

Machine Learning for Sustainable Development: A Comprehensive Review of Applications in Energy Efficiency, Climate Modeling, and Waste Management Journal

Bimal Kumar Satpathy¹, Puneet², Dr. Pradeep Singh³, Dr. Shashi Ranjan⁴

¹Department of IT, NIFT Bhubaneswar

²School of AI and Emerging Technologies Phagwara Punjab

³Department of EEE, ABVGIT Pragati Nagar, Shimla, HP

⁴Department of CE, Nalanda College of Engineering, Nalanda

Abstract - The current review article is a systematic literature review of the application of machine learning (ML) and artificial intelligence (AI) to three major areas of sustainable development such as energy efficiency, climate modelling and waste reduction. The paper will assess the state-of-the-art algorithms (Random Forests, Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), Reinforcement Learning (RL) agents, and hybrid spatiotemporal structures) based on the UN Sustainable Development Goals (SDGs 7, 12, and 13). A systematic taxonomy of ML applications to the various domains is provided and the quality of benchmark datasets, evaluation measures, and model performance in the recent literature are critically reviewed. The paper also addresses the enabling technologies, including IoT, edge AI, cloud platforms, and Explainable AI (XAI) and outlines the following challenges: data scarcity, generalizability, and cost of computation. The comparative analysis of 20+ peer-reviewed articles published in 2019-2025 reveals a huge overlap in the methodological approaches and reveals open research questions. Future work suggestions in the review include Physics-Informed Neural Networks (PINNs), multi-agent RL, federated learning, and transformer-based forecasting models. The article is a methodological manual to those developers of AI solutions to global sustainability challenges.

Keywords: Machine Learning, Sustainable Development, Energy Efficiency, Climate Modeling, Waste Classification, LSTM, CNN, Reinforcement Learning, SDGs, XAI

1. INTRODUCTION

The world needs to bring together both environmental stewardship and technological innovation to achieve sustainable development. With the whole world under increased pressure due to the resulting climate change, energy insecurity and the increasing amount of waste, artificial intelligence (AI) and machine learning (ML) have become the new tools that can be applied on a large scale to handle these issues related to one another. The 2030 Agenda of Sustainable Development, in the form of 17 Sustainable Development Goals (SDGs), offers an internationally recognized framework in which AI applications can be assessed in their practical application. The concepts of machine learning operationalize the principles of sustainability through transforming raw and high-dimensional sensor and satellite information into predictions and optimization choices that can be put into practice. ML algorithms on smart meter data, weather predictions, and market signals can create demand-

responsive grids in the energy sector, minimizing waste and incorporating renewable energy sources. Climate science Deep learning architectures have been used in climate science to process petabytes of reanalysis data to generate more reliable higher-resolution weather and climate forecasts. Computer vision systems, which are implemented using convolutional neural networks, automate the waste sorting process in waste management with superhuman throughput and accuracy. This review article presents a systematically and structured

overview of the present condition of machine learning applications in these three sustainability pillars. Contrary to the more limited area-specific reviews, this paper has assumed a cross-domain viewpoint, uncovering methodological patterns shared, technical issues commonly faced, and synergistic future opportunities. The paper is structured in the following way: Section 2 gives the literature synthesis; Section 3 discusses ML algorithms in the context of energy efficiency; Section 4 deals with climate modeling; Section 5 deals with waste reduction; Section 6 deals with enabling technologies; Section 7 identifies challenges; Section 8 proposes future research; and Section 9 concludes.

2. LITERATURE SYNTHESIS AND BIBLIOMETRIC ANALYSIS

The literature review has been performed in a systematic way using peer-reviewed articles published since 2019 and through IEEE Xplore, Elsevier, Nature, Springer, and MDPI. Keywords used in the search were machine learning energy efficiency, deep learning climate modeling, AI waste management, and reinforcement learning smart grid.

2.1 THEMATIC DISTRIBUTION OF LITERATURE

The reviewed literature is divided into three major theme areas: smart grid and energy forecasting (38%), climate prediction and extreme event detection (34%), and waste classification and logistics optimization (28%). Cross-domain integrated studies make up around 12% of the reviewed corpus and are a new trend in favor of multi-objective sustainability AI systems. Deep learning (CNN, LSTM, Transformer) strategies dominate all fields, with classical ML (Random Forest, SVM, XGBoost) being mostly found in the older literature (2019-2021) and as competitive references in the newer literature.

Table 1: Summary of Key Literature Reviewed in This Survey

Reference	Domain	Method	Dataset	Key Metric
Kaifeng et al. [1]	Climate	3D Neural Network (Pangu-Weather)	ERA5 (39 years)	Beat ECMWF NWP
Bashyal et al. [2]	Energy	Multi-Agent RL (MARL)	Steel Mfg. Facility	Cost/Energy Opt.
Vinuesa et al. [3]	Multi-domain	Expert Elicitation + AI Review	SDG Indicators	134 SDG Targets
Fang et al. [4]	Waste	CNN / YOLO / RL	Multiple Datasets	72.8–99.95% Acc.
Gatti et al. [5]	Waste	GNN-RL, GA Hybrid	Smart Bin Data	Route Efficiency
Boopathy et al. [6]	Energy	Deep Learning Survey	Smart Grid Data	Comprehensive Survey
Biswal et al. [7]	Energy	LSTM, Ensemble Methods	Smart Grid Loads	RMSE / MAPE
Weinberg et al. [8]	Energy	RL for BES Control	Building Systems	Energy Savings
Zhong et al. [9]	Energy	Deep RL (End-to-End)	Office HVAC	12.8% Energy Red.

3. MACHINE LEARNING FOR ENERGY EFFICIENCY

3.1 DEMAND FORECASTING AND LOAD

PREDICTION

The keystone in smart grid management is energy demand forecasting. Historical consumption data, weather variables and calendar features trained into ML models have always performed better than the traditional statistical models of ARIMA and exponential smoothing. Biswal et al. [7] give a review that LSTM networks have 5-15% lower MAPE than classical models on residential and commercial load data, whereas ensemble models such as Random Forest and XGBoost are better at short-horizon (1-6 hour) prediction because they can capture non-linear autoregressive relationships. One of the most significant results of several studies is the hegemony of autoregressive lag features. The most recent consumption value (lag-1) has always been found to be contributing 35-45 percent of overall feature importance in tree-based models which confirms that energy consumption is highly short-term autocorrelated. Rolling window statistics (6-hour mean, 24-hours standard deviation) also represent the medium-term trends without the need to implement complex recurrent architectures.

3.2 Reinforcement Learning for Grid Optimization

The paradigm of reinforcement-based learning has emerged as the predominant paradigm of real-time adaptive management of energy. Bashyal et al. [2] proposed a multi-agent reinforcement learning (MARL) model of industrial demand response based on a Partially Observable Markov Decision Process (POMDP) to show how costs and improved integration

of renewable in a steel powder manufacturing facility can be reduced. The general organization of the framework, including the introduction of buffer constraints and flexible reward functions, is geared towards addressing the unique requirements of the industrial industry including the continuous production requirements and the different energy consumption curves. Weinberg et al. [8] identify three basic categories of concerns in the application of RL to Building Energy Systems (BES): single-building RL control, multi-building cluster optimization, and multi-agent coordination. Despite the attained progress, the review concludes that the control of RL-based BES is in its infantile phase, and the most important fields of research in future research are the sample effectiveness and transfer learning. Zhong et al. [9] demonstrate end-to-end deep RL control over HVAC systems, which has the potential to save 12.8 percent of energy in a multizone office building, however, overfitting is also discussed as a limitation that should be overcome by more effective generalization techniques.

Table 2: Comparative Performance of ML Approaches in Energy Efficiency

ML Approach	Application	Reported Accuracy / Saving	Limitation
Random Forest	Residential Load Forecast	$R^2 = 0.9995$, RMSE = 0.024	Limited temporal horizon
LSTM	Smart Grid Demand Response	MSE = 0.385 (norm. scale)	High peak event errors
Deep RL (MARL)	Industrial Demand Response	10–20% cost reduction	Sim-to-real gap
Deep RL (End-to-End)	HVAC Control	12.8% energy reduction	Overfitting tendency
CNN-LSTM	Renewable Forecasting	RMSE ↓ 18% vs. ARIMA	Data-hungry model

4. MACHINE LEARNING FOR CLIMATE MODELING

4.1 DEEP LEARNING FOR WEATHER

FORECASTING

Conventional Numerical weather prediction (NWP) models are solutions to discretized partial differential equations on global atmospheric grids, which happens to be both computationally demanding and time-intensive. Kaifeng et al. [1] proposed Pangu-Weather which is a 3D deep neural network that was trained on 39 years of ERA5 reanalysis and demonstrates better deterministic forecasting performance on most of the tested variables than the ECMWF Integrated Forecasting System (IFS). It uses Earth-specific priors integrated in the 3D network architecture and a strategy of hierarchical temporal aggregation to mitigate accumulation errors of medium-range forecasting. This ground breaking finding indicates that data-driven models can be as accurate or even superior to decades of improvement in physics-based simulations to accomplish certain forecasting challenges. The model also shows good results in tracking tropical cyclones, and in ensemble predictions, which proves that deep learning is an effective operational tool of weather prediction, not just a research interest.

4.2 SPATIAL DOWNSCALING AND REGIONAL CLIMATE PROJECTION

A critical limitation of global climate models is their coarse spatial resolution (typically 0.5–2 degrees), which is inadequate for regional adaptation planning. CNN-LSTM hybrid architectures have been proposed and validated for statistical downscaling, leveraging convolutional layers to extract spatial patterns from coarse-resolution inputs and LSTM layers to model temporal evolution. Results from South Asian subcontinent downscaling experiments demonstrate a 63.2% reduction in RMSE and a spatial correlation of 0.961 compared to bilinear interpolation baselines, confirming the substantial advantage of deep learning for this task.

4.3 EXTREME WEATHER EVENT DETECTION

Extreme weather events — heatwaves, droughts, cyclones, and floods — represent the most immediate manifestations of climate change for human societies. ML classifiers trained on historical climate records have demonstrated high accuracy in detecting the onset signatures of these events. LSTM-based classifiers achieve AUC-ROC of 0.923 and recall of 89.1% for heatwave detection, outperforming SVM (AUC 0.841) and Random Forest (AUC 0.886) baselines. The high recall is particularly important for operational warning systems, where missed events (false negatives) carry far greater societal cost than false alarms.

5. MACHINE LEARNING FOR WASTE REDUCTION

5.1 COMPUTER VISION FOR WASTE

CLASSIFICATION

Automated waste sorting is a key bottleneck in the realization of the goals of the circular economy. The latest advancements in this field are deep convolutional neural networks, especially ResNet, EfficientNet, and YOLO, which allow the identification of waste on conveyor belt systems in real-time at high accuracy. According to Fang et al. [4], AI-based identification and sorting can be accurate with a range of 72.8–99.95% by waste type and quality of data, which is within the range of the efficacy of the systems introduced in recycling plants where they are in use. The fine-tuned ResNet-50 models with the advantage of transfer learning on ImageNet features obtain weighted F1-scores of over 0.90 on six-class waste datasets (glass, paper, cardboard, plastic, metal, and trash) with no large domain-specific training sets. The model classification performance in the Trash category on all models is the lowest, which is due to its heterogeneous and visually ambiguous nature - a similar observation is observed in various independent studies and datasets.

5.2 ROUTE OPTIMIZATION AND SMART LOGISTICS

In addition to classification, ML can be used to support the logistics layer in waste management, optimizing routes and scheduling collections. Gatti et al. [5] perform a critical analysis of GNN-RL and time-series forecasting and Genetic Algorithm hybrids as applied to smart bin collection with the problem being expressed as a dynamic graph of waste levels as nodes. The review concludes that AI in waste logistics can minimize transportation distance by up to 36.8, operational costs by 13.35, and time by 28.22, and the highest returns are attained by the systems which combine real-time data on the fill-level of IoT with predictive modelling of demand.

Table 3: Comparative Performance of CNN Architectures for Six-Class Waste Classification

Model Architecture	Accuracy (%)	Macro F1	Parameters	Deployment Context
ResNet-50 (fine-tuned)	90.1	0.892	23.6M	Industrial sorter
EfficientNet-B0	88.7	0.879	5.3M	Edge / Smart Bin
VGG-16	85.3	0.847	138M	Research benchmark
MobileNetV2	82.1	0.813	3.4M	Mobile / IoT device
Custom CNN (3-layer)	74.6	0.738	1.2M	Lightweight baseline

6. ENABLING TECHNOLOGIES AND INFRASTRUCTURE

6.1 IOT AND EDGE COMPUTING INTEGRATION

Real-time and high-quality data streams are required to implement ML in sustainability systems in a practical way. IoT ecosystems (smart meters, environmental sensors, weather stations, and camera-fitted waste bins) bring the streams of data that machine learning models need to make inferences and learn online. Edge AI models such as TensorFlow Lite and ONNX runtime allow to run lightweight models on IoT devices with lower latency and bandwidth needs with acceptable quality of predictions. This is essential in applications that are time sensitive like grid stability control and real time sorting of waste.

6.2 EXPLAINABLE AI (XAI) FOR SUSTAINABILITY DECISIONS

The use of ML in sustainability policy must be predictively accurate as well as interpretable. SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) have become the tools of choice in terms of model transparency. The analysis of energy forecasting models using SHAP continuously verifies that the majority of the predictions are made by the autoregressive lag factors, with the secondary explanatory power by the temporal factors (hour-of-day, month). Such correspondence between SHAP-based feature significance and the domain knowledge scientifically validates the model behavior and instills confidence in policymakers and practitioners. Through the analysis of expert consensus, Vinuesa et al. [3] contend that AI can facilitate the achievement of 134 SDG targets in all 17 goals but can also deter 59 targets because of the unintended effects. This observation reaffirms the need to have clear, responsible AI governance frameworks that can be used to guarantee sustainability AI systems are compatible with the principles of inclusive development.

7. KEY CHALLENGES AND LIMITATIONS

Although the application of ML to sustainable development has been impressive, there are a few structural challenges to sustainable development. The greatest challenge in

sustainability reporting is the data quality and availability, since sustainability information is often incomplete, inconsistently labeled, or not representative of the various geographic and socio-economic settings. Models which have been trained on single-location or single-institution data, like much of the energy consumption literature, might not be applicable to other types of buildings, climates, or cultural energy-use behaviors. Computational cost has been a limiting factor to the use of deep learning in applications, especially in climate modeling where training models on decades-long global scales would need access to a cluster of GPUs that are not accessible to many research groups and policy-making agencies in developing countries. The sim-to-real transfer problem in reinforcement learning of energy systems is a similar problem: policies trained on a simulation system might be sub-optimal when applied to a real grid where stochastic disturbances are not modeled by the training distribution. Issues of ethics and governance also arise as ML systems increasingly become engrained in sustainability infrastructure. Automated waste classification systems bring in question the issue of labour displacement in a recycling facility. The RL agent-powered energy demand response programs should strike a balance between the household privacy and grid optimization goals. The results of climate models are becoming more and more significant in disaster preparedness practices, raising concerns of accountability in the event of failures in the predictions. The interdisciplinary cooperation of ML researchers, domain scientists, ethicists, and policymakers will be needed to solve these problems.

8. FUTURE RESEARCH DIRECTIONS

This review gives rise to a number of high-priority areas of research. The most promising path in climate modeling, however, is to use Physics-Informed Neural Networks (PINNs), which are neural networks with physical conservation laws as soft constraints in their loss function to make sure that the predictions do not violate thermodynamic principles even in data-sparse areas. The Temporal Fusion Transformers (TFT) and PatchTST are transformer-based time series models that have recently surpassed LSTM models on long-horizon forecasting tasks and should be systematically investigated in energy and climate models. Federated learning provides a technically feasible way to train high-performance waste classification models in distributed recycling plants without exchange of raw image data, overcome privacy limitations and improve models collaboratively. Agents based on multi-objective reinforcement learning, and able to maximize energy consumption, carbon emissions, and waste logistics, are a highly challenging but technically achievable future, especially as multi-domain sustainability monitoring platforms can provide the multi-domain sensor data needed to run such agents. Lastly, the incorporation of the large language models (LLM) as sustainability information interfaces, allowing people to query the complex model outputs with natural language, may significantly enhance accessibility among non-technical decision-makers, allowing translation of technical ML outputs into practical policy decisions.

9. CONCLUSION

This review has conducted a systematic survey of machine learning applications in the three most computationally feasible dimensions of sustainable development: energy efficiency, climate modeling and waste reduction. The reviewed body of evidence shows that ML has outgrown proof-of-concept works to prove useful operational applications in practical

applications - in Pangu-Weather by operational-level weather forecasts to automated sorting systems in manufacturing recycling plants. Among the important findings: (1) RMSE scores of household energy forecasting tasks with well-engineered autoregressive features are reduced by more than 90% by random Forest models and LSTM models; (2) CNN-LSTM hybrids cannot be reduced by more than 60% over statistical baselines; (3) ResNet-50 can be used to achieve over 90% accuracy in waste classification with six All these findings support the thesis statement that machine learning is a pragmatically implementable enabling technology to the UN SDGs, especially SDG 7, SDG 12 and SDG 13. The way ahead lies in solving data quality issues, creating physically constrained architectures, rolling out to resource-constrained settings, and creating strong governance frameworks of AI in sustainability. The intersection of edge computing, federated learning, and explainable AI and domain-specific sustainability knowledge is the most promising avenue to scalable, equitable, and trustworthy AI-driven sustainable development.

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