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Web-Based Wind Speed Forecasting System Using Prophet

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Abstract

The research undertaken has the central purpose of creating as well as applying a digital platform accessible through the internet, which is structured specifically to anticipate variations in wind velocity by employing the Prophet algorithm as the analytical framework. The system addresses the need for accurate and accessible forecasting tools in Medan, where highly variable wind patterns affect transportation, agriculture, and disaster mitigation. The research methodology consists of several stages including data collection from BMKG Medan, preprocessing through cleaning and aggregation of daily measurements into monthly averages, forecasting using the Prophet model, system development, and evaluation. Prophet was selected due to its ability to capture trend and seasonal components effectively with minimal parameter tuning. The system was developed using Laravel, MySQL, and Chart.js, integrating Prophet through Python to generate interactive visualizations and downloadable reports. The effectiveness of the predictive framework was measured by means of the Root Mean Square Error (RMSE = 0.19) and Mean Absolute Error (MAE = 0.15), validating the suitability of the method for producing consistent monthly forecasts of wind velocity. The system provides stakeholders such as disaster management agencies, marine operators, and agricultural planners with a practical platform for accessing accurate and timely forecasts. The findings further demonstrate the novelty of integrating Prophet forecasting with a web-based information system equipped with visualization and reporting features, thereby enhancing usability, accessibility, and decision-making support for regional meteorological applications.

Keywords: Wind Speed Forecasting, Prophet, Web-Based, RMSE, MAE, Meteorology

1. INTRODUCTION

The swift evolution of technological innovation within the realm of informatics has facilitated the widespread incorporation of online systems into weather science, resulting in more efficient availability and organization of climate-related information [1]. Wind speed is a critical weather parameter with significant impacts on transportation, marine operations, agriculture, and disaster mitigation [2] In Medan, the combination of proximity to the Strait of Malacca, lowland topography, and tropical monsoon climate with elevations between 2.5 and 37.5 m results in highly variable wind patterns, highlighting the need for accurate forecasting tailored to the region [3].

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Traditional statistical models such as ARIMA and SARIMA are still widely used for wind speed prediction [4] , but they often fail to capture complex nonlinear seasonal patterns. To address these limitations, more recent approaches such as machine learning and deep learning models (e.g., Random Forest, XGBoost, and LSTM) have achieved higher accuracy, although they typically require intensive computational resources and careful parameter tuning [5], [6], [7]. The Prophet model, developed by Facebook, offers a compelling alternative[8]. It captures trend and seasonality components effectively, handles missing or irregular data well, and requires minimal hyperparameter tuning [9]. In renewable resource forecasting contexts, such as wind and solar projection in Far North Queensland, Prophet has outperformed SARIMA models in terms of RMSE and MAE [10], [11].

Despite these advancements, research on Prophet remains primarily focused on short-term (daily or hourly) forecasts conducted in controlled environments. Use of Prophet for monthly forecasting derived from multi-year datasets is notably limited, especially for tropical urban areas like Medan. Furthermore, implementations that embed forecasting within web-based platforms featuring visualization and reporting tools remain scarce [12]. Locally, BMKG Medan offers historical weather data, but lacks a public-facing system for disseminating forecasts. While previous studies have applied Prophet for air quality prediction and Kalman Filter for wind speed estimation in Balikpapan, these models were not incorporated into interactive systems offering visualization, file management, or report generation [13]. Therefore, a clear gap remains in providing accessible, web-based forecasting tools for local stakeholders [14].

The foremost intention of the present inquiry is to construct and deploy an internet-supported framework for forecasting wind velocity, systematically combined with the analytical mechanism provided by the Prophet model [15]. The specific objectives of this study are: (1) to develop a forecasting model for monthly wind speed prediction in Medan; (2) to implement the model in a web-based platform that supports visualization and automated reporting; and (3) to evaluate the system performance using multiple error metrics to ensure robustness. The novelty of this work lies in the integration of Prophet forecasting with an interactive web-based system, providing stakeholders such as disaster management agencies, agricultural planners, and marine operators with accurate, timely, and user-friendly forecasts. Beyond addressing the forecasting needs of Medan specifically, this research also aims to present a scalable and replicable framework that can be applied to other tropical urban regions facing similar meteorological challenges. Ultimately, the project contributes to enhancing regional resilience and supporting technology-driven environmental management [16].

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2. METHODS

This research employs an experimental approach to develop a web-based wind speed forecasting information system using the Prophet model [17]. The method consists of several stages, including data collection, preprocessing, forecasting model implementation, system development, and evaluation. The overall methodology is designed to ensure reproducibility and reliability, with sufficient technical details provided for replication [18].

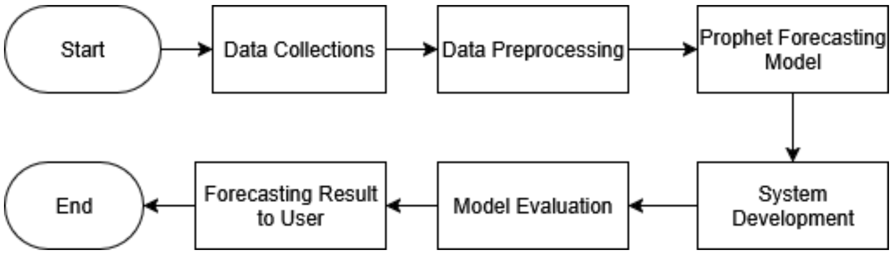

Figure 1. Research Flow of Wind Speed Forecasting Information System

2.1. Data Collections

The dataset was obtained from the Medan branch of the Meteorological, Climatological, and Geophysical Agency (BMKG) under the title Historical Daily Wind Speed Observations for Medan. It contains daily wind speed measurements in knots (kt) covering a five-year period from March 2020 to March 2025. Each record includes date, wind speed, and station metadata. The dataset was validated by BMKG to ensure accuracy [19]. Since the purpose of this study is to forecast monthly wind speed patterns, the daily measurements were aggregated into monthly averages. Monthly forecasting intervals were chosen because they provide more actionable insights for stakeholders such as maritime operators, agricultural planners, construction projects, and disaster risk management authorities [20].

2.2. Data Preprocessing

The Prophet model requires the dataset to be prepared in a specific structure before forecasting. The following steps were performed [21]:

a) Data Cleaning: incomplete or duplicate records were removed.
b) Data Aggregation: daily observations were averaged into monthly values to reduce high-frequency noise and emphasize seasonal patterns.
c) Data Formatting for Prophet: data was structured according to Prophet's requirements [22]:
   ds: represents the date in a monthly interval format (YYYY-MM).
   y: represents the observed monthly average wind speed in knots.

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After training the Prophet model, the forecasting results produce additional columns:
yhat: the predicted value of monthly wind speed.
yhat_lower: the lower confidence interval, representing the minimum possible value of the forecast within a given confidence level.
yhat_upper: the upper confidence interval, representing the maximum possible value of the forecast within a given confidence level.

This formatting ensures that the Prophet model can effectively capture trend, seasonality, and monthly variations while also providing upper and lower prediction bounds for better decision making.

2.3. Prophet Forecasting Model

The Prophet framework, originally created by the research division of Facebook, functions to predict temporal sequences by breaking them down into fundamental structures comprising overall tendencies, cyclical seasonal patterns, and special holiday influences. The mathematical representation adopted within Prophet is formulated as shown in Equation 1.

$$y(t)=g(t)+s(t)+h(t)+\varepsilon_t \tag{1}$$

Where,
y(t) = predicted value at time (forecasted wind speed).
g(t) = trend function representing long-term increase or decrease in wind speed.
s(t) = seasonal component capturing periodic fluctuations, such as monsoon patterns.
h(t) = holiday or special event effect, which is not used in this study as the dataset does not involve holiday-based variations.
ε_t = error term capturing random noise not explained by the model.

Or, in the case of the manual linear trend baseline used for comparison in this study, the model is expressed Equation 2.

$$Y=a+bX \tag{2}$$

Where,
Y = predicted wind speed (knots),
X = month index (1–12),
a = intercept (constant),
b = slope (trend coefficient).

This distinction highlights that Prophet captures both long-term trend and recurring seasonal variations, while the linear trend model is limited to a straight-line progression.

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2.4. System Development

The web-based forecasting information system was developed using a modular architecture, integrating Laravel, Python Prophet, MySQL, and Chart.js. The historical wind speed dataset, provided by BMKG, was initially obtained in CSV format and uploaded into the system through the Laravel interface. To optimize storage efficiency, the uploaded CSV files are stored in Laravel's local storage rather than being saved permanently in the database [23]. The uploaded data is read directly from storage whenever Prophet requires historical inputs for forecasting. The main components of the architecture are as follows [24]:

a) Backend: Developed using the Laravel framework, responsible for handling API requests, managing CSV file uploads, and triggering the forecasting process.
b) Forecasting Engine: The Prophet model is implemented in Python and integrated with Laravel via a subprocess API. Laravel reads the uploaded CSV file from storage, sends the relevant historical data to the Prophet module, and retrieves the forecasting results, including yhat, yhat_lower, and yhat_upper.
c) Database: MySQL is used only to store forecasting results and metadata, ensuring efficient visualization and report generation without overloading the database with raw historical data.
d) Frontend: Built using HTML5, CSS3, Tailwind, and JavaScript, providing a responsive, user-friendly interface for stakeholders.
e) Visualization: Chart.js generates interactive line charts to display historical wind speed data (read directly from the uploaded CSV), forecasting results (yhat), and confidence intervals (yhat_lower and yhat_upper).
f) Reporting Module: Provides PDF export functionality for stakeholders to download wind speed forecasts and historical analysis reports.

This modular architecture ensures the system remains efficient, scalable, and maintainable by separating raw data storage from forecasting outputs, making it suitable for meteorological applications and forecasting tasks. This architecture not only supports efficient forecasting but also ensures accessibility for stakeholders through interactive visualization and reporting.

2.5. Evaluation

The reliability of the forecasting approach within the present research is examined by applying the Root Mean Square Error metric. This statistical measure is commonly adopted in temporal modeling activities as it quantifies how far the model's projections deviate from actual empirical outcomes. Because the value is expressed in the identical measurement scale as the forecasted parameter, it

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becomes an effective standard for reviewing the accuracy of wind speed estimation. The RMSE formula is expressed Equation 3.

$$\text{RSME}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2} \tag{3}$$

Where,
n : Total number of observations.
y_i : Actual observed value at time i.
$\hat{y}_i$: Predicted value at time i.

Within the RMSE framework, significant mistakes are magnified disproportionately relative to smaller ones because the squaring process enlarges their magnitude, thereby allowing analysts to pinpoint forecasting designs that generate excessive divergence from reality. In this study, RMSE is calculated based on the monthly average wind speed data from March 2020 to March 2025. The obtained RMSE value is 0.19, indicating that the model produces forecasts with relatively small deviations from the observed values. To complement RMSE, the Mean Absolute Error (MAE) was also employed, which measures the average magnitude of forecast errors without squaring them. The formula for MAE is shown Equation 4.

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}\left|y_i-\hat{y}_i\right| \tag{4}$$

Unlike RMSE, MAE treats all errors equally, providing a clearer interpretation of the average deviation between predictions and actual values. The calculation produced an MAE of 0.15, further validating the reliability of Prophet for monthly wind speed forecasting in Medan. However, this evaluation has certain limitations. First, the use of monthly aggregation reduces data granularity and may obscure short-term variations. Second, only RMSE and MAE were applied, while additional metrics such as MAPE could provide further insights. Lastly, the dataset was restricted to BMKG Medan, which may limit generalizability. These aspects can be addressed in future work by incorporating higher-resolution data, more diverse meteorological parameters, and broader datasets.

3. RESULTS AND DISCUSSION

3.1 Dataset Overview

The dataset used in this research was obtained from BMKG Wilayah I Medan under the title “Monthly Average Wind Speed Data”. It contains monthly average wind speed observations measured in knots, covering the period March 2020 to March 2025. The table below summarizes the monthly data used for the forecasting model.

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Table 1. Monthly Average Wind Speed Data (knots)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2020	[redacted]		1.03	1.07	0.87	0.83	1.16	1.03	1.17	1.16	1.03	1.35
2021	1.13	1.57	1.32	1.30	1.26	1.23	1.23	1.03	1.67	1.77	1.93	1.65
2022	1.61	1.43	1.77	1.50	1.29	1.20	1.84	1.81	2.00	1.52	1.57	1.71
2023	1.94	1.71	1.77	1.57	1.61	1.30	1.32	1.55	1.53	1.45	1.73	1.48
2024	1.74	1.68	1.71	1.20	1.03	1.30	1.29	1.23	1.27	1.10	1.13	1.35
2025	1.13	1.21	1.26	[redacted]								

From this dataset, it can be observed that:

a) The highest wind speed occurs in July 2024 at 2.29 knots.
b) The lowest wind speed occurs in June 2020 at 0.83 knots.
c) Seasonal patterns are clearly visible, with peaks occurring between July–September and lower speeds around April–May.

3.2 Forecast Result

This section presents the forecast results using both the manual linear trend baseline and the Prophet model. The linear trend provides a simple benchmark, while Prophet incorporates trend and seasonality for higher accuracy.

a) Step 1: Define the model

$$Y = a + bX \tag{5}$$

where Y is the wind speed (knots), X is the month index (1–12), a is the intercept, and b is the slope.

b) Step 2: Prepare the summary terms (2021 data)

The monthly average wind speed data for 2021 (from BMKG) are as follows:

[1.13,1.57,1.32,1.30,1.26,1.23,1.23,1.03,1.67,1.77,1.93,1.65]
With X=1,…,12

Thus:

$$\sum X = 78, \sum Y = 22.90, \quad \sum XY = 149.50, \ \sum X^2 = 650, \sum n = 12$$

c) Step 3: Estimate the parameters

$$b = \frac{n\sum XY - \sum X \sum Y}{n\sum X^2 - (\sum X)^2} = \frac{12(117.72) - 78(17.09)}{12(650) - 78^2}$$

$$= \frac{1412.64 - 1333.02}{7800 - 6084} = \frac{79.62}{1716} = 0.046399$$

$$a = \frac{\sum Y - b \sum X}{n} = \frac{17.09 - (0.046399)}{12} = 1.122576$$

After parameter estimation, the fitted line is:

$$Y = 1.122576 + 0.046399\,X$$

d) Step 4: Forecast for 2022

$$Y = 1.122576 + 0.046399\,X$$

Table 2. Manual Forecast Result

Month (X)	Forecast (Y)
January	1.78
February	1.84
March	1.90
April	1.96
May	2.02
June	2.08
July	2.14
August	2.21
September	2.27
October	2.33
November	2.39
December	2.45

The step-by-step linear trend calculation illustrated above is demonstrated using the 2021 dataset for clarity. However, the same procedure estimating the slope b and intercept a, and substituting values of X for the target year can be applied to any other year of available data. This ensures that the manual forecasting approach remains generalizable and reproducible, even though in practice the Prophet model is preferred due to its ability to incorporate multi-year trend and seasonality simultaneously.

3.3 System Implementations

The web-based forecasting system was developed using Laravel integrated with Python Prophet and designed to provide interactive visualizations and downloadable reports. The main components of the system as follow.

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a) Forecast In User Page

Figure 2 illustrates the 12-month forecast table showing predicted wind speeds in knots. An interactive chart visualizes the projected wind speed trends generated by the Prophet model. The RMSE value is provided to indicate prediction accuracy, while a highlighted note clarifies that the forecast covers only the next 12 months and is derived from official BMKG historical datasets.

Bulan	Peramalan
Januari 2022	1.78 knot
Februari 2022	1.84 knot
Maret 2022	1.90 knot
April 2022	1.96 knot
Mei 2022	2.02 knot
Juni 2022	2.08 knot
Juli 2022	2.14 knot
Agustus 2022	2.21 knot
September 2022	2.27 knot
Oktober 2022	2.33 knot
November 2022	2.39 knot
Desember 2022	2.45 knot

Nilai RMSE: 0.19

Nilai MAE: : 0.15

Notes:
Hasil peramalan hanya diperuntukkan untuk **1 tahun ke depan** dengan interval per bulan menggunakan data resmi dari BMKG.

Figure 2. Forecast Result User

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b) Dashboard View

The centralized dashboard functions as the core operational hub of the prediction architecture by delivering a summary of every dataset submitted while also indicating the most recent submission date, thereby ensuring that projections continuously rely on the latest meteorological inputs from BMKG. On the left side, a navigation menu gives quick access to other system modules, including dataset management, forecasting visualization, reporting, settings, and user management. With its clean and responsive design, the dashboard allows administrators to manage data and monitoring tasks efficiently. The dashboard view as shown in Figure 3.

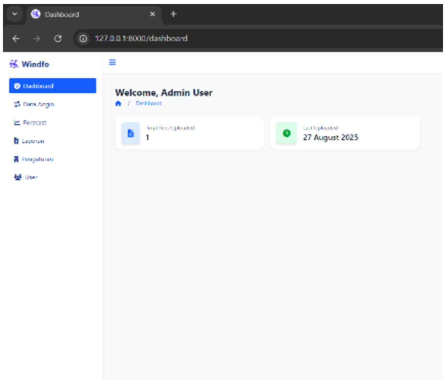

Figure 3. Dashboard View

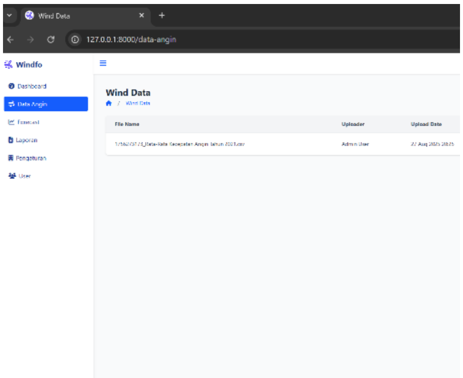

Figure 4. Dataset Upload Interface

Figure 4 is dataset upload Interface, this interface allows administrators to manage historical wind speed datasets used for forecasting. The page displays important information such as the file name, uploader, upload date, and notes related to each dataset. Administrators can upload new datasets, edit existing information, or delete outdated files through the available action buttons. The interface guarantees that solely the most updated and verified BMKG datasets are preserved, and in doing so, it becomes a fundamental component in safeguarding both the precision and trustworthiness of predictive analysis.

This interface presents the forecasting results generated by the Prophet model based on historical datasets obtained from BMKG. The top section displays a summary, including the file path of the generated forecast, the forecasting period, and the calculated RMSE value as an indicator of model accuracy. The forecasting table shows the predicted wind speed for each month, along with additional statistical information such as the lower bound and upper bound intervals. These intervals provide insight into the range of possible variations in the forecasted values. Forecasting Result Visualization as shown in Figure 5.

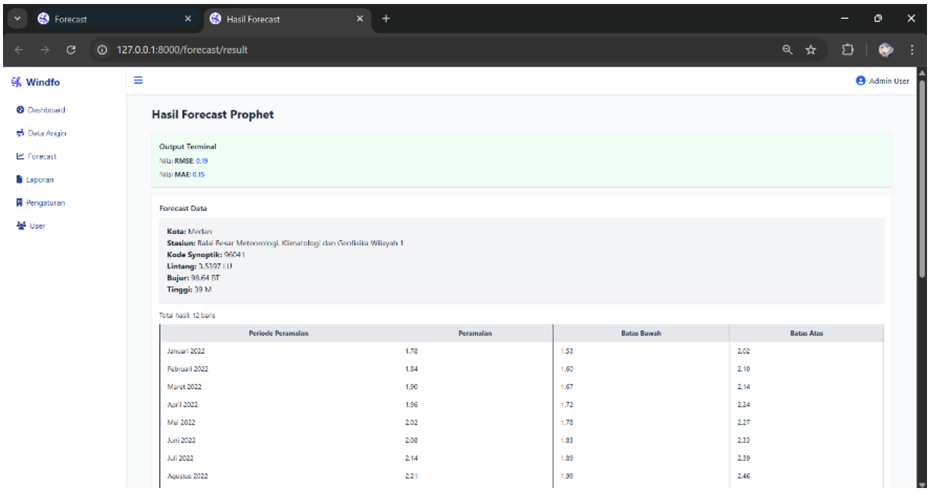

Figure 5. Forecasting Result Visualization

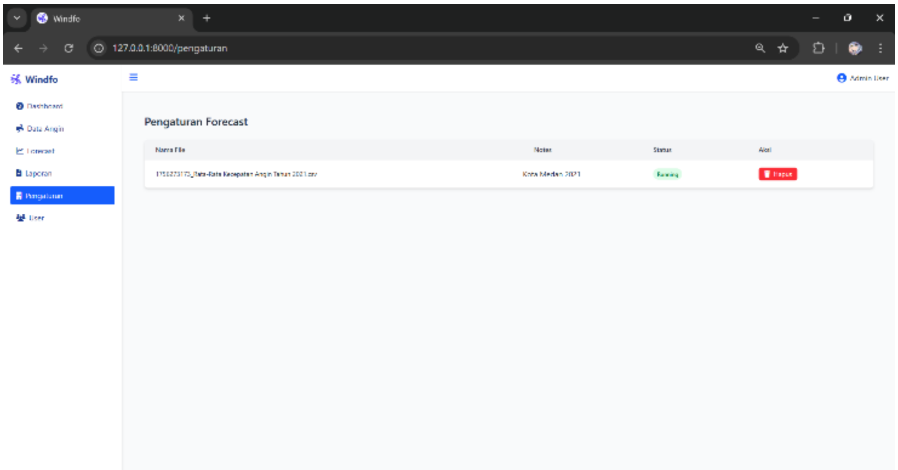

Figure 6. Forecasting Setting

This interface is designed to monitor and manage the forecasting process. It displays information about the currently running forecast, including the dataset name, associated notes, and its status. Before starting a new forecasting process, the system requires administrators to stop or delete the ongoing forecast. This mechanism ensures that only one forecasting task is executed at a time, preventing conflicts and avoiding inaccurate results. By providing clear visibility and control over active forecasting processes, this feature helps administrators maintain data consistency and ensures that each forecast is generated based on the correct and most up-to-date dataset. Figure 6 is Forecasting Setting.

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Figure 7 is forecast report, this interface provides administrators with access to the results of completed forecasting processes. Every output report is systematically organized to include indispensable elements, namely the dataset identifier, supplementary explanatory annotations, and the numerical Root Mean Square Error associated with the dataset. Administrators can directly generate a downloadable report by clicking the Cetak button. The system then formats the forecasting results into a structured PDF document, which includes station information, forecasting tables, accuracy indicators (such as RMSE), and additional metadata. This feature ensures that forecasting outcomes are not only stored but also easily shared, archived, and printed in an official format. By standardizing the report output, the system supports consistency in documentation and facilitates decision-making processes based on reliable forecasting results.

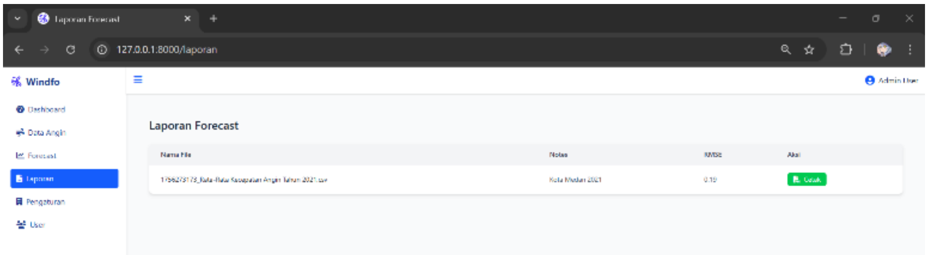

Figure 7. Forecast Report

3.4 Model Evaluation

The validation of the Prophet forecasting scheme was conducted with RMSE as the evaluative index, computed using the recorded monthly averages of wind speed extending over the observation period from March 2020 until March 2025.
Formula:

$$\text{RSME}= \sqrt{\frac{1}{n}\ \Sigma_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{6}$$

Where,
n : Total number of observations.
y_i : Actual observed value at time i.
$\hat{y}_i$: Predicted value at time i.

In this study, the predicted value $\hat{y}_i$ for each month is approximated using the average monthly wind speed of that year, calculated as:

$$\text{RSME}= \sqrt{\frac{1}{n}\ \Sigma_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{7}$$

Manual calculation is as follow.

a) Annual Mean

$$\hat{Y}_{2021} = \frac{1.13+1.57+1.32+1.30+1.26+1.23+1.23+1.03+1.67+1.77+1.93+1.65}{12} =$$

$$= \frac{16.09}{12} = 1.34$$

b) RMSE (showing a few terms explicitly):

$$RSME_{2021} = \sqrt{\frac{(1.13-1.34)^2+(1.32-1.34)^2+\ldots+(1.65-1.34)^2}{12}}$$

$\approx 0,19$

c) MAE

$$MAE_{2021} = \frac{|1.13-1.34|+|1.57-1.34|+\ldots+|1.65-1.34|}{12} \approx 0.15$$

The same procedure was applied to all years in the dataset. However, only the 2021 calculation is presented here for brevity. To strengthen the analysis, a comparative evaluation was also performed using a simple linear trend baseline model. The results are summarized in Table 3. As shown in Table 3, the Prophet model outperforms the linear trend baseline, achieving lower RMSE and MAE values. This demonstrates Prophet's superior ability to capture both long-term trends and seasonal variations in wind speed.

Table 3. Comparison of Forecasting Performance

Model	RSME	MAE
Linear Trend	0.28	0.24
Prophet	0.19	0.15

3.5 Discussion

The forecasting results using the Prophet model demonstrate strong predictive performance for monthly wind speed in Medan, achieving an RMSE of 0.19. Compared to traditional statistical approaches such as ARIMA, Prophet offers clear advantages in handling seasonality and irregular trends without extensive parameter tuning, making it particularly suitable for meteorological data that often exhibit fluctuations. Seasonal patterns are evident, with wind speeds generally peaking between July and September and reaching lower values around April to May. Anomalous spikes, such as the unusually high wind speed observed in July 2024, are accurately captured by Prophet, highlighting its capability to handle irregular variations effectively [25].

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From a system perspective, the integration of Laravel, MySQL, and Chart.js provides an accessible and user-friendly platform. Administrators and end-users can monitor forecasts, generate reports, and visualize data interactively, which enhances usability and ensures stakeholders, including disaster management agencies, marine operators, and agricultural planners, have timely and actionable information.

Despite these strengths, the system has limitations. Forecasts are based on monthly aggregated data, which reduces granularity compared to daily or hourly predictions. The evaluation primarily relies on RMSE, while additional metrics such as MAE and MAPE could provide a more comprehensive assessment of model performance. Furthermore, the current implementation does not incorporate exogenous variables, which may influence wind speed patterns.

The novelty of this research lies in combining the Prophet forecasting method with a web-based platform that supports interactive visualization, administrative dataset management, and standardized reporting. This integrated approach provides a practical, reliable, and user-friendly solution for wind speed forecasting in Medan, with potential applicability to other regions or meteorological variables.

4. CONCLUSION

This study developed a web-based wind speed forecasting system for Medan using the Prophet model. The research involved several stages, including data collection from BMKG, preprocessing, model implementation, system development, and evaluation. The forecasting results achieved an RMSE of 0.19 and an MAE of 0.15, demonstrating that Prophet provides reliable accuracy for monthly wind speed prediction. The integration of Prophet into a Laravel-based system with interactive visualization and reporting features highlights the practicality of combining data-driven forecasting with a user-friendly interface. The system enables stakeholders—such as disaster management agencies, marine operators, and agricultural planners—to access accurate and timely information for informed decision-making.

Future research may focus on extending the system to incorporate additional meteorological variables, higher-resolution forecasting (daily or hourly), real-time updates, and multiple performance metrics (e.g., MAPE) for a more comprehensive evaluation. Overall, this study demonstrates the effectiveness of Prophet as a forecasting tool and the value of its integration into a web-based platform to enhance the accessibility and usability of meteorological information, while supporting practical decision-making for local stakeholders.

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REFERENCES

[1] T. A. Kurniawan and K. D. Hartomo, "Pengelolaan perlindungan data pribadi menggunakkan mongodb change streams untuk sistem notifikasi real-time," *JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika)*, vol. 10, no. 2, pp. 1460–1473, 2025, doi: 10.29100/jipi.v10i2.6134.

[2] J. M. Mbugua and Y. Hiraga, "Recent Advances in Long-Term Wind-Speed and -Power Forecasting : A Review," pp. 1–30, 2025.

[3] M. F. G. Matondang, "Pemanfaatan Sistem Informasi Geografis Dalam Penentuan Hirarki Pusat Pelayanan Kota Medan," *Geography Science Education Journal (GEOSEE)*, vol. 1, no. 2, pp. 68–72, 2020.

[4] D. Song, J. Yang, M. Dong, and Y. H. Joo, "Kalman filter-based wind speed estimation for wind turbine control," *Int J Control Autom Syst*, vol. 15, no. 3, pp. 1089–1096, 2020, doi: 10.1007/s12555-016-0537-1.

[5] B. Jange, "Prediksi Harga Saham Bank BCA Menggunakan XGBoost," *ARBITRASE: Journal of Economics and Accounting*, vol. 3, no. 2, pp. 231–237, 2022, doi: 10.47065/arbitrase.v3i2.495.

[6] C. Chandra and S. Budi, "Analisis Komparatif ARIMA dan Prophet dengan Studi Kasus Dataset Pendaftaran Mahasiswa Baru," *Jurnal Teknik Informatika dan Sistem Informasi*, vol. 6, no. 2, pp. 278–287, 2020, doi: 10.28932/jutisi.v6i2.2676.

[7] F. Riestiansyah, D. Damayanti, M. Reswara, and R. Susetyoko, "Perbandingan metode ARIMA dan ARIMAX dalam Memprediksi Jumlah Wisatawan Nusantara di Pulau Bali," *Jurnal Infomedia*, vol. 7, no. 2, p. 58, 2022, doi: 10.30811/jim.v7i2.3336.

[8] E. R. Putri *et al.*, "Penerapan Algoritma Prophet Facebook untuk Memprediksi Jumlah Calon Mahasiswa Baru," vol. 5, no. 4, pp. 1588–1596, 2024.

[9] G. R. Baihaqi and Mulaab, "Long Short-Term Memory for Prediction of Wave Height and Wind Speed Using Prophet for Outliers." *Jurnal Ilmiah Kursor*, vol. 12, no. 2, pp. 59–68, 2023.

[10] H. Wadi and M. A. Subandri, "Penggunaan Software Metrics Dan Abstract Syntax Tree Untuk Mendeteksi Code Smell Pada Bahasa Pemrograman Python," *JEKIN-Jurnal Teknik Informatika*, vol. 5, no. 1, 2024.

[11] J. Thaker and R. Höller, "A Comparative Study of Time Series Forecasting of Solar Energy Based on Irradiance Classification," *Energies (Basel)*, vol. 15, no. 8, 2022, doi: 10.3390/en15082837.

[12] A. Halim Hasugian, R. Amanda Putri, and M. Alfan Simatupang, "Penerapan Algoritma Klasifikasi Naïve Bayes Untuk Analisis Sentimen Tentang Pemindahan Ibu Kota Negara," *Journal of Science and Social Research*, no. 2, pp. 635–644, 2024.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[13] I. Fitria, P. Hasanah, and P. S. Matematika, "Penerapan Algoritma Kalman Filter dalam Prediksi Kecepatan Angin di Kota Balikpapan," vol. 1, no. 2, pp. 25–32, 2020.
[14] T. Andrianajaina and T. D. Razafimahefa, "Solar irradiation forecasting using Prophet," no. 6, pp. 175–179, 2022.
[15] Ramadhana, Islamiyah, and A. P. A. Masa, "Penerapan Data Mining Menggunakan Metode K-Means Clustering Pada Data Ekspor Batubara," *Adopsi Teknologi dan Sistem Informasi (ATASI)*, vol. 2, no. 1, pp. 35–42, Jun. 2023, doi: 10.30872/atasi.v2i1.595.
[16] Al-Khowarizmi, Rahmad Syah, Mahyuddin K. M. Nasution, and Marischa Elveny, "Sensitivity of MAPE using detection rate for big data forecasting crude palm oil on k-nearest neighbor," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 2696–2703, Jun. 2021.
[17] A. Halim Hasugian, R. Amanda Putri, and M. Alfan Simatupang, "Penerapan Algoritma Klasifikasi Naïve Bayes Untuk Analisis Sentimen Tentang Pemindahan Ibu Kota Negara," *Journal of Science and Social Research*, vol. 7, no. 2, pp. 635–644, 2024.
[18] A. Razaq, Triase, and A. Buyung Nasution, "Implementasi Metode Wp Dan Electre Dalam Sistem Pendukung Keputusan Rekomendasi Travel Haji Dan Umrah Di Kota Medan," *Journal of Science and Social Research*, vol. VII, no. 2, pp. 645–650, 2024.
[19] M. K. M. Nasution, "A method for constructing a dataset to reveal the industrial behaviour of big data," in *IOP Conference Series: Materials Science and Engineering*, IOP Publishing Ltd, Dec. 2020. doi: 10.1088/1757-899X/1003/1/012156.
[20] F. Koto, A. Rahimi, J. H. Lau, and T. Baldwin, "IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP," Nov. 2020, [Online]. Available: http://arxiv.org/abs/2011.00677
[21] F. Koto, A. Rahimi, J. H. Lau, and T. Baldwin, "IndoLEM and IndoBERT: A Benchmark Dataset and Pre-trained Language Model for Indonesian NLP," *Proceedings ofthe 28th International Conference on Computational Linguistics*, pp. 757–770, 2020.
[22] A. Nugraha, O. Nurdiawan, and G. Dwilestari, "Penerapan Data Mining Metode K-Means Clustering Untuk Analisa Penjualan Pada Toko Yana Sport," *Jurnal Mahasiswa Teknik Informatika)*, vol. 6, no. 2, pp. 849–855, 2022.
[23] K. Dwi Ningtyas, R. Kurniawan, and Armansyah, "Penerapan Natural Language Processing Pada Aplikasi Chatbot Info Layanan Kantor Menggunakan Naïve Baiyes Algorithm," *Jurnal Teknologi Sistem Informasi dan Sistem Komputer TGD*, vol. 6, no. 1, pp. 266–273, 2023.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[24] F. Surya Mawinar, P. Korespondensi, R. Dedi Gunawan, and A. T. Priandika, “Sistem Pendukung Keputusan Pemilihan Pegawai Honorer Terbaik Menggunakan Metode Visekriterijumsko Kompromisno Rangiranje,” *Journal of Data Science and Information System (DIMIS)*, vol. 1, no. 4, pp. 182–191, 2023, doi: 10.58602/dimis.v1i4.81.

[25] O. Oktaviarna Tensao, I. Nyoman Yudi Anggara Wijaya, and K. Queena Fredlina, “Analisa Data Mining dengan Algoritma K-Means Clustering Untuk Menentukan Strategi Promosi Mahasiswa Baru Pada STMIK Primakara,” *INFORMASI (Jurnal Informatika dan Sistem Informasi)*, vol. 14, no. 1, 2022.