proposed Methodology Schema

METHODOLOGY

This study employs two ML models, namely: Gaussian Process Regression (GPR) and Feed Forward Neural Network (FFNN) for the prediction of wind speed of Kano, State. One of the major cities in Nigeria with an extensive thought of the data set collection from this area. So, for the development of GPR and FFNN, the data was divided into two sets, 70% for calibration and 30% for verification. The first set of calibration is used for the training of the data while on the other hand verification phase is used to test the accuracy of each of the models. Additionally, the input data is gathered, managed, verified, transformed, and analyzed before lettering the data process to the range of selecting the best model at the end.

Figure 2**:** Displays the basic proposed methodology flowchart used in the study. In order to reduce the redundancy and increase the data integrity, Equation (1) was used to normalize the data used in the study.

$$y = \left(\frac{x - xmin}{xmax - xmin}\right) \qquad Eq\ (1)$$

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Where y is the normalized data, x is the measured data, and Xmax and Xmin are the maximum and minimum values of the measured data, respectively. The combination of the model is present in equation 2

$$Wind\ Speed\ (m/s) = f\begin{pmatrix} M1 = Temperature\ ) \\ M2 = Temperature + solar\ Radiation \\ M3 = Temperature + Solar\ Radiation + Load\ demand \end{pmatrix}$$

Eq (2)

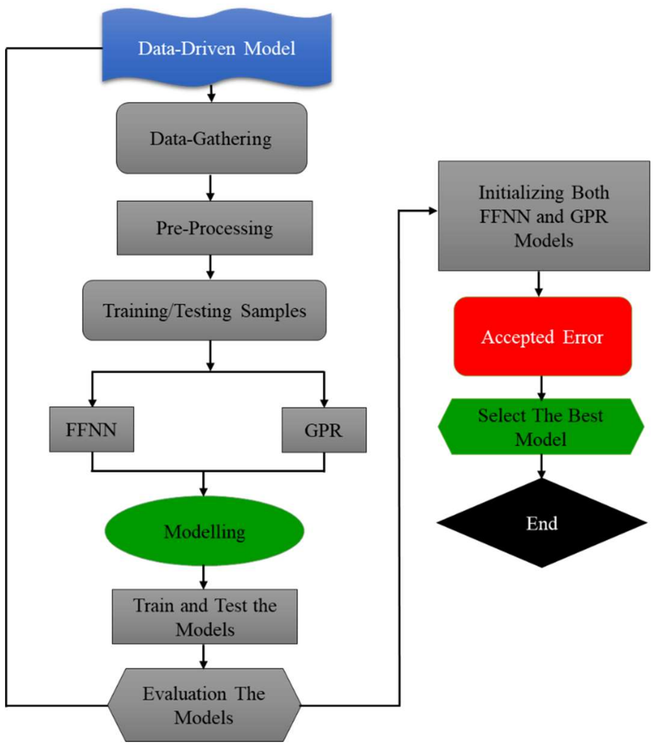

Fig 2: The proposed methodology flow chart use in the study

Feed Forward Neural Network (FFNN)

The feed-forward neural network is one of the AI models used for kinds of literature and is among the coolest models of ANN. However, FFNN represents ANN in terms of literature, having a neuron as the main character. In addition to that, FFNN is made of three layers, which are the input, output as well as hidden layers. The layers have a different number of neurons on their specific. The number of neurons in the input and output layer are the same as those of input and output data, separately. To solve a problem on a conflicting FFNN the number of neurons in the hidden layer has to be adjusted to be contingent on the obscurity of the tax for precise outcomes (Etxegarai et al., 2022). In the FFNN Model, the neuron serves as the eventual constituent of a neural network that takes the inputs, and the input is used in uniting with changeable parameters, covered in more detail in a successive subtopic. Feed-forward neural network is a sub-type of ANN, also a powerful machine learning technique used for regression and classification problems (Maduranga & Abeysekera, 2022). Feed-forward neural network (FFNN) MODEL is a versatile technique for making a good prediction. The model is often

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used in research for its known to give a good approximation, abilities, and its universal model (Putu et al., 2022).

$u_k = \sum_{j=1}^{n} \quad w_{kj}.x_j + b_k$
Eq (7)
$y_k = \phi(u_k)$
Eq (8)

Where x_j is the input vector of the cell, w_{kj} is the weights matrix, b_k is the bias vector,u_k is then output before the activation function, ϕ is the activation function, and, y_k is the output of the cell. k is the number of the cell of the hidden layer, and n is the number of inputs

Gaussian Process Regression (GPR)

Gaussian process regression (GPR) is among the ML methods that is parametrically handled. Different kinds of literature applied it for problem-solving and multivariate regression. The GPR model surpassed many models in different research aspects e.g., Model SVR and RF. The scheme for the GPR model is a valuable method for an initial distribution of supple regression models and categories, used to provide ultimate elucidation to different matters of research. The Gaussian technique is the change of covariance function as it's among the most vibrant features. For researchers to make dreadful collections to create an unremitting structure of different degrees, the GPR model uses significant features that are useful in statistical modeling (Liu et al., 2018). Gaussian process regression (GPR) has become an outstanding method for solving nonlinear regression glitches, which forecast and offer a variance of valuations. The kernels and mixture composed by GPR can find the best exposition of physical world extrapolation assignment. Having a Campuses characteristic with industrial process modeling GPR demonstrates adaptability and flexibility because of the mixture of it. However, the model becomes the most effective nonlinear modeling technique (Ghasemi et al., 2021).

$$y_i = + \sum_{d=1}^{p} \quad w_d x_{id} + \epsilon i \ (i = 1, \dots \dots \dots, n) \quad (9)$$

Where n is the number of data points, x_{id} is the death covariate of $x_i$and $\epsilon_i$is the Gaussian noise with zero mean and variance $\sigma_\epsilon 2$

Evaluating Criteria of The Models

In other to judge the accurateness and effectiveness of the model, four statistical measures were (performance evaluation criteria) employed, which comprise of Linear Correlation Coefficient (R), Coefficient of Determination (R^2), Mean Square error (MSE), as well as Root Mean Square Error (RMSE) (Abdulazeez et al., 2023; Abdullahi et al., 2021; Ghali et al., 2020; Pham et al., 2019a, 2019b, 2019b; Saood et al., 2022; Usman et al., 2021).

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi})^2}{\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi})^2} \quad \text{Eq (3)}$$

$$RMSE = \frac{\sqrt{\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi})^2}}{N} \quad \text{Eq (4)}$$

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$$R = \frac{\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi})(Y_{obsi} - Y_{comi})}{\sqrt{\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi}i)^2}} \qquad \text{Eq (5)}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N} \quad (Y_{obsi} - Y_{comi})^2 \qquad \text{Eq (6)}$$

N donates the number of instances in the dataset, Yobsi means the observed value, Ycomi indicates the predicted value, and Ycomi^{i} the predicted mean of the instances.

RESULT AND DISCUSSION

The main purpose of this research study is to enhance and predict wind speed by using some noble ML models (FFNN and GPR) and also compare their aptitude in producing the best result for the WS of a remote area located in Kano State, Nigeria. The data was collected through a survey of the wind profile of a remote block of flats consisting of 12 apartments. And 24-hour data was gathered through physical monitoring and recording of an hourly variation of the wind in a 24 window. Nevertheless, this part of the paper comes out with the results in this state for both training and testing phase. The intermediate connection of the state shows the variables used with a target value to get, such as wind speed (m/s) temperature (^{o}C) solar radiation (Wh/m^{2}), and Load demand (W). Moreover, a strong time series for wind speed was detected for the state as many mathematical and some physical offshoots were occupied for this study. For the reason of the utmost contribution given by AI models. A linear with a physical model was used for the prediction. Additionally, before the modeling stage, figure 3 displays the relationship between the input and target variable.

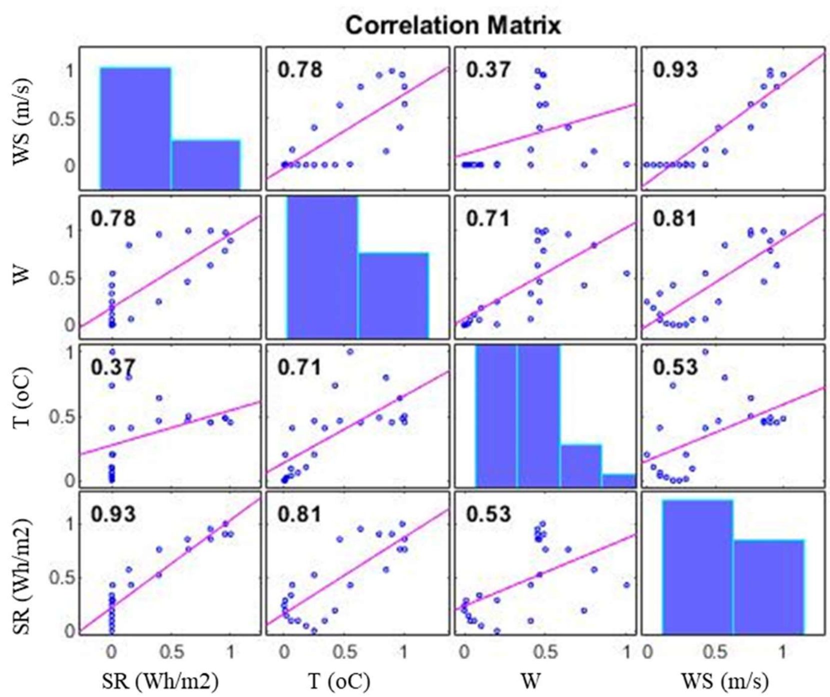

Fig 3: Relationship Between the Input and Output Variable

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A descriptive statistic, or descriptive statistics, is a subset of statistics that deals with the meaningful and systematic gathering, analysis, interpretation, and presentation of data. Table 1 summarizes the input and target variable employed in the study. These statistics give an overview of the salient elements of a dataset, revealing the primary traits and trends within the data. Central tendency measures, which give an idea of the typical or central value in a dataset, include the mean, median, and mode. These are common measures of descriptive statistics. Variance, standard deviation, and range are examples of measures of dispersion that provide information about the variability or spread of the data points. Measures like percentiles, which show the relative position of a specific value within the collection, are examples of further descriptive statistics. For researchers, analysts, and decision-makers in a variety of sectors, descriptive statistics are a fundamental tool that aids in the comprehension, synthesis, and communication of important features of data distributions.

Table 1: Descriptive Statistics of the Wind Speed Data

Variables	*SR (Wh/m2)*	*T (oC)*	*W*	*WS (m/s)*
Mean	263.25	24.8916 7	11591.66 7	4.35833 3
Median	7	23.65	12850	4.2
Mode	0	20.7	13200	3.6
Standard Deviation	346.9483	3.9565	4586.835 3	0.7058
Kurtosis	-0.9617	-1.4540	-0.4072	-1.4700
Skewness	0.8736	0.4376	0.4182	0.3191
Minimum	0	20.6	5800	3.4
Maximum	907	31	22200	5.5

The above table reviews statistical landscapes critical for wind speed estimation (WE) based on Solar Radiation (SR), Temperature (T), Load Demand (LD), and Wind Speed (WS) itself. Wind Speed averages 0.47619 with modest erraticism (standard deviation: 0.3276) and a fairly flat distribution (negative kurtosis). SR and LD exhibit positive skewness, indicating a leaning near lower values. T and WS show slight positive skewness, portentous to a similar circulation trend. These statistics summarize the distribution, essential bent, and sparseness of each variable, providing valuable insights for assembling predictive models attentive to WS using SR, T, and LD as analysts.

The computational modeling was done in MATLAB19 and the architecture of FFNN AND GPR models were trained effectively and selected based on the input features. According to Abba et al. (2021), The optimal model chosen relies on statistical standards, evaluating performance criteria such as R2, R, MSE and RMSE during both training and testing phases. This satisfy that the selective model efficiently imitates values and meets rigorous statistical standards. The combined results in terms of quantitative evaluation are represented in Table 2; however, the result description from the table shows that the FFNN model supers GPR and showed the best performance accuracy

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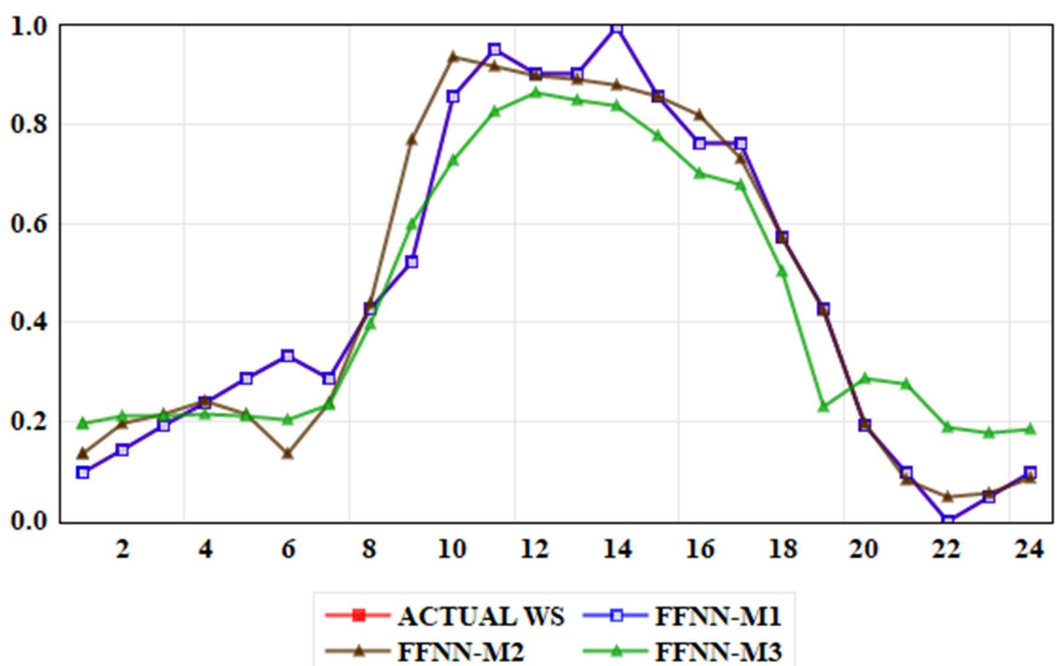
Table 2: Result of the Two ML Models

MODEL	TRAINING PHASE				TESTING PHASE			
	R2	R	MSE	RMSE	R2	R	MSE	RMSE
GPR-M1	0.9463	0.9728	0.0054	0.0732	0.3755	0.6128	0.0246	0.1567
GPR-M2	**0.9728**	**0.9863**	**0.0027**	**0.0521**	**0.9782**	**0.9890**	**0.0009**	**0.0293**
GPR-M3	0.9644	0.9820	0.0035	0.0596	0.9753	0.9876	0.0010	0.0312
FFNN-M1	**1.0000**	**1.0000**	**0.0000**	**0.0000**	**1.0000**	**1.0000**	**0.0000**	**0.0000**
FFNN-M2	0.9185	0.9584	0.0081	0.0901	0.9975	0.9987	0.0004	0.0203
FFNN-M3	0.9254	0.9620	0.0074	0.0862	0.8711	0.9333	0.0209	0.1447

From table 2, it can be seen that FFNN-M1 has performed well during the training and phase of the model with $R^2 = 1$, R= 1 with minimum MSE and RMSE of 0.0 in both training and phase respectively, followed by GPR-M2 with also exhibit a high accuracy of the model with R^2 and R value of 0.9782 and 0.9890 with minimum MSE and RMSE of 0.009 & 0.0293 in the testing phase. Figure 4 displays A time series graph, which is a graphic depiction of data points arranged chronologically, with a time stamp assigned to each data point. These graphs are very helpful when examining patterns, trends, and changes in data over time. Typically, the variable of interest is displayed on the y-axis, and the x-axis denotes the time scale. Time series graphics are frequently utilized in many disciplines, including epidemiology, finance, economics, and climate research.



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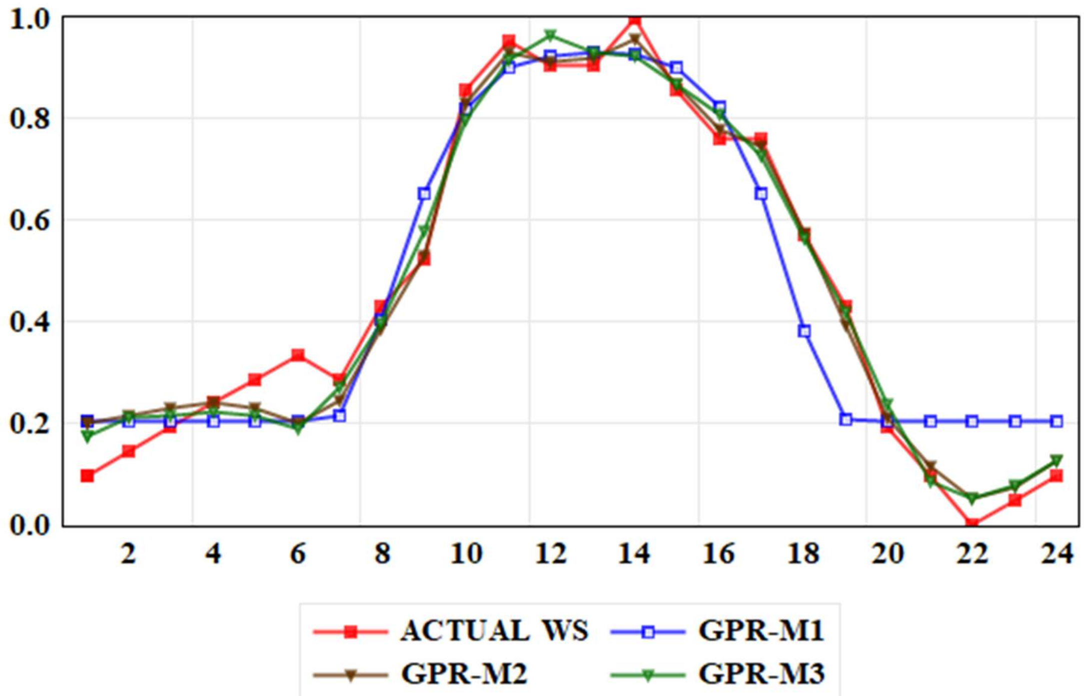

Fig 4: The time series plot of both training and testing GPR

Furthermore, figure 5 shows the scatter plot, which is frequently used to illustrate the relationship between two variables, is a graphical depiction of data points in a two-dimensional space. With one variable represented on the x-axis and the other on the y-axis, each point on the plot represents a pair of values. For evaluating the correlation, trend, or patterns between the two variables graphically, scatter plots are useful tools.

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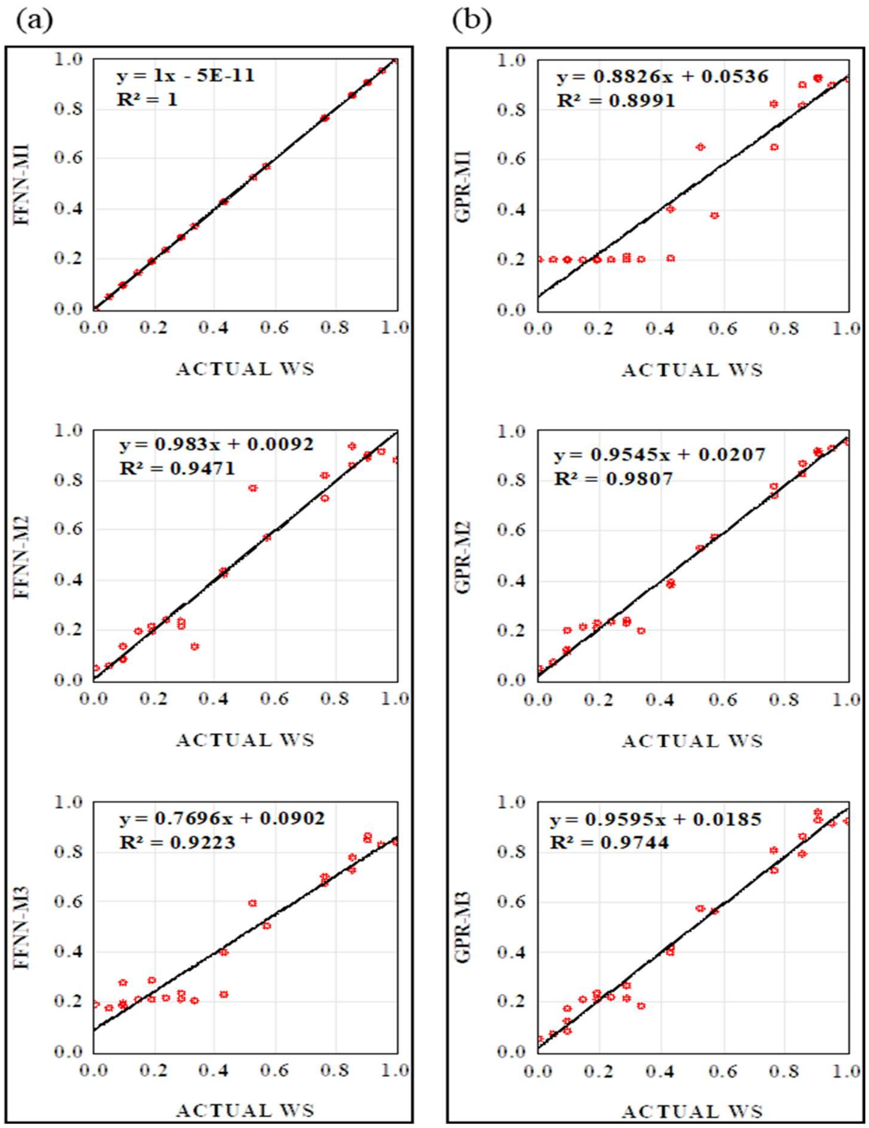

Fig 5: Scatter Plot for both Testing and Training FFNN and GPR

A radar plot, sometimes referred to as a polar plot or a spider plot is displayed in figure 6, is a two-dimensional graphical representation of multivariate data. This kind of layout makes use of a circular grid with spokes that, like the spokes of a wheel, radiate outward from a central point. The length of each spoke reflects the size or value of a certain variable or category that it represents.

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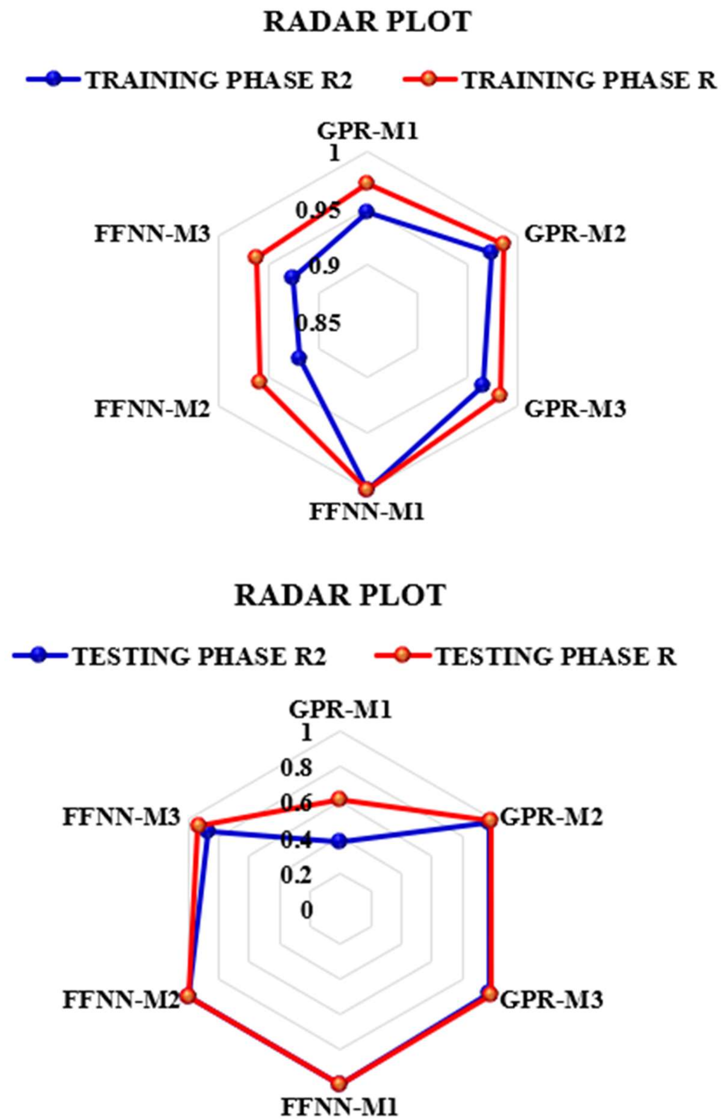

Fig 6: Radar plot for comparative result of the R2 and R in both training and testing Phase

CONCLUSION

This study's finding emphasizes how important renewable energy sources, especially WP which are used to reduce the negative effects of climate change on the world's cities. Predicting wind energy becomes a critical priority in order to fulfill the growing global demand for electricity. Recognizing the difficulties caused by wind power's unpredictability, machine learning techniques Gaussian Process Regression (GPR) and Feed Forward Neural Network (FFNN) in particular, have made a substantial contribution to the field of wind speed estimation. The paper assesses the forecast performance of these machine learning models through an experimental approach using 24-hour time-series data. Feed Forward Neural Network (FFNN) outperforms the Gaussian Process Regression (GPR) in terms of results, as

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measured by metrics. Like coefficient of determination (R^2), linear correlation coefficient (R), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The FFNN shows its efficacy and precision in wind speed prediction with R^2=1, R =1, MSE = 6.62E-20, and RMSE = 2.57E-10, opening the door for more dependable and precise renewable energy optimization tactics in the face of climate change issues.

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Declarations

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Ethical Approval: No

Authors' Contributions: all authors contributed equally to this research

Consent for publication: yes

Availability of data and material: All the data and materials are accessible upon demand

Code availability: Accessible upon demand

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