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Analysis and Comparison of Modeling Methods for Energy Consumption Forecasting Based on Big Data

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ABSTRACT

Abstract: *This study presents a systematic literature review aimed at analyzing and comparing modeling methods used in forecasting energy consumption based on big data. Literature sources were selected from Google Scholar, DOAJ, and SCOPUS, spanning the years 2014-2024. The research findings indicate that the use of machine learning models, such as SVM, ANN, RF, and classical statistical models, has demonstrated superiority in capturing complex energy consumption patterns. However, the importance of selecting exogenous data and time lags in the complexity and accuracy of machine learning model predictions is also highlighted. The involvement of diverse prediction methods allows researchers to accommodate variations in data characteristics and environmental conditions. Additionally, a strong theoretical foundation and exploration of advanced data analysis methods are crucial in maximizing the potential of big data in predicting energy consumption. These findings affirm that there is no single model suitable for all situations, and careful evaluation of contextual factors and data characteristics is essential in selecting the most appropriate forecasting method. Lastly, the importance of human factors and work culture in modeling performance is also emphasized, underscoring the integration of human factors in the development and implementation of predictive models. Thus, this research provides valuable insights for the development of effective modeling methods in forecasting energy consumption based on big data.*

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A. INTRODUCTION

In the digital era marked by the increasing utilization of big data-based technologies, energy consumption has emerged as a focal point. With the widespread adoption of these technologies, the demand for energy has escalated (Saputra et al., 2020).This phenomenon poses significant challenges in efficiently managing energy resources. One pivotal aspect in addressing these challenges is the accurate modeling to forecast future energy consumption. The importance of precise and reliable modeling is increasingly felt, as it provides a robust foundation for making informed decisions in energy resource management. With models capable of delivering accurate predictions, stakeholders can devise more effective strategies for energy utilization, spanning from household to industrial scales. Consequently, the success in tackling the current energy consumption challenges critically hinges on the ability to develop and implement reliable and sophisticated modeling techniques (Wahyono, 2021).

Modeling plays a crucial role in the endeavor to forecast energy consumption supported by big data. In this context, accurate predictions are highly prioritized as they provide insights into future energy needs. However, to achieve reliable predictions, the selection and application of appropriate modeling methods are crucial (Lustono; et al., 2023). Various modeling methods offer different approaches in interpreting and analyzing large and complex energy data. Therefore, selecting methods that align with the data characteristics and specific analytical needs is a crucial initial step (Sachrrial & Iskandar, 2023).The right selection enables users to optimize model performance and obtain more accurate prediction results. In the context of big data, where data volume and diversity are often high, it is important for researchers and practitioners to choose methods capable of not only handling data complexity but also providing reliable estimates. Thus, the success in forecasting energy consumption based on big data heavily relies on the selection and application of appropriate modeling methods (Suryana, 2014).

Various modeling approaches to forecast energy consumption have been a primary focus in related literature. A variety of methods and techniques have been examined and tested in efforts to enhance the accuracy of energy consumption predictions across different contexts and scales. However, despite numerous studies, there remains a pressing need to continuously identify and evaluate the most effective and efficient current methods and models (Suhartono, 2017). With the advancement of technology and rapid growth in the field of big data, new challenges arise alongside increasing data complexity (Yudistira, 2021). Therefore, continuous efforts are necessary to investigate and evaluate the performance of various state-of-the-art methods and models that can accommodate these challenges. Careful evaluation of these methods and models is required to ensure that they can provide accurate and reliable predictions for future energy consumption. Thus, this research not only focuses on the introduction and understanding of various existing methods and models but also emphasizes the importance of discovering and evaluating the latest methods and models that can serve as effective solutions to address challenges in forecasting energy consumption based on big data (Munawar et al., 2020).

Numerous studies have been conducted to understand the best modeling methods for forecasting energy consumption based on big data. However, these studies often have limitations, such as being confined to specific scopes or not accounting for recent advancements in the field. (Azis, 2021) proposed a model capable of managing consumption data from thousands of customers and improving prediction accuracy on large datasets. (Suprayogi & Rahmanesa, 2019) developed a hybrid model architecture that combines machine learning models and artificial neural networks, significantly enhancing prediction accuracy and stability. (Abdussyukur, 2023) proposed a novel approach using new optimization algorithms and LSTM-based models, which succeeded in accurately forecasting energy consumption. They suggested a forecast energy usage model using LSTM and explainable artificial intelligence, achieving the lowest mean squared error scores. (Made et al., 2023) presented a hybrid deep learning-based model design for multi-step forecasting, demonstrating excellent predictive capabilities. These studies provide important evidence of the diversity of methods and models that can be used in forecasting energy consumption based on big data, highlighting the importance of continuously developing more sophisticated approaches to enhance energy prediction accuracy in the future.

To conduct an in-depth analysis and comparison of modeling methods used in forecasting energy consumption based on big data, several papers have evaluated various models. LSTM and GRU models have shown promising results in accurately predicting energy consumption with low root mean square error (RMSE) values (Karyadi, 2022). The multistage Facebook Prophet model has also demonstrated high accuracy in forecasting consumption. Single-layer LSTM, double-layer LSTM, and bidirectional LSTM models have achieved the lowest RMSE scores in energy usage forecasts. The proposed interpretable model, N-BEATS, has enhanced prediction accuracy on large datasets containing energy consumption profiles from multiple customers (Siahaan & Nababan, 2017). Linear regression, random forest, and artificial neural network models have been used to predict energy usage, with their effectiveness compared using RMSE, R squared, MAE, and MAPE measurements (Pengaruh et al., 2019). Each model has its own strengths and weaknesses, such as complexity, interpretability, and performance, which must be considered when selecting the appropriate model for forecasting energy consumption.

This research provides valuable insights for researchers and practitioners in the fields of energy modeling and big data. The study offers a methodology for selecting input variables based on explainable artificial intelligence (XAI) for consumption prediction (Studi et al., 2014). Additionally, the study proposes a forecasting model for energy usage employing Long Short-Term Memory (LSTM) and XAI, which successfully achieved low root mean squared error (RMSE) values. Furthermore, the research presents methods based on Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) for estimating energy consumption, enhancing prediction accuracy (Adherda & Hikmatyar, 2023). Moreover, this study constructs a regression prediction model for energy consumption based on parallel random forest algorithm, providing insights into the relationship between input, model parameters, and output. These findings can guide decision-makers in selecting the appropriate methods for future energy consumption forecasting needs.

The purpose of this research is to conduct an in-depth analysis and comparison of the modeling methods used in forecasting energy consumption based on big data. Considering the complexity and significance of energy consumption issues in the digital era supported by big data technology, the main objective is to evaluate the effectiveness and efficiency of various existing modeling methods in predicting energy consumption. This research aims to identify the strengths and weaknesses of each modeling method, providing valuable insights for researchers and practitioners in the fields of energy modeling and big data. Through a better understanding of the performance and practical applications of various modeling methods, it is hoped that this research can serve as a guide for decision-makers in selecting the most suitable modeling methods for future energy consumption forecasting needs. Thus, the ultimate goal of this research is to enhance the ability to manage energy resources efficiently and sustainably, as well as to support more accurate and effective decision-making in an environment dominated by big data.

B. METHOD

This study aims to conduct an analysis and comparison of the modeling methods used to forecast energy consumption based on big data. The main focus is to identify the strengths, weaknesses, and characteristics of each modeling method in capturing complex energy consumption patterns. Literature search was conducted through three main indexing sources, namely Google Scholar, DOAJ, and SCOPUS, spanning the years from 2014 to 2024. Keywords used included phrases such as "energy consumption," "big data," "modeling methods," and other related keyword variations. Additionally, references from relevant articles were also investigated to ensure comprehensive coverage (Aulia et al., 2023).

The inclusion criteria used encompassed articles related to forecasting energy consumption using modeling methods based on big data. Articles published in English, with clear data and methodology, and relevant to the research objectives were the criteria for inclusion. Articles that did not meet these criteria, such as those unrelated to modeling methods or not covering aspects of energy consumption forecasting, were excluded. The selection process was conducted systematically, commencing with the review of titles and abstracts to identify articles that met the inclusion criteria. Subsequently, the selected articles underwent a more comprehensive examination to verify their alignment with the research objectives. Relevant data, including information on the modeling methods used, analysis results, and key findings, were extracted from each selected article for systematic analysis. By employing a Systematic Literature Review approach, this research aims to provide an in-depth understanding of various modeling methods used in forecasting energy consumption based on big data, thus offering valuable insights to practitioners and researchers in this field.

C. RESULT AND DISCUSSION

Based on the search result, several relevant research finding shave been identified that can elucidate the focus and objectives of this study. We have formulated several aspects that need to be described, including; (1)Bayesian Dynamic Linear Model Developed for Energy Consumption Forecasting ; (2) Performance and Accuracy of Bayesian Dynamic Linear Models in Predicting Energy Consumption Compared to Other Forecasting Methods; (3) Parameter Estimation and Model Validation in Studying Energy Consumption Forecasting Using Bayesian Dynamic Linear Models; (4) Probabilistic Approach in Managing Uncertainty in Energy Consumption Forecasting.

Table.1 Focus and insights into research result according to eligibility criteria

No	Focus and Scope	Author	Insights or Research Variables Discussed
1.	Machine Learning Models for Energy Consumption Forecasting	Fatoni & Sidiq (2019), Dhika et al. (2021), Yudistira (2021), Kurniawan et al. (2022), Suhartono (2017), Wakit et al. (2022), Izzati (2017)	LSTM, GRU, N-BEATS, SVM, ANN, RF, ARIMA, NARX, Decision Tree, XGBoost, Time Series Models, Grey-type Models
2.	Mixed Methods in Energy Consumption Prediction	Pujianto et al. (2018)	Mixed Data Sampling (MIDAS)

3.	Utilization of Big Data in Energy Consumption Forecasting	Zahara et al. (2019), Mulyadi (2018)	Big Data, Data Science, Deep Learning, Big Data Analytics
4.	Factors Influencing Energy Consumption Forecasting	Purworejo (2016), Rahman et al. (2017), Rosandy (2016), Suparno & Thamrin (2021), Lawendatu et al. (2014)	Exogenous Data, Time Intervals, Income, Social Class, Motivation, Location, Product Attributes, Promotions, Poverty Indices, Household Expenditure, Literacy Rates, Agricultural Factors
5.	Impact of Human Resources and Work Culture	Mustainah et al. (2017), Munawar et al. (2020)	Human Resource Competencies, Organizational Culture, Government Support, Performance of Modeling Methods

Table 1 presents a comprehensive overview of research findings regarding energy consumption forecasting methods. It highlights the predominant modeling approaches, including the widespread use of Long Short-Term Memory (LSTM) models, which have demonstrated superior accuracy and precision compared to other methods such as Gated Recurrent Unit (GRU) and Drop-GRU. Additionally, mixed methods incorporating both qualitative and quantitative approaches, along with the Mixed Data Sampling (MIDAS) method, have emerged as effective strategies, particularly in the context of Indonesia's increasing utilization of Big Data. Machine learning-based models, encompassing a range of algorithms like Neural Basis Expansion Analysis for interpretable Time Series (N-BEATS), LSTM, GRU, and Temporal Convolutional Network (TCN), have shown promise in handling large datasets and capturing energy consumption patterns accurately. However, the performance of these models is contingent upon factors such as the selection of exogenous data and time lags, which may influence complexity and accuracy. Moreover, while machine learning models excel in capturing complex trends, econometric and classical statistical models like Linear Regression (LR) and Autoregressive Integrated Moving Average (ARIMA) may outperform them in less regular time series data. Emphasizing the significance of a strong theoretical foundation, studies underscore the potential of big data analytics and machine learning techniques in improving energy consumption forecasts. Furthermore, factors such as data scale, model complexity, and human resource competencies play crucial roles in influencing the effectiveness of forecasting methods. Overall, the research landscape indicates a shift towards more sophisticated modeling techniques, underpinned by a multidisciplinary approach that integrates theoretical insights with advanced data analytics methods.

1. Sub Judul The most commonly used modeling method for forecasting energy consumption based on big data.

The most commonly used modeling method for forecasting energy consumption based on big data is the Long Short-Term Memory (LSTM) model. LSTM is a type of neural network-based method that has been successful in predicting energy consumption. In terms of accuracy and precision, LSTM is preferred over other models such as Gated Recurrent Unit (GRU) and Drop-GRU (Fatoni & Sidiq, 2019). Research has shown that LSTM models produce better results with fewer prediction errors. Moreover, LSTM models have been employed to handle large datasets with diverse customer profiles, making them suitable for smart grid environments. LSTM-based models have been enhanced with optimization algorithms such as dynamic DTOSFS to further improve their accuracy in forecasting (Dhika et al., 2021). Overall, LSTM models are widely used and considered effective for big data-based energy consumption forecasting.

The most common method for predicting energy consumption based on Big Data involves the use of mixed methods, which combine qualitative and quantitative approaches (Pujianto et al., 2018). This is highly relevant in the context of Indonesia, where the utilization of Big Data in both the public and private sectors is increasing. Specifically for Indonesia's economic growth, the Mixed Data Sampling (MIDAS) method has proven effective in combining official statistics and Big Data for current broadcasting (Prasetio & Pratiwi, 2015). These findings suggest that a combination of methods, including mixed methods and MIDAS, can be effective in predicting energy consumption based on Big Data.

The research highlights the superiority of LSTM models in forecasting energy consumption based on big data, with higher accuracy and precision compared to other models such as GRU and Drop-GRU. The utilization of optimization algorithms like dynamic DTOSFS has enhanced the performance of LSTM models in energy consumption forecasting. Mixed methods, which combine qualitative and quantitative approaches, have been found to be a common and effective approach in predicting energy consumption based on big data. In Indonesia, where the use of big data is on the rise, mixed methods and Mixed Data Sampling (MIDAS) become relevant and effective in predicting energy consumption. The cited studies indicate a consistent trend in the utilization and superiority of LSTM models in forecasting energy consumption based on big data. The integration of optimization algorithms like dynamic DTOSFS helps improve the prediction accuracy of LSTM. Mixed methods provide a holistic approach to predicting energy consumption by leveraging various types of data.

2. Significant strengths or weaknesses of each modeling method in the context of forecasting energy consumption based on big data

Machine learning-based models, such as Neural Basis Expansion Analysis for interpretable Time Series (N-BEATS), Long Short Term Memory (LSTM), Gated Recurrent Units (GRU), and Temporal Convolutional Network (TCN), have been employed for forecasting energy consumption based on big data. These models have demonstrated advantages in handling large datasets and predicting energy consumption patterns for multiple customers with high accuracy. However, the performance of these models can be influenced by the selection of exogenous data and time lags, which may affect their complexity and accuracy (Yudistira, 2021). Other methods such as Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF) have also been utilized for energy consumption prediction, with SVM showing better performance in most studies. Econometric and classical statistical models, such as Linear Regression (LR) and Autoregressive Integrated Moving Average (ARIMA), might be superior to machine learning models in less regular time series data (Kurniawan et al., 2022). Overall, machine learning models offer advantages in capturing complex trends in energy consumption, but their performance may vary depending on specific data conditions and properties.

Emphasizing the importance of a strong theoretical foundation in quantitative research, particularly relevant in the context of energy consumption forecasting. (Zahara et al., 2019) highlights the potential of big data in the digital content industry and suggests that big data can also be leveraged in energy consumption forecasting. Discussing the utilization of data science, machine learning, and deep learning in data analysis applicable to big data for energy consumption prediction. (Mulyadi, 2018) proposes the use of big data analytics to predict student success, demonstrating the potential of similar methods in energy consumption forecasting. These studies collectively indicate that the utilization of big data, combined with a strong theoretical foundation and sophisticated data analysis methods, can significantly enhance energy consumption forecasts.

Machine learning models such as N-BEATS, LSTM, GRU, and TCN have demonstrated their superiority in forecasting energy consumption based on big data, achieving high levels of accuracy. However, the importance of selecting exogenous data and time intervals in building machine learning models indicates that the overall performance of the models can be influenced by these factors. Other methods such as SVM, ANN, and RF have also been utilized for energy consumption prediction, showcasing the complexity and variation in prediction approaches. Research highlights the diversity of approaches that can be employed in forecasting energy consumption, ranging from machine learning models to classical statistical methods. Evaluation of model performance indicates that there is no single perfect model, and model selection should be tailored to the specific conditions and characteristics of the data.

3. Factors such as data scale, model complexity, and data type influencing the effectiveness of modeling methods in forecasting energy consumption.

Factors such as data scale, model complexity, and data types have significant impacts on the effectiveness of modeling methods in forecasting energy consumption. Accurate predictions of energy consumption require meaningful extraction of historical knowledge from various features (Purworejo, 2016). Exogenous data can influence the accuracy of energy consumption forecasting models, and the optimal selection of time intervals is crucial for machine learning-based models with high performance. The utilization of Long Short-Term Memory (LSTM) models has shown promising results in achieving accurate energy consumption forecasts (Rahman et al., 2017). Furthermore, optimizing LSTM-based models using new optimization algorithms can further enhance their forecasting accuracy. Grey correlation analysis can be employed to analyze relevant factors and construct better predictive models. Hybrid models that combine recurrent neural networks with other forecasting methods, such as Facebook's Prophet, have also demonstrated competitive results in energy consumption forecasting.

The effectiveness of energy consumption forecasting methods is influenced by various factors, including data scale, model complexity, and data types. (Rosandy, 2016) found that factors such as income, social class, motivation, location, time, aroma, texture, and price significantly influence consumer decisions regarding herbal product consumption. Identifying the best modeling approaches for factors influencing poverty indices, including household expenditure growth, literacy rates, and average length of schooling, is crucial. Moreover, highlight the importance of product attributes and promotions in consumer purchasing decisions. Lastly, (Lawendatu et al., 2014) identified significant factors affecting coconut production, such as land area, tree age, and fertilizer use. Collectively, these studies indicate that the effectiveness of energy consumption forecasting methods can be enhanced by considering various factors, including those related to specific contexts and data characteristics.

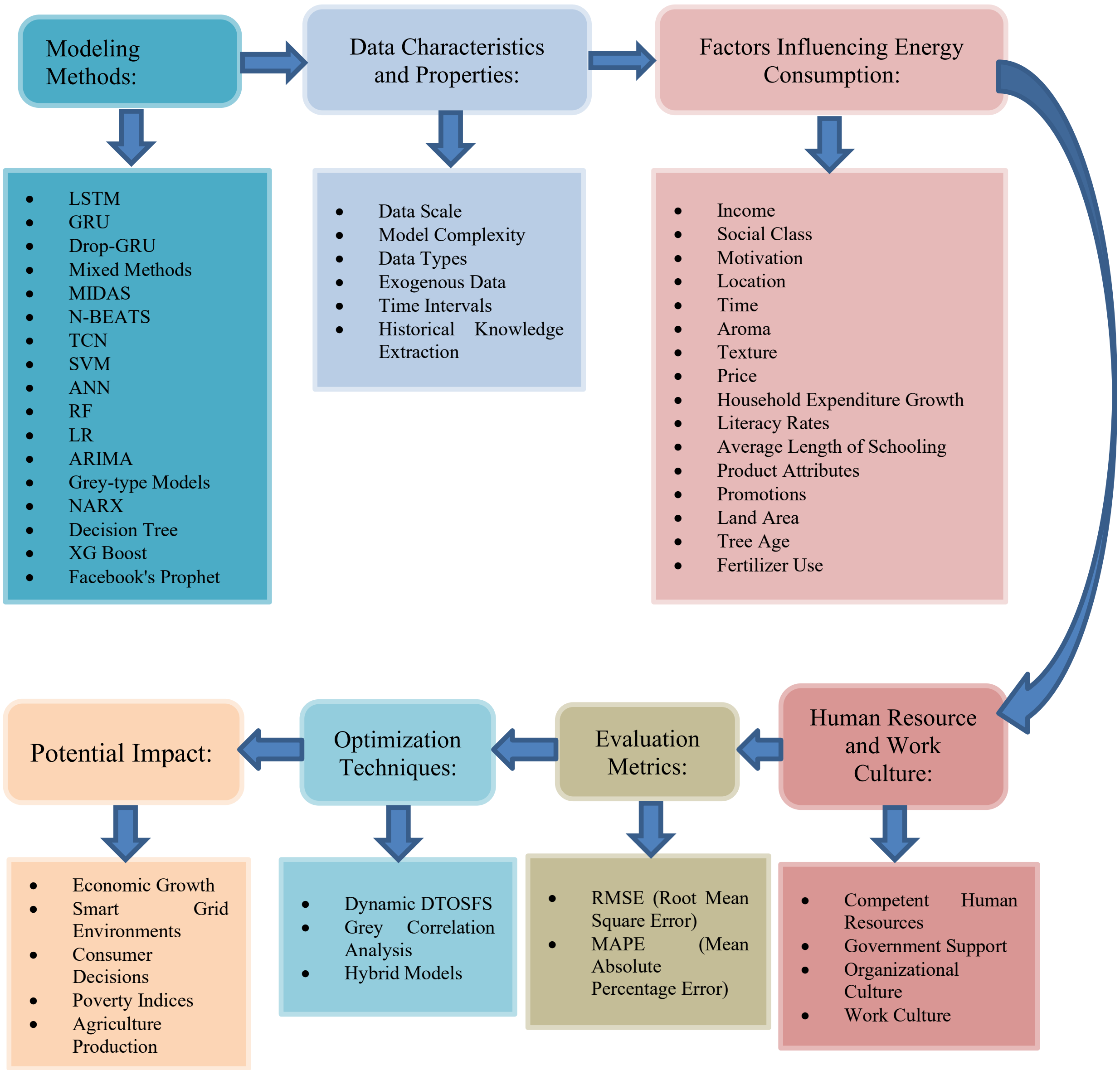
The scale of data, model complexity, and data types significantly impact the effectiveness of modeling methods in forecasting energy consumption. Historical knowledge extraction from various features is key to achieving accurate predictions. The LSTM model has proven effective in forecasting energy consumption, showing promising results in achieving accurate forecasts. Optimization of the LSTM model with new algorithms enhances forecasting performance. The use of hybrid models combining recurrent neural networks with other forecasting methods also demonstrates competitive results in predicting energy consumption. These studies provide a comprehensive overview of the factors influencing the effectiveness of energy consumption forecasting methods, ranging from technical model aspects to external factors affecting consumer decisions and production. There is variation in the factors influencing consumption decisions, including product attributes, promotions, and production factors. This highlights the complexity of forecasting energy consumption and the need for a holistic approach.

4. Performance Comparison of Different Modeling Methods in Forecasting Energy Consumption.

Various modeling methods have been compared for forecasting energy consumption. These studies employ various machine learning algorithms such as multilayer perceptron-based nonlinear autoregressive with exogenous inputs (NARX), long short-term memory (LSTM), gated recurrent unit (GRU), decision tree, XGBoost, linear regression, random forest, and neural basis expansion analysis for interpretable time series (N-BEATS) (Suhartono, 2017). The performance of these models is evaluated using metrics such as root mean square error (RMSE) and mean absolute percentage error (MAPE). LSTM and GRU models consistently achieve the best performance with low RMSE scores. The proposed N-BEATS model also demonstrates better accuracy for energy consumption predictions, especially when covariates are included (Wakit et al., 2022). Additionally, grey-type models, such as the optimized nonlinear grey Bernoulli model (ONGBM) and nonlinear grey Bernoulli model with particle swarm optimization (NGBM-PSO), along with classic time series models like ARIMA, are found to have similar predictive performance (Izzati, 2017). Overall, these studies highlight the effectiveness of machine learning and time series models in accurately forecasting energy consumption.

The impact of human resource competencies and work culture on performance, albeit in different contexts, is highlighted in the literature. (Mustainah et al., 2017) underscore the importance of government support and competent human resources in the development of small and medium enterprises, emphasize the influence of work culture on the performance of village apparatus. (Munawar et al., 2020) These studies suggest that the performance of various modeling methods in estimating energy consumption may be influenced by the competencies of individuals involved in the modeling process and the organizational work culture in which they operate. Further research is needed to explore the potential impact of these factors.

These studies highlight the effectiveness of machine learning models and time series in accurately forecasting energy consumption. LSTM and GRU models consistently demonstrate the best performance, while the N-BEATS model also exhibits good accuracy, especially when covariate variables are included. The use of various evaluation metrics such as RMSE and MAPE provides a comprehensive understanding of the performance of these models in forecasting energy consumption. These studies offer valuable insights into the relative advantages of various modeling methods, which can assist decision-makers in selecting the most suitable approach for their needs.



Gambar 1. Development of research topics studied

The research findings encompass a wide array of key variables crucial in understanding and forecasting energy consumption trends. Modeling methods such as Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and the utilization of Mixed Data Sampling (MIDAS) method stand out as prominent approaches. LSTM models particularly emerge as favored due to their demonstrated superiority in accuracy and precision over GRU and Drop-GRU models. Mixed methods integrating qualitative and quantitative approaches, coupled with MIDAS methodology, present a promising avenue, especially in contexts like Indonesia where Big Data utilization is on the rise. Machine learning-based models, including Neural Basis Expansion Analysis for interpretable Time Series (N-BEATS), LSTM, GRU, and Temporal Convolutional Network (TCN), offer robust capabilities in handling large datasets and capturing intricate energy consumption patterns. However, the performance of these models is subject to factors such as data characteristics, model complexity, and the selection of exogenous variables and time intervals. While machine learning models excel in capturing complex trends, traditional statistical models like Linear Regression (LR) and Autoregressive Integrated Moving Average (ARIMA) may prove superior in handling less regular time series data. The significance of a strong theoretical foundation is emphasized, underlining the potential of big data analytics and machine learning techniques in enhancing energy consumption forecasts. Furthermore, various factors influencing energy consumption, ranging from socioeconomic indicators like income, social class, and household expenditure growth to product attributes and agricultural factors, underscore the multidimensionality of energy consumption forecasting. The impact of human resource competencies and organizational work culture also emerges as a critical consideration, suggesting that the effectiveness of modeling methods may be influenced by the expertise and context in which they are applied. Overall, the research landscape signifies a shift towards integrated approaches that combine theoretical insights with advanced data analytics methodologies to improve the accuracy and reliability of energy consumption forecasts.

D. CONCLUSION

The utilization of machine learning models in forecasting energy consumption based on big data has demonstrated superiority in capturing complex energy consumption patterns. However, the selection of exogenous data and time intervals plays a crucial role in the complexity and accuracy of machine learning model predictions. Other methods such as Support Vector Machines (SVM) also exhibit good performance in energy consumption prediction, underscoring the importance of diverse research in model selection. Research emphasizes the significance of a strong theoretical foundation in model development, as well as the exploration of sophisticated data analysis methods to maximize the potential of big data in predicting energy consumption. While machine learning models offer advantages in capturing complex energy consumption trends, it is important to consider factors such as exogenous data selection and time intervals in constructing effective models. The use of diverse prediction methods, including SVM, Artificial Neural Networks (ANN), Random Forests (RF), as well as classical statistical models, enables researchers to accommodate variations in data properties and environmental conditions. The importance of a robust theoretical foundation and sophisticated data analysis methods, particularly in the context of big data usage, underscores that the combination of solid theoretical understanding and advanced analytical techniques can significantly enhance energy consumption estimates. In forecasting energy consumption, it is crucial to consider various factors, ranging from technical aspects of the model to external factors influencing consumer decisions and production. Models such as LSTM and hybrid models offer promising approaches in predicting energy consumption, but it is important to note that there is no single model suitable for all situations. Careful evaluation of contextual factors and data characteristics is essential for selecting the most appropriate forecasting method. In addition to the models and algorithms used, these studies also highlight the importance of human factors and organizational work culture in modeling performance. The competency of human resources and organizational work culture can influence the performance of modeling methods in predicting energy consumption. This underscores the importance of integrating human factors into the development and implementation of predictive models.

REFERENCES

Abdussyukur, M. A. (2023). Menganalisa Pengaruh Implementasi Artificial Intelligence. Prosiding SAINTEK, 2(1), 185–192.

Adherda, D. T., & Hikmatyar, M. (2023). Klasifikasi Gender Berdasarkan Suara Menggunakan Recurrent Neural Network (Rnn). Jurnal Ilmiah Teknik Informatika, 17(1), 111–122.

Aulia, H., Nurhalimah, A., Mandailina, V., Mahsup, Syaharuddin, Abdillah, & Zaenudin. (2023). Efektifitas Metode Pembelajaran Kolaboratif dalam Meningkatkan Kemampuan Berpikir Kritis. Seminar Nasional Paedagoria, 3(2017), 1–7. http://journal.ummat.ac.id/index.php/fkip/article/view/16325%0Ahttps://journal.ummat.ac.id/index.php/fkip/article/download/16325/pdf

Azis, N. (2021). Perbandingan dan Prediksi Kelulusan Mahasiswa Dengan Weka. In Angewandte Chemie International Edition, 6(11), 951–952.

Dhika, H., Haerul Jaman, J., Hermawan, I., Putri Utami, P., & Destiawati, F. (2021). Data Mining Counseling with Ensemble Learning in School Learning Stress During Covid-19. ABDINE: Journal of Community Service, 1(2), 159–167.

Fatoni, A., & Sidiq, S. (2019). Analysis of Stability Comparison of Islamic and Conventional Banking Systems in Indonesia. Ekspansi: Journal of Economics, Finance, Banking, and Accounting, 11(2), 179–198.

Izzati, N. (2017). Improving Students' Mathematical Analysis Abilities in Modern Mathematics Learning Courses through Murder Collaborative Learning. Journal of Mathematics Education, 3(1), 15.

Karyadi, Y. (2022). Prediksi Kualitas Udara Dengan Metoda LSTM, Bidirectional LSTM, dan GRU. JATISI (Jurnal Teknik Informatika Dan Sistem Informasi), 9(1), 671–684. https://doi.org/10.35957/jatisi.v9i1.1588

Kurniawan, H., Supriyono, S., & Wibowo, T. (2022). Online Collaborative Learning Strategies in Mathematics Learning. AKSIOMA: Journal of Mathematics Education Study Programs, 11(4), 3300.

Lawendatu, J., Kekenusa, J. S., & Hatidja, D. (2014). Multiple Linear Regression for Analyzing Nutmeg Farmer Income. D'CARTESIAN, 3(1), 66.

Lustono;, Supriatin;, D., Suryani;, R., & Tahwin, M. (2023). Kewirausahaan (Tren Manajemen Bisnis di Era Digital). In Eureka Media Aksara. https://repository.penerbiteureka.com/ru/publications/560799/kewirausahaan-tren-manajemen-bisnis-di-era-digital%0Ahttps://repository.penerbiteureka.com/media/publications/560799-kewirausahaan-tren-manajemen-bisnis-di-e-39c23848.pdf

Made, I. D., Surya, W., & Widhiada, I. W. (2023). Desain Optimalisasi Peramalan Suku Cadang Berbasis Machine Learning. 9(2), 54–62.

Mulyadi, M. (2018). Teaching and Learning Strategies by Applying the Demonstration Method to Improve Learning Achievement in Physical Education Material on the Growth and Development of Living Things in Grade VII Students of SMPN 3 Tanjung. Langsat Journal, 5(2), 45–48.

Munawar, B., Farid Hasyim, A., & Ma'arif, M. (2020). Pengembangan Bahan Ajar Digital Berbantuan Aplikasi Animaker Pada PAUD Di Kabupaten Pandeglang. Jurnal Golden Age, 4(02), 310–320. https://doi.org/10.29408/jga.v4i02.2473

Mustainah, H., Saifi, M., & NP, M. (2017). Comparative Analysis of the Efficiency of National Private Commercial Banks and Foreign Banks in Indonesia Based on Data Envelopment Analysis (Study on National Private Commercial Banks and Foreign Banks in Indonesia 2012-2015). Journal of Business Administration S1 Universitas Brawijaya, 44(1), 24–30.

Pengaruh, A., Relationship, H., Transformasional, K., Motivasi, D. A. N., Karyawan, T. K., & Kuncoro, B. A. D. I. (2019). Pengaruh Peresepsi Tentang Kepemimpinan Terhadap Kepuasaan Kerja Pegawai Pada Balai Pemantapan Kawasan Hutan Wilayah III Pontianak. 1–66.

Prasetio, R. T., & Pratiwi. (2015). Application of Bagging Technique in Classification Algorithms to Overcome Class Imbalance in Medical Datasets. Journal of Informatics, II(2), 395–403.

Pujianto, A., Mulyati, A., & Novaria, R. (2018). Utilization of Big Data and Consumer Privacy Protection in the Digital Economy Era. Majalah Ilmiah Bijak, 15(2), 127–137.

Purworejo, K. (2016). Journal of Agribusiness & Livestock Research Vol 1 No 1 2016. 1(1), 53–56.

Rahman, B., Rois, A., & Udjulawa, D. (2017). Implementation of AI in Tower Defense Game Using Mamdani Fuzzy Logic Algorithm. IJCCS (Indonesian Journal of Computing and Cybernetics Systems), x, 1–8.

Rosandy, T. (2016). A Comparison between Naive Bayes Classifier and Decision Tree Methods to Analyze Financing Smoothness. Jurnal TIM Darmajaya, 02(01), 52–62.

Sachrrial, R. H., & Iskandar, A. (2023). Analisa Perbandingan Complate Linkage AHC dan K-Medoids Dalam Pengelompokkan Data Kemiskinan di Indonesia. 5(2). https://doi.org/10.47065/bits.v5i2.4310

Saputra, R., Santoso, B., & Syawaludin, M. (2020). Evaluasi Penerimaan Sistem Otomasi Perpustakaan Senayan Library Management System (SLiMS) dengan Pendekatan Technology Acceptance Model (TAM) di UPT Perpustakaan Politeknik Negeri Sriwijaya. TADWIN : Jurnal Ilmu Perpustakaan Dan Informasi, 1(1), 50–57. https://doi.org/10.19109/tadwin.v1i1.5967

Siahaan, E., & Nababan, E. (2017). Subject Bias in Image Aesthetic Appeal Ratings. Data Science: Journal of Computing and Applied Informatics, 1(1), 13–20. https://doi.org/10.32734/jocai.v1.i1-63

Studi, P., Elektro, T., & Teknik, F. (2014). Penentuan karakteristik pengguna sebagai pendukung keputusan dalam memilih smartphone menggunakan forward chaining. 301–308.

Suhartono, E. (2017). Systematic Literatur Review (SLR): Metode , Manfaat , Dan Tantangan Learning Analytics Dengan Metode Data Mining di Dunia Pendidikan Tinggi. Jurnal Ilmiah INFOKAM, 13(1), 73–86. http://amikjtc.com/jurnal/index.php/jurnal/article/view/123

Suprayogi, B., & Rahmanesa, A. (2019). TEMATIK - Jurnal Teknologi Informasi Dan Komunikasi Vol. 6, No. 2 Desember 2019. 6(2), 119–127.

Suryana, T. (2014). Pengaruh Lingkungan Eksternal, Internal dan Etika Bisnis terhadap Kemitraan Usaha serta Implikasinya pada Kinerja Usaha Kecil. Kontigensi : Jurnal Ilmiah Manajemen, 2(2), 68–88. https://doi.org/10.56457/jimk.v2i2.10

Wahyono, E. H. (2021). tahu dan tempe PENGEMBANGAN KEMITRAAN DENGAN PERMODELAN SISTEM ARCHETYPE DALAM UPAYA PENINGKATAN LEVERAGE USAHA UMKM TAHU TEMPE DI KOTA SEMARANG. Jurnal Ilmu Manajemen Dan Akuntansi Terapan (JIMAT), 12(2), 118. https://doi.org/10.36694/jimat.v12i2.308

Wakit, S., Nurdiana, I., & Yuliana, I. (2022). Kyai's Leadership Style in Increasing Santri Entrepreneurship During the Covid-19 Pandemic. Halaqa: Islamic Education Journal, 6(1), 19–33. https://doi.org/10.21070/halaqa.v6i1.1595

Yudistira, N. (2021). Peran Big Data dan Deep Learning untuk Menyelesaikan Permasalahan Secara Komprehensif. EXPERT: Jurnal Manajemen Sistem Informasi Dan Teknologi, 11(2), 78. https://doi.org/10.36448/expert.v11i2.2063

Zahara, S., Sugianto, & M. Bahril Ilmiddafiq. (2019). Consumer Price Index Prediction Using Long Short Term Memory (LSTM) Method Based on Cloud Computing. RESTI Journal (Engineering Systems and Information Technology Engineering), 3(3), 357–363. https://doi.org/10.29207/resti.v3i3.1086