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An Overview of Carbon Footprint Mitigation Strategies. Machine Learning for Societal Improvement, Modernization, and Progress

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Chapter 1
Machine Learning for Ecological Sustainability:
An Overview of Carbon Footprint Mitigation Strategies

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ABSTRACT

Among the most pressing issues in the world today is the impact of globalization and energy consumption on the environment. Despite the growing regulatory framework to prevent ecological degradation, sustainability continues to be a problem. Machine learning can help with the transition toward a net-zero carbon society. Substantial work has been done in this direction. Changing electrical systems, transportation, buildings, industry, and land use are all necessary to reduce greenhouse gas emissions. Considering the carbon footprint aspect of sustainability, this chapter provides a detailed overview of how machine learning can be applied to forge a path to ecological sustainability in each of these areas. The chapter highlights how various machine learning algorithms are used to increase the use of renewable energy, efficient transportation, and waste management systems to reduce the carbon footprint. The authors summarize the findings from the current research literature and conclude by providing a few future directions.

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INTRODUCTION

Human existence is inextricably intertwined with nature. Ecology by its inherent trait supplies humanity with vast natural resources. It aids in the sustenance of the huge living population and compensates for the ecological imbalances that surface repeatedly. Due to the rising global population, the consumption of nature's wealth is ever-increasing. The surge in production of energy, food, goods, services, etc., to meet the demand and supply gaps has led to a colossal depletion of raw materials worldwide over the years. Overexploitation of the flora and fauna has endangered numerous species while putting several others in the high-risk category threatening the ecosystem's equilibrium.

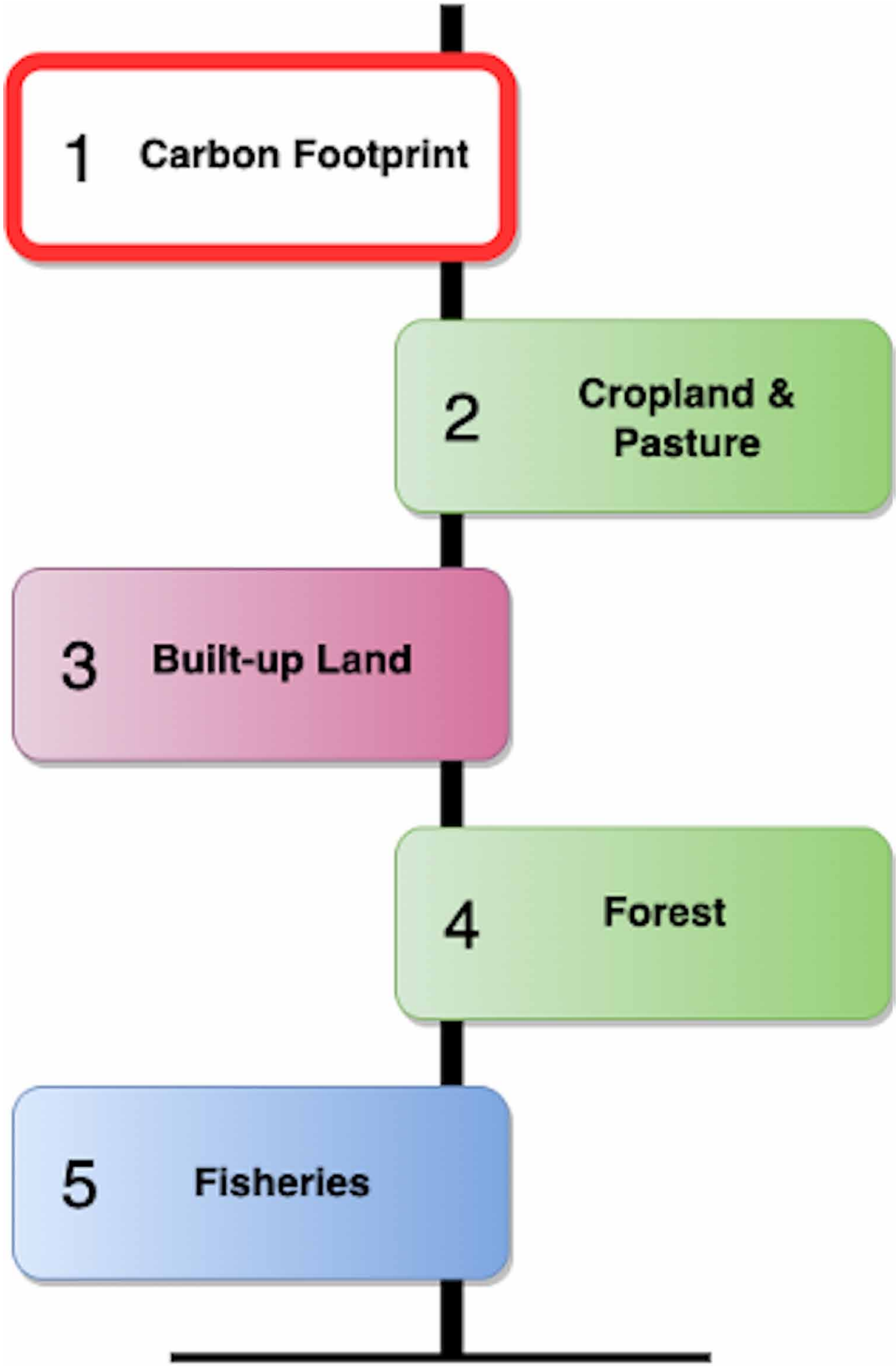
A sustainability metric for measuring human impact on Earth's ecosystems called the "*Ecological Footprint*" was proposed in the early 1990s by two Ph.D. researchers at the University of British Columbia (Wackernagel & Rees, 1996). Considering the dependency of humanity on the biosphere, Ecological Footprint (EF) is defined as a measure of the area necessary to sustain any given population. In its broadest sense, it is a measure that incorporates all forms of water and energy use, infrastructure, forest management, and other material inputs required by humans to flourish day in and day out, as well as accounting for the land devoted to waste assimilation. Ecological Footprint per capita is one of the most widely recognized indicators of environmental sustainability. Human society becomes unsustainable when its Ecological Footprint surpasses its biocapacity. Considering the sustainability of natural resources becomes essential due to the burgeoning demands of the growing population. Ecological Footprint and sustainability are emerging research areas that have grabbed the attention of contemporary researchers and policymakers.

The carbon component of the Ecological Footprint, highlighted in red in Figure 1, is also an indication of the amount of forest land that will be required to absorb the Greenhouse Gas (GHG) emissions from the burning of fossil fuels. The carbon footprint measures the amount of greenhouse gas released due to the consumption of fossil fuels excluding the fraction absorbed by the oceans. The amount of greenhouse gas emitted into the atmosphere when fossil fuels are burned contributes directly to an ecological footprint. As more greenhouse gases are released into the atmosphere, there will be a need for more sea and forest areas to remove them. Lacking the requisite sea and forest areas will increase the carbon footprint. A larger carbon footprint implies a more substantial ecological footprint. In this chapter, we examine the use of Machine Learning to address the problem of increasing carbon footprint in the context of ecological footprints and sustainability.

Machine Learning (ML) is a progressive technology that has the potential to offer practical solutions for environmental sustainability. Machine Learning has much to offer in terms of monitoring, analyzing, and resolving sustainability issues. Even with exceptional advancements in the field, the area continues to have a lot of scope for improvement. The discipline's ever-expanding horizons still hold plenty of opportunities for solving challenging real-world problems. Artificial Intelligence (AI) and ML handle complex data, enabling data scientists to make accurate forecasts. These technologies can recommend comprehensive rational solutions that help in achieving sustainable development across the globe.

Prior research on Machine Learning applications in the sustainability domain is promising, and we believe that Machine Learning can support the development of culturally tailored organizational processes and individual responsibilities to cut down natural resources and energy consumption. We believe that ecological sustainability is the key to balancing the rising Ecological Footprint. Eventually, AI/ML will be highly valuable in contributing to environmental governance and not just limited to minimizing society's energy, water, and land usage intensities. In this survey, we study the applications of Machine Learning to analyze and predict the impact of the Ecological Footprint and to strategize carbon footprint reduction.

Figure 1. Components of Ecological Footprint



METHODOLOGY

We started by framing the following research questions:

RQ1: What are the important areas of ecological sustainability and social innovation that can take advantage of Machine Learning and related algorithms?
RQ2: Can the carbon or ecological footprint be analyzed and predicted using Machine Learning and statistical models?
RQ3: How can Machine Learning help at the production end, given that renewable energy is critical to sustainable progress?
RQ4: Given that transportation is a major domain at the ecological consumption end of the spectrum, how is Machine Learning being used to optimize transportation logistics?
RQ5: Are there any ways that Machine Learning can help with waste management to aid sustainability?

Based on the above research questions, we conducted a keyword-based search on Google Scholar to gather research articles and abstracts to support this chapter. Google Scholar can rank articles based on the number of citations, authors, and publishers and allows filtering by published year which allows us to find the latest research articles in this domain. Search terms include "ecological footprint using Machine Learning", "energy consumption forecasting using Machine Learning", "sustainable development using Machine Learning", etc. We then went through a screening process to identify the most relevant articles satisfying the criteria below:

- The theme of the paper must be directed at sustainable development
- The approach must be data-driven
- The approach to solving the sustainability problem must employ Machine Learning methods

Furthermore, we screened articles that were cited in the articles selected above as additional candidate articles to support the survey. We reviewed the articles to understand the problem domain and the Machine Learning methods used. The answer to RQ1 is too extensive to be detailed in this chapter but confirmed that the remaining research questions are in the right direction. Therefore, we are set to answer the remaining research questions with the overall aim to provide an overview of the usage of Machine Learning for sustainable development.

ECOLOGICAL FOOTPRINT ANALYSIS AND PREDICTION

RQ2: *Can the carbon or ecological footprint be analyzed and predicted using Machine Learning and statistical models?*

Environmental degradation and the climate crisis demand the most advanced and innovative strategies in an increasingly complex world. AI/ML will truly succeed when it can promote and facilitate environmental governance, not simply reduce energy, water, and land consumption (Nishant et al., 2020). **Table 1** shows a general review of Machine Learning models and statistical methods employed in analyzing and forecasting Ecological Footprint.

Table 1. Summary of Machine Learning/Statistical methods for ecological footprint

Application	Area Under Study	Years	Data	Machine Learning/ Statistical methods	Key Contributors	References
Ecological Footprint Prediction	Beijing, China	1996-2015	Data concerning retail sales, coal consumption, energy consumption, urbanization rate, population, GDP, the proportion of industries, total foreign trade	SVM BPNN	Construction Land	(Liu & Lei, 2018)
Ecological Footprint Analysis and Prediction	Tianjin, China	1994-2014	Data concerning energy consumption, urbanization rate, population, GDP, proportion of industries	ARIMA–BPNN	Population, Industrial Infrastructure	(Wu et al., 2019)
Ecological Footprint Analysis and Prediction	41 countries	1971-2014	Energy consumption data, Ecological Footprint data, and population data + Synthetic data using SMOGN algorithm	Correlation K-Nearest Neighbor regression Random Forest regression ANNs (ReLU, SPOCU)	Fossil Fuels	(Jankovic et al., 2021)
Environmental Performance and Global Convergence Analysis	188 countries and territories	1961-2016	cross-sectional time-series data on ecological indicators and socio-economic indicators	Panel Kernel Regularized Least Squares, Dynamic Bootstrap-corrected fixed-effects panel	Carbon Footprint, Population Density, Global Economic Development, International Trade, Economic Growth and Income Levels	(Sarkodie, 2021)

An urban Ecological Footprint prediction may emphasize the interdependency between the urban social economy and the natural environment, and serve as a data source for urban planning. The Ecological Footprint can exhibit dynamic and nonlinear characteristics depending on a combination of economic development, energy use, and population. Therefore, it is necessary to consider Machine Learning models that can handle non-linearity. Machine Learning has wide applicability in such complex non-linear problems, providing deep insights, and high prediction accuracies that significantly reduce the labor, and mitigate the need for repetitive experimentation that may often result in unnecessary resource consumption (Roohi et al., 2020).

To determine the most suitable prediction model for Beijing's Ecological Footprint, researchers (Liu & Lei, 2018) compared two nonlinear models, Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM). Their experiments concluded that the SVM performed better than BPNN. Support Vector Machines offer the potential to avoid not only the limitations of linear models but also the need to determine the nodes in backpropagation neural networks. Human involvement in the prediction process is thereby further reduced. Furthermore, SVM trains faster than BPNN over a shorter learning period. BPNN has the disadvantage of getting trapped in local minimums, which significantly slows the convergence rate.

Beijing's ecological footprint between 1996 and 2015 was calculated using Partial Least Squares (PLS) to identify 6 major indicators of ecological footprint changes – Gross domestic product (GDP), population, retail sales of consumer goods, industrial production, foreign trade, and energy consumption. PLS provides an evaluation metric called Variable Importance for Projection (VIP) that allows one to determine which variable between multiple independent variables with multicollinearity is most meaningful. Six of the indicators mentioned earlier had VIPs > 1. The BPNN's predictive accuracy has been compared with that of the SVM using six indicators as inputs and ecological footprint as output. Using this model, an ecological footprint forecast for Beijing in 2020 was established. In 2014, the relative error of the prediction and the actual value was 2% and 1%, and in 2015 it was 3% and 0.53%, respectively. The fact that the standard deviation of the SVM is close to zero indicates its higher stability and accuracy than that of the BPNN. According to the results, Beijing's Ecological Footprint doubled between 1996 and 2015. Additionally, the model predicted that Beijing's Ecological Footprint would triple by 2020 (Liu & Lei, 2018).

Societies rely heavily on energy as it aids in human sustainability. Carbon footprints make up a large part of the ecological footprint primarily because of energy consumption. Energy consumption and associated CO_2 emissions around the world have increased rapidly in the past few decades due to the rising population and living standards. As a result of a growing dependence on energy, there are significant costs to be considered. The processes involved in the generation, consumption, and disposal of energy have an enormous impact on the environment. According to data collected from multiple sources representing 41 countries from 1971 to 2014, the total Ecological Footprint of each country's energy consumption and the availability of fossil fuels correlated strongly (Jankovic et al., 2021).

To predict the Ecological Footprint of energy consumption, researchers (Jankovic et al., 2021) evaluated four hybrid Machine Learning models based on Bayesian parameter estimation. Among the models developed are K-nearest neighbor regression, Random Forest Regression (RFR), and two artificial neural networks (ANN) with different activation functions in hidden layers. The parameters of the model are crucial to how well it performs. In modeling Artificial Neural Networks, for example, selecting an appropriate number of hidden layers and hidden nodes is critical. This is because the incorrect choice of hidden layers or nodes will impact the model's generalization capability, resulting in overfitting or underfitting. Bayesian optimization can be used to achieve the best set of hyperparameters faster and better generalization performance on test sets. When choosing what hyperparameter is set to test next, it considers the combinations it has seen so far. **Table 2** shows the model parameters suggested by the parameter optimization technique and the resulting model performances. Among the three models, K-Nearest Neighbor regression had the lowest errors and fastest computation time. A further test with the Synthetic Minority Over-Sampling Technique for Regression with Gaussian Noise (SMOGN) generated data established that the model is effective (Jankovic et al., 2021).

Large portions of the global economy depend on conventional energy sources to fuel their productivity, so countries with limited fossil fuel reserves must import fuel from countries with abundant supplies. Consequently, environmental degradation is transferrable both directly and indirectly based on economic status. Upon closer examination, a study confirmed that the degree of environmental degradation is the same across nations under similar conditions regardless of income level.

According to their 56-year mean trends of biocapacity, ecological status, ecological and carbon footprint measurements compared with the worldwide average, China, India, Japan, Russia, and the United States have been identified as global Ecological Footprint hotspots. Global partnership is crucial for the achievement of environmental sustainability, as shown by this fact. Using Ecological Footprint and biocapacity as indicators, an empirical study (Sarkodie, 2021) analyzed the ecological performance of countries. Two estimation approaches derived from machine learning and econometrics were used for estimating environmental performance, Ecological Footprint, and carbon footprint.

Table 2. Hyper parameter optimization recommendations by Jankovic et al. using Bayesian Optimization algorithm and resulting model performance

Model	K-Nearest Neighbor regression	Random Forest regression	ANN ReLU	ANN SPOCU
Parameters	Number of neighbors = 2 Type of algorithm = brute p=1 Leaf size = 69	Number of estimators = 93 Bootstrap = False Minimum samples split = 2 Maximum depth = 33 Maximum features = sqrt	Batch Size = 256 Number of neurons = (120, 136) Number of hidden layers = 2 Dropout = 0.3	Batch Size = 32 Number of neurons = (14, 168) Number of hidden layers = 2 Dropout = 0.3
Results	MASE = 0.029 NRMSE = 0.006 MAPE = 5.136 SMAPE = 5.214 Training Time = 0.129s Validation Time = 1.878s	MASE = 0.032 NRMSE = 0.007 MAPE = 5.688 SMAPE = 5.520 Training Time = 0.319s Validation Time = 3.322s	MASE = 0.064 NRMSE = 0.015 MAPE = 13.3794 SMAPE = 13.428 Training Time = 1.743s Validation Time = 7.767s	MASE = 0.089 NRMSE = 0.011 MAPE = 22.454 SMAPE = 18.311 Training Time = 5.743s Validation Time = 18.009s

Panel kernel regularized least squares and a dynamic bootstrap-corrected fixed-effects panel are the approaches. These were used to account for omitted variable bias, heterogeneous effects across countries, and misspecification errors. As a result of resource exploitation, environmental degradation is caused by economic development, as outlined in the scale effects hypothesis. Internationally, fossil fuels are transportable and are traded. Renewable energy sources, however, are localized, so there is no between-nation emission flow. Therefore, it may have policy implications for understanding how natural resources are depleted and how it contributes to environmental degradation. Technologies that harness renewable energy must be embraced at a global level. Their efficiency must also be improved to compete with fossil fuels, and clean and modern energy investments must be made (Sarkodie, 2021).

Using an Ecological Footprint approach to study Tianjin in China provides theoretical support and scientific evidence for sustainable urban growth. To forecast the state of sustainability and varying trends in the ecological parameters of Tianjin, the Autoregressive Integrated Moving Average – Back Propagation Neural Network (ARIMA–BPNN) model was used, resulting in solid policy recommendations. As the population increases, Ecological Footprint becomes an imperative issue. Hence, a population policy was recommended to promote population migration from primary and secondary industrial areas to the tertiary sector. Further, the introduction of regulations to control the expansion of energy-intensive industries was suggested to popularize the use of modern technology, and renewable energy, and reduce energy consumption. It is possible to influence the overall energy efficiency by optimizing the industrial structure and influencing the energy consumption structure (Wu et al., 2019).

Time series datasets tend to have both linear and nonlinear attributes. When ARIMA or BPNN are used exclusively, they do not adequately capture the attributes of time series, which can lead to biased results (Zhang, 2003). ARIMA, for example, assumes a linear time series, i.e., the future value of a variable is a linear function of the past observations and random errors. Therefore, it performs poorly with non-linear data. Although BPNN does a good job setting data with non-linearity, its forecasting performance is inferior to linear data (Marugán et al., 2018). In a hybrid ARIMA-BPNN model, the limitations of each method are overcome by the other, resulting in robust forecasts. Despite the ARIMA, BPNN, and hybrid models' ability to replicate real-world data's trajectory, the comparison of hybrid model results to ARIMA and BPNN showed a better fit to historical data. ARIMA-BPNN's RMSE and MAPE values were distinctly lower than those of ARIMA. The hybrid model showed a significant improvement in prediction performance compared to ARIMA or BPNN models alone (Wu et al., 2019).

SUSTAINABILITY

It is the consumers who demand and burn fossil fuels that drive the energy companies' production and supply. Consumption patterns in society are driven by lifestyle choices such as those that shape food, housing, mobility, consumer goods, and communication. All of these have interplay with each other causing unsustainable trends. Lifestyles need to change to ensure the transition to a low-carbon footprint. There is a need to understand the underlying lifestyle factors that contribute to carbon-intensive consumption patterns. While creating awareness among the population helps, the use of technology can aid in accomplishing sustainability goals more efficiently. Technology empowers humanity to maximize productivity while resulting in huge savings. The gains are many including optimal usage of resources, reduced operational costs, minimal waste production, reuse-reduce-recycle of waste generated, supervising, and tracking progress. AI/ML in particular can address sustainability effectively.

The raison d'être of the concept of sustainability is that the naturally available resources are limited in quantity. Therefore, resources must be used conservatively to satisfy the present requirements and as much as possible, preserved for future consumption. A society thrives when all parties that make up the community work toward the common goals of sustenance. The population must utilize resources judiciously, be socially accountable, and focus on the protection of the ecosystems through calculated expanding and implementing strategies for replenishing the used-up raw materials whenever possible. Taking the above steps becomes vital to restore ecological stability and save nature's assets for upcoming times. Understanding the short- and long-term benefits of adopting sustainable development practices becomes easier when humanity realizes the price they will need to pay for non-compliance. The world will exhaust fossil fuel reserves due to excessive usage, once abundant animal species may need to be classified as rare or extinct due to a decline in their number, food/water/air i.e., environmental toxicity are some adverse effects (not limited to) humans may have to deal with. The following sections examine various aspects of sustainability and how Machine Learning can help with each.

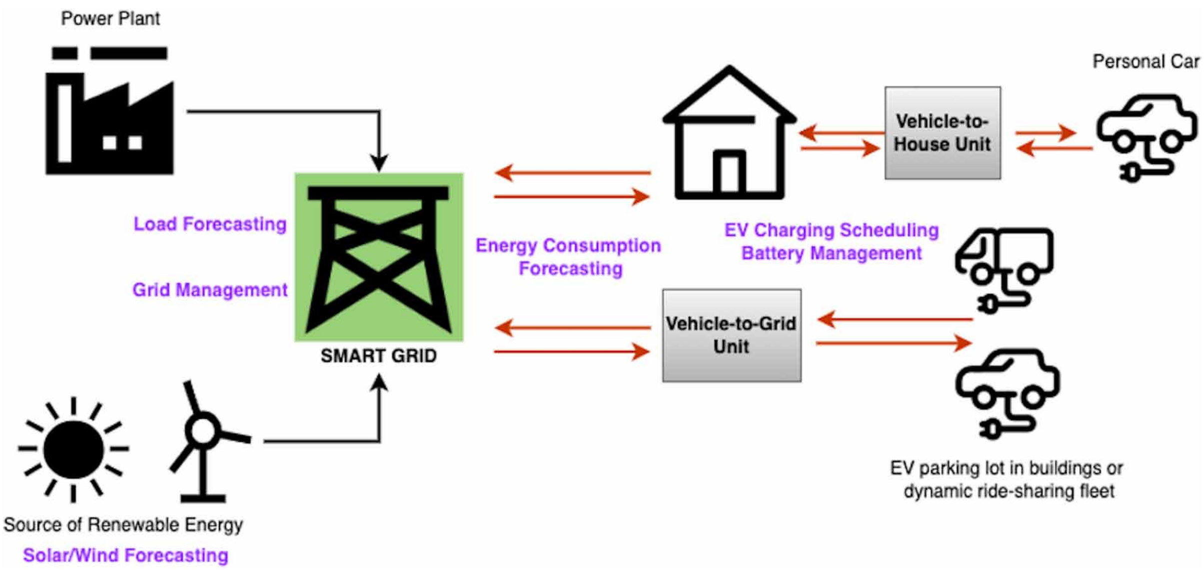
Renewable Energy

RQ3: *At the production end, given that renewable energy is critical to sustainable progress, how can Machine Learning help in this domain?*

For better sustainability, green energy must become the norm in the future. A growing number of developed countries are focusing on generating renewable energy. The energy industry has made enormous progress in the field of renewable energy. Nevertheless, the industry still faces a few challenges since we rely on sources that are out of our control. As depicted in Figure 2, AI and ML have the potential to turn the renewable energy industry into an industry of the future. Power companies can more effectively forecast, manage power grids, and schedule maintenance using AI.

Since 2013, IBM has been working with the US Department of Energy on ways to leverage Watson, its AI engine, for cleaner energy. Data about the weather and the atmosphere were gathered from about 1,600 locations across the United States to build the Machine Learning model. This model became more accurate over time at predicting power output. Today, over 150 companies use IBM's forecasting

Figure 2. Machine Learning applications in building smart energy, smart grids, and vehicle-to-grid technologies



technology to predict solar and wind conditions for 15 mins to 30 days in advance (Environment - Solutions for Environmental Sustainability - 2013 IBM Corporate Responsibility Report, n.d.). Likewise, in 2018, DeepMind started applying Machine Learning algorithms to 700 MW of Google's wind power capacity in the central US. To give the readers an idea, 700 MW can power a medium-sized city. The neural network used historical turbine data and weather forecasts to predict wind power output 36 hours in advance (Machine Learning Can Boost the Value of Wind Energy, 2019).

Renewable energy is, without a doubt, the way of the future, but are they reliable? Resources like sunlight, wind, and water are crucial to the production of renewable energy. Resources such as these are dependent on the weather, which is out of human control. The predictive capabilities that Machine Learning offers can prove to be invaluable in this field. **Table 3** shows a review of Machine Learning models applied in this area. Existing literature suggests that given the stochastic nature of wind speed and solar irradiance, it is irrational to compare the superiority of one model over the other. Instead, it is crucial to evaluate what Machine Learning model is most appropriate under concerning conditions for forecasting energy generation.

Additionally, it is extremely important to evaluate a model's performance based on how well it can generalize for different climatic zones and times of the year. If the forecast is evaluated over only a few months with clear skies and low illuminance variability, it will not be clear how the algorithm performs in other highly variable months. The top-performing models for solar forecasting differ for clear- and all-sky conditions, making it more challenging to prescribe one model. The best approach is therefore to consider a family of models.

Research (Yagli et al., 2019) recommends the tree-based method family – Cubist (CUB), Extremely Randomized Trees (ERT), and Random Forest (RF) as a less risky choice because these algorithms consistently performed well in all climates and for all-sky scenarios. Under clear sky conditions, Multi-Layer Perceptron (MLP) and Support Vector Regression (SVR) families performed better than others. Besides model performance, it is also crucial to choose a model based on its training time because, in a real-time scenario, where there is a need to forecast on an hourly basis if the training time of the model exceeds an hour, the model becomes useless irrespective of its high prediction capabilities. Several methods such as Quantile Regression with ANN (ANNqr), ERT, Tree Models using Genetic Algorithms (EVTREE), and Gaussian Process with Polynomial Kernel (GPPoly) require more time than the one-hour limit making them inappropriate for one-hour-ahead forecasting under hourly rolling training (Yagli et al., 2019).

A wide range of Machine Learning models is constantly being revamped using hybridization and ensembles to improve computation complexity, functionality, robustness, and accuracy. Ensemble models have long been popular in classification and regression problems because of the ability to retain the bias of their learners while reducing their variance. In simple terms, in an ensemble learning process, even if one learning model predicts incorrectly, another learning model can rectify the mistake and offer a stable conclusion. Further, integrating the models with data processing approaches and optimization algorithms to develop several hybrid algorithms can aid in improving the forecasting models.

In wind energy forecasting, Support Vector Regression and Multilayer Perceptron are the most frequently used Machine Learning techniques. The emphasis is, however, on ensemble methods for forecasting wind and solar energy due to their variability. The input patterns for a study (Torres-Barrán et al., 2019) to predict wind energy were taken from the European Center for Medium Weather Forecasts (ECMWF) numerical weather prediction system (NWP). NWP forecasts are given for several weather variables at each point of a rectangular grid covering the study areas. Due to their large grids and a potentially substantial number of features at each grid point, these problems apply to Big Data research. Due to the hourly nature of renewable energy forecasts, an ML perspective will see a small sample size: even if a year has 8760 hours, NWP forecasts are produced every three hours, which results in 2920 patterns. This suggests that the pattern dimension becomes extremely large despite the modest sample size. These large dimensions become particularly relevant when working with regression trees. In practice, the splitting features are picked at random from a fraction of the dimensions. These are combinations between a grid point and a weather variable, and some combinations are more significant than others. Even though random feature selection is unaware of such properties, it can nonetheless produce subsets with disparate feature relevance.

Random Forest Regression, Gradient Boosting Regression (GBR), and Extreme Gradient Boosting (XGB) ensemble methods were compared with Support Vector Regression and Multi-Layer Perceptron models in this context and there was no clear winner. In predicting wind energy at the farm level, Random Forest regression and Extreme Gradient Boosting outperformed Support Vector Regression whereas Gradient Boosting Regression and Extreme Gradient Boosting were no better than Support Vector Regression for predicting wind energy in peninsular regions. Moreover, Gradient Boosting Regression and Extreme Gradient Boosting performed better for solar radiation predictions compared to Support Vector Regression and Random Forest regression. Multi-Layer Perceptron fell behind for all the use cases. This further emphasizes that several predictive approaches may need to be employed for forecasting purposes and to keep a close eye on their performances (Torres-Barrán et al., 2019).

EnsemLSTM employs a nonlinear learning ensemble technique using Long Short-Term Memory (LSTM), Support Vector Regression Machine, and External Optimization (EO) for the prediction of wind speed, which is vital for obtaining the most power from wind turbines. Compared to other extremely popular prediction models, such as ARIMA, Support Vector Regression, Artificial Neural Network, KNN, and Gradient Boosting Regression Trees, the EnsemLSTM achieved better forecasting results with minimal values for evaluation metrics, MAE, RMSE, and MAPE and maximum R (Correlation coefficient) values. In addition, the external optimization of the nonlinear-learning top-layer of the Support Vector Regression Machine is superior when compared to ANNLSTM, MeanLSTM, and single LSTMs (Chen et al., 2018).

Machine Learning has also been used to predict energy load patterns by understanding consumer behavior for efficient and effective grid management. Sustainable energy systems must manage their grids effectively. Anticipating the amount of energy that may be needed soon ranging from the next hour to the upcoming weeks is crucial for power companies. Keeping track of this can help them manage their grids effectively to minimize outages. Increasing energy production will be necessary if consumption is predicted to be high. Alternatively, they may choose to reduce production during periods of low energy demand. For gathering data, energy providers install smart meters that periodically send usage information. Individuals and communities consume in diverse ways, so gathering the necessary data is essential to predicting and managing loads.

With data-driven predictive capabilities integrated into smart grids, countries will be able to rely more effectively on renewable energy and avoid dealing with solar and wind energy irregularities. For real-time energy consumption data, hybrid models are recommended. Normally, these models offer much higher precision than single models or even ensembles. This is because they can incorporate the advantages of and compensate for the deficiencies of individual models and optimize algorithms to improve prediction accuracy. Hybrid models, however, require a deep understanding of individual models and techniques to optimize them for the desired outcome (Chou & Tran, 2018). A summary of the use of Machine Learning models for renewable energy applications is presented in Table 3. As can be seen, Machine Learning models played a significant role in this domain.

Table 3. Summary of Machine Learning Models used in literature for Renewable Energy applications

Application	Area Under Study	Years	Data	Machine Learning models	References
Solar Irradiance Forecasting	7 stations in 5 different climate zones in the continental United States	2013–2016	satellite-derived irradiance data	68 models evaluated, tree-based methods - CUB, ERT, and Random Forest found superior	(Yagli et al., 2019)
Solar Irradiance Forecasting	Sotaventos, Peninsular Spain	2011 - 2013	Numerical Weather Predictions	GBR and XGB	(Torres-Barrán et al., 2019)
Wind Energy Forecasting	Sotaventos, Peninsular Spain	2011 - 2013	Numerical Weather Predictions	SVR, MLP RFR, GBR, and XGB	(Torres-Barrán et al., 2019)
Wind Speed Forecasting	Wind farm in China	*10 min ahead forecasting:* Nov 23, 2012 - Nov 28, 2012 *1-hour ahead forecasting:* April 1, 2013, to April 30, 2013	*Short-term forecasting* - every 10 min wind speed data *1-hour ahead forecasting* - mean one-hour wind speed data	EnsemLSTM	(Chen et al., 2018)
Load Forecasting and Grid Management	Not specified	Four weeklong sliding windows	Real-time energy consumption data collected from the smart grid network	SARIMA-MetaFA-LSSVR and SARIMA-PSO-LSSVR (Hybrid Models)	(Chou & Tran, 2018)

Smart Transportation

RQ4: *Transportation being a major domain at the ecological consumption end of the spectrum, how is Machine Learning being used to optimize transportation logistics?*

Transport systems make up a web of interconnected systems that is crucial for the development and expansion of any society. Globally, a large amount of transportation occurs daily, but a lot of it is inefficient, causing unnecessary greenhouse gas emissions. Transportation sector emissions represent about a quarter of total CO_2 emissions (Global Warming of 1.5 ℃, n.d.). Given a wide variety of vehicles on the road today, many require high fuel density which limits switching to low-carbon alternatives, making transportation an area that is exceedingly difficult to decarbonize. Reducing transportation and its frequency, improving vehicle efficiency, using alternative fuels, or switching to low-carbon modes of commute may contribute to mitigating greenhouse gas emissions from transportation.

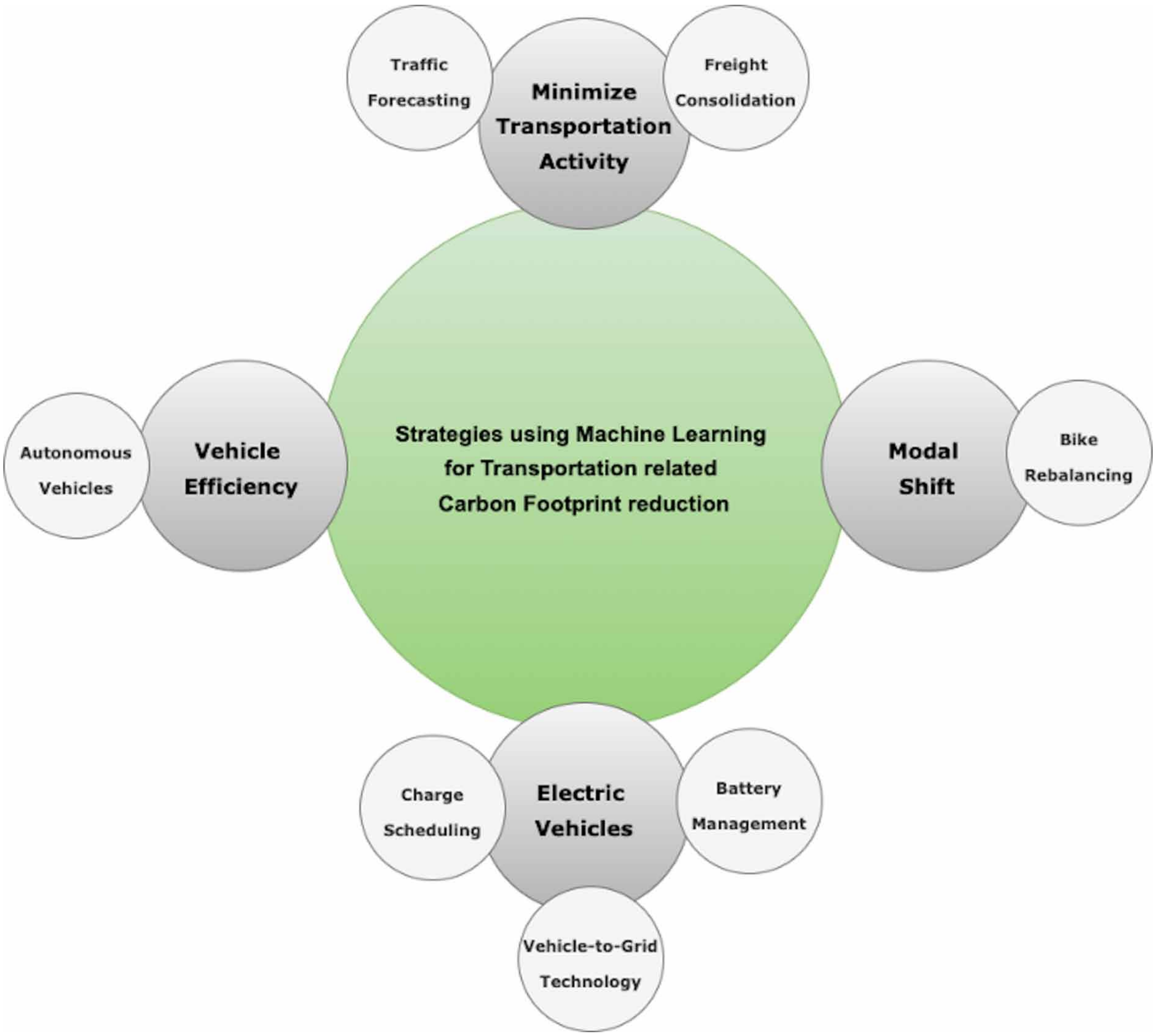
Fortunately, as can be seen from Figure 3, Machine Learning has much to offer in each of these mitigation options. Machine Learning can enable intelligent infrastructure to build Smart Transportation Systems in cities. As Machine Learning solutions become more prevalent, they tend to recommend changes in planning, maintenance, and operations of transportation systems, and therefore, results become apparent over time. **Table 4** shows a few applications discussed for enabling Smart Transportation.

In smart transportation systems, traffic prediction is essential. Planning routes, directing dispatching, and alleviating traffic congestion is made easier with accurate traffic predictions. It can be challenging to solve this problem due to the complex and dynamic spatial-temporal relationships between different regions within the road network. There have been several traditional Machine Learning methods proposed for traffic prediction, including Support Vector Regression, Random Forest regression, and Multi-Layer Perceptron. In addition to processing high-dimensional data, these methods can capture non-linear relationships, both of which are complex. The Random Forest and Linear Regression models were effective when traffic patterns were almost linear; however, they had large RMSE values when traffic patterns abruptly changed.

In contrast, Support Vector Regression, and Artificial Neural Network (ANN) models such as Multi-Layer Perceptron were able to adapt to abrupt changes in speed. It was found that Linear Regression (LR) and Random Forest models are less accurate when speeds vary widely than Neural Network and Support Vector Regression models. For larger changes in the traffic flow, the Neural Network model had better predictability, while the Support Vector Regression model had better accuracy during shorter changes. As compared to the other three models, the Neural Network model had the most near-zero errors in its predictions. Both linear and non-linear patterns were handled by the Neural Network and Support Vector Regression models (Bratsas et al., 2019). Research efforts have advanced traffic prediction capabilities in recent years, particularly using deep learning methods. Deep Learning algorithms are a specific set of Machine Learning algorithms involving Artificial Neural Networks. A variety of architectures have been developed for handling large-scale, Spatio-temporal data (Yin et al., 2021).

Combining small shipments into vehicle loads is an efficient and frequent method of shipping since it concentrates large volumes onto a small number of transportation routes. This is commonly known as freight or shipment consolidation. As a result of freight consolidation, the number of trips is dramatically reduced resulting in decreased greenhouse gas emissions. Logistics providers and freight forwarders often decide how freight is consolidated and routed. This complex interaction of shipments, modes, origin-destination pairs and service requirements can be optimized using Machine Learning. For

Figure 3. A few strategies to reduce the carbon footprint from transportation using Machine Learning



example, clustering algorithms can be used to group suppliers that are geographically close and ship to the same production sites.

Often, regenerative problems arise in shipping consolidation, where one decides how to strike a balance between shipping cost and delay. Upon arriving in a warehouse, orders are shipped sequentially to customers, so it is critical to keep track of all orders that need to be delivered to one location. In response to a new order, the warehouse decides whether to consolidate all incoming orders and ship them together or wait for additional orders. Research suggests that by learning the optimal actions directly from the input data without constructing explicit predictions of future inputs, it is possible to adapt to changes in the input distribution more effectively.

Using a model-based approach to solve the Markov Decision Process (MDP) exhibits high run-time complexity since every time a prediction is updated, a new MDP must be solved. Meanwhile, it should be noted that deep learning models such as Deep Reinforcement Learning (DRL) and Imitation Learning (IL) can adapt automatically to changes in input distribution as they learn policies directly from historical data and merely require an inference by neural networks at run-time (Jothimurugan et al., 2021). In contrast to DRL, imitation learning is useful in situations where it is easier to demonstrate the desired behavior rather than specifying a reward function that would generate the same behavior or directly learning the policy.

Ride-sharing companies can reduce their environmental impact dramatically by leveraging Machine Learning. Despite contradictory studies suggesting that ride-hailing services contribute to traffic congestion and air pollution, low-carbon transportation options such as pooled trips and electric vehicles can minimize - or even eliminate - such disadvantages. Based on observations from Hangzhou, China, pooled trips have the potential to decrease vehicle travel distance by 58,124 km per day, decrease vehicle usage by 3,061 vehicles per day, and ultimately affect car ownership and travel habits (Chen et al., 2021; Zheng et al., 2019). Based on the analysis, a pooled trip can reduce emissions by 33%, a ride-hailing trip by about 53%, and a pooled trip by about 68% compared to a private vehicle trip (Anair et al., 2020).

For ridesharing platforms, enhancing operational efficiency is a major challenge. Rider sharing requires sophisticated optimization of all the integrated components, from the perspective of the platforms, drivers, and passengers. Oftentimes, operational decisions in this domain are sequential and strongly spatially and temporally dependent. It is due to the highly stochastic nature of demand and supply in the domain. The use of RL in ridesharing has been proven to be an excellent method for solving optimization problems such as ride-sharing matchups, vehicle repositioning, ride-pooling, routing, and dynamic pricing (Qin et al., 2021).

These optimization procedures aim to resolve sequential decision-making problems in a stochastic environment with a long-term objective. A ride-sharing platform's decision system must make decisions for assigning available drivers to passengers within a large spatial decision-making region as well as for repositioning drivers who do not have any orders nearby. It is critical to note that these decisions affect revenue and driver availability in the short to medium term. In addition, they also affect the distribution of available drivers in the city over the long term. To guarantee that future orders are met efficiently, these distributions are crucial. Consequently, the problem has characteristics unique to reinforcement learning due to the exploration-exploitation dilemma and the delayed effects of assignment actions.

Table 4. Summary of Machine Learning Models used in literature for carbon footprint reduction from transportation

Application	Machine Learning models	References
Shared Mobility Optimization	Reinforcement Learning	(Qin et al., 2021)
Bike Rebalancing	GBM, LSTM, GRU, RF	(Regue & Recker, 2014, Wang & Kim, 2018)
Traffic Forecasting	ANN, SVR, RFR, MLP	(Bratsas et al., 2019, Yin et al., 2021)
Freight Consolidation	MDP, DRL, IL	(Jothimurugan et al., 2021)
EV Routing and Battery Management	MLR + NN	(Cauwer et al., 2017)
EV Energy Consumption Charge Scheduling	MLR, Transfer Learning	(Fukushima et al., 2018)
Vehicle-to-Grid Technology	Reinforcement Learning	(Vázquez-Canteli & Nagy, 2019)
Autonomous Vehicles	Reinforcement Learning	(Lee et al., 2020, Li & Görges, 2019)

Thanks to Machine Learning, self-driving cars are becoming a reality. Despite a great deal of uncertainty surrounding autonomous driving, the development of self-driving cars is currently one of the top trends in the world of AI and ML. There is evidence that energy emissions would be substantially lower in the future when shared autonomous vehicles (AV) are preferred to personal vehicles. Introducing fully automated self-driving cars may attract new customers, which could lead to more trips and vehicle miles traveled, resulting in higher energy consumption. Shared autonomous vehicles provide both a means of reducing traffic congestion and energy consumption while still maintaining the benefits of driverless driving and convenient point-to-point mobility (Ross & Guhathakurta, 2017). It is reasonable to say that autonomous vehicles are considered the future of transportation and most vehicle manufacturers and ride-sharing companies are invested in this direction.

Considering the advent of autonomous vehicles, eco-driving research has become increasingly relevant. Optimization of the speed profile of the vehicle is a challenging problem. This requires consideration of a variety of factors, including the vehicle's energy consumption, the slope of the road, and the traffic and other drivers on the road. Optimizing the vehicle speed profile can be extremely helpful, as vehicle efficiency can be increased without requiring any changes to the vehicle hardware and the technology can be applied to any vehicle. As more vehicles can be operated without human drivers soon, devising an eco-driving strategy that optimizes the vehicle speed profile is of importance. Machine Learning algorithms in the self-driving car need to render the surrounding environment continuously and predict potential changes to that environment.

Reinforcement learning can be applied as a real-time controller by adapting to the environment as it learns through the interaction between the agent and the environment. Considering this fact, reinforcement learning is an excellent way to approach the eco-driving control problem, since it is based on the probabilistic approach to finding the optimum solution when faced with a variety of complex environments. There has been research on the effect of reinforcement learning on eco-driving. To improve eco-driving, researchers developed a model-based reinforcement learning algorithm. This algorithm separates vehicle energy consumption estimation from driving environment estimation. Reinforcement learning involves domain knowledge of vehicle dynamics and powertrain systems while retaining model-free properties by updating the approximation model through experience replay.

To compare the proposed algorithm with dynamic programming (DP) and conventional cruise control, the researchers performed a vehicle simulation. Simulation results showed that the speed profile optimized using model-based reinforcement learning had similar performance characteristics to the global solution which was obtained via dynamic programming and was more energy-efficient than cruise control, which proved the strength and feasibility of this approach. As compared to cruise control, the proposed algorithm saved 1.2% - 3.0% in terms of energy (Lee et al., 2020). A multi-objective deep Q-learning approach was used in another study to arrive at the best route to minimize fuel consumption and traveling time for the eco-routing problem (Li & Görges, 2019).

Electric Vehicles (EVs) are thought to be the primary aid to decarbonizing transportation, whether using batteries or hydrogen fuel cells or by electrifying roads and railways. In general, electric vehicles emit little greenhouse gas, depending however on the carbon intensity of the electricity they run on. EVs will become more popular as more people drive them, so it will be important to understand how they are used. Since EVs have a limited drive range, it is important to suggest rest areas along highways so that the vehicle does not run out of battery power.

In-vehicle sensors and communication data now exist and offer a way to learn about the charging behavior of EV owners and to place charging stations more efficiently. An evaluation of EVs' energy consumption is imperative when determining the most suitable rest areas. Multiple Linear Regression (MLR) was applied to predict the energy consumption of EVs which resulted in high accuracy for existing EV models. It is difficult to forecast EV energy consumption accurately due to a lack of data. The study outlined a method for building a transfer learning model based on previous research to fill that gap (Fukushima et al., 2018).

Alternative solutions to the problem of the limited range are energy-efficient routes. To optimize EV routing, an energy consumption prediction method was developed based on a data-driven methodology. Using real-world measurement data, weather data, and geographical data from EVs, the proposed method combines Machine Learning and statistical methods. Global Positioning System (GPS) coordinates are used to link real-world driving, energy, weather, and geographical data to individual road segments by location. Multiple Linear Regression over the underlying physical attributes such as speed and acceleration, and an artificial neural network to account for external disturbances such as weather conditions and road characteristics on the speed profile are used for the estimation of energy consumption.

The regression model forecasts the energy consumption based on the predicted values for the microscopic driving parameters from the Neural Network, besides the measurable road and external parameters in addition to being computationally simple, the Multiple Linear Regression method allows for enhanced interpretability of the model due to the causal relationships embedded in the model. To assess the influence of individual parameters on energy consumption, trips were further segmented into shorter trips, to ensure the variances are captured in the data. It is necessary to allocate a cost for energy utilization to each segment of the road network to implement energy-efficient routing. Given the complex interactions between road characteristics, traffic situations, and drivers that are likely to have non-linear and interdependent relationships with speed and acceleration, Neural Networks were used. Neural Networks are powerful algorithms capable of predicting nonlinear, complex relationships through black-box function approximation (Cauwer et al., 2017).

Another topic of interest when considering EVs is Vehicle-to-Grid (V2G) technology which is shown in Figure 2. It allows plug-in electric vehicles to communicate with power grids and serve as power reserves for grids to draw from. Battery-powered electric vehicles can be used as energy storage during natural disasters or other emergencies when not in use. It is crucial to incorporate user feedback and consumption patterns into the demand response control loop in the future. It is possible to achieve this through reinforcement learning. Utilizing EVs in vehicle-to-grid technology has been explored using this approach (Vázquez-Canteli & Nagy, 2019).

Bike-sharing is an environmental-friendly and sustainable form of urban transportation. One of the biggest challenges in bike-sharing is the bike-rebalancing problem. By improving forecasts of bike demand and inventory, Machine Learning can assist bike-sharing companies with the rebalancing problem, where shared bikes accumulate in one area while being lacking in other areas. When Gradient Boosting Machine was applied to the Hubway Bike Sharing system in Boston for demand forecasting, it produced higher prediction accuracy when compared to Neural Network and Linear Regression. For the 20, 40, and 60-min predictions, GBM models without calibration performed 1.33%, 8.7%, and 13.27% better than the equivalent Neural Network models. Moreover, the results show that the same parameters - algorithmic and others, can be applied for every station, resulting in a faster computation process. While the Gradient Boosting Machine model has limited application in the transportation sector, it has been successfully used for forecasting traffic under abnormal conditions and enhancing the accuracy of real-time risk assessment (Regue & Recker, 2014).

Among the principal advantages of the Gradient Boosting Machine are that it is unlikely to be influenced by outliers and is robust to transformations in the explanatory variables. The decision tree internally selects the variables, making the algorithm robust enough to process irrelevant input variables, and it does not rely on imputed missing values. To counter overfitting in Gradient Boosting Machine, a variety of constraints or regularization methods can be utilized. In addition, when new data are acquired, Gradient Boosting Machine does not have to be retrained since the boosting process can be carried over from the previous model (Friedman, 2001). Also, recurrent neural networks (RNN) such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), and tree-based methods such as Random Forest have shown effectiveness in forecasting station-level availability of bike-sharing. Random Forest performed better for short-term forecasting, that is, when the time intervals were shorter (Wang & Kim, 2018).

Waste Management

RQ5: *Are there any ways that Machine Learning can help with waste management to aid sustainability?*

In addition to the amount of land and water resources required for the sustenance of an individual, the ecological footprint measures the ability of these resources to absorb waste products generated by their consumption. Carbon footprint is an important indicator of Greenhouse Gas (greenhouse gas) emissions (Wiedmann & Minx, 2008). Globally, landfills and waste are the biggest sources of greenhouse gas emissions. The decomposition of organic materials/waste releases greenhouse gas such as carbon dioxide and methane.

Additionally, the production of inorganic products and management of inorganic waste such as plastic consume enormous amounts of natural resources such as natural gas, oil, and coal. It leads to the emission of many pollutants and greenhouse gases. Waste management activities such as incineration and transportation add to the emission of greenhouse gas thus increasing the ecological footprint. As a result, more forest cover and natural water resources will be needed to absorb these toxic greenhouse gases. Consequently, more countries are embracing waste disposal, prevention, and recycling technology to improve waste management.

Waste management has been an ongoing research topic and there are multifarious publications on the usage of AI/ML in this area of research. AI/ML can be used to solve many Solid Waste Management (SWM) problems, such as forecasting waste characteristics, detecting of waste in bins, setting up process parameters, rerouting vehicles, and overall planning of waste management. Further, it has found its application in many areas of waste management. One such application scenario is the introduction of autonomous robots for sorting distinct types of waste using visual recognition capabilities. The other is to use Machine Learning for the prediction of waste generation to assess the availability of dust bins or dumping grounds. Yet another is to avoid food waste using dynamic pricing methodologies for about-to-expire products encouraging customers to buy them at discounted prices (Wasteless, n.d.). **Table 5** is a review of some of the Machine Learning methodologies used in literature for waste management applications.

Waste generation has been estimated by several Machine Learning Models on a national and municipal level. For instance, using 10-year daily collection data from the New York City Department of Sanitation, a research study was conducted with the objective of route optimization for waste collection trucks in dense urban environments besides waste generation predictions. The Machine Learning model, Gradient Boosting Regression Trees (GBRT) was applied to estimate weekly and daily waste generation at the building scale for over 750,000 residential properties in the City. Gradient Boosting Regression

Table 5. Summary of Machine Learning Models used in literature for Waste Management Applications

Application	Area Under Study	Years	Data	Machine Learning models	References
Waste Generation Estimation and Collection Truck Route Optimization	New York City	Over 10 years	individual building attributes, neighborhood socioeconomic characteristics, weather, and daily waste collection data	GBRT	(Kontokosta et al., 2018)
Plastic Waste Generation Estimation	Dhanbad, India	One week	Survey Questionnaire followed by waste sampling bags to sample households	ANN, SVM, and RF	(Kumar et al., 2018)
Waste Classification	Not specified	Not specified	TrashNet image dataset	ResNet-50 (CNN) (Transfer Learning)	(Adedeji & Wang, 2019
Recyclable Waste Classification	Not specified	Not specified	TrashNet image dataset	MobileNetV2 (CNN) (Transfer Learning)	(Ziouzios et al., 2020)
Compostable Waste Classification	Not specified	Not specified	TrashNet image dataset augmented with the addition of photos of food waste and landfill waste	CompostNet (CNN) (Transfer Learning)	(Frost et al., 2019)

Tree minimizes overfitting through hyperparameter tuning, and it can compensate for complex, nonlinear relationships between variables, which is a significant improvement over a simple linear model.

Additionally, Gradient Boosting Regression Trees are robust to outliers in the data and collinearity within features, unlike linear models. Gradient Boosting Regression Trees resulted in an R-squared value of 0.87 for waste generation prediction and the truck route validation use cases, the model resulted in 99.8% and 93.9% prediction accuracy, respectively (Kontokosta et al., 2018). In recent years, non-linear Machine Learning models have gained popularity due to their high prediction capabilities for complex problems, ability to work on non-linear data, and are free from any assumptions to be made. For instance, in linear models, a linear relationship is assumed between the dependent variable and the independent variables. On the contrary, as opposed to making assumptions, a non-linear model such as an artificial neural network learns the interactions between the independent variables through iteration.

Massive amounts of plastic are disposed of in landfills and in the ocean, where they take centuries to decompose. Hence, recycling all recyclable plastic is necessary to reduce landfills, preserve energy and conserve the environment. To make informed decisions, it is imperative to understand the sources of plastic waste generation, the rate at which it is generated, and how it can be recycled. Researchers at the Indian Institute of Technology used three non-linear methods - Artificial Neural Network, Support Vector Machine, and Random Forest to forecast different types of plastic waste generation. In this study, income, education, occupation, and type of house were used as independent variables, while the plastic waste generation rate was regarded as a dependent variable. Artificial Neural Network ($R^2 = 0.75$) was better than the Support Vector Machine ($R^2 = 0.74$) and Random Forest model ($R^2 = 0.66$) in predicting the outcome (Kumar et al., 2018).

Recycling is vital for a sustainable future. The process plays a significant role in our planet's economic and environmental wellbeing. Municipal Solid Waste (MSW) needs to be managed using sustainable recycling and waste reusing methods, according to researchers (Demirbas et al., 2016). As observed in (Krizhevsky et al., 2012), ever since the convolutional neural network (CNN) algorithm was successfully used to win the 2012 ImageNet large-scale visual recognition challenge (ILSVRC), many different CNN architectures have been developed in recent years, solving a variety of image classification problems. To separate different components of waste, ResNet-50, a CNN that is 50 layers deep, combined with Support Vector Machine was employed achieving an accuracy of 87% (Adedeji & Wang, 2019). This Machine Learning application has enormous potential to achieve a faster waste separation process and reduction of manual labor. Features extracted from a pre-trained ResNet-50 model were input to a multi-Class Support Vector Machine model. The SoftMax layer of the pre-trained model was replaced with Support Vector Machine as there is evidence of better performance with classification tasks (Tang, 2013).

Another study extended the waste classification problem to separate the recyclable contents from the waste using the MobileNet model, a convolutional neural network (CNN) that is 53 layers deep, and the model was trained on a TrashNet dataset created by researchers at Stanford University (Yang & Thung, 2016). MobileNetV2 is a recommendation by the Google Research team (Sandler et al., 2018). Data augmentation and hyperparameter tuning were applied to improve classification accuracy. Consequently, the model achieved an accuracy of 96.57%. The model confused glass for plastic and metal. The authors concluded that without the knowledge of weight and properties, humans would find it hard to distinguish them too (Ziouzios et al., 2020). Students at the University of California, Santa Cruz, developed an iPhone application to help users identify if their waste is recyclable. To maximize the efficiency of recycling, they designed and implemented CompostNet, CNN, which is believed to be the first of a kind as it can classify compostable waste as well. This study further emphasizes how transfer learning yields reliable results when there is not much data availability (Frost et al., 2019).

FUTURE RESEARCH DIRECTIONS

The purpose of the present research is to contribute to the literature on how to promote sustainability by reducing the ecological footprint and in particular, the carbon footprint. The following are some of the research directions that can be further pursued.

- A social and economic lockdown unprecedented in history occurred globally in the year 2020, owing to the COVID-19 outbreak. A comprehensive study of greenhouse gas emissions associated with energy consumption in the industrial, agricultural, tertiary, and residential sectors of the Italian economy and in the provinces of Italy has shown that a considerable reduction in carbon footprint has occurred from 2015-2019 by around 20%. The cause is believed to be the drastic reduction in natural gas, oil, and petroleum product consumption (Rugani & Caro, 2020). By extending these studies to assess the impact of COVID-19-related lockdown on greenhouse gas emissions worldwide, relevant information might be gained regarding potential climate implications. This could be a key to future opportunities to mitigate greenhouse gas emissions. In addition, the pandemic situation has also presented a unique chance to evaluate and calibrate energy production and consumption models to help countries meet their sustainability goals, which may be pursued as a future research topic.
- We focused solely on the carbon part of the ecological footprint in this chapter. The carbon footprint was surveyed in the areas of renewable energy, transportation, and waste management. Food

consumption is another major driver of carbon footprints (Ivanova et al., 2016), and Machine Learning can be used to advance sustainability in agriculture. Besides carbon footprint, food consumption could also have a large impact on other components of the ecosystem footprint - cropland, grazing land, fisheries, built-up land, and forested areas. It is reasonable to state that a future survey of the research literature should be in the direction of providing a more comprehensive overview of other mitigation strategies not covered in this chapter to aid ecological sustainability.
- The United Nations 2030 Sustainable Development Goals have become the subject of more research studies in recent years. Studies continue to use statistical methods for modeling Ecological Footprint from various perspectives to study how it is affected in different countries. Research that relates to Machine Learning applications for ecological footprints is limited. As researched in this paper, Deep Learning and Reinforcement Learning methods are being widely used due to their ability to handle complex, high-dimensional data that are highly dynamic and nonlinear in spatial-temporal environments. Factors affecting ecological footprint are a fitting example to which such methods can be applied with a certain degree of reliability. Future research in this direction may yield good results.
- Machine Learning models are energy-intensive and leave a large carbon footprint due to their computational demands. Despite efficiency improvements, GPUs are more power-demanding than their CPU predecessors and, as such, they consume more power resulting in a much higher environmental impact. Machine Learning, as a technology, can contribute to sustainable ecological development. However, we must set up Machine Learning procedures in ways that minimize the carbon footprint of the process. Otherwise, it may negate the benefits of Machine Learning for sustainable development. Research is already underway on model reusability, data collection and filtering, multi-objective optimization of hyperparameters, and other approaches that can potentially reduce the footprint of Machine Learning (Shterionov & Vanmassenhove, 2022). There is still quite some potential in this direction.

Akin to the way our brains work, Machine Learning can draw rapid inferences and solve problems using deep neural networks. Machine Learning algorithms, like human beings, learn from experience. Each new data point allows a Machine Learning algorithm to refine its inferences and predictions. For certain tasks, it is, however, much faster than humans at performing this process. Having the ability to predict needs and wants is a dream of every business owner and policymaker. Machine Learning models and appropriate data can help make this a reality. The ability to find patterns within patterns in data is the hallmark of deep learning which will help them make sense of complex consumption patterns. Today, it is imperative that the latest developments in AI and Machine Learning be leveraged to make confident predictions about their behavior. Researchers should continue to build on existing research in this area to fight ecological sustainability problems.

CONCLUSION

Environmental sustainability is far from assured, and societal decisions will play a significant role in determining it. The world is on a never-ending quest for energy and natural resources, and Machine Learning can help create a sustainable future. An integrated portfolio of approaches will be needed across policy, industry, and academia to encourage the application of Machine Learning to reduce footprints while also being aware of the impact of such applications that might contradict sustainability goals. With the rapid spread of Machine Learning and the increasing urgency of environmental degradation, society today is faced with a critical window of opportunity to shape Machine Learning's impact for decades to come.

As one of the most relevant indicators of sustainable development, studies on reducing ecological footprints have evolved over the years with technological innovations, research, and development planning. Sustainable development calls for low carbon emissions. Low carbon emissions are achieved through energy conservation and emissions reduction. Applying AI/ML to promote ecological sustainability by adopting low-carbon solutions will benefit society at large and help with making further advances in the field of AI/ML. Machine Learning has been critical in helping develop strategies across different domains to mitigate the carbon footprint problem. The greatest power of Machine Learning lies in its ability to learn from experience, compiling gigantic amounts of data from its environment, intuiting connections that humans miss, and recommending appropriate actions based on that knowledge. The world may not always become a better place because of Machine Learning and ethical issues will persist. But it can, if the technology is used properly, as we demonstrated in this chapter.

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LIST OF ABBREVIATIONS

AI/ML: - Artificial Intelligence/Machine Learning
ANN: - Artificial Neural Network
ANNqr: - Quantile Regression with ANN
ANN ReLU: - ANN Rectified Linear Unit
ANN SPOCU: - ANN Scaled Polynomial Constant Unit

ARIMA–BPNN: - Autoregressive Integrated Moving Average - Back Propagation Neural Network
AV: - Autonomous Vehicle
BPNN: - Back Propagation Neural Network
CNN: - Convolutional Neural Network
CUB: - Cubist
DP: - Dynamic Programming
DRL: - Deep Reinforcement Learning
ECMWF: - European Center for Medium Weather Forecasts
EF: - Ecological Footprint
ERT: - Extremely Randomized Trees
EV: - Electric Vehicle
EVTREE: - Tree Models using Genetic Algorithms
GBR: - Gradient Boosting Regression
GBRT: - Gradient Boosting Regression Tree
GDP: - Gross Domestic Product
GHG: - Green House Gas
GPPoly: - Gaussian Process with Polynomial Kernel
GPS: - Global Positioning System
GRU: - Gated Recurrent Unit
IL: - Imitation Learning
ILSVRC: - Image-Net Large-Scale Visual Recognition Challenge
KNN: - K-nearest neighbors
KNNReg: - K-nearest neighbors Regression
LR: - Logistic Regression
MASE: - Mean Absolute Scaled Error
MAPE: - Mean Absolute Percentage Error
MetaFA: - Metaheuristic Firefly Algorithm
MetaFA-LSSVR: - Metaheuristic Firefly Algorithm-based Least Squares Support Vector Regression
MDP: - Markov Decision Process
MLP: - Multi-Layer Perceptron
MLR: - Multiple Linear Regression
MSW: - Municipal Solid Waste
NRMSE: - Normalized Root-mean-squared Error
NWP: - Numerical Weather Prediction system
PLS: - Partial Least Squares
PSO: - Particle Swarm Optimization
NN: - Neural Network
RF: - Random Forest
RFR: - Random Forest Regression
RL: - Reinforcement Learning
RNN: - Recurrent Neural Network
SARIMA: - Seasonal Autoregressive Integrated Moving Average
SMAPE: - Symmetric Mean Absolute Percentage Error
SMOGN: - Synthetic Minority Over-Sampling Technique for Regression with Gaussian Noise

SVM: - Support Vector Machine
SVR: - Support Vector Regression
SWM: - Solid Waste Management
VIP: - Variable Importance for Projection
XGB: - Extreme Gradient Boosting