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Powering a sustainable future: AI-driven integration of renewables for optimized grid management

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ABSTRACT

This research investigates how Deep Learning (DL) and Artificial Intelligence (AI) can be combined to advance energy systems' sustainability with an eusemphasis on Renewable Energy Sources (RESs). The study analyzes three main datasets: Wind Power Forecasting data from January 2018 to March 2020 and the Global Energy Consumption and Renewable Generation Dataset, which follows the world's energy production from renewable and non-renewable sources from 1997 to 2017. Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) are the three machine learning algorithms that provide the highest Mean Absolute Error (MAE) of 0.1463, 0.0926, and 0.1463, respectively, when used for wind power forecasting. Additionally, 34 days of data on solar power generation from two solar power plants in India show that Random Forest performs better than other algorithms, with an accuracy of 99.03 %, followed by Linear Regression at 98.37 %. These results show how AI may be used to optimize energy production, improve the management of RESs, and help accomplish the Sustainable Development Goals (SDGs). According to the findings, AI and DL technologies have the potential to increase energy systems' sustainability and efficiency, especially those that rely on RESs like solar and wind.

1. Introduction

Climate change, environmental damage, and global warming are commonly discussed topics among researchers, academics, and the business community. It is widely known that the main reason for environmental damage and global warming issues is the release of greenhouse gases resulting from the use of non-renewable energy sources such as coal, oil, and petroleum [1]. Hence, society is increasingly adopting Renewable Energy Sources (RESs) because of their cost-effectiveness and substantial contribution to reducing carbon emissions [2]. Consequently, RESs are gaining popularity in the energy sector. Fig. 1 displays a range of resources, including bioenergy, wind energy, hydropower, and Photovoltaic (PV) energy. Below is a concise overview of several key types of renewable energy. These RESs are frequently operated in a network-connected manner [3].

In most locations across the world, solar and wind energy are produced by putting up PV panels and Wind Turbines (WTs), respectively, to supply consumers' energy needs. While WTs produce electricity from the wind, solar panels turn direct sunlight into electricity. The primary characteristics of this energy source are poor predictability, limited controllability, and identical power output variation to that of RESs. It is dependent on environmental elements, like temperature and solar radiation [4,5]. Wind direction and speed. In the case of strong solar radiation (clear sky), PV panels, for instance, provide increased energy. When it's cloudy or at night, the power is at its lowest (it may be zero) [6]. Contrarily, WTs produce minimal power (which may be zero) in situations where the lower and higher wind speeds are than cutting and cutting speed, respectively [3]. Fig. 2 shows the renewable energy in microgrids architecture.

As a result, significant swings in the output of PV power plants and WTs pose a number of difficulties for voltage regulators, including concerns with backup power flow and power distribution. Additionally, power users sporadically show up behavior in energy usage is caused by a variety of variables, including changes in the environment and consumer preferences. Integrating RESs complicates power systems. Small networks and network operations pose maintenance challenges in

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balancing energy production and consumption [7–10]. Therefore, precise predictions of RES power generation (i.e., from PV panels and WTs) as well as predictions of electrical load are crucial in the current smart grid. By employing demand forecasting, utility companies can effectively manage consumer demand. Insufficient power resources lead to a situation where demand-driven supply creates surplus capacity from alternative resources. Forecasting wind and solar electricity generation, as well as predicting the performance of solar panels, using weather tracking systems is a difficult task [11,12]. This is because these forecasts solely depend on weather conditions such as humidity, temperature, radiation, and so on [7]. Various methods can be employed for prediction, including physical models, Machine Learning (ML) [13–17], and more recently Deep Learning (DL) [18]. Over the past decade, ML and DL techniques have been applied in various domains of computational intelligence and prediction, showcasing promising effectiveness [19].

More and more sectors are feeling the effects of Artificial Intelligence (AI). Both the near and far futures are likely to see far-reaching effects of AI in a variety of domains, including global production, equality and inclusion, environmental results, and many more [21]. There are pros and cons to AI's effects on sustainable development, according to the research. There isn't yet a published study that looks at how AI could affect sustainable development in every way imaginable. All 169 of the Sustainable Development Goals (SDGs) and the 2030 Agenda for Sustainable Development's internationally accepted targets are referred to as sustainable development in this research. We have found that AI can affect the attainment of the SDGs [21,22], so the existence of this knowledge gap is very crucial.

There has been a time of revolutionary transformation in several fields, including sustainability, with the development of AI and DL technologies. Particularly in the fields of renewable energy and environmental health, these cutting-edge tools have shown enormous promise in advancing sustainable practices [23–25]. There has been growing recognition of AI and DL's ability to reduce energy usage and environmental damage. Smart building energy management systems have played a significant role in the success of renewable energy projects.

Problem Statement:

Energy management in smart grids and microgrids is increasingly complex due to the integration of RESs such as wind and solar power, which exhibit high variability and uncertainty. Traditional energy forecasting methods often struggle to accurately predict the fluctuating energy generation from these renewable sources, leading to inefficiencies in grid operation and increased risk of energy imbalances. Current models fail to sufficiently account for the dynamic nature of renewable energy production, leading to challenges in load forecasting, energy storage, and overall grid optimization. Additionally, the growing reliance on ML and DL techniques for energy forecasting has yet to fully address the need for hybrid models that can enhance prediction accuracy while considering multiple influential factors like weather conditions, seasonal variations, and historical data.

Objectives of the Current Study:

- **To develop a hybrid DL model** that integrates advanced forecasting techniques for accurate and reliable predictions of renewable energy production (specifically wind and solar power) within smart grids and microgrids.
- **To employ state-of-the-art feature extraction methods** such as wavelet transform (WT), Empirical Mode Decomposition (EMD), and other decomposition techniques to improve the quality of input data and capture intricate patterns in renewable energy generation.
- **To optimize the proposed model** using advanced ML optimization techniques to enhance the model's forecasting capabilities and its adaptability to diverse environmental conditions.
- **To evaluate the performance** of the proposed model against existing forecasting methods in terms of prediction accuracy, robustness, and computational efficiency, ensuring its practical applicability in real-world smart grid environments.
- **To provide actionable insights** for energy managers, utilities, and policymakers by offering a reliable tool for improving the integration of renewable energy into the grid and reducing the challenges posed by its intermittency.

The main contributions in this paper are as follows:

This paper highlights the revolutionary potential of AI in improving energy sustainability by making multiple groundbreaking contributions to the nexus of AI, DL, and renewable energy systems. To anticipate wind and solar power generation, we first provide a novel framework that uses cutting-edge ML models, such as Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN). By using cutting-edge AI algorithms to maximize predictions for renewable energy, this strategy distinguishes itself

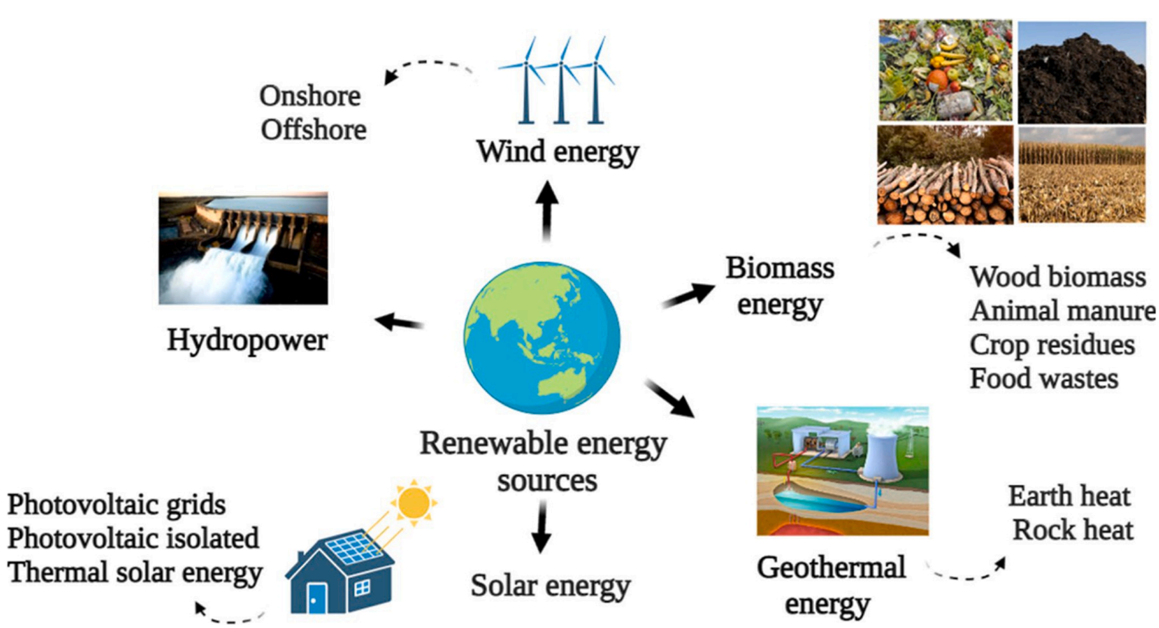

Fig. 1. Renewable energy types [20].

from traditional approaches and eventually improves resource management and energy integration within existing infrastructures.

This work's primary innovation is the thorough comparison of different ML models, which not only demonstrates each model's unique performance but also offers insightful information on how to use them in actual energy systems. This study creates a strong evaluation framework for the energy sector by thoroughly assessing the models across a range of different datasets, from global patterns of energy consumption to detailed data on wind and solar power generation. This opens the door to better decision-making and increased operational efficiency.

Additionally, we situate our research in the framework of global sustainability initiatives, showing how AI may help accomplish SDGs of the UN, especially in areas like responsible consumption, renewable energy, and climate action. By doing this, our work contributes significantly to the continuous quest for a more sustainable and greener future while also pushing the limits of AI applications in renewable energy.

2. Literature review

Energy management in smart grids and microgrids has been the subject of a tremendous deal of research, with many papers outlining current problems, possible solutions, and plans. Current smart grid issues are prompting researchers to investigate ML, DL, and AI solutions. These techniques offer robust tools for advanced smart grid and renewable energy system design, modeling, monitoring, problem diagnosis, and fault-tolerant operation. The research community has published numerous review and survey articles to organize and compile the current state of DL-based methods for energy and load forecasting. We provide a summary of these articles here.

Niu et al. [26] introduced a sequence-to-sequence model for wind power forecasting that can predict multiple steps ahead. Unlike recursive strategies, their method relies on a strategy that takes a vector of values as input in a single simulation and generates multiple outputs at varied time steps. There are two groups of Gated Recurrent Unit (GRU) blocks that make up the model's architecture: one for encoding and one for decoding. Decoders can predict future sequences of data because the encoder converts the input sequence into a context vector. The results show that when tested on three steps, their model performs better than the other four models. When attempting to predict wind speed and power, the attention mechanism also gave wind power the highest priority. All the research points to the Long Short-Term Memory (LSTM) model as the best. Two LSTM-based models, one using Autoregressive Integrated Moving Average (ARIMA) and the other using ARMA, as well as Autoregressive Moving Average (ARMA), ARIMA, and Seasonal Autoregressive Integrated Moving Average (SARIMA), are among the three statistical methods compared in [27]. When given historical PV power data, a bidirectional LSTM can only produce accurate predictions for a one-hour time window, according to the results.

Researchers have contemplated a variety of structural changes to LSTM-based forecasting models. To illustrate the point, in place of the sigmoid activation function, Shahid et al. used the four wavelet activation kernels, Gaussian, Morelet, Ricker, and Shan-non in [28]. Their proposed model outperforms ensemble methods utilizing Deep Neural Networks (DNNs), Support Vector Machines (SVMs), ARIMA, and genetic programming for predicting short-term wind power output.

M. Mishra et al. [29] used discrete WT and an LSTM model to predict PV power using data on solar power. From the wind speed data presented in [30], Fei Li et al. utilized discrete WT to extract the mean wind speed and turbulence intensity. A higher turbulence level indicates more wind speed uncertainty. Finally, the prediction result is combined using an LSTM that has been trained and evaluated using two ensemble methods. The results demonstrate that the multi-step prediction is enhanced by the turbulence intensity feature, particularly when the data resolution is higher. As described in [31,32], EMD is combined with three models: LSTM, GRU, and DNN to forecast the generation of renewable energy in the future. According to the results of the experiments, the hybrid model that uses DNN to make predictions performs the best in [32], while the hybrid model that uses GRU to make predictions has the lowest error rate in [31].

To decompose the data on solar irradiance, Gao et al. [33] employed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) method [33]. An enhanced version of this method is the Ensemble Empirical Mode Decomposition (EEMD) technique, which sorts the data into signals with different frequencies. With an eye toward

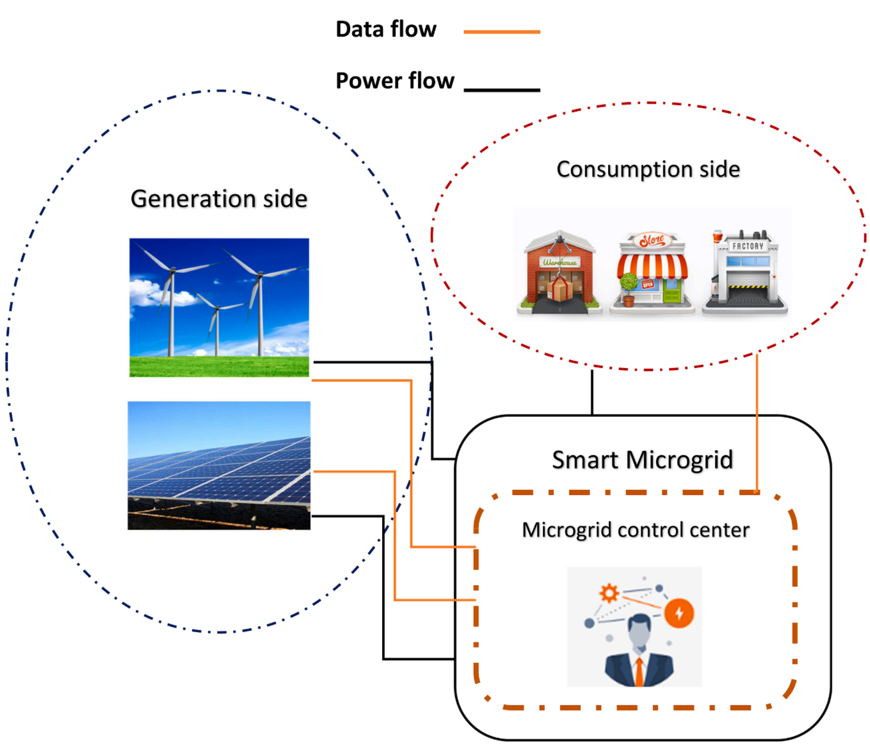

Fig. 2. Microgrids architecture.

hourly solar irradiance forecasting, they compared five different Convolutional Neural Networks (CNN) and LSTM hybrid model topologies. Many studies used multiple decomposition methods to get more detailed original time-series components and better predictions. Zang et al. [34] used VMD to separate seasonal, trend, and random components from historical PV power series. The random component is then further divided into a number of stationary ones using EWT. Reconstructing two-dimensional feature maps required combining decomposed data with weather data collected over the past two weeks. Plus, two-dimensional maps were also kept for the various weather conditions: sunny, partly cloudy, overcast, and rainy. The two-dimensional maps were used to train two CNN models, ResNet and DenseNet, for day-ahead PV power forecasting.

Furthermore, the framework developed by Fu et al. [35] utilized the Time-Varying Filter-based Empirical Mode Decomposition (TVF-EMD) method to further subdivide the wind speed data into multiple intrinsic mode functions corresponding to different frequencies. As a subsequent step, the Fuzzy Entropy (FE) values of all the intrinsic mode functions were calculated. Following this, SSA is used to separate the output values into their respective high-frequency and low-frequency parts. Following that, Kernel-based Extreme Learning Machine (KELM) is used to forecast high-frequency data. In Afrasiabi et al. [36], the time series data were transformed into two-dimensional vectors. A system for predicting the output of wind and solar power plants, with feature extraction performed by CNN and GRU blocks and forecasting outputs generated by a dense block. A summary of the relevant research was presented in Table 1.

Research Gaps in Earlier Studies:

Energy management in smart grids and microgrids has been the subject of a great deal of research, but there are still several important gaps that prevent further development. The following issues still need significant attention despite the abundance of knowledge on AI, DL, and ML solutions applied to smart grid systems:

- **Model Scalability and Real-World Applicability:** Most of the research that has been done so far has concentrated on theoretical models and simulations that have little bearing on actual situations. Although methods such as those employed by Sharadga et al. [27] and Niu et al. [26] have shown promise in forecasting tasks, it is yet unknown if these models can be scaled for large-scale, dynamic grid systems. Real-world limitations are frequently disregarded, including hardware limitations, communication breakdowns, and network delays.
- **Comprehensive Hybrid Models:** A lot of research focuses on employing separate DL models, like CNNs, GRUs, and LSTMs—to manage forecasting jobs. Nevertheless, little research has been done on hybrid models that blend several DL approaches with complimentary feature extraction techniques. For instance, hybrid models combining CNNs and LSTMs have been proven by Gao et al. [33] and Fu et al. [35]. However, more study is required to determine alternative hybrid configurations that can produce superior outcomes in various grid situations.
- **Data Preprocessing and Feature Engineering:** As seen in studies like those by Sharadga et al. [27] and Shahid et al. [28], most of the research depends on fundamental data preprocessing methods like normalization and outlier removal. In the context of energy management systems, more sophisticated feature engineering techniques like wavelet transforms, turbulence intensity analysis, and decomposition techniques like EMD and CEEMDAN are still not fully understood. More comprehensive studies should investigate how these techniques can be applied to improve the forecasting accuracy and resilience of smart grid systems.
- Numerous studies, such those by Niu et al. [26] and Li et al. [30], concentrate on short-term forecasting for wind and solar power generation; however, there is a dearth of attention to long-term forecasting models that take seasonal variations and long-term trends into account. Planning and decision-making in smart grids may benefit greatly from the development of models that can forecast energy generation and demand over long timeframes (weeks or months, for example).
- **Optimization Techniques and Hyperparameter Tuning:** Several studies employ basic optimization methods like grid search and cross-validation (as seen in [26] and [27]) for model selection and hyperparameter tuning. However, more advanced optimization techniques, such as metaheuristic algorithms (e.g., genetic algorithms, particle swarm optimization) or reinforcement learning-based optimization strategies, remain largely underutilized. These approaches could significantly enhance the performance of forecasting models by optimizing model configurations and feature selection.
- **Taking Uncertainty and Fault Tolerance into Account:** Current forecasting models, including those created by Mishra et al. [29] and Zang et al. [34], sometimes overlook the inherent uncertainties that come with producing renewable energy, like weather-related unpredictability. Furthermore, the existing literature has not sufficiently addressed the problem of fault tolerance and resilience in smart grids, especially when intermittent energy sources are present. Models that include resilient performance in fault-prone situations and uncertainty quantification should be considered in future studies.
- Interdisciplinary Approaches: The current body of work on energy management in smart grids primarily focuses on a narrow range of

Table 1
Related studies summarization.

Ref.	Prediction aims	Future timeframe	preprocessing	Deep learning	Optimization
Wen et al. [37]	Load and PV power	Short (1 h)	Data normalization	DRNN + LSTM	Regularization, dropout
Niu et al. [26]	Multistep wind power	Short	Data normalization, changing resolution	GRU with attention mechanism	Grid search
Sharadga et al. [27]	PV power	Short (1, 2, 3 h)	Removing outliers	Bidirectional LSTM	Cross- validation
Shahid et al. [28]	Wind power	Short	Data normalization	LSTM with wavelet activation kernels	RMSProp
Memarzadeh et al. [38]	Wind speed	Short	MI, WT	Hybrid model of WT, FS, and LSTM	Crow Search
Li et al. [30]	Multistep wind speed	Short (10–12 h)	DWT	Hybrid model of DWT + LSTM	Dropout
Mishra et al. [29]	Multistep PV power	Short (1–60D)	DWT	Hybrid model of DWT, and LSTM	Dropout
Gao et al. [33]	Solar irradiance	Short (1 h)	CEEMDAN	Hybrid model of CEEMDAN, CNN, and LSTM	Grid search
Nam et al. [32]	Wind and solar power	Mid (7D)	EMD	Hybrid model of EMD, LSTM, EMD, GRU, EMD, and DNN	ReLU, dropout
Afrasiabi et al. [36]	Wind speed and solar irradiance	Short (1D)	None	Hybrid model of CNN, and GRU	ReLU, dropout

topics, including power generation forecasting and demand prediction. There is a need for more interdisciplinary research that combines insights from control theory, optimization, communication systems, and AI to provide holistic solutions for smart grid energy management.

Contributions and Novelty:

This study presents a comprehensive exploration of the integration of AI and DL techniques in advancing sustainability, with a particular emphasis on the promotion of RESs. The motivations driving this research stem from the growing global demand for clean, efficient energy solutions and the need for effective strategies to achieve SDGs, specifically those related to energy, environmental protection, and sustainable resource management.

What sets this study apart from existing literature is its holistic approach to renewable energy forecasting, where multiple AI and DL models are applied across various datasets and energy sources. Unlike traditional studies that focus on a single energy source or isolated applications, this research adopts a multi-dimensional framework by:

1. **Utilizing Diverse Datasets**: This work integrates several real-world datasets, including global energy consumption patterns, wind power forecasting, and solar power generation data, enabling a broad analysis of energy systems. These datasets represent a wide range of RESs, providing a comprehensive understanding of energy generation and consumption patterns worldwide.
2. **Evaluating Multiple ML Algorithms**: A key contribution of this study is the comparative analysis of various ML algorithms, such as Support Vector Regression (SVR), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). This analysis helps to identify the most effective models for different renewable energy forecasting tasks, offering valuable insights into algorithm performance across diverse energy contexts.
3. **Real-World Relevance**: By focusing on data collected from actual energy facilities in different regions, this study bridges the gap between theoretical models and practical applications. The use of real-world datasets from wind and solar power facilities ensures that the proposed solutions are both realistic and actionable, making this study particularly valuable for stakeholders in the energy sector.
4. **Linking AI to SDGs**: A major novelty of this work is its direct connection between AI applications and the achievement of SDGs. This study demonstrates how AI and DL can support the global transition to sustainable energy practices, contributing to SDG 7 (Affordable and Clean Energy), SDG 13 (Climate Action), and SDG 12 (Responsible Consumption and Production), among others. It emphasizes the potential of AI to optimize energy management, improve power grid stability, and enhance the efficiency of renewable energy systems globally.

This research offers a fresh perspective on the role of AI in renewable energy systems, providing a roadmap for future advancements in the intersection of technology, sustainability, and energy management.

3. Forecasting of renewable energy power generation framework

Deep Learning (DL) algorithms are extensively utilized across diverse domains. They have attained exceptional outcomes, specifically in relation to personalized recommendation systems. Due to the enhanced precision in prediction, DL has sparked the curiosity of researchers in correlated domains. Fig. 3 illustrates the various stages of the system for managing energy in a microgrid, which encompass data monitoring, analytical data processing, forecasting, optimization, and real-time control. The application incorporates power generation and consumption predictions and forecasts.

As part of the data monitoring process, information is gathered from various sources including RERs, conventional generators, Energy Storage Systems (ESS), Demand Response (DR), weather forecasts, the grid, Electric Vehicles (EVs), and other sources. Before conducting the analysis, it is necessary to perform pre-processing to remove any unwanted noise and discrete data from the dataset, which is typically obtained in its raw form [39].

The data currently being prepared for analysis utilizes advanced techniques such as DL and ML. After the analysis process, a knowledge model that may be applied to forecasting, prediction, classification, and regression applications will be created. The four key components that make up the proposed forecasting framework are (i) Data Pre-Processing, (ii) Feature Selection, (iii) Data Visualization, and (iv) Model Building, as illustrated in Fig. 4.

3.1. Data pre-processing

Data preprocessing is performed to enhance the quality and suitability of the data for the particular data mining task. Through data Preprocessing step, several stages are performed, which are data cleaning, data normalization, and data splitting. Data cleaning is the first step in the process, and it involves processing the used data to fix missing or null values and remove outlier items. Finally, the normalization process normalizes this cleaned data. Normalization improves the effectiveness and accuracy of gradient descent [40]. The study utilizes the widely used technique of min-max normalization to scale data within specific ranges. This is accomplished by applying a linear transformation to the original data. Let's assume that the smaller value is denoted as R_{min} and the larger value is denoted as R_{max}. Next, the normalized value R_{norm} is determined by applying Eq. (1) to assign a value within the range $[R_{min}, R_{max}]$

The normalized value of R, denoted as R_{norm} can be calculated using the formula (1):

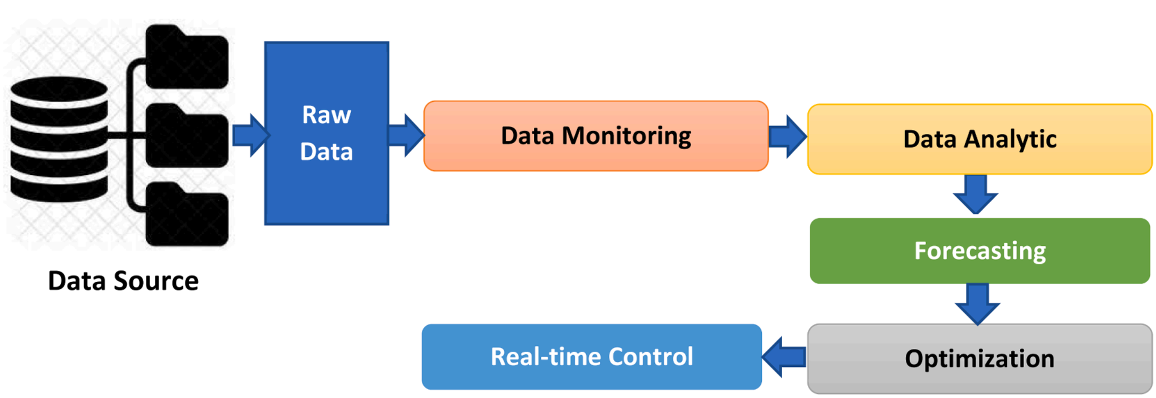

Fig. 3. The various stages of the system for managing energy on microgrid.

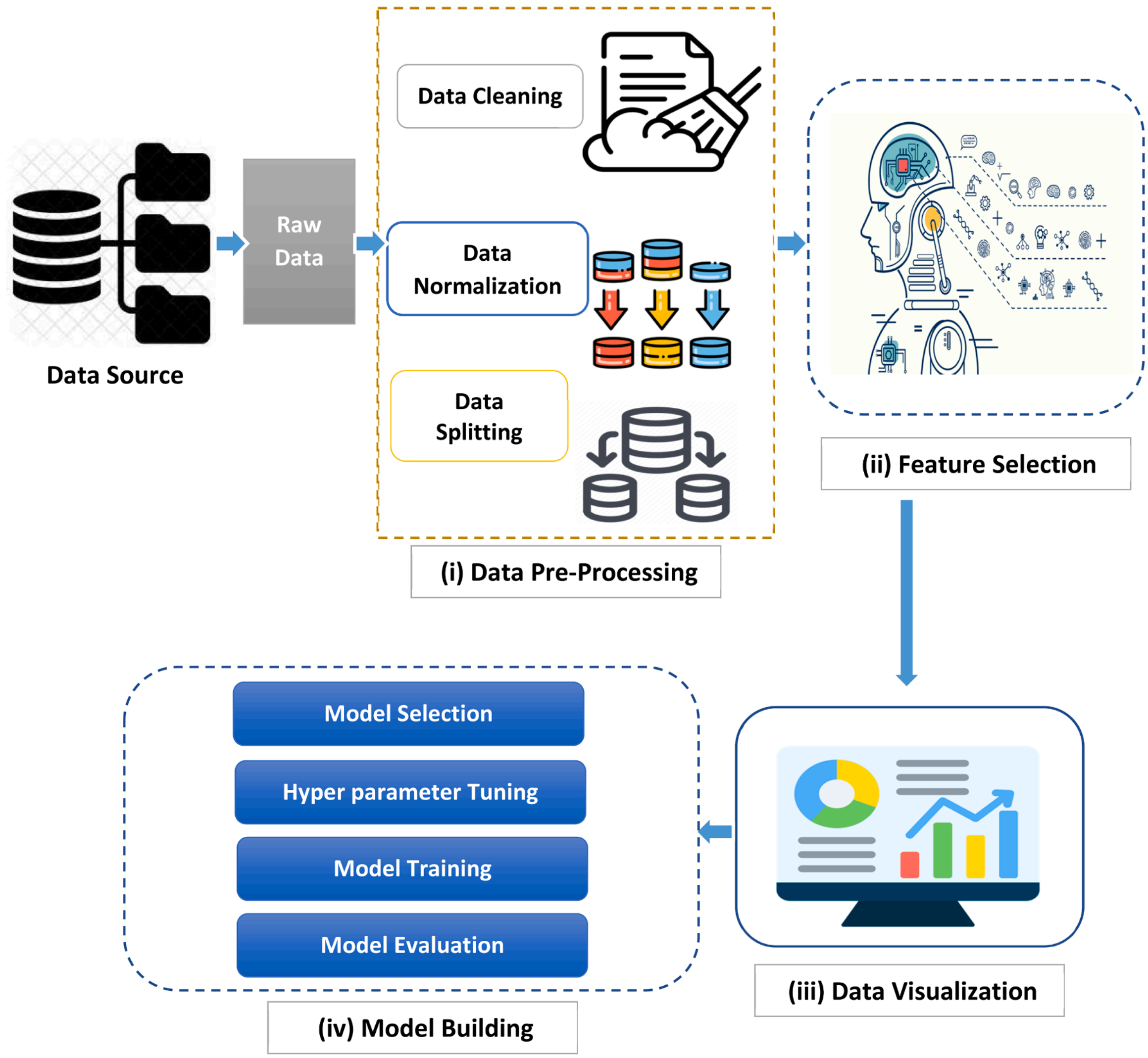

Fig. 4. The proposed forecasting framework.

$$R_{norm} = \frac{R - R_{min}}{R_{max} - R_{min}} \quad (1)$$

R_{norm} stands for the value after normalization, while R stands for the starting point. R_{min} and R_{max} represent the lower and upper bounds of the values, at the same order.

3.2. Feature selection

Building an ML model that takes advantage of every single variable in a dataset is an extremely rare occurrence. A classifier's generalizability and, by extension, its accuracy, are both diminished by repeated elements. As more variables are added to a model, its overall complexity increases. To build a model, feature selection involves picking out a subset of relevant characteristics (variables, predictors) [41]. Feature

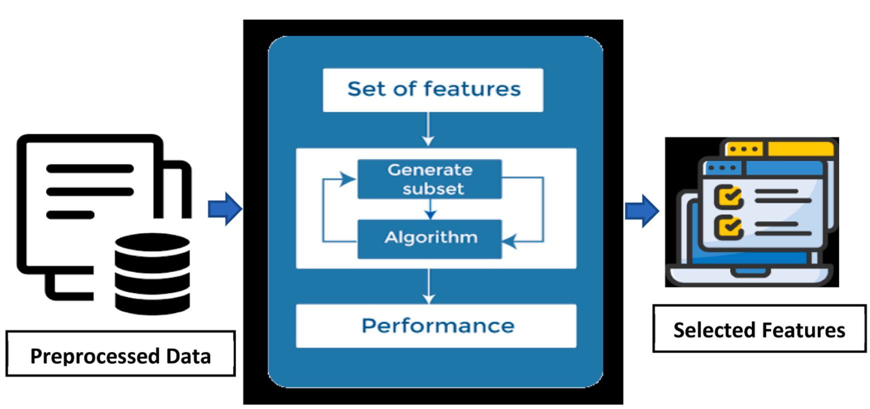

Fig. 5. Feature selection process.

selection is a technique used to enhance the accuracy of a classifier by removing unnecessary data points. Hence, the process of selecting features is vital for improving the effectiveness of learning algorithms [41, 42]. As seen in Fig. 5, it's crucial to use a feature selection strategy to pick the best features in order to maximize response time and enhance the effectiveness of the proposed forecasting methodology.

The Butterfly Optimization Algorithm (BOA) was employed in this study to identify the most significant features. BOA is a metaheuristic algorithm that falls under the category of bio-inspired algorithms. It draws influence from the natural environment. Butterflies are employed as search agents in the optimization process of BOA, leveraging their foraging behavior as a basis [43,44]. Butterflies possess olfactory sensors that enable them to perceive the aroma of food and the fragrance of flowers. Chemoreceptors are sensory receptors that are distributed throughout the anatomical structure of the butterfly. BOA suggests that butterflies possess the ability to generate a scent or fragrance with a distinct degree of potency [43,44]. The butterfly's olfactory sense is crucial for its survival and reproductive success, as indicated by the primary objective of the issue at hand. Consequently, the butterfly's fitness will undergo changes as it transitions from one location to another within the search space. Butterflies release scents that can be detected by other butterflies nearby, which then leads to the development of a shared social learning process. Upon detecting the olfactory cues emitted by the most superior butterfly in its vicinity, the butterfly promptly navigates towards it. This is known as the BOA's global search phase. The failure of a butterfly to detect the scent of another butterfly in the search space is commonly known as the local search phase, which entails the butterfly taking random steps [43–46].

There are three steps to the BOA algorithm: startup, iteration, and the last step [47]. The initialization step is where the algorithm's settings are specified. After that, it creates a random beginning population. Based on the likelihood of a switch, p, the search agents iteratively go through two phases: a global search phase and a local search phase. The truth is that p decides how the algorithm searches for both local and global queries [48]. These are the formulas that BOA uses to determine its global and local searches.

$$A_i(t+1) = A_i(t) + \left(rand^2 * A_{best}(t) - A_i(t)\right) * f_i \text{ for } rand(0,1) \le p \tag{2}$$

$$A_i(t+1) = A_i(t) + \left(rand^2 * A_j(t) - A_k(t)\right) * f_i \text{ for } rand(0,1) > p \tag{3}$$

Where in the $(t+1)$ cycle, the position of the i^{th}butterfly donates by $A_i(t+1)$. $A_i(t)$ represents the t cycle position. One to one hundred random integers distributed uniformly are represented by the variable rand. Additionally, $A_{best}(t)$ indicates the position of the good butterfly in cycle t, $A_j(t)$ and $A_k(t)$ show the locations of the $j^{th}$and k^{th}butterflies in the present iteration t, respectively, where p is a constant number ranging from 0 to 1. Equation (4) is used to calculate the perceived intensity of the fragrance, f.

$f = cI^a$(4)

Algorithm 1
Conventional BOA.

Inputs
- N=No. of butterflies in the swarm "swarm size".
- A=A_1….A_N; group of butterflies in the swarm.
- Initiate c; sensory modality
- Initiate a; the power exponent.
- Initiate rand∈[0-1]; random value.
- Initiate p∈[0-1]; switch probability.

Output
U= the best butterfly of the whole swarm (Z_{Global}).

Steps
1: Begin
// **Set the parameters value**
2: Identify c, a, and p
// Generate the initial swarm
3: Randomly generate initial swarm
// Evaluate the fitness function for each butterfly
4: For every A_i∈A
5: Evaluate the fitness of each butterfly A_i
6: End for
// Calculate fragrance for each butterfly
7: For every A_i∈A
8: $f = cI^a$
9: End for
// Generate random value r∈[0-1] and update positions
10: For every A_i∈A
11: **Generate random value r∈[0-1]**
12: **if r≤p**
13: $A_i(t+1) = A_i(t) + \left(rand^2 * A_{best}(t) - A(t)\right) * f_i$
14: **Else**
15: $A_i(t+1) = A_i(t) + \left(rand^2 * A_j(t) - A_k(t)\right) * f_i$
16: **End if**
17: End for
// Update the optimum butterfly of the whole swarm (A_{Global}).
18: For every A_i∈A
19: Update A_{Global} according to the best fitness value on the whole swarm
20: End for
21: **if (termination conditions not satisfied) then**
22: *Go to step4*.
23: **Else**
24: *Return* A_{Global}
25: **End if**
26: End

Where A stands for the power exponent, I for the stimulus intensity, and c for the sensory modality in this context. Algorithm 1 depicts the traditional BOA method, and Fig. 6 shows the convolutional BOA algorithm's flow diagram.

3.3. Data visualization

A simpler, easier to comprehend model is used in visualization approaches to approximate the network predictions. Other methods use dimension reduction techniques to translate high-dimensional activations into comprehensible 2-D or 3-D space.

3.4. Model building

During this phase, a specific group of models is trained and tested. The model that demonstrates the best performance is then chosen based on the steps outlined in Algorithm 2.

The SVR optimization formula is given by:

$$min_{w,b,\epsilon}\left(\frac{1}{2}\ \ \| w\|^2\ + C\sum_{i=1}^{n}\epsilon_i\right) \tag{5}$$

This equation minimizes the error while maintaining a margin. It is employed to minimize the error while maintaining a margin for generalization. This approach effectively balances the complexity of the model and the accuracy of predictions. In the context of our research, SVR has shown promising results, especially in forecasting energy generation from renewable sources. By leveraging this formula, we ensure that the model achieves an optimal trade-off between fitting the data closely and avoiding overfitting, which is crucial for making reliable predictions on real-world energy consumption and production patterns.

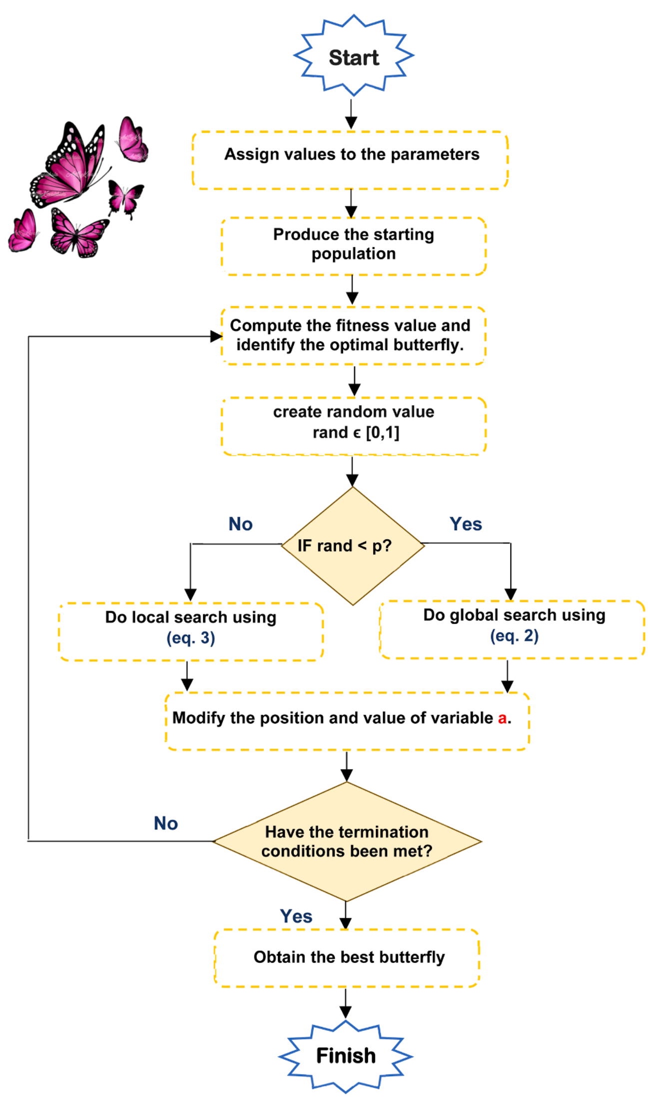

Fig. 6. Flow chart of BOA.

4. Results

This section provides an analysis of the datasets that were utilized, followed by a discussion of the evaluation of performance. To evaluate the ML algorithms, Mean Absolute Error (MAE) is used which can be calculated using the following equation [6]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

4.1. Global energy consumption and renewable generation dataset [49]

There are four datasets that compare renewable and non-renewable energy sources in terms of terawatt hours (TWh) produced and one that shows the usage of renewable energy in the top twenty countries. Included in the dataset on renewable power generation is the timeframe for the primary RESs hydro, wind, biofuel, solar PV, and geothermal from 1997 to 2017. Each of the renewable category data sets also includes country information for the Top 20 Countries Power Generation dataset. Finally, we have global TWh production broken down by renewable and non-renewable sources. A sample of the used data is shown in Table 2. The top 20 countries' total renewable energy generation are illustrated in Fig. 7. The amount of energy used per year is shown in Figs. 8–10. The total consumption vs renewable production is shown in Fig. 11.

As presented in Table 2 and Fig. 7, China leads in total energy production of 1819.94 TWh, with a heavy reliance on hydro of 1189.84 TWh and biofuel of 295.02 TWh. USA has a significant amount of hydro of 315.62 TWh and biofuel of 277.91 TWh, with a solid contribution from geothermal of 18.96 TWh, but much lower solar of 58.95 TWh. Brazil has a high hydro production of 370.90 TWh and a reasonable amount of biofuel of 42.37 TWh, with smaller contributions from solar of 52.25 TWh. Canada relies heavily on hydro of 383.48 TWh but has relatively small amounts of other renewable sources like biofuel of 29.65 TWh and solar of 7.12 TWh.

India has a good share of hydro of 141.80 TWh and biofuel of 51.06 TWh, and a decent amount of solar of 43.76 TWh. Germany stands out with a high contribution from biofuels of 111.59 TWh and a fair amount of solar of 45.10 TWh. Russia has a much smaller total energy production of 188.33 TWh, with some contribution from hydro of 187.13 TWh and negligible amounts from other sources. Japan has lower total production of 187.35 TWh, with some contributions from hydro of 90.67 TWh, biofuel of 7.63 TWh, solar of 19.01 TWh, and geothermal of 2.44 TWh.

4.2. Wind power forecasting

Several rotors, turbines, and meteorological characteristics are present [50]. The data collection period spanned from January 2018 to March 2020. A reading has been recorded every ten minutes. A comparison of the outcomes from each ML algorithm is shown in Table 3 and Figs. 12–14. It is shown in Table 3 that Support vector regression (SVR), LSTM, and CNN all donate MAE and loss values of 0.1493, 0.0926, and 0.1463 in that proportion.

As illustrated in Table 3 and Figs. 12–14, SVR seems to be performing the best, with both the training loss with a value of 0.0941and validation loss with a value of 0.0766 being the lowest compared to the others. While LSTM has a slightly higher validation loss with a value of 0.1211

Algorithm 2
Model building algorithm.

- **Input**
  - Training data
- **Output**
  - Evaluated Model
- **Steps**

1. **Import the needed module.**
2. **For each dataset file do**
3. *Do some preprocessing on dataset to prepare it for training*
4. **End for**
5. **For each model do**
6. *Specify various hyperparameters necessary for the model.*
7. *Adjust the learning rate based on the number of epochs.*
8. *Define basic model architecture.*
9. *Test the model*
10. *Evaluate each model*
11. *Select the model with the highest performance*
12. **End for**

Table 2
A sample of the used data.

	Country	Hydro (TWh)	Biofuel (TWh)	Solar PV (TWh)	Geothermal (TWh)	Total (TWh)
0	China	1189.84	295.0200	79.43	0.1250	1819.9400
1	USA	315.62	277.9100	58.95	18.9600	758.6190
2	Brazil	370.90	42.3700	52.25	0.0000	466.3500
3	Canada	383.48	29.6500	7.12	0.0000	424.0900
4	India	141.80	51.0600	43.76	0.0000	262.6500
5	Germany	24.17	111.5900	45.10	0.1600	227.1800
6	Russia	187.13	0.1400	0.08	0.4300	188.3300
7	Japan	90.67	7.6300	19.01	2.4400	187.3490

compared to SVR, the training loss is also a bit lower with value of 0.0926. This suggests it might be overfitting a bit more than SVR. CNN has the highest loss and validation loss, which might indicate it’s not the best fit for this task or dataset.

4.3. Solar power generation data

Data was collected at two solar power facilities in India for a duration of 34 days [51]. The system includes two sets of files, each containing a dataset for power generation and a dataset for sensor readings. The power generation datasets are collected at the inverter level because each inverter is connected to multiple solar panel lines. At the plant level, a carefully positioned array of sensors collects the necessary data. Table 4 and Fig. 15 provide a visual representation of the results obtained from each ML algorithm used in the study.

As shown in Table 4 and Fig. 15, Linear Regression is performing very well and provides 98.3650 % accuracy. In linear regression, typically used for continuous predictions, you’re looking at how well the model fits the data and predicts the target variable. An accuracy of 98.3650 % is unusually high for linear regression, as it usually indicates a strong fit and minimal errors. While KNN is a classification algorithm that works by finding the closest neighbors to make predictions. While 88.33 % is still good, it’s lower compared to Linear Regression and Decision Tree, suggesting KNN might not be capturing the data’s

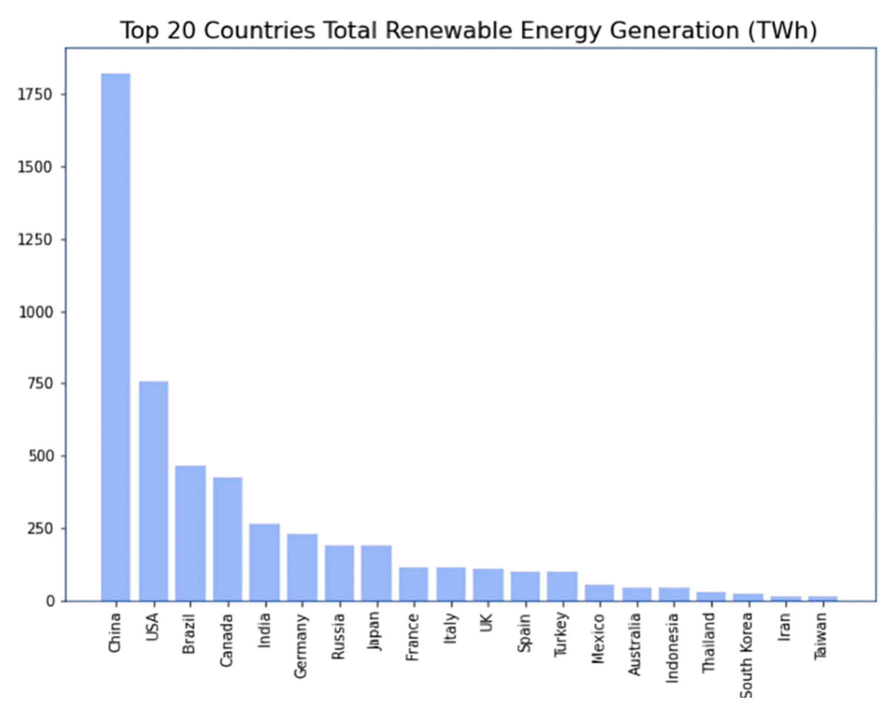

Fig. 7. The top 20 countries total renewable energy.

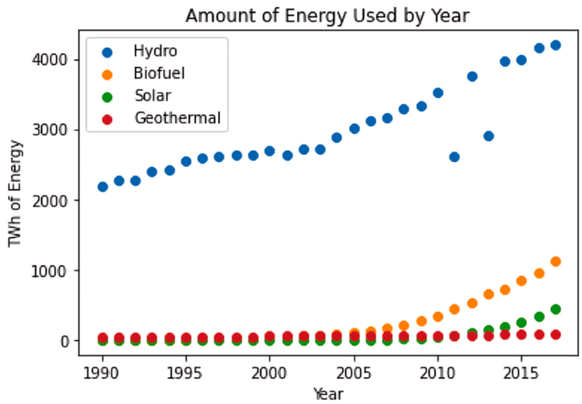

Fig. 8. The amount of energy used by year.

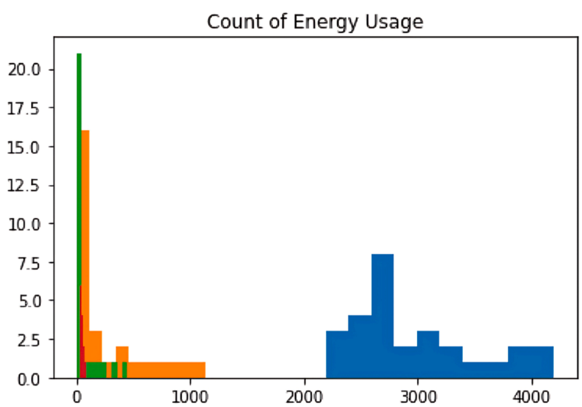

Fig. 9. Count of energy usage.

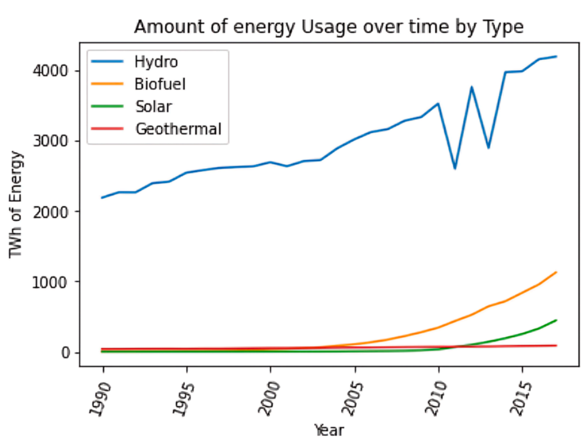

Fig. 10. Amount of energy over time.

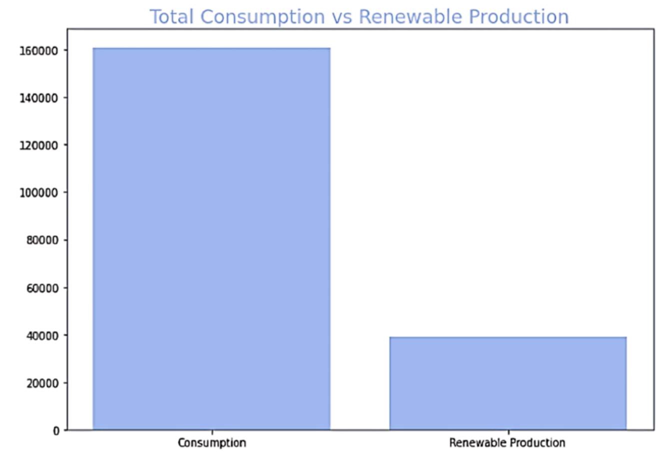

Fig. 11. Total consumption vs renewable production.

Table 3
Displays the comparison between the results of each used algorithm.

ML algorithm	Loss	MAE	Val_loss	Val_MAE
SVR	0.0941	0.0941	0.0766	0.0766
LSTM	0.0926	0.0926	0.1211	0.1211
CNN	0.1463	0.1463	0.1023	0.1023

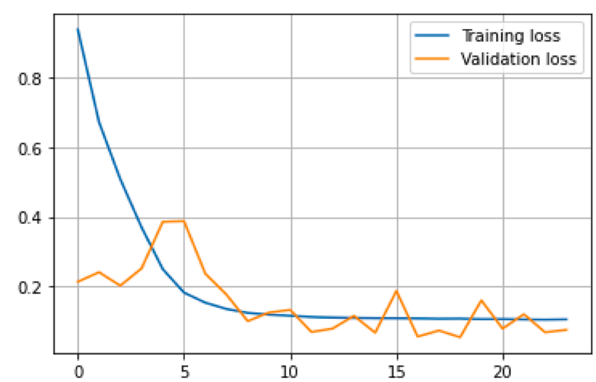

Fig. 12. Results of SVR.

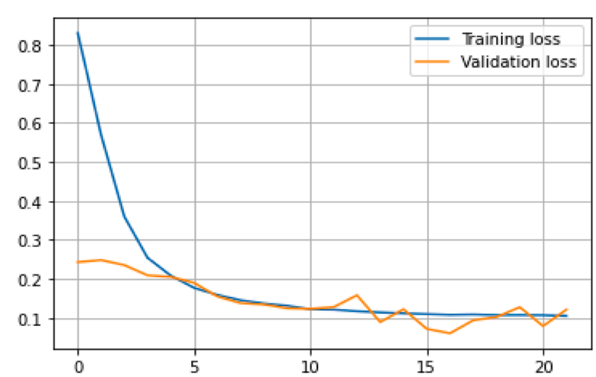

Fig. 13. Results of LSTM.

structure as effectively as the other models in this case. Also, Decision Tree uses a tree-like structure to make decisions based on input features.

The high accuracy (98.28 %) shows that the decision tree is likely making accurate predictions and might be overfitting the data to some extent (especially if the model is too complex or the data is very clean). Random Forest is an ensemble method that builds multiple decision trees and combines their predictions. This often leads to better performance and lower overfitting. A 99.03 % accuracy suggests that Random Forest is the most accurate among the models tested here, capturing the data's patterns very well.

Considering existing literature, our results indicate that the performance of the models we tested aligns with findings from prior research. Specifically, the high accuracy observed in Linear Regression, Decision Tree, and Random Forest models reflect the robust ability of these algorithms to capture complex patterns within the data. Previous studies have also highlighted the effectiveness of ensemble methods like Random Forest, which typically outperform individual models due to

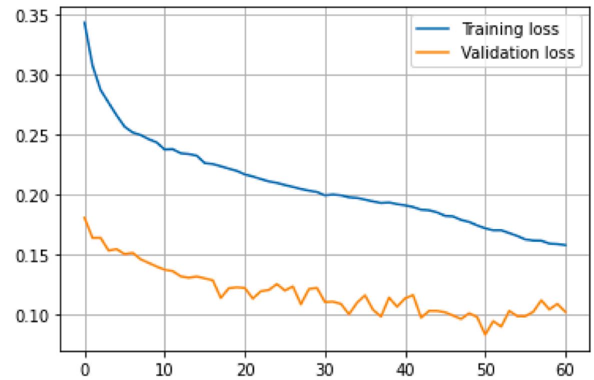

Fig. 14. Results of CNN.

Table 4
Displays the comparison between the results of each used algorithm.

ML algorithm	Accuracy
Linear Regression	98.3650 %
KNN	88.3269 %
Decision Tree	98.2838 %
Random Forest	99.0277 %

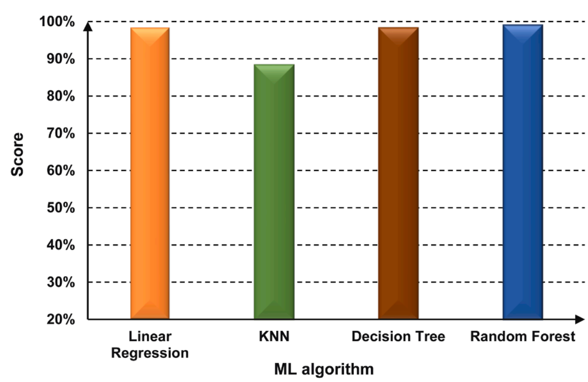

Fig. 15. Results of ML algorithms.

their ability to reduce overfitting and improve predictive accuracy. Furthermore, the relative performance of KNN suggests that while it performs well, it may not be as adept at capturing intricate data relationships compared to other methods, a finding consistent with some earlier studies on KNN's limitations in certain contexts.

5. Conclusion

This study has reviewed the current state of the art and applications of DL and AI in the promotion of sustainability across several industries. Achieving the Sustainable Development Goals (SDGs), switching to renewable energy, protecting the environment, and controlling building energy use efficiently are all on the list. The use of AI has the potential to greatly impact 134 out of the 169 SDG objectives, making it a powerful tool for promoting sustainable practices. To ensure openness, safety, and compliance with ethical standards, comprehensive regulatory oversight is necessary, especially given the rapid development of AI and DL technologies. Renewable energy has a lot of potential for AI and DL to enhance energy management, find problems, and keep power networks stable. Along with their promise in waste management, these technologies have also shown promise in predictive analysis for solar power facilities. Because of this, renewable energy systems are becoming more efficient and sustainable over time.

Additionally, three main datasets were used and discussed in this work: (i) the Global Energy Consumption and Renewable Generation Dataset, which shows the global production from both renewable and non-renewable sources; (ii) the Wind Power Forecasting, consisting of two sets of files, each containing a dataset for power generation and another for sensor readings, and (iii) Solar Power Generation Data. The main contribution of this study is to highlight the significance of AI and renewable energy in accomplishing SDGs.

This study has reviewed the current state of the art and applications of DL and AI in promoting sustainability across several industries, with a particular focus on renewable energy systems. The potential for AI and DL to contribute to achieving the SDGs is substantial, particularly in advancing renewable energy technologies, energy efficiency, and environmental sustainability. However, there are several limitations to this study that should be acknowledged:

- Data Limitations: The datasets used in this study, while comprehensive, have inherent limitations in terms of temporal coverage, granularity, and geographic scope. For example, the Global Energy Consumption and Renewable Generation Dataset covers data up to 2017, which may not fully reflect the latest trends and advances in renewable energy production. Additionally, the datasets on wind and solar power forecasting are limited to specific geographical regions (e.g., India for solar data), which may not capture global variability in renewable energy patterns.
- Model Generalization: The machine learning models used in this study, while effective for the provided datasets, may not generalize well to other geographical regions or different renewable energy technologies without further adaptation and tuning. Factors such as local climate conditions, technological infrastructure, and energy consumption behaviours may require models to be retrained or adjusted for different contexts.
- Algorithmic Limitations: Although the algorithms explored in this study (SVR, LSTM, CNN, Random Forest, etc.) have demonstrated good performance in their respective domains, their limitations should be acknowledged. For instance, some models may be prone to overfitting or may not perform well in the presence of noisy or incomplete data. Future work could explore hybrid models or newer AI techniques, such as reinforcement learning, to address these challenges.

Future Research Directions:

- Expanding Data Sources: Future studies should aim to integrate more diverse datasets, including real-time data from various regions, to improve the robustness of the predictive models. The inclusion of more granular and up-to-date data could help better capture recent advancements in renewable energy production and consumption patterns.
- Enhancing Model Generalization: To improve the generalizability of the models, future research should focus on cross-regional comparisons and the incorporation of additional factors like energy policy changes, technological innovation, and economic factors. This could involve the use of transfer learning or multi-task learning techniques to adapt models across different settings.
- Exploring Advanced AI Techniques: While traditional ML algorithms performed well, there is significant potential to explore more advanced AI techniques, such as deep reinforcement learning for dynamic energy management and optimization. These methods could further improve predictive accuracy and enable real-time decision-making in energy systems.
- Integration with Smart Grids and IoT: Future work could investigate the integration of AI-powered forecasting models with smart grids and IoT systems to enable automated, real-time energy distribution and consumption management. Such integration could significantly

enhance the efficiency and reliability of energy systems, especially in the context of renewable energy variability.

CRediT authorship contribution statement

Fatma M. Talaat: Writing – original draft, Visualization, Resources, Investigation, Formal analysis, Data curation, Conceptualization. **A.E. Kabeel:** Writing – review & editing, Supervision, Project administration. **Warda M. Shaban:** Writing – review & editing, Validation, Resources, Methodology, Investigation, Data curation.

Declaration of competing interest

No conflicts of interest.

Data availability

No data was used for the research described in the article.

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