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Exploring the Role of Deep Learning in Forecasting for Sustainable Development Goals: A Systematic Literature Review

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ABSTRACT

This paper aims to explore the relationship between deep learning and forecasting within the context of the Sustainable Development Goals (SDGs). The primary objective is to systematically review 38 articles published between 2019 and 2023, following PRISMA guidelines, to understand the current landscape of deep learning forecasting for SDGs. Using data from 2019-2023 allows capturing the latest developments in deep learning forecasting for Sustainable Development Goals (SDGs), while excluding data before 2019 and after 2023 is based on the desire to avoid including potentially less relevant or unpublished research and to maintain focus on the most current and contextually relevant literature. The methodological approach involves analyzing the application of deep learning methods for forecasting within various SDG fields and identifying trends, challenges, and opportunities. The literature review results reveal the popularity of LSTM models, challenges related to data availability, and the interconnected nature of SDGs. Additionally, the study demonstrates that deep learning models enhance forecast accuracy and computational performance, as measured by Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R2). The findings underscore the importance of advanced data preparation techniques and the integration of deep learning with SDGs to improve forecasting outcomes. The novelty of this research lies in its comprehensive overview of the current landscape and its valuable insights for researchers, policymakers, and stakeholders interested in advancing sustainable development goals through deep learning forecasting. Finally, the paper suggests future research directions, including exploring the potential of hybrid forecasting models and investigating the impact of emerging technologies on SDG forecasting methodologies. Innovative methods for imputing missing values in deep learning forecasting models could be further explored to enhance predictive accuracy and robustness.

1. Introduction

The versatility of deep learning extends far beyond traditional applications, encompassing diverse fields such as stress classification [1], social distancing monitoring [2], human facial expression identification [3], and face mask detection [4], [5]. It demonstrates its adaptability in more specialized contexts, such as Indonesian sentence boundary detection [6], Javanese gamelan note generation [7], and generative association rule-based recommendations [8]. This broad spectrum of applications highlights deep learning's capacity to thrive in various intersecting fields, showcasing its versatility and potential for innovation.

In today's complex world, effective decision-making heavily relies on accurate forecasting, a process increasingly empowered by advancements in deep learning technology. Across diverse domains, from healthcare [9], [10] and finance [11], [12] to disaster management [13], [14] and climate forecasting [15], deep learning has wielded transformative influence. For example, its algorithms have facilitated the early detection of diseases like cancer and tuberculosis [16], [17], forecasted crude palm oil prices [18], [19] and predicted PM2.5 levels in polluted cities like Beijing [20]. Beyond these applications, deep learning has been instrumental in predicting traffic patterns [21], forecasting energy usage [22], [23], and even anticipating stock prices in diverse markets like Indonesia [24]. This pervasive utilization underscores the critical role of deep learning in shaping contemporary decision-making processes, one of which is forecasting.

Forecasting, the art of predicting future trends, has emerged as a focal point for organizations, policymakers, and stakeholders seeking to navigate an increasingly complex world [25]. As we delve into the intersection of deep learning and forecasting, particularly within the context of Sustainable Development Goals (SDGs), the potential to revolutionize decision-making processes becomes abundantly clear [26]. This integration of deep learning methodologies holds promise in providing actionable insights for addressing the myriad challenges outlined in the SDGs. However, despite these advancements, there exists a critical gap in the literature regarding the integration of deep learning and forecasting within the context of SDGs.

The SDGs are a set of 17 global objectives established by the United Nations in 2015 to address various social, economic, and environmental challenges worldwide by 2030. These goals encompass a wide range of issues, including poverty eradication, quality education, gender equality, clean water and sanitation, affordable and clean energy, climate action, and sustainable cities and communities. The SDGs represent a comprehensive framework for guiding international efforts towards a more sustainable and equitable future for all. In order to achieve these ambitious targets, innovative approaches are required, with technology-intensive learning playing a crucial role [27]. Deep learning forecasting models offer a promising avenue for leveraging technology to analyze complex data and identify trends and patterns essential for advancing SDGs [28]. By harnessing the power of deep learning, organizations and policymakers can optimize resource allocation, monitor progress, and evaluate the impact of policies and interventions, thereby accelerating progress toward sustainable development goals.

Deep learning techniques offer promising solutions to various challenges outlined in the SDGs. For instance, in the healthcare sector (SDG 3: Good Health and Well-being), deep learning algorithms applied to medical imaging data can enable early detection and diagnosis of diseases like cancer [29], [30], tuberculosis [31], or diabetic retinopathy [32], reducing mortality rates from non-communicable diseases. Similarly, in education (SDG 4: Quality Education), deep learning models can personalize learning experiences by analyzing student performance data to adapt instructional materials according to individual learning styles and needs, enhancing educational outcomes and reducing dropout rates [33], [34]. Moreover, in environmental sustainability (SDG 13: Climate Action), deep learning techniques can analyze satellite imagery and sensor data to monitor deforestation [35], track changes in biodiversity [36], and predict natural disasters like wildfires or hurricanes, thus supporting efforts to combat climate change and its impacts [27]. In poverty reduction (SDG 1: No Poverty), deep learning algorithms can analyze large-scale datasets to identify poverty hotspots [37], understand socio-economic dynamics [38], and target interventions more effectively, contributing to efforts to alleviate poverty and promote inclusive economic growth. Finally, in promoting gender equality (SDG 5: Gender Equality), deep learning techniques can analyze text and speech data to detect gender bias in communication and facilitate gender-sensitive language use [39], thereby promoting inclusive representation and empowering women and girls [40]. These examples demonstrate how integrating deep learning techniques into various sectors can effectively address specific challenges outlined in the SDGs, thereby enhancing the relevance and applicability of research in this field.

The gap in research on the dynamics between deep learning and forecasting within the context of SDGs is significant for several reasons. Firstly, despite rapid advancements in deep learning technology, comprehensive studies systematically exploring the application of deep learning models in forecasting for SDGs are lacking. This gap impedes the development of effective forecasting methodologies tailored to address the complex challenges outlined in the SDGs. Moreover, existing research may have limitations regarding the scalability, interpretability, or generalizability of deep learning forecasting models within SDGs. Failure to address these limitations risks overlooking critical factors that could impact the accuracy and reliability of SDG-related forecasts, hindering progress toward achieving the 2030 sustainable development targets.

Additionally, real-world challenges such as data scarcity, model complexity, and ethical considerations in utilizing deep learning for forecasting SDGs remain unresolved. These challenges underscore the importance of conducting a systematic literature review to identify gaps, limitations, and potential avenues for improvement in leveraging deep learning for SDG forecasting. Therefore, by addressing these issues and providing a detailed rationale for the research gap, the literature review aims to advance knowledge in this area, inform future research directions, and support evidence-based decision-making for sustainable development initiatives. The Research Questions (RQ) in this research are:

1. What specific deep learning methods are utilized in forecasting within the scope of SDGs, and how do they contribute to addressing the multifaceted challenges outlined in the SDGs?
2. Which fields or domains within the SDGs have been extensively researched using deep learning models for forecasting, and what are the key findings and advancements in each domain?
3. What are the existing deficiencies or limitations in current deep learning forecasting methodologies within the context of SDGs, and what potential avenues for improvement can be identified to enhance the effectiveness and applicability of these methodologies in addressing SDG-related challenges?

Furthermore, this paper aims to contribute to the advancement of knowledge in the field by proposing a structured framework for integrating deep learning into SDG forecasting methodologies. By identifying deficiencies and limitations in existing approaches, we aim to pave the way for future research endeavors aimed at enhancing the effectiveness and applicability of deep learning forecasting models within the context of sustainable development. Ultimately, our goal is to inform evidence-based decision-making and support sustainable development initiatives by leveraging the power of deep learning technology.

The research contribution of this paper is twofold. Firstly, it offers a comprehensive synthesis of existing literature on the application of deep learning in forecasting within the context of SDGs, thereby providing researchers and practitioners with a holistic understanding of the current state of the field. Secondly, it proposes a structured framework for integrating deep learning techniques into SDG forecasting methodologies, offering novel insights and directions for future research aimed at enhancing the effectiveness and applicability of such models in supporting sustainable development efforts.

The paper is organized to provide a comprehensive analysis, starting with an introduction highlighting the significance of deep learning in forecasting for SDGs, followed by a methodology section detailing the SLR process. Subsequently, the results and discussion section present findings on deep learning methods employed in SDG forecasting, extensively researched SDG fields, and potential avenues for improvement. A case study on energy usage forecasting exemplifies the application of deep learning models within the SDG context. Recommendations and future research directions underscore the need to integrate deep learning techniques with data preparation methods to enhance SDG forecasting accuracy. The conclusion summarizes key findings and emphasizes the importance of continued research efforts to advance sustainable development initiatives effectively.

2. Method

This research utilized the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to conduct a systematic literature review (SLR) aimed at investigating the utilization of deep learning forecasting methods within the context of SDGs (Fig. 1). The PRISMA flowchart process, depicted in Fig. 2, encompasses distinct stages designed to ensure a methodical and comprehensive review of existing literature in the field.

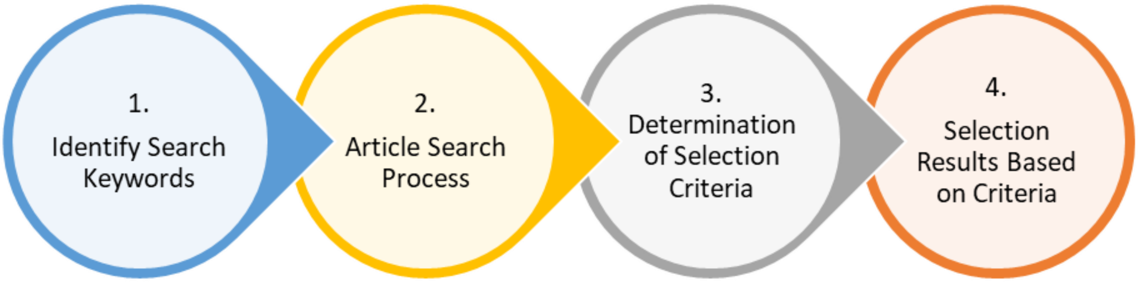


Fig. 1. SLR process

A thorough selection of identified search terms was the initial stage in the SLR strategy, which followed the SLR methodology. The objective of this step was to provide a solid foundation for the subsequent article search strategy [41], which would include ensuring a comprehensive review of the literature concerning deep learning forecasting and the SDGs. During this investigation, articles were searched using the keywords “Forecasting” and “Sustainable Development Goals.” Specific search terms were selected to target literature that explicitly addressed deep learning forecasting techniques applied in the pursuit of SDGs. By incorporating these terms, the search strategy aimed to encompass a broad spectrum of studies relevant to the intersection of deep learning and sustainable development. This rationale underscores the methodological rigor employed to identify and select relevant literature, thereby enhancing the credibility and comprehensiveness of the review process.

The research continues with the article search process armed with the identified search keywords. This phase includes thoroughly exploring academic databases, scientific journals, and other related sources [42] to assemble a diverse and inclusive collection of articles on the intersection between deep learning forecasting and the SDGs. In this study, the search was carried out only on the Scopus database, which yielded results of 829 documents.

For strategic reasons, this study relies only on Scopus for literature searches. Scopus's reputation for extensive coverage across many fields matches the multidisciplinary SDGs, allowing a broad examination of the application of deep learning forecasting models to sustainable development. The database's quality and rigor lend legitimacy to the selected articles, making the literature review more reliable [43]. Scopus's worldwide viewpoint, which includes international publications, matches SDGs' global character. Researchers' experience with Scopus improves search efficiency [44]. While admitting the benefits, the research methodology clearly states that using Scopus alone has drawbacks and may exclude other datasets. Scopus's limitations as the sole source of literature in this research may not encompass all relevant publications, especially those from niche or regional journals that might not be indexed in its database. Based on the article search keywords that had been determined previously, it was necessary to select criteria relevant to the research topic in the selection of articles.

The study defined stringent selection criteria to ensure the inclusion of high-quality and pertinent literature [45]. These criteria served as the lens through which articles were evaluated, considering factors such as relevance, methodological rigor, and alignment with the study's focus.

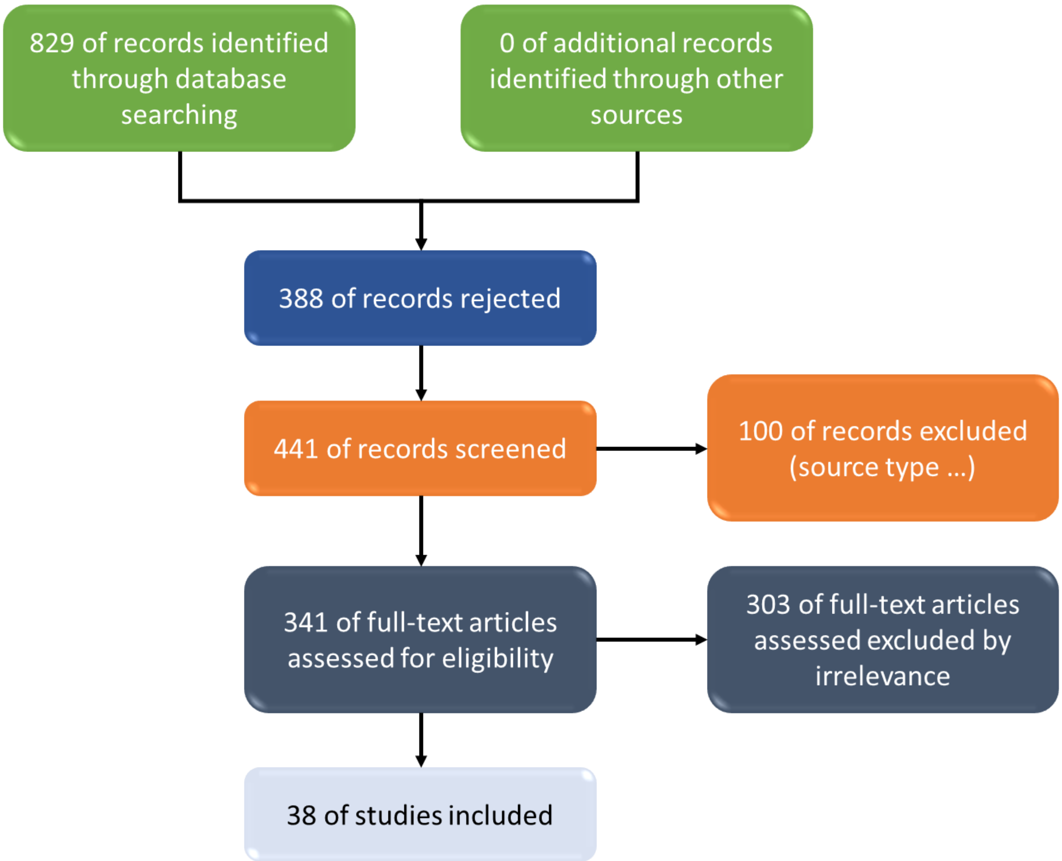


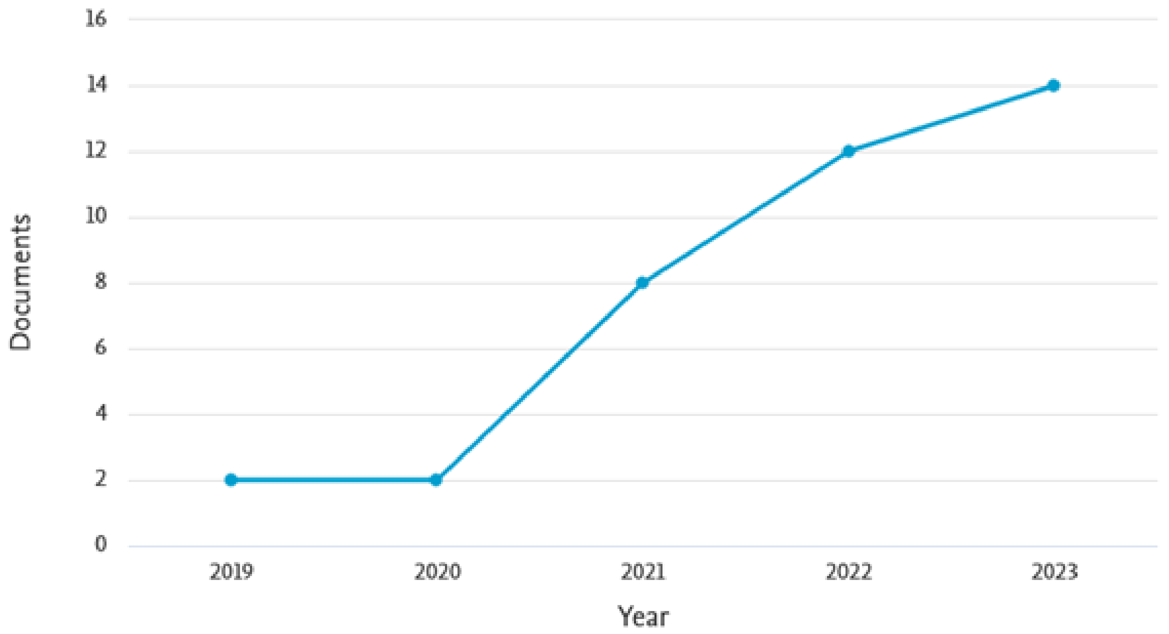
Fig. 2. PRISMA method flowchart

This process in the Scopus database can be done using the filter feature. Some criteria that need to be defined in the selection of articles are as follows. The inclusion criteria comprised studies published between 2019 and 2023, written in English, and focusing on deep learning forecasting methods within the context of SDGs. Specifically, articles needed to employ deep learning techniques for forecasting purposes related to SDGs. Additionally, both journal articles and conference papers were considered eligible for inclusion. Conversely, studies outside the specified publication timeframe, not written in English, not addressing deep learning forecasting methods for SDGs, or not published in peer-reviewed journals or conference proceedings were excluded from the review. These criteria were meticulously applied during the article selection process to ensure the inclusion of high-quality and pertinent literature relevant to the research objectives.

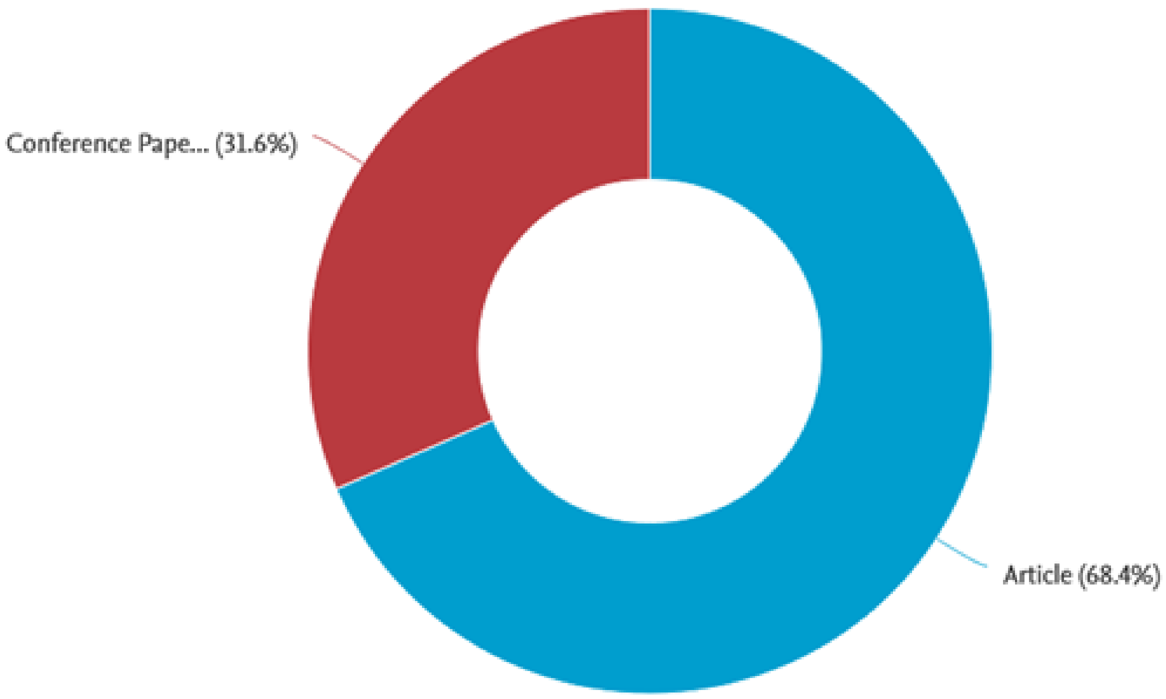
The decision to restrict the selection of articles to those published between 2019 and 2023 in the Scopus database for the systematic literature review is justified by several factors. Firstly, this timeframe ensures the inclusion of the most recent research, enabling the review to capture the latest advancements and methodologies in deep learning forecasting for Sustainable Development Goals (SDGs). By focusing on recent publications, the review can provide insights relevant to current practices and developments in the field. Additionally, limiting the search to this timeframe helps manage the volume of literature to be reviewed while ensuring that the selected articles meet specific quality criteria, thereby enhancing the rigor and reliability of the review process. Furthermore, given the urgency of addressing sustainable development challenges outlined in the SDGs by 2030, prioritizing recent publications ensures that the review generates insights that inform timely decision-making and policy formulation processes. Overall, selecting articles published between 2019 and 2023 balances capturing the most relevant and recent research while effectively managing the review process.

The research conducted a thorough examination and chose articles based on their strict conformity to the specified parameters, expanding on the existing criteria for selection [46]. The objective of this phase was to carefully choose a high-quality collection of literature that would significantly contribute to the study's overall objectives.

Throughout this procedure, papers were chosen according to pre-established selection criteria, resulting in the selection of 38 articles. Fig. 3 (a) to Fig. 3 (c) display the distribution of selected articles.



(a)



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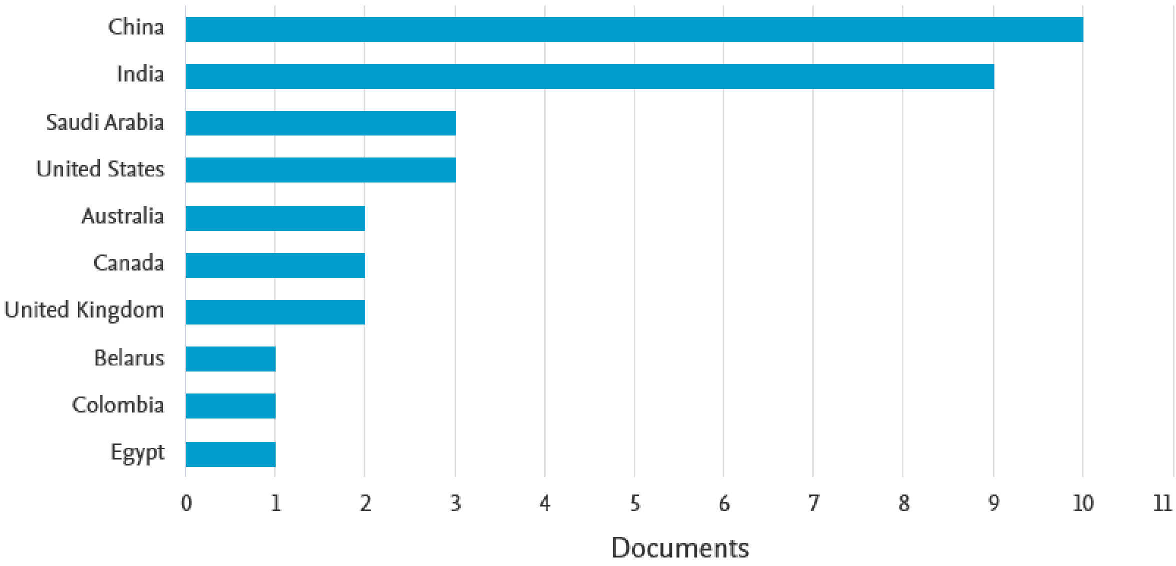

(c)

Fig. 3. The distribution of selected articles document (a), by year (b), by type (c). by demographic

Fig. 3 (a) displays the distribution over the past five years. The research trend in this Systematic Literature Review (SLR) exhibits a consistent upward trajectory each year. Analysis of this trend indicates a consistent upward trajectory in the number of publications each year, suggesting a growing interest and investment in research related to deep learning forecasting methods for SDGs. This trend reflects the increasing recognition of the importance of leveraging advanced computational techniques to address complex sustainability challenges. Fig. 3 (b) shows that the percentage breakdown by category indicates 26 journal articles and 12 conference papers. This analysis offers insights into the dissemination channels preferred by researchers in the field. The predominance of journal articles suggests a strong emphasis on peer-reviewed research, indicating a commitment to rigorous scholarly inquiry and contributing to the academic discourse on deep learning forecasting for SDGs. However, the inclusion of conference papers also highlights the significance of conference proceedings as platforms for sharing preliminary findings and fostering collaboration within the research community. Fig. 3 (c) illustrates that the concentration of research articles from China underscores the country's leadership in leveraging deep learning approaches for addressing sustainable development challenges. Similarly, the substantial representation of research from India highlights its growing contributions to the field. However, the limited representation of certain regions, such as Belarus, Colombia, and Egypt, suggests disparities in research capacity and infrastructure, warranting further attention to foster greater inclusivity and collaboration on a global scale.

By following this systematic process, the study aimed to synthesize existing knowledge, identify trends, and address gaps in understanding how deep learning forecasting models are applied in pursuing Sustainable Development Goals. The subsequent sections of this research will expound upon the findings derived from this comprehensive SLR process, shedding light on the field's current state and paving the way for future research and development.

3. Results and Discussion

In this part, we give a complete presentation and analysis of the survey findings, as presented in Table 1. We begin by offering a fundamental review of the selected publications, providing insights into the more extensive literature landscape under consideration. This summary serves as a basis for a more in-depth examination of the survey findings, providing context for the research environment.

Table 1 provides an overview of several deep-learning methods used for projecting SDGs, encompassing environmental factors, disease transmission (including the influence of COVID-19) [61], [57], [69], and economic forecasts [48], [59]. The integrated techniques encompass the fusion of natural language processing with CNN and using RNN for power load forecasting [48]. These novel ideas demonstrate how deep learning significantly contributes to comprehending, forecasting, and handling many issues connected to the SDGs, hence improving sustainable development efforts in diverse areas.

Table 1. Summary of selected articles

No	Author	Title	Method	SDGs	Novelty	Result
1	[47]	Urban Land Use and Land Cover Change Prediction via Self-Adaptive Cellular Based Deep Learning with Multisourced Data	LSTM (Long Short-Term Memory)	11	The novelty of this research lies in the proposed self-adaptive cellular-based deep learning analysis method for predicting urban land use and land cover changes.	The proposed algorithm outperforms the greedy algorithm by 29.95% and BDMA method by 8.27%.
2	[48]	Predicting economic development using geolocated wikipedia articles	Combination of Wikipedia article embeddings generated using Doc2Vec with Convolutional Neural Network (CNN)	8	The novelty of this research lies in using geolocated Wikipedia articles and modern NLP techniques to predict socio-economic indicators, demonstrating the potential of Wikipedia as a valuable data source for social science research and policy decisions.	The research results show that the proposed method outperforms previous benchmarks for predicting community-level asset wealth and education outcomes using geolocated Wikipedia articles.
3	[49]	A Review of Artificial Intelligence Applications to Achieve Water-related Sustainable Development Goals	Convolutional Neural Network (CNN	6	The novelty of this research lies in the application of Artificial Intelligence (AI) in the water sector to achieve water-related SDGs.	The article reviews artificial intelligence applications aimed at achieving Water-related Sustainable Development Goals.
4	[50]	Time series prediction of under-five mortality rates for Nigeria: comparative analysis of artificial neural networks, Holt-Winters exponential smoothing and autoregressive integrated moving average models	Group Method of Data Handling (GMDH)-type Artificial Neural Network (ANN)	3	This research's novelty lies in applying the GMDH-type ANN for modeling and forecasting Nigeria's long-term under-five mortality rate and comparing it with conventional statistical methods.	The research results show that the GMDH-type ANN predicted the under-five mortality rate for Nigeria more accurately compared to ARIMA regression and Holt.
5	[51]	Wind power forecasting – A data-driven method along with gated	Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM)	7	This research's novelty lies in applying advanced data filtering, feature engineering, and	The research results show that the GRU deep learning neural network outperformed LSTM in predictive

No	Author	Title	Method	SDGs	Novelty	Result
		recurrent neural network			model optimization techniques to improve deep learning models' accuracy and computational performance for wind power prediction.	accuracy, achieving over 92% accuracy in wind power forecasting.
6	[52]	Sustainable development goals monitoring and forecasting using time series analysis	Long Short-Term Memory (LSTM)	17	The novelty of this research lies in incorporating intra-entity and inter-geographic causal relationships between sustainable development goals (SDGs) in the forecasting framework.	The result of the research is that the SDG-TTF framework improves the prediction of SDG attainment, with the ACA mechanism being the most effective causal inference mechanism.
7	[53]	Air Quality Forecast using Convolutional Neural Network for Sustainable Development in Urban Environments	Convolutional Neural Network (CNN)	11	The novelty of this research lies in the utilization of CNN for air quality forecasting in urban environments, contributing to sustainable development efforts.	The result of the research is the application of the CNN model on air quality datasets to detect patterns and predict future air quality levels.
8	[54]	Energy Demand Forecast in Yunnan Province Based on Seq2Seq Model	Long Short-Term Memory (LSTM)	7	The novelty of this research lies in the coupling of deep learning and ridge regression methods for energy demand forecasting in Yunnan Province.	The research results show an increase in total energy consumption in Yunnan Province from 2021 to 2025, with a decline in coal consumption and an increase in electricity consumption.
9	[55]	Prediction of electrical energy consumption through recurrent neural networks	Recurrent Neural Network (RNN)	7	The novelty of this research lies in implementing RNN for short-term load forecasting in smart meters, comparing their performance with other prediction models, and determining the optimal learning rate for improved accuracy.	The research results show that the learning rate of 0.005 generates the highest correlation coefficient of approximately 0.95, indicating a substantial similarity between the predicted and actual power consumption.
10	[56]	Decomposition-based hybrid wind speed forecasting model using deep bidirectional LSTM networks	Bidirectional LSTM (BiDLSTM)	7	This research's novelty lies in combining data decomposition techniques (such as WT, EMD, EEMD, and EWT) with BiDLSTM networks for wind speed forecasting, resulting in improved	The research results show that the proposed hybrid model, combining data decomposition techniques and BiDLSTM networks, outperformed other models in wind speed forecasting, with 95.38% of total data

No	Author	Title	Method	SDGs	Novelty	Result
					accuracy compared to other models.	points within the ±25% boundary lines.
11	[57]	Forecasting of COVID-19 cases using deep learning models Is it reliable and practically significant	LSTM, Stacked LSTM, Bi-directional LSTM, Convolutional LSTM, and Prophet	3 and 11	The novelty of this research lies in its comprehensive analysis and comparison of various deep learning models for predicting COVID-19 cases, as well as its country and city-specific case studies and the potential impact on sustainable development goals.	The research results show that the Stacked LSTM model outperformed other models with MAPE values of 0.2, 0.43, and 0.9 for confirmed, death, and recovered cases, respectively.
12	[58]	Short-Term Traffic Flow Prediction: A Method of Combined Deep Learnings	Convolutional Neural Network-Dynamic Weighted Combination (CDLP)	9	The novelty of this research lies in the combination of CNN-LSTM-attention and CNN-GRU-attention models in the CDLP model for traffic flow prediction.	The research results show that the CDLP model outperforms the baseline models regarding prediction accuracy, with lower MAPE, MAE, and RMSE values.
13	[59]	Artificial Intelligence Algorithm-Based Economic Denial of Sustainability Attack Detection Systems Cloud Computing Environments	CNN-LSTM	9	The novelty of this research lies in developing a system that effectively classifies and predicts Economic Denial of Sustainability (EDoS) attacks in cloud computing environments using machine learning and deep learning algorithms.	The research results show that the Random Forest Tree algorithm achieved the highest testing accuracy of 99% in detecting EDoS attacks on cloud computing platforms using binary classification.
14	[60]	Deep Learning Based Purchase Forecasting for Food Producer-Retailer Team Merchandising	Back-propagation neural network (BPN)	12	The novelty of this research lies in developing a strategy model that utilizes artificial neural networks to accurately forecast the purchase volume of foods with a short shelf life, reducing error fluctuations in purchasing and enhancing the sustainable operation ability of team merchandising.	The result of the research is that the proposed model effectively reduces the error in purchasing, with a mean-square percentage error (MSPE) of less than 6%.
15	[61]	AGventure Creating a Sustainable Economy by Reducing Food Surpluses and Food Wastages	Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)	2	The novelty of this research lies in developing the mobile application "AGventure," which integrates multiple solutions for farmers, including crop	The research proposes AGventure, a mobile application leveraging Deep Learning to address food surplus and wastage issues in Sri Lanka through improved crop

No	Author	Title	Method	SDGs	Novelty	Result
		through the Crop Management			selection, price prediction, pest identification, and cloud marketing.	management, price prediction, disease detection, and cloud-based stock forecasting.
16	[62]	Methodology Based on Machine Learning and Deep Learning To Predict Dengue Transmissions	Recurrent Neural Network (RNN)	11 and 13	The novelty lies in correlating flooded areas, climate parameters, and dengue contagion using a decoder recurrent neural network, enabling proactive infection prediction for public health.	The research achieves a prediction model for dengue infection cases in the Castilla district, showcasing the potential for preventive measures and crisis avoidance in regions with similar conditions.
17	[63]	Reflection of EO Data in Blue Economy: Sustainable Growth	Deep Learning	14 and 8	The novelty lies in highlighting the role of Earth Observation (EO) data, including Artificial Intelligence, Machine Learning, and Deep Learning technologies, in revolutionizing emerging sectors of the Blue Economy and efficiently addressing global challenges for sustainable development.	Emphasizes the potential applications of Earth Observation (EO) data, AI, ML, and Deep Learning in promoting Blue Growth and facilitating decision-making for sustainable development in the maritime sector.
18	[64]	A Baselined Gated Attention Recurrent Network for Request Prediction in Ridesharing	Baselined Gated Attention Recurrent Network (BGARN)	11	The novelty of this research lies in the introduction of BGARN, which combines multi-head gated attention, a recurrent module, and a tuning approach to improve prediction accuracy in ridesharing.	The research results show that BGARN outperforms other models in terms of RMSE, MAPE, and MAE for both the Demand and OD tasks.
19	[65]	Long-Term Wind Speed and Power Forecasting Based on LSTM A Comprehensive Study	Attention Based CNN-BiLSTM	7	The novelty of this research lies in the combination of CNN, BiLSTM, and attention mechanism in the proposed model, which improves the accuracy of wind speed and power prediction.	The research results show that the proposed model outperforms existing models, achieving an accuracy of 98.17% for power forecasting.
20	[66]	Deep Learning Approaches for Long-term Global Horizontal Irradiance Forecasting for Microgrids Planning	Recurrent Neural Networks (RNN).	7	The novelty of this research lies in the application of RNNs for long-term solar radiation forecasting, specifically for optimal sizing of off-grid hybrid	The research results show that the proposed RNN approach outperformed the feed-forward neural network (FFNN) approach regarding forecasting

No	Author	Title	Method	SDGs	Novelty	Result
					renewable energy systems.	performance for solar radiation.
21	[67]	Non-intrusive load monitoring A promising path to the society for responsible energy utilization and sustainability	Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN	7 and 11	The novelty of this research lies in the application of non-intrusive load monitoring (NILM) for energy disaggregation, anomaly detection, predictive maintenance, load forecasting, and distributed energy resources in buildings.	Non-intrusive load monitoring (NILM) and the potential applications of NILM in achieving responsible energy utilization and effective energy management for the development of innovative, sustainable cities.
22	[68]	Scale Effects of the Monthly Streamflow Prediction Using a State-of-the-art Deep Learning Model	Hybrid model combining Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU).	13	The novelty of this research lies in its large-scale application of deep learning for monthly streamflow prediction, including numerous watersheds from different climate regimes.	The research results show that the watershed area and the length of the training period influence the predictive performance of the deep learning model. Watersheds with larger drainage areas and more extended training periods tend to have better predictive performance, with median NSE increasing from 0.31 to 0.40 and median MRE decreasing from 53.2% to 46.2% for watersheds with areas larger than 3,000 km2.
23	[69]	Time Series Forecasting of HIVAIDS in the Philippines Using Deep Learning: Does COVID-19 Epidemic Matter	Multilayer Perceptron (MLP)	3	The novelty of this research lies in the use of an ANN model to forecast the monthly incidence of HIV in the Philippines and evaluate the impact of the COVID-19 outbreak on HIV response.	Using a Multilayer Perceptron Neural Network, the study forecasts cumulative HIV/AIDS cases of 145,273 by 2030 in the Philippines during the COVID-19 pandemic, highlighting the effectiveness of deep learning in predicting epidemic patterns.
24	[70]	Wind Speed Forecasting Using Attention-Based Causal Convolutional Network and Wind Energy Conversion	Convolutional Neural Network (CCN)	7	The novelty of this research lies in the combination of Singular Spectrum Analysis (SSA), Convolutional Neural Network (CCN), and Attention Mechanism (ATT) to improve wind speed forecasting accuracy.	The result of the research shows that the proposed SSA-CCN-ATT model outperforms other models in terms of forecasting accuracy, with an improvement of up to 8.7% in Mean Absolute Error (MAE) and 7.9% in

No	Author	Title	Method	SDGs	Novelty	Result
						Root Mean Square Error (RMSE).
25	[71]	Wind Power Prediction Based on Machine Learning and Deep Learning Models	Deep Neural Network (DNN) and Long Short-Term Memory (LSTM)	7	The novelty of this research lies in the proposed optimization approach using particle swarm optimization (PSO) to enhance the performance of the LSTM model for wind power prediction.	The proposed approach achieved the best results among the baseline models, with a Mean Absolute Error (MAE) of 0.000002, Normalized Standard Error (NSE) of 1.2 × 10^(-7), Mean Bias Error (MBE) of 0.00001, R-squared (R2) of 99.99%, and Root Mean Square Error (RMSE) of 0.00002.
26	[72]	Empirical assessment of transformer-based neural network architecture in forecasting pollution trends	Transformer-based neural network architecture called PolTrans.	11 and 13	The novelty of this research is evaluating the performance of the PolTrans model in pollution forecasting and comparing it with other deep learning and statistical models.	The result of the research shows that the PolTrans model performs comparatively better than existing deep learning methods for pollution forecasting in cities like Beijing, Delhi, and Ulaanbaatar but lags behind statistical and machine learning methods by a range of 1.5-15 units in terms of root mean square error.
27	[73]	Intelligent energy storage management trade-off system applied to Deep Learning predictions	Deep Reinforcement Learning	7	The novelty of this research lies in the application of artificial intelligence techniques, specifically Deep Learning and Deep Reinforcement Learning, to predict electricity demand and optimize energy storage management in buildings with photovoltaic generation.	The research demonstrates that deep learning models can accurately predict electricity power consumption and photovoltaic power generation, enabling intelligent energy management and improving energy efficiency in buildings.
28	[74]	A Multiobjective Deep Learning Solution for Optimizing Cooling Rates of Urban Courtyard Blocks in Hot Arid Zones	MLP Regressor, RNN LSTM, and RBFN.	7 and 11	The novelty of this research lies in optimizing urban courtyard blocks in hot and arid zones using deep learning algorithms to predict cooling per square meter while considering the geometric and height aspects of the blocks.	The research results in developing models that can accurately predict cooling per square meter in urban courtyard blocks, contributing to the design of sustainable and energy-efficient urban environments.
29	[75]	Deep learning approach to forecast air	Long Short-Term Memory (LSTM)	3, 7, and 11	The novelty of this research is the development of two	The research results show that the proposed combination

No	Author	Title	Method	SDGs	Novelty	Result
		pollution based on novel hourly index			new indexing methods, the Hourly Relative Mean Index and the Hourly Weighted Index, which simplify the prediction model and improve its performance.	of approaches outperforms traditional methods, achieving superior performance with reduced complexities and requiring fewer inputs for predictions.
30	[76]	Fine-scale characterization of irrigated and rainfed croplands at national scale using multi-source data, random forest, and deep learning algorithms	Deep Neural Network (DNN).	1 and 2	The novelty of this research lies in the comprehensive and spatially explicit methodological framework that integrates low-cost earth observation technologies, multiple data sources, and accurate classification algorithms to identify and map national-scale irrigated and rainfed croplands in South Africa.	The result of the research is that the random forest model achieved a classification accuracy of 0.77 for identifying land-use and land cover types, while the DNN model achieved an accuracy of 0.71 for differentiating rainfed and irrigated croplands at a national scale.
31	[77]	CorrDQN-FS A two-stage feature selection method for energy consumption prediction via deep reinforcement learning	Deep Forest-Deep Deterministic Policy Gradient (DF-DDPG)	7	The novelty of this research lies in the introduction of Correlation-based Deep Reinforcement Learning for Feature Selection (CorrDQN-FS), which integrates correlation analysis and deep reinforcement learning techniques for optimal feature subset selection in energy consumption prediction.	The experimental results demonstrate that CorrDQN-FS outperforms other feature selection techniques, effectively enhancing the accuracy of energy consumption prediction with MAPE 11.688.
32	[78]	A Robust Approach for the Detection of Diabetic Retinopathy at an Early Stage Using Deep CNN	Concatenated neural network based on the Xception and ResNet50v2	3	The novelty of this research lies in using a highly advanced deep convolutional neural network that concatenates two architectures to predict and diagnose diabetic retinopathy at an early stage.	The research achieved an accuracy of 98% in predicting the severity of diabetic retinopathy using the proposed concatenated neural network.
33	[79]	Leveraging topology for domain adaptive road segmentation in satellite and aerial imagery	Deep learning-based automatic segmentation	9	The novelty of this research lies in the proposed topology-aware unsupervised domain adaptation approach for road segmentation in remote sensing imagery, which incorporates	The research results show that the proposed approach outperforms existing state-of-the-art methods by a minimum margin of 6.6% in IoU, 6.7% in F1-score, and 9.8% in APLS for the

No	Author	Title	Method	SDGs	Novelty	Result
					connectivity-based pseudo-label refinement and structural conformity preservation to improve the accuracy of road segmentation in unseen target domains.	SpaceNet to DeepGlobe adaptation.
34	[80]	Mid-Long-Term Prediction of Surface Seawater Organic Carbon in the Southern South China Sea Based on Multi-Applicability CNN-LSTM Prediction Model	CNN-LSTM	13 and 14	The novelty of this research lies in predicting organic carbon in tropical oligotrophic marginal reef seas using the CNN-LSTM model, which has not been done before.	The result of the research shows that the CNN-LSTM model can predict particulate organic carbon (POC) and colored dissolved organic matter (CDOM) in the Liyue Tan area of the Southern East China Sea for up to one year, with Pearson correlation coefficients of 0.514 and 0.524, respectively.
35	[81]	Accurate combination forecasting of wave energy based on multiobjective optimization and fuzzy information granulation	BPnn, NARnn, and LStm	7 and 13	The novelty of this research lies in integrating multiple deep learning models using a multiobjective optimization algorithm, which improves the accuracy and stability of wave height predictions for renewable energy applications.	The research results show that the proposed combined wave height forecasting system outperformed traditional forecasting methods, achieving a lower MAE value of 0.1400 and a higher R2 value of 0.9800.
36	[82]	Theoretical and Methodological Approaches to Analysis and Forecasting of the Labour Market within the Framework of Sustainable Development	XGBoost Deep Learning	8	The novelty of this research lies in its approach of supplementing sustainable development indicators with characteristics of vacancies in the labor market in the context of digitalization.	The research results include developing a conceptual model for labor market analysis and anticipation, combining various databases, and utilizing Big Data and AI technologies, with a forecast error of 7,011.44 and a coefficient of determination of 0.23.
37	[83]	Novel MIA-LSTM Deep Learning Hybrid Model with Data Preprocessing for Forecasting of PM2.5	Long Short-Term Memory (LSTM)	11	The novelty of this research is the proposed MIA-LSTM model, which combines iterative imputation and LSTM for anomaly detection and prediction.	The research results show that the MIA-LSTM model achieved significantly smaller RMSE and MAE values than other models, indicating improved accuracy in predicting

No	Author	Title	Method	SDGs	Novelty	Result
						air pollutant concentrations.
38	[84]	Multi-step short-term solar radiation prediction based on empirical mode decomposition and gated recurrent unit optimized via an attention mechanism	Gated Recurrent Unit (GRU)	7	The novelty of this research lies in the hybridization of the empirical mode decomposition (EMD), GRU, and attention mechanism to enhance solar radiation prediction performance.	The research results show that the proposed EGA model achieved an R2 of 0.983, 0.972, and 0.960 for one to three-step solar radiation forecasting, respectively.

Interpreting the findings from Table 1 within the broader SDGs framework reveals the significant potential of deep learning methodologies in addressing complex sustainability challenges. These findings hold crucial implications for policymakers and decision-makers, offering actionable insights essential for informed interventions. Firstly, many of the studies directly contribute to specific SDGs, such as those focused on air quality forecasting and renewable energy prediction, aligning with goals related to clean energy and sustainable cities [51], [53], [66]. The integration of deep learning with other methodologies, as demonstrated in various studies, underscores the interconnectedness of SDGs and emphasizes the importance of holistic approaches to achieve sustainable development targets [48], [84].

The superior performance of deep learning models in forecasting indicators like disease transmission and energy demand provides valuable decision support for policymakers [51], [57], [69], [75]. Accurate predictions enable proactive measures to mitigate risks and design targeted interventions, particularly crucial during health crises like the COVID-19 pandemic. Additionally, the data-driven nature of deep learning facilitates evidence-based policy formulation by leveraging diverse data sources to gain comprehensive insights into sustainability trends [51], [53], [66], [75]. This approach enhances the effectiveness and efficiency of policy interventions aimed at achieving SDGs.

Furthermore, the adoption of deep learning fosters innovation and collaboration across disciplines, accelerating the development of scalable solutions with broader applicability [48], [51], [66]. By identifying marginalized communities at risk and designing targeted interventions, deep learning methodologies also contribute to promoting equity and inclusion in sustainable development efforts [51], [57], [69], [75]. In conclusion, the findings underscore the transformative potential of deep learning in advancing sustainable development, offering a pathway to a more resilient and equitable future through informed policy-making and decision support.

The integration of deep learning with domain-specific knowledge from fields such as ecology, public health, and economics offers a promising avenue for addressing complex sustainability challenges [73], [76], [83]. By combining the computational capabilities of deep learning with the nuanced understanding provided by experts in these domains, interdisciplinary collaboration can lead to more holistic and impactful solutions. For instance, in ecology, deep learning algorithms can analyze ecological data to inform conservation efforts and ecosystem management practices while incorporating ecological principles ensures that predictive models account for factors such as habitat loss and biodiversity conservation [66], [82]. Similarly, in public health, the integration of deep learning with epidemiological knowledge enables the development of predictive models for disease outbreaks and healthcare resource optimization, facilitating proactive interventions and improved population health outcomes [57], [69], [73], [85].

Moreover, in economics, deep learning techniques can analyze socioeconomic data to inform policy-making and sustainable development planning, with input from economists ensuring that predictive models account for economic dynamics and market behavior [48], [59], [82]. By emphasizing interdisciplinary collaboration and knowledge integration across these diverse fields, researchers can develop comprehensive strategies that address the interconnected environmental, social, and economic dimensions of sustainability challenges. This collaborative approach not only enhances the relevance and impact of research outcomes but also fosters innovation in addressing multifaceted sustainability issues, ultimately contributing to a more resilient and equitable future.

Several limitations and challenges accompany the application of deep learning in addressing SDGs. These include the requirement for large volumes of high-quality data [81], concerns about data bias and accuracy [72], challenges related to interpretability and transparency due to the black-box nature of deep learning algorithms [80], and the need for substantial computational resources [79]. Additionally, issues such as the potential exacerbation of inequalities and biases, ethical considerations regarding privacy and fairness, and the need for capacity building and knowledge transfer pose significant challenges [69], [74], [75], [77]. Addressing these limitations will necessitate interdisciplinary collaboration, robust governance frameworks, and ongoing investment in capacity building to ensure that deep learning contributes effectively to sustainable development goals.

3.1. RQ 1: What Specific Deep Learning Methods are Utilized in Forecasting within the Scope of SDGs, and How do They Contribute to Addressing the Multifaceted Challenges Outlined in the SDGs?

The objective of RQ 1 is to analyze the various deep learning methods employed in SDG prediction. This investigation seeks to provide a comprehensive understanding of the various deep-learning methods used to address SDG forecasting challenges.

The research in Table 1 exemplifies a wide array of deep learning methodologies employed to estimate outcomes within SDGs. These techniques include established frameworks like LSTM [47], [52], [54], [75], [83], CNN [49], [53], GRU [84], and other comparable methods [58], [64], [68]. Each of these techniques has unique features, with LSTM being well-known for its ability to capture long-term dependencies [86], CNN for its effectiveness in processing spatial data [87], and GRU for its efficiency in swiftly handling sequential information [88].

Furthermore, the research highlights the resourcefulness and adaptability of deep learning models for specific prediction tasks. Prominent examples encompass using LSTM and GRU to anticipate under-five mortality rates [50], applying CNN to predict air quality in urban settings [53], and developing a hybrid model that integrates empirical mode decomposition with GRU for solar radiation prediction [84], [89]. The extensive array of deep learning methodologies illustrates the versatility of these techniques in addressing the complex and varied challenges associated with SDGs.

In addition, RQ 1 reveals a diverse array of advanced deep learning methods being employed to tackle forecasting difficulties within the framework of SDGs. The findings indicate that scholars are employing diverse frameworks, tailoring them to tackle specific challenges within sustainable development, and contributing to the growing body of knowledge in deep learning and forecasting for SDGs. The distribution of deep learning methods across different SDG domains is shown in Table 2.

From Table 2, LSTM is the most often employed deep learning method for forecasting related to SDGs in RQ 1. The popularity of LSTM has increased because of its capacity to accurately model sequential and time-series data, making it highly suitable for forecasting applications [90]. Although deep learning methods are widely used, it is crucial to thoroughly investigate other approaches to grasp their advantages and limitations [91]. In order to enhance the variety of techniques employed and mitigate excessive dependence on LSTM, researchers may explore other designs, including GRU, CNN, Bidirectional LSTM (BiLSTM), and Transformer-based models.

In order to make use of these various methodologies, researchers might conduct comparison studies to evaluate their effectiveness in specific forecasting scenarios. Every deep learning architecture possesses distinct attributes that might render it more appropriate for particular data kinds or specific forecasting assignments [92]. For example, CNN is adept at capturing spatial relationships [93], BiLSTM models consider the context from both directions [94], and Transformer-based models excel in capturing long-range relationships in sequential data [95].

Table 2. Distribution of deep learning methods across different SDGs

Number	SDGs	LSTM	CNN	RNN	GRU	Bi-LSTM	Other Methods
1	No poverty	0	0	0	0	0	1
2	Zero hunger	1	0	1	0	0	1
3	Good health and well-being	2	1	0	0	1	2
4	Quality education	0	0	0	0	0	0
5	Gender equality	0	0	0	0	0	0
6	Clean water and sanitation	0	1	0	0	0	0
7	Affordable and clean energy	6	3	4	2	2	3
8	Decent work and economic growth	1	2	1	1	1	1
9	Industry, innovation, and infrastructure	1	3	0	0	0	0
10	Reduced inequalities	0	0	0	0	0	0
11	Sustainable cities and communities	5	2	3		1	3
12	Responsible consumption and production	0	0	0	0	0	1
13	Climate action	2	2	1	1	0	1
14	Life below water	2	2	1	1	1	0
15	Life on land	0	0	0	0	0	0
16	Peace, justice and strong institutions	0	0	0	0	0	0
17	Partnerships for the goals	1	0	0	0	0	0
	Total	21	16	11	5	6	13

Collaborative initiatives to provide benchmark datasets and standardized assessment criteria might be advantageous for the research community in promoting various deep learning approaches. In addition, it is possible to provide teaching materials, seminars, and tutorials to acquaint researchers with the use and enhancement of different deep learning structures. By cultivating a climate of trial and investigation, researchers may make well-informed decisions on the most appropriate techniques for achieving their particular forecasting goals within the context of the SDGs.

The discussion extensively covers various deep learning methodologies commonly employed in SDG forecasting, including LSTM, CNN, RNN, GRU, and Bi-LSTM. However, it is essential to evaluate the limitations and challenges associated with each method critically. LSTM, while popular for its ability to capture long-term dependencies, faces challenges such as the vanishing gradient problem and computational complexity [96]. CNNs, effective in capturing spatial relationships, may struggle with variable-length sequential data and are prone to overfitting, particularly with small datasets [97]. Traditional RNNs suffer from short-term memory limitations and training instability, albeit partially mitigated with LSTM and GRU variants [98]. GRUs offer computational advantages but may have reduced modeling capacity [99], while Bi-LSTMs, though capable of capturing bidirectional context, incur increased computational complexity and are susceptible to overfitting [100]. These limitations underscore the importance of careful consideration and exploration of strategies to address them in order to enhance the reliability and performance of deep learning-based forecasting models within the context of SDGs.

Although LSTM is still widely used, researchers may improve the reliability and versatility of prediction models by investigating and using different deep-learning techniques. This technique guarantees a more comprehensive comprehension of the advantages and constraints of various designs, ultimately aiding the progress of forecasting approaches within the framework of SDGs.

It is important to take into account potential biases or limitations that may exist in the studies reviewed when discussing deep learning methodologies in SDG forecasting. One notable aspect is the uneven representation of SDG domains and geographic regions within the literature. Certain SDG domains or specific targets may be overrepresented while others are underrepresented, leading to potential biases in the applicability of deep learning methods across different contexts. For example, studies focusing on health-related SDGs, such as maternal and child health or infectious diseases, might be more prevalent compared to those addressing environmental sustainability or economic development goals. Additionally, there may be geographic biases, with research primarily focused on regions with better data availability or more research infrastructure, potentially neglecting the needs and challenges of underserved regions. Acknowledging these biases is essential for obtaining a more balanced perspective on the effectiveness and generalizability of deep learning methods for SDG forecasting across diverse domains and geographic contexts. Further efforts to address these biases can enhance the inclusivity and relevance of forecasting research within the SDG framework.

3.2. RQ 2: Which Fields or Domains within the SDGs Have Been Extensively Researched using Deep Learning Models for Forecasting, and What are the Key Findings and Advancements in Each Domain?

RQ 2 investigates the precise domains within the SDGs that have been extensively examined using deep learning models to make predictions. This analysis explores several domains under the SDGs that have undergone extensive examination by utilizing deep learning methodologies.

The SDGs are a collection of 17 worldwide objectives established (Fig. 4) by the United Nations to tackle diverse issues and enhance the welfare of humanity and the environment [101]. These goals encompass various domains: poverty, health, education, climate action, and other areas. The significance of the SDGs resides in its comprehensive approach to establishing a sustainable and inclusive future for all individuals [102]. Comprehending and evaluating the advancement towards these objectives is crucial for efficient decision-making and policy execution.

Fig. 4. 17 Sustainable development goals (SDGs)

Table 3 shows 17 worldwide objectives established and their application. From Table 2, the study of SDG 7 (Affordable and Clean Energy) has gained significant attention in academics because of its central role in tackling the urgent global issue of ensuring sustainable access to energy. The objective's focus on guaranteeing accessible and sustainable energy aligns with the urgent requirement for eco-friendly measures, given the growing apprehensions about climate change [62], [68]. The multidisciplinary aspect of SDG 7 appeals to experts from diverse professions, promoting a comprehensive comprehension of the intricate matters related to sustainable energy. The progress in renewable energy technology and smart grid solutions has generated increased attention [66], [66], [81], as the tangible social and economic advantages linked to clean energy inspire academics to contribute to this crucial worldwide initiative. The worldwide community's dedication to addressing climate change offers a cooperative structure, highlighting SDG 7 as a crucial study field that enhances academic understanding and contributes to policy-making and industrial practices, resulting in significant beneficial effects.

From Table 3, SDG 7, emphasizing Affordable and Clean Energy, stands out among the Sustainable Development Goals due to its global significance and multidisciplinary appeal. The urgent need to address climate change, coupled with the imperative to ensure access to sustainable energy sources, renders SDG 7 a focal point for researchers, policymakers, and practitioners worldwide. Its prominence stems from the recognition of energy access as a fundamental driver of socioeconomic development and environmental sustainability. Moreover, the tangible economic and social benefits associated with clean energy investments, including job creation and improved public health, incentivize extensive research and innovation in this domain. Rapid technological advancements in renewable energy and energy efficiency further fuel interest in exploring solutions aligned with SDG 7 targets. Policy attention and dedicated funding opportunities, alongside the presence of measurable indicators for tracking progress, provide a robust framework for research initiatives aimed at advancing affordable and clean energy access on a global scale.

Table 3. 17 worldwide SDGs established and their application

Number	SDGs	Paper	Number of Paper
1	No poverty	[76]	1
2	Zero hunger	[61] [76]	2
3	Good health and well-being	[50] [57] [69] [75] [78]	5
4	Quality education	-	0
5	Gender equality	-	0
6	Clean water and sanitation	[49]	1
7	Affordable and clean energy	[51] [54] [55] [56] [65] [66] [67] [70] [71] [73] [74] [75] [77] [81] [84]	15
8	Decent work and economic growth	[48] [63] [82]	3
9	Industry, innovation, and infrastructure	[58] [59] [79]	3
10	Reduced inequalities	-	0
11	Sustainable cities and communities	[47] [53] [57] [62] [64] [67] [72] [74] [75] [83]	10
12	Responsible consumption and production	[60]	1
13	Climate action	[62] [72] [80] [81]	4
14	Life below water	[63] [80]	2
15	Life on land	-	0
16	Peace, justice and strong institutions	-	0
17	Partnerships for the goals	[52] [68]	2

In order to conduct a more thorough analysis of other SDG statistics, researchers might implement other measures. Initially, they should broaden their attention by choosing SDGs corresponding to various sectors and disciplines. The collaboration of academics with expertise in different SDGs can enhance information sharing and multidisciplinary methodologies. Incorporating insights from interdisciplinary collaborations can significantly enhance the accuracy and relevance of SDG forecasting research. By integrating expertise from fields such as economics, sociology, and environmental science into deep learning models, researchers can gain a more comprehensive understanding of the complex dynamics underlying sustainable development. Ensuring data availability is a crucial aspect (Table 4), and researchers should proactively engage in discovering or contributing to creating unexplored datasets connected to the SDGs.

Table 4 outlines the status of SDGs dataset collections across prominent platforms such as UCI Machine Learning, Kaggle, and Google Search. While some SDGs exhibit comprehensive dataset coverage, denoted by checkmarks (√), others marked with (x) indicate potential gaps or limited availability. In light of this information, researchers are encouraged to proactively engage in discovering or creating datasets for the underrepresented SDGs, fostering a more balanced and inclusive approach to research. This collaborative endeavor addresses existing data gaps and lays the foundation for more comprehensive and robust investigations into the multifaceted challenges the SDGs encompass. Researchers can advance knowledge and generate actionable insights for sustainable development by leveraging diverse platforms and contributing to dataset development.

To summarise, academics should proactively broaden their scope of study, foster interdisciplinary collaboration, and contribute to developing datasets about less explored SDGs, notwithstanding the potential bias towards more extensively researched SDGs driven by data availability and global importance. This methodology guarantees a fair and thorough comprehension of how deep learning may contribute to predicting all aspects of the SDGs.

Table 4. SDGs Dataset Collection Information

Number	SDGs	UCI Machine Learning	Kaggle	Google Search
1	No poverty	x	√	√
2	Zero hunger	x	√	√
3	Good health and well-being	√	√	√
4	Quality education	√	√	√
5	Gender equality	√	√	√
6	Clean water and sanitation	√	√	√
7	Affordable and clean energy	√	√	√
8	Decent work and economic growth	√	√	√
9	Industry, innovation, and infrastructure	√	√	√
10	Reduced inequalities	x	x	√
11	Sustainable cities and communities	x	x	√
12	Responsible consumption and production	√	√	√
13	Climate action	x	√	√
14	Life below water	x	√	√
15	Life on land	X	√	√
16	Peace, justice and strong institutions	x	x	√
17	Partnerships for the goals	x	x	x

3.3. RQ 3: What are the Existing Deficiencies or Limitations in Current Deep Learning Forecasting Methodologies within the Context of SDGs, and What Potential Avenues for Improvement Can Be Identified to Enhance the Effectiveness and Applicability of these Methodologies in Addressing SDG-Related Challenges?

RQ 3 aims to discover possible ways to enhance forecasting by utilizing deep learning techniques in the context of SDGs. The objective is to determine how these findings might influence future research and development endeavors. This inquiry seeks to identify areas for improvement to boost the efficacy of deep learning models in their contribution towards attaining SDGs.

The examination of the chosen studies in Table 1 reveals many possible opportunities for enhancing the use of deep learning in projecting SDGs. The primary focus is on the recurring topic, highlighting the necessity for ongoing improvement and optimization of deep learning models. This involves investigating innovative structures, enhancing current algorithms, and using sophisticated methods like attention processes [58], [64], [65], [70], [84] and feature engineering [51], [77] to enhance prediction precision.

The results indicate the significance of tailoring to various domains. Customizing deep learning models to the distinct attributes of each SDG area and integrating domain expertise can significantly augment the models' pertinence and efficacy. An example of domain-specific customization is creating a self-adaptive cellular-based deep-learning analysis method that predicts urban land use changes [47]. This method incorporates intra-entity and inter-geographic causal relationships in its forecasting framework, demonstrating its potential for sustainable development goals.

Enhancing the interpretability and transparency of deep learning models is essential for fostering trust and accountability in the forecasting process. Techniques such as attention mechanisms and model visualization can provide insights into the factors driving predictions and help identify areas where biases may be present [103]. Transparent reporting of model performance metrics and validation procedures further promotes accountability and enables stakeholders to assess the reliability and fairness of model predictions.

Beyond technical considerations, interdisciplinary collaboration with experts in ethics, sociology, and policy is critical for navigating the ethical complexities inherent in SDG forecasting. Community engagement processes, such as participatory modeling workshops and stakeholder consultations, can facilitate mutual understanding and trust between model developers and stakeholders, leading to more inclusive and socially responsible forecasting practices.

Establishing ethical guidelines and governance frameworks for SDG forecasting using deep learning provides a necessary framework for addressing ethical considerations and promoting the responsible use of predictive technologies. By integrating these broader socio-economic and ethical considerations into the discussion of improvement opportunities, researchers and practitioners can contribute to the development of more equitable, transparent, and socially responsible predictive models that support sustainable development goals.

Scalability and generalizability are crucial considerations for deploying deep learning models in diverse geographical or socio-economic contexts for forecasting SDGs. Resource constraints, including limited data availability, computational resources, and technical expertise, pose significant challenges to model deployment. Addressing these challenges requires multi-faceted strategies, such as enhancing data accessibility, investing in scalable computing infrastructure, and fostering technical capacity-building efforts.

Ensuring the transferability of models across different contexts demands careful validation and adaptation processes that account for contextual variability and stakeholder perspectives. By integrating technical innovation with socio-economic considerations, we can overcome these challenges and harness the transformative potential of deep learning for sustainable development.

The findings of the study hold significant implications for future research, policy development, and practical applications in sustainable development. By identifying scalability and generalizability challenges, the study emphasizes the need for targeted research efforts to overcome barriers in deploying deep learning models, particularly in resource-constrained environments. Policy development stands to benefit from incorporating data-driven insights into decision-making processes, enabling more effective allocation of resources and tracking of progress towards sustainable development goals.

Additionally, the practical applications of deep learning models span various domains, including environmental conservation, socio-economic development, and disaster preparedness, offering opportunities to inform policy interventions and enhance resilience in the face of complex challenges. Ultimately, leveraging the insights gained from the study can contribute to more equitable and sustainable development outcomes by harnessing the power of predictive technologies and multi-stakeholder collaboration.

4. Case Study SDGs Forecasting: Energy Usage

According to the results of RQ2, Affordable and Clean Energy (SDG number 7) is the most numerous SDG field used for forecasting in research using deep learning. So, in this article, we also conduct a case study of energy usage forecasting using various deep learning methods. The hourly energy demand generation and weather dataset from Kaggle was the source of the dataset utilized in this research [104]. This dataset contains statistics on electricity production, pricing, use, and climatic conditions in Spain for four years (January 2015 to December 2018). This dataset consists of 29 attributes with 35064 instances with the float data type. The target attribute used in this study is the actual total load attribute. Deep learning methods include RNN [8], LSTM [105], Bi-LSTM [22], GRU [24], and CNN [106].

RNNs are a class of neural networks designed for sequential data processing, making them suitable for tasks where the order of inputs matters. LSTM is a specialized RNN architecture capable of learning long-term dependencies and is particularly effective in handling sequential data with long-range dependencies. Bi-LSTM extends LSTM by processing input sequences in forward and backward directions, capturing contextual information from past and future time steps. GRU is another variant of RNNs designed to address some limitations of traditional RNNs, with simpler architecture and faster training times. CNNs are primarily used for image processing tasks but can also be applied to sequential data by treating input sequences as images. The setting of each parameter of the deep learning method is obtained from the results of grid search hyperparameter tuning, as shown in Table 5.

The provided case study involves the application of various deep learning and machine learning models for a specific task, with the evaluation metrics being Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R2) value, as in Table 6.

Table 5. Setting of hyperparameter

Parameter	Value
Batch Size	100
Epoch	50
Hidden Layer	2
Loss Function	MSE
Neuron	32
Optimizer	Rmsprop

Table 6. Setting of hyperparameter

Method	MAPE (%)	RMSE	R2	Computational Time (s)
RNN	3.990	0.065	0.894	195
LSTM	3.946	0.064	0.899	173
Bi-LSTM	8.637	0.134	0.854	203
GRU	4.075	0.067	0.885	217
CNN	4.946	0.077	0.847	113
MLP	9.321	0.688	0.805	271
BPNN	9.245	0.674	0.845	264

From Table 6, the provided metrics show that deep learning models (RNN, LSTM, Bi-LSTM, GRU, and CNN) consistently outperform traditional machine learning models (MLP and BPNN) across all evaluation metrics. Specifically, deep learning models exhibit lower MAPE and RMSE values, indicating better accuracy in predicting the outcome variable. Moreover, deep learning models achieve higher R2 values (0.847-0.899), implying a better fit of the model to the observed data.

This superiority of deep learning models can be attributed to their ability to effectively capture complex patterns and dependencies in the data, especially in sequential data tasks like forecasting. The specialized architectures of deep learning models, such as LSTM and Bi-LSTM, enable them to retain and utilize long-term information, leading to more accurate predictions. Additionally, CNNs can capture spatial patterns in sequential data, further enhancing their predictive capabilities. In contrast, traditional machine learning models like MLP and BPNN may struggle to capture the intricate relationships in the data, particularly in sequential tasks where temporal dependencies are crucial. Their relatively simple architectures and lack of memory make them less suitable for such tasks, resulting in inferior performance compared to deep learning models.

To increase the contribution of the research, let us compare the results obtained in the given case study with the results of similar methods used in previous studies. Because the best results in this experiment belong to LSTM, we also compare the performance of LSTM in forecasting using the same energy data belonging to Guo et al. with the title “An Empirical Study of AI Model's

Performance for Electricity Load Forecasting with Extreme Weather Conditions" [107]. The evaluation metric used in their work only uses MAPE values, whereas in our study, besides using MAPE, there are also RMSE, R2, and computational time.

Although a direct comparison of metrics cannot be performed due to the differences in tasks, we can highlight that both studies demonstrate the effectiveness of LSTM in time series prediction tasks. The results of their research showed a high MAPE of 7.873%, while in our study, the MAPE was smaller, namely 3.946%. The smaller the MAPE, the better the forecasting results.

By comparing the results with similar methods from previous studies, the research contribution is enhanced by validating the effectiveness of deep learning, primarily LSTM, in energy usage estimation while providing context in the broader literature regarding time series prediction tasks. This comparison strengthens the case for applying deep learning models, especially LSTMs, in real-world applications such as energy usage forecasting.

Deep learning models generally require more computational resources and longer training times compared to traditional machine learning models due to their complex architectures and the need to process large volumes of data. However, in the case study provided in Table 5, it is notable that certain deep learning architectures, such as CNN, exhibit relatively faster training times (113 seconds) compared to others like MLP (271 seconds). This highlights the efficiency of specific deep learning architectures in processing sequential data, leveraging techniques such as parallelization and convolutional operations to expedite computation.

Despite the inherent complexity of deep learning models, advancements in hardware acceleration techniques and distributed computing frameworks have contributed to reducing training times, making them more feasible for real-world applications. Therefore, while deep learning models generally entail higher computational costs, their ability to process data in parallel and exploit spatial and temporal dependencies efficiently often results in faster processing times compared to traditional machine learning models, especially in tasks involving large-scale datasets and complex patterns.

Overall, the results of this case study highlight the effectiveness of deep learning models, particularly RNN, LSTM, Bi-LSTM, GRU, and CNN, in predictive modeling tasks, showcasing their superiority over traditional machine learning models like MLP and BPNN in terms of accuracy and predictive performance.

Enhancing the interpretability of deep learning models in critical domains such as energy usage forecasting is essential to instill trust and facilitate their adoption by stakeholders, policymakers, and end-users. Various strategies can be employed to achieve this goal. Firstly, conducting feature importance analysis and visualizing the model's internal mechanisms provide insights into which input features drive the model's predictions and how information is processed over time or across spatial dimensions. Sensitivity analysis further elucidates the model's behavior by assessing the impact of changes in input variables on predictions.

Comprehensive documentation of the model's architecture, training process, and evaluation metrics, coupled with clear communication of outputs and uncertainty estimates, promotes transparency and builds trust among stakeholders. Moreover, involving domain experts throughout the model development process ensures that predictions are grounded in domain-specific knowledge and align with real-world phenomena, enhancing the relevance and interpretability of the model's outputs. By employing these strategies, stakeholders can interpret and trust the predictions generated by deep learning models, fostering informed decision-making in critical domains like energy usage forecasting.

5. Recommendation and Future Research

In light of the findings from this systematic literature review (SLR), it is imperative to chart a clear path forward for advancing the field of SDG forecasting through integrating deep learning techniques and robust missing value imputation methods. The thematic map presented in Fig. 5

delineates the current landscape, indicating a promising intersection between deep learning forecasting and SDGs, albeit with varying levels of investigation.

Recognizing the potential opportunities unearthed by this SLR, it is essential to delineate actionable steps for future research endeavors. First and foremost, researchers should prioritize the development of practical implementation strategies that bridge the gap between theoretical insights and real-world applications. Concrete examples, case studies, and implementation guidelines can facilitate the adoption of deep learning techniques in SDG forecasting initiatives.

Moreover, while deep learning models offer promising capabilities in handling missing values, it is imperative to acknowledge their inherent limitations and challenges. Researchers must address model interpretability, scalability, and generalization concerns, ensuring that forecasting models remain robust and reliable in diverse real-world scenarios. Additionally, the complexities associated with deep learning methodologies necessitate careful consideration of computational resources, data requirements, and expertise for model training and deployment.

Furthermore, integrating deep learning techniques with missing value imputation methods should not overshadow broader socio-economic, ethical, and regulatory considerations. Researchers must prioritize data quality, integrity, and transparency, ensuring that forecasting initiatives uphold fairness, accountability, and inclusivity principles. Collaborative efforts between researchers, policymakers, and stakeholders can foster greater alignment between technical solutions and societal needs, promoting responsible innovation in SDG forecasting.

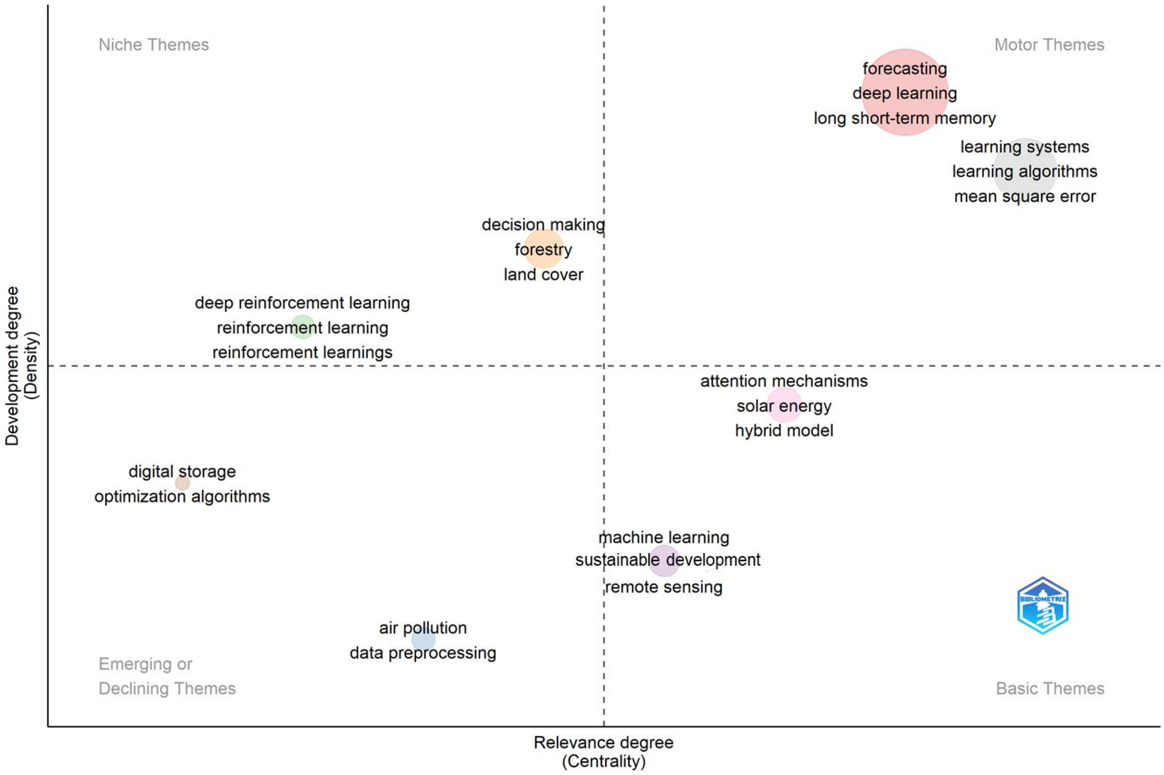

Fig. 5. Thematic map based on selected publication articles

Empirical validation studies are paramount to substantiating the efficacy and performance of deep learning-based forecasting models in SDG contexts. Rigorous evaluation frameworks, benchmarking protocols, and validation metrics can provide empirical evidence of model effectiveness and guide decision-making processes. Moreover, longitudinal studies can elucidate the long-term impact of forecasting initiatives, informing iterative improvements and adaptive strategies over time.

When considering future research paths and addressing the gaps identified in this SLR, it is crucial to recognize the potential opportunities for advancing the field of Forecasting Deep Learning concerning SDGs. The theme map depicted in Fig. 5 highlights that research on deep learning forecasting related to SDGs predominantly falls within the third and fourth quadrants

From Fig. 5, this positioning suggests that while deep learning techniques, particularly the Long Short-Term Memory (LSTM) approach, have gained prominence in forecasting research (fourth quadrant), the exploration of SDGs remains relatively understudied and emerging (third quadrant). Possible explanations for the underrepresentation of SDGs in deep learning forecasting research could include data availability and quality challenges, as SDGs encompass diverse socio-economic, environmental, and health indicators that may not be readily accessible or standardized across regions. Additionally, the complexity of forecasting interactions between various SDGs and their interconnected nature may pose methodological challenges that require innovative approaches and interdisciplinary collaboration. Therefore, future research endeavors should address these gaps by leveraging advancements in deep learning methodologies, enhancing data collection efforts, and fostering interdisciplinary partnerships to facilitate comprehensive and accurate forecasting of SDGs.

To foster interdisciplinary research collaboration in the field of SDG forecasting using deep learning techniques, specific initiatives and funding mechanisms can be established. Firstly, dedicated interdisciplinary research grants should be introduced by funding agencies to support collaborative projects involving experts from diverse fields such as data science, environmental science, public health, economics, and policy-making. These grants would target projects focused on developing innovative deep learning-based forecasting models tailored to address specific SDGs. Additionally, organizing interdisciplinary workshops and conferences dedicated to SDG forecasting and deep learning would provide platforms for researchers to exchange ideas, share expertise, and establish collaborative networks. Funding could be allocated to support the organization of such events, including travel grants for researchers from underrepresented regions.

Moreover, establishing online collaborative platforms and data-sharing initiatives dedicated to SDG forecasting could facilitate data sharing, collaboration, and knowledge exchange among researchers. These platforms would receive funding to develop and maintain them, ensuring accessibility and usability for researchers worldwide. Furthermore, investing in training and capacity-building programs aimed at building interdisciplinary skills in SDG forecasting and deep learning would foster collaboration among researchers from diverse backgrounds. These programs would receive funding to support workshops, courses, and mentorship initiatives focused on interdisciplinary research methods and data science techniques. Lastly, establishing joint research centers or institutes dedicated to SDG forecasting and deep learning would provide physical spaces for interdisciplinary collaboration and innovation, bringing together researchers, practitioners, policymakers, and stakeholders to work on cutting-edge research projects and develop practical solutions [108]. Through the implementation of these initiatives and funding mechanisms, stakeholders can support and promote interdisciplinary collaboration in SDG forecasting, ultimately advancing our understanding of sustainable development challenges and informing evidence-based decision-making processes.

Aside from the recognized research possibilities, addressing a crucial element sometimes disregarded in deep learning forecasting, specifically with time-series data containing missing values, is crucial. There is a widespread misunderstanding that ignoring missing values in time-series data is acceptable since deep learning models can effectively handle sequential data [109]. However, when it comes to time-series forecasting, dealing with missing values becomes a crucial step in the preprocessing phase before starting the forecasting process.

Contrary to the common perception that missing values may not matter, particularly in deep learning, it is essential to emphasize that meticulous management of missing values is vital for precise time-series forecasting. This entails utilizing many therapeutic modalities, with imputation emerging as a notable strategy [110]. Imputation is particularly significant since it offers advantages over other approaches to handling missing values.

The indication for the opportunity in innovative research lies in the visualization provided by Fig. 5, which underscores the growing subject of data preparation optimization for managing missing values in SDG-related data. This visualization suggests a notable gap in current research, where integrating deep learning within the context of SDGs, coupled with advanced data preparation techniques, could significantly contribute to the scientific knowledge base. By addressing missing values and improving data quality, researchers can enhance the robustness and reliability of forecasting models tailored to SDGs, facilitating more accurate predictions and informed decision-making processes. This paper advocates for integrating deep learning forecasting techniques with a specific focus on SDGs, complemented by improved data preparation tools, as a novel and influential direction for future research endeavors. Such an approach aligns with the broader goal of promoting sustainable development by applying innovative technological methods, ultimately driving positive societal impact and progress toward achieving the SDGs.

This nuanced viewpoint on handling missing values in time-series data emphasizes the significance of integrating thorough preprocessing techniques into the deep learning forecasting framework, particularly in the context of SDGs. Hence, future research efforts in deep learning forecasting for SDGs should incorporate and utilize sophisticated missing value treatment techniques like imputation to improve their forecasting models' reliability and precision. Acknowledging and incorporating methods for addressing missing values align with the overarching goal of improving SDG forecasting approaches through careful data preparation procedures.

Deep learning holds significant potential in imputing missing values within datasets across various domains. Imputation of missing values is a crucial step in data preprocessing, especially in scenarios where missing data can significantly impact downstream analysis and modeling. Applying deep learning techniques in this context offers several advantages, as shown in Fig. 6.

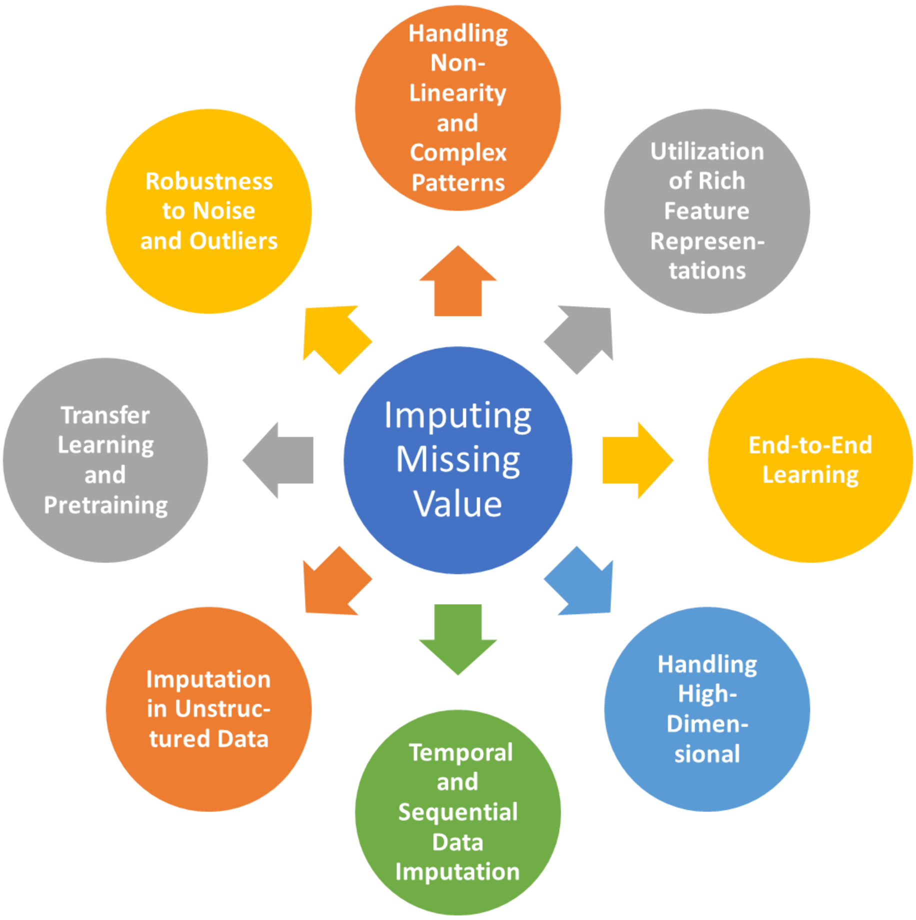

Fig. 6. Deep learning potential in imputing missing value

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From Fig. 6, deep learning models can first handle non-linearity and complex patterns. Their ability to capture complex nonlinear relationships within data makes them well-suited for imputing missing values, particularly in datasets with intricate patterns. Traditional imputation techniques may struggle to capture such complexities effectively.

Second, utilize rich feature representations. Deep learning models can automatically learn and extract rich feature representations from the data, which can be leveraged to impute missing values accurately. By encoding the underlying structure of the data, deep learning models can capture latent dependencies between variables.

Third, deep learning frameworks enable end-to-end learning. Where the model learns the imputation task directly from the data without relying on handcrafted features or preprocessing steps, this facilitates a more streamlined and efficient imputation process.

Fourth, deep learning models can handle high-dimensional data effectively and make them suitable for imputing missing values in datasets with a large number of features. This scalability is advantageous in modern datasets from various sources, such as sensor data, images, and text.

Fifth, deep learning can handle temporal and sequential data imputation; for datasets containing temporal or sequential data, recurrent neural networks (RNNs) and their variants (e.g., LSTM, GRU) can be employed to impute missing values while considering the temporal dependencies inherent in the data. This is especially useful in time series datasets or sequences where missing values may occur intermittently.

Sixth, deep learning can be used for imputation in unstructured data. Deep learning techniques, such as convolutional neural networks (CNNs), excel in processing unstructured data, such as images, audio, and text. These models can be adapted to impute missing values in unstructured datasets, where traditional imputation methods may not be applicable.

Seventh, the transfer learning and pretraining techniques can leverage knowledge from large, pre-trained deep learning models for imputation tasks. By fine-tuning pre-trained models on domain-specific data, researchers can improve imputation performance, especially in scenarios with limited labeled data.

Last, the deep learning models inherently exhibit robustness to noise and outliers in the data, which can be beneficial for imputing missing values in noisy datasets or datasets with outliers. The model's ability to learn robust representations helps mitigate the impact of noisy or erroneous data points on the imputation process.

Overall, the potentials of deep learning in imputing missing values lie in its ability to capture complex patterns, leverage rich feature representations, handle high-dimensional and sequential data, and adapt to various types of datasets. As research in deep learning continues to advance, further improvements in imputation techniques are expected, ultimately enhancing the reliability and accuracy of imputed datasets for downstream analysis and decision-making.

Ensuring transparency, accountability, and fairness in the development and deployment of deep learning-based forecasting models for SDGs is essential for upholding ethical standards and fostering trust among stakeholders. One strategy to achieve this is by promoting open data and code-sharing practices, encouraging researchers to openly share datasets, code, and model architectures to facilitate transparency and reproducibility. Additionally, integrating explainable AI techniques into deep learning models enhances transparency by providing interpretable explanations for model predictions. Ethical guidelines and standards should be developed and adhered to, addressing issues such as data privacy, bias mitigation, and algorithmic fairness. Implementing robust mechanisms for bias detection and mitigation is crucial to ensure fairness and equity, while community engagement and stakeholder consultation promote transparency and accountability by involving affected communities in the decision-making process. Algorithmic governance and oversight mechanisms, such as independent review boards, provide guidance and accountability for forecasting initiatives. Continuous monitoring and evaluation systems enable ongoing assessment of model performance and impact, supporting iterative improvements and ensuring adherence to ethical principles and regulatory requirements throughout the forecasting process. These strategies collectively contribute to building trust, promoting ethical conduct, and enhancing the societal value of deep learning-based forecasting models for SDGs.

6. Conclusion

In conclusion, this SLR has illuminated the promising application of deep learning methodologies in forecasting within the framework of SDGs. By delineating key areas for improvement, such as enhancing precision, reliability, and contextual awareness of forecasting models, our findings underscore the potential to significantly bolster their efficacy in supporting sustainable development initiatives. There is a critical need to foster continued exploration at the intersection of deep learning and SDGs, particularly focusing on integrating imputation techniques to address data-related challenges. Furthermore, the newly formulated theoretical contributions of this study lie in its emphasis on the integration of imputation techniques with deep learning models, presenting a promising avenue for advancing forecasting frameworks within the context of SDGs.

While this SLR provides a solid foundation for future research endeavors, it is essential to acknowledge its limitations, such as potential biases in study selection and constraints in data availability due to using only the Scopus database. Despite these constraints, the study's unique contributions to the existing body of knowledge are significant, particularly in highlighting the potential impacts of more reliable and precise forecasting models on sustainable development initiatives. By summarizing the key results and re-emphasizing their significance, this SLR underscores the importance of collaborative efforts and knowledge-sharing among stakeholders to harness the transformative potential of deep learning forecasting.

Future research should focus on addressing the identified limitations and further exploring the integration of imputation techniques with deep learning models. Moreover, research efforts should aim to translate the insights gained from this SLR into actionable strategies or initiatives for policymakers, practitioners, and stakeholders involved in sustainable development. By doing so, we can advance progress towards achieving the SDGs and contribute to a more sustainable future for all.

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