Exploring a Pragmaticandexponentialadvancementinthe useofMachineLearningand Artificial Intelligence systems.

Abstract

With the advent of the Internet of Things (IoT) with sensors and connected devices, data generation is increasingly peaking at an unprecedented pace. However, energy consumptionis also on the rise based on traditional energy sources, such as fossil fuels. This is not sustainableandcouldhurttheenvironment whilebeingquiteexpensive to run e.g., empowering irrigation systems using sensors. In this context, using data as an energy source for future machines could be a promising solution to mitigate the energy crisis and reduce the carbon footprint. The concept of data as a new form of energy will be discussed,examiningthebenefits andchallengesassociatedwiththis method.Thispaperalso proposes other potential applications for using data as an energy source, including powering self-driving cars, drones, and smart irrigation systems a data-driven approach.

Key Words: Data, Energy Consumption, Future Machines, IoT, Machine Learning, Artificial Intelligence,energy source,machine learning,healthcare

1.0 Introduction

Data is a new form of energy that has emerged in recent years. The volume of data generated globally is growing, and this data can be harnessed and transformed into energy. Data can be used to train machine learning models, and this process requires a considerable amount of computational power, which can be converted into energy. Moreover, data can be used to powerautonomous machines by processing data from sensors and using it to make decisions. The use of machine learning and artificial intelligence is expanding quickly across a broad spectrum of industries, including manufacturing, finance, healthcare, and transportation. The high energy requirements of these machines can make their adoption and sustainability extremely difficult. However, conventional energy sources like electricity and fossil fuels are not sustainable and may harm the ecosystem. The idea of harnessing process as a source of energy for future machines has surfaced as a potential remedy to the challenge. With the aid of machine learning technology, future machines directly learn from examples and experiences stored in data. Bridge *et al,* (2014), Sarah, *et al.* (2017). Being data-driven refers to the approach ofdeciding on a course of action after analyzing and interpreting data. In a data-driven approach, data is collected, analyzed, and interpreted togain insights and inform decisions. With the increasing availability of data and the development of advanced data analysis tools, organizations can now leverage data-driven approaches to optimize their operations, improve their decision-making processes, and power the operation and functionality of a future machine. In a transition from device-driven to data-derive example, sensor devices decide whether to power a water pump machine or not which are computationally expensive both in energy and time. This is an effect of the Internet of Things building a smart platform by adopting a data-driven approach. This approach is widely used in various fields, as mentioned above. The data-driven approach involves collecting data from various sources, such as surveys,customerfeedback,andperformancemetrics,andthenanalyzingthisdatatoidentify patterns, trends, and insights. Based on these insights, organizations can make data-driven decisions thataremoreaccurateand effective than decisions basedon intuition or guesswork. Overall, being data-driven can lead to more informed decisions, better outcomes, and a more competitive advantage in today's rapidly changing business environment. Data, also known as information in an electronic form that can be stored and used by adevice, is information, particularly facts or statistics that has been gathered for analysis, consideration, and application to aid decision-making. Cambridge Dictionary (2023). Furthermore, data types, Quantitative and Qualitative are described in their forms of input/output and can be discrete and continuous respective Qualitative vs Quantitative Data (2023). They are managed and handled through a different approach, for instance, you cannot utilize Natural Language Processing techniques on discrete values or calculate statistics for qualitative data. Data are classified into quantitative and qualitative. Quantitative data are presented and measured in their types of numbers and statistics. It is a solution to questions like how much, how many, and how frequent or occurrence. They are more descriptive and numerical. In contrast, Qualitative data could be used to characterize a group of people in a room, including their feelings, appearance, attire, and reasons for being there.

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YngviBjörnsson. (2008), Sarikaya et al, (2014). A group of researchers in their collective ideas formed the phrase "Artificial Intelligence" at, the Dartmouth Conference in 1956 and founded the discipline of AI. The domain of AI is responsible for civilization and advancement into the future. In the past few years, particularly since 2015, AI has grown rapidly. The primary cause ofthis is the ubiquitous accessibility of GPUs, which accelerates, lowers the cost, and increases the power of parallel computing. The one-two punch of almost limitless storage and an influx of data of all types (the "BigData movement"), including images, text, transactions, mapping data, and others, all play a role. Deng and Yu (2014); Mohri, Rostamizadeh, Talwalkar, and Ameet (2012). Traditional energy sources also known as conventional energy sources are primarily classifiedintoprimaryenergysources e.g. fossilfuels(coal,oil,andnaturalgas),nuclear energy, geothermal energy, falling water, and secondary energy sources like electricity and petrol.

Figure1.a.Primaryenergysourcesrangingfromcoal, and naturalgastoliquidhydrocarbon. [Source: Ministry of new and renewable energy (2023)]

The secondary energy sources are derivative of the primary source. Generally, conventional energy sources are management expensive, furthermore, not sustainable but have a long year of availability. These resources cannot be renewed. By the end of thetwenty-first century, natural gas and petroleum reserves are expected to be exhausted. Large volumes of CO_2 are produced by burning fossil fuels, adding to global warming. Given the impurities like damaging petrol emissions from the soil, which are a major cause of pollution, the issues linked with it are tremendous. The winds carry SO2, which then precipitates as acid rain. When mercury travels on air currents, falls as particulate dust, or mixes with precipitation in other places, it bio-accumulates and biomagnifies via ecosystems and may result in skin cancer. With the introduction of the Internet of Things (IoT), sensors, and connected devices, data generation is increasing at an unprecedented pace. Powering sensors and devices are effectually in- efficient as a long-term approach. This demands a better approach to power our machines in thefuturebyprovidinglowerenergyconsumptionmeansthroughadoptingdataasanenergy sourceforfuturemachines.Thetargetofthis paperis thepotential advantageofthetransition to data energy to power our future machines mainly in decision-making.

2.0 RelatedWork

Smart Agriculture is a data data-driven system known as Agriculture 4.0, which is related to the generalapproachtoagriculture.Atthis pointofconventionalagriculture,thesupplyofpower to meet the demand of over 8 billion people in the world begins with the type of soil, climate irrigation methods, energy consumption, water consumption, etc. To achieve this, several tools like Machine Learning and Artificial Intelligencemodels must be deployed to have data as an energy source for future machines in Agriculture ecosystems. The industry ecosystem has recently made investments in technical innovation, with a particular emphasis on low-cost, decreased energy consumption, reduced carbon footprint, and highly effective production operations with knowledge-based development gained via years of visualization and data gathering. These efforts have paid off in the creation of an IoT system based on smart irrigation and water reuse, which has reduced yearly water usage by 44% and saved 5.5 billion m3 annually. China has 20% of the world's population and only6% of the world's water. The Chinese government has developed and created technologies to encourage Water-Saving Irrigation (WSA) and advance towards Agriculture 4.0 in response to this data. By developing solutions based on cloud computing, the Internet of Things (IoT), and SOA technology, Kamienski et al. (2019) addressed the issue of water scarcity, a crucial component of agricultural output.

2.1 Understandingof Terminologiesin Data asan Energy Source

a. **Data:** data referred to in this paper is a collection of historical facts stored, analyzed, and used for the prediction of possibilities using a selected parameter generally known as the dataset. The main focus is smartirrigationsystems switchingfromsensorinputtodatainputbyapplyingmachine learning algorithms. The dataset is a collection of documents or files Snijders *et al* (2012).

b. **Energy Consumption:** This much energy is often used in home or industrial production. Global energy consumption decreased by 4.5% in 2020 before increasing by 5% in 2021. In the face of a global pandemic, Fig. 1.a determined that global energy consumption recovered with a 5% recovery in 2021 following a 4.5% fall in 2020. This recovery is three pointshigher than the 2%/year average from the 2000 to 2019 period.

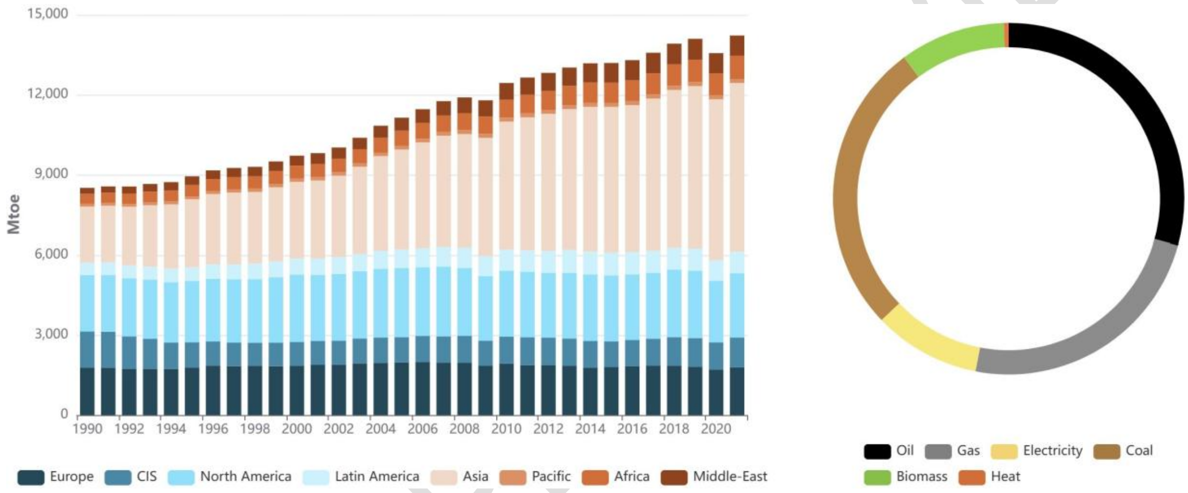

Figure2.GlobalEnergyConsumptionGlobalEnergyConsumption (2023)

MajorlychainChinawillaccountfor25%oftheworld'senergyconsumptionin2021,up1.5 percentagepoints from 2019.Thisspontaneousincreasein energyconsumptionaffects the world GDP negatively. And also increase in the price of goods and services. All are negative impacts of traditional energy sources.

3. **Future Machines:**these machinesarethe coretarget of the paper, what energy source would be efficient for optimal functionality of the systems without stoppage, Zhong *et al* (2011). The data energy source is the answer to reduce energy consumption and cost. The future machines will run on data data-driven approach which sources energy from data.

4. IoT: The Internet of Things are actual root idea of the paper, where energy consumed in powering sensors is replaced with energy sources like data which are more efficient and affordable. Datasets aregeneratedbasedonfeaturesextracted,theparametersarehyper-tunedtogetoptimal prediction which indicates water machine ON/OFF deploying parameters like soil moisture, temperature, status, and classes. The phrase "Internet of Things" (IoT) has gained popularity over the past ten years because it conjures up images of a vast network of physically connected items that may be connected at any time, anywhere Kosmatos, Tselikas, and Boucouvalas (2011).

5. Machine Learning and Artificial Intelligence: Artificial intelligence's field of machine learning has been extensively applied in the medical sector. Information such as patient information, medical treatment records, and medication status have been digitized because of the advancement of ICT technology and the advent of the era of big data, and a significant quantity of data has been produced in the field of medicine and healthcare. Kumar, (2016). In the industry of Agriculture, where crop irrigation is very paramount. The transition of energy sources from conventional methods to process as a source of energy, machine learning, and artificial intelligence are theforerunners of the system. Thereby determine thecondition of the soil per time either wet or dry from the historic data collected from functional soil moisture.

2.1.1 Self-driving cars

The first self-driving car was successfully piloted from Pittsburgh to San Diego in 1995which depended solemnly on the levels of autonomy, although it was not a standard production vehicle. The Navlab5, the fifth of ten cars that The Robotics Institute at Carnegie Mellon retrofitted, was an autonomous vehicle that could steer itself. These were predominantly powered by sensors or cameras that detect objects etc which consumes a lot of energy to make decisions, not in real-time. The level of autonomy where data are directly powering the decision of future machines isthe context of the paper. In this paper, data as energy source transition focuses on replacing energy sources, in powering of future machines. Adaptation of machine learning and artificial intelligence simplifies the data-driven machines for the future. This reduces energy contributing to a sustainable inhabitable ecosystem. Conventional auto producers are under pressure to transition from a mechanically operated car to a data-driven car. There is a clear need to become software-driven companies tocompetewiththefast-changingmarketshapedbyfuture-generationconnectivity, autonomous technologies, electrification, and shared mobility. The key to success is the simultaneous targeting of data as an energy source for next-generation vehicles.

Figure2.a.ArtificialIntelligent;Self-DrivenCar[source:Xie*etal* (2022)]

Fig 2.a. Fossil fuel power cars, known as mechanically driven, will soon reach their end. A transition to a data energy source car reduces energy consumption, and the cost of operation and making it more sustainable. Electric vehicles (EVs) will eventually take the place offossil fuel-powered transportation, but this transition won't happen quickly. The 2030 prohibition forbids the sale of brand-new petrol or diesel vehicles, but those who currently own them are still permitted to operate them on public highways. (2023) Mobility.

3.0 SmartIrrigation SystemusingML andAI

The research paper on the data as an energy source for future machines. The research focuses mainly on smart irrigation systems with the generic idea of replacement of soil moisture devices using a data-driven approach to determine when a machine is to power on or off. After running the system for several hours, data are collected for features like soil moisture, humidity, temperature, and soil type. The labels, which are the outcomes of the predictionare: very wet, wet, very dry, and dry.

Figure3. IoT-BasedSmartIrrigation System

The data asan energy sourcefor afuture machine is acleardescription ofthesmart irrigation systemwheredatageneratedbyFig3.isusedforprediction.Theapplicationofmachine learning and AI techniques determines the machine`s state (water pump) in the feature labeled status.

	A	B	C	D	E	F	G	H	I	J
1	id	temperatur	pressure	altitude	soilmiostur	note	status	class	date	time
2	1	29.1	9984.53	12.21-	377	0	0	Very Dry	08/10/2022	22:06:24
3	2	29.08	9984.36	12.22-	379	0	0	Very Dry	08/10/2022	22:06:24
4	3	29.06	9984.56	12.20-	376	0	0	Very Dry	08/10/2022	22:06:24
5	4	29.05	9984.39	12.22-	377	0	0	Very Dry	08/10/2022	22:06:24
6	5	29.03	9984.42	12.21-	379	0	0	Very Dry	08/10/2022	22:06:24
7	6	29.02	9984.59	12.20-	376	0	0	Very Dry	08/10/2022	22:06:24
8	7	29	9984.42	12.21-	380	0	0	Very Dry	08/10/2022	22:06:24
9	8	28.99	9984.27	12.23-	380	0	0	Very Dry	08/10/2022	22:06:24
10	9	28.97	9984.1	12.24-	380	0	0	Very Dry	08/10/2022	22:06:24
11	10	28.96	9984.1	12.24-	379	0	0	Very Dry	08/10/2022	22:06:24
12	11	28.95	9984.3	12.23-	379	0	0	Very Dry	08/10/2022	22:06:24
13	12	28.94	9984.13	12.24-	378	0	0	Very Dry	08/10/2022	22:06:24
14	13	28.92	9983.98	12.25-	379	0	0	Very Dry	08/10/2022	22:06:24
15	14	28.91	9984.16	12.24-	382	0	0	Very Dry	08/10/2022	22:06:24
16	15	28.9	9983.98	12.25-	380	0	0	Very Dry	08/10/2022	22:06:24
17	16	28.89	9984.16	12.24-	379	0	0	Very Dry	08/10/2022	22:06:24
18	17	28.88	9983.98	12.25-	381	0	0	Very Dry	08/10/2022	22:06:24
19	18	28.87	9983.98	12.25-	376	0	0	Very Dry	08/10/2022	22:06:24
20	19	28.86	9983.66	12.28-	377	0	0	Very Dry	08/10/2022	22:06:24
21	20	28.85	9984.01	12.25-	381	0	0	Very Dry	08/10/2022	22:06:24
22	21	28.83	9983.69	12.28-	380	0	0	Very Dry	08/10/2022	22:06:24
23	22	28.82	9983.34	12.31-	381	0	0	Very Dry	08/10/2022	22:06:24
24	23	28.81	9982.83	12.35-	384	0	0	Very Dry	08/10/2022	22:06:24
25	24	28.8	9982.52	12.38-	383	0	0	Very Dry	08/10/2022	22:06:24

Figure3.a.DatageneratedfromSmartIrrigationSystem[Chinedua(2023)]

The features specified in Fig 3.a. range from temperature, altitude, class, soil moisture, date, time, and status of the pump. The total number of data samples collected is 4689 and 10 columns. The features of interest are soil moisture, pressure, temperature, class (very wet, wet, dry, very dry), and water pump status (On/Off). Two machine learning classification algorithms were selected at random, naïve Bayes and randomforestwithacloseraccuracyvalueaftertheexperiment.Accuracyisnotthe most suitable metric for judgment on the performance of machine learning algorithms. With this will the f1 score, precision, and recall from the classification report where adopted?

	precision	recall	f1-score	support
Dry	0.86	0.79	0.82	183
Very Dry	0.93	0.95	0.94	511
Very Wet	0.99	1.00	1.00	921
Wet	0.99	0.99	0.99	729
accuracy			0.97	2344
macro avg	0.94	0.93	0.94	2344
weighted avg	0.97	0.97	0.97	2344

Figure3.b. NaïveBayes MLAlgorithmClassification Report

The classification report describes the collection of selected metrics, the precision, recall, and f1-score. Looking atthe metrics values for the performanceof the model considering the analysis the metric precision will be considered as a criterion of judgment due to variance or differences in each performance value.

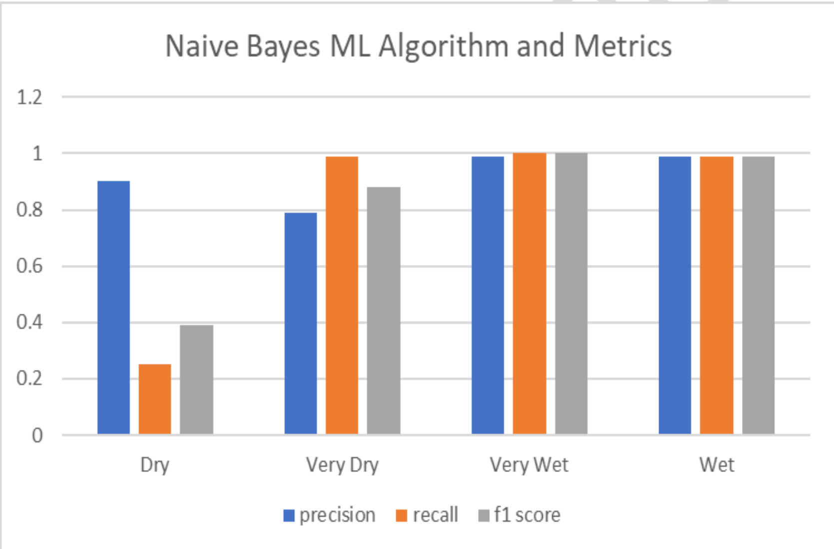

Figure3.c.NaïveBayes MLAlgorithmVisual Analysis

The fig 3.c. is visually represented. The paper concentrates on precision as a metric of judgment because of a good variation among the classifications. The class is between the dry, very dry, very wet, and wet.

	precision	recall	f1-score	support
Dry	0.90	0.25	0.39	183
Very Dry	0.79	0.99	0.88	511
Very Wet	1.00	1.00	1.00	921
Wet	1.00	1.00	1.00	729
accuracy			0.94	2344
macro avg	0.92	0.81	0.82	2344
weighted avg	0.95	0.94	0.93	2344

Figure3.d.RandomForest MLAlgorithm Classification Report

From classification report, this a collection of selected metrics (precision, recall, and f1-score). The features selected are pressure and soil moisture. The performance of the ML algorithm using the precision metric

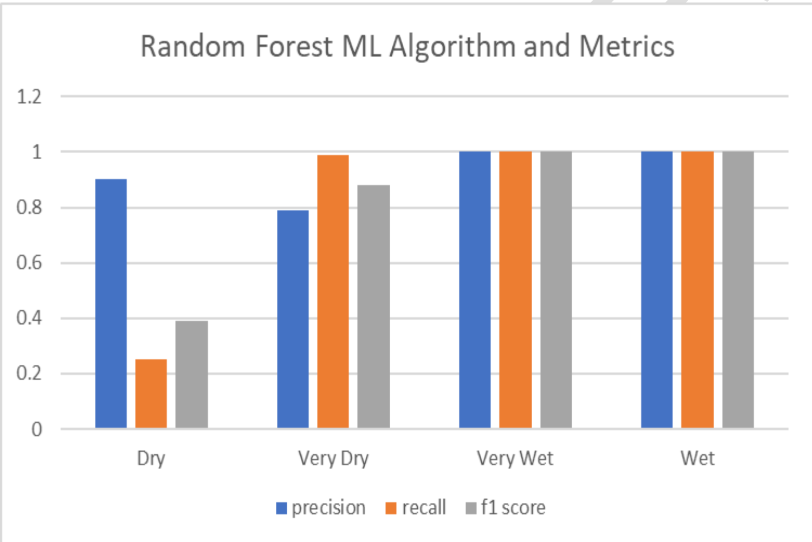

Figure3.e. RandomForest MLAlgorithm VisualAnalysis

Fig 3. e shows precision is a good metric for judgment overthe performance machine learning model random forest.

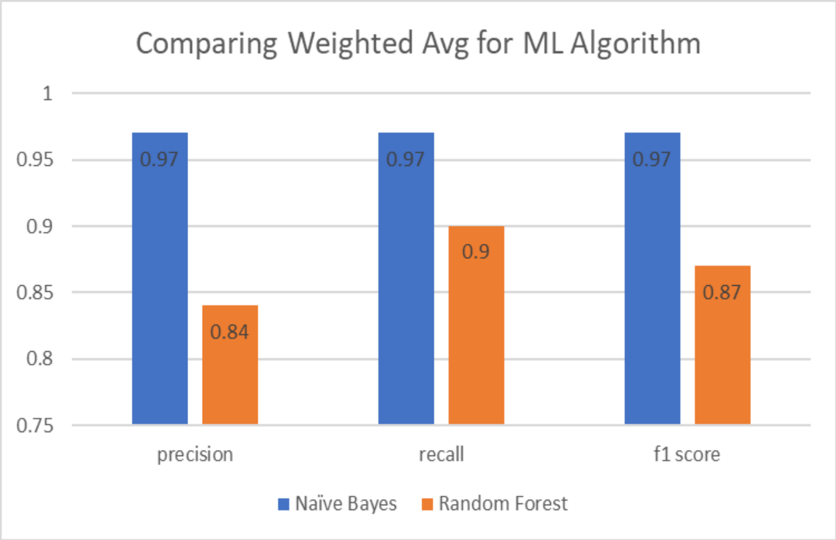

Figure3. f.ThecomparativeanalysisbetweenMLModels

Fig 3.f., comparing the weighted average value, between naïve Bayes and random forest ML algorithm using themetric precision for the judgment. Naïve Bayes performance was rated 97 percent of good prediction score which is averagely okay and subject to optimization. This willbeusedfora real-timeimplementationofasystemthatpredicts theconditionofthesoilto be either dry, very dry, very wet, or wet. Once the system predicts dry or very dry the water pump goes ON while when predicts wet or very wet water pump goes OFF.

3.1 Benefits ofthe Transition

The benefits are affordability and efficiency of a system running without a stoppage in operationalprocessesofthesystemdueto highconsumptionofenergysources.Usingdataas an energy source offers several potential benefits.

a. Itcansignificantlyreducethe energyconsumptionofdata centers.
b. It can increase the processing speeds of machines by eliminating the need to transfer data between processing and memory units.
c. Itcan improvedata securitybyreducing theneedto transferdata overnetworks.

3.2 Challenges posedbyTechnologies Adopted

There are many threats to the proper transition of energy from conventional energy to data energy sources. Several challenges need to be addressed before data can be used as an energy source to power future machines.

a. Theenergygeneratedbydataistypicallyverysmall,whichmakesitchallenging to harness. Chinedu B (2023).

b. The techniques used to harness the energy potential of data arenot yet matureenough to be used in large-scale applications.

c. Thecost of implementingthese techniquesisstill very high.

4.0 Discussion and Recommendation

Transitioning from conventional energy sources to data energy source answers the questionof affordability and efficiency of supplying energy consumption and looking at thedestructive effect of conventional energy sources on the human body and ecosystems. Data as an energy source is a recommendation for future machines where processing speeds of machines by eliminating the need to transfer data between processing and memory units, data security is efficient. Furthermore, on the outcome of the analytical experiment on the smartirrigationsystem,adoptingMLalgorithmtopredictandmakedecisions todeterminethe actual condition of the soil Fig 3.d is a clear example of data as an energy source for future machines. Naïve Bayes with a precision score of 0.97 will be used to implement a real-timesystem to predict the condition of the soil by supplying parameter values like pressure, temperature, and soil moisture to determine whether the soil is dry or wet to trigger the machine OFF or ON.

6 Conclusion

Data is a new form of energy that has emerged in recent years. Using data as an energysource has several potential benefits, including sustainability and the ability to power machines that are not connected to the grid. Furthermore, in smart irrigation systems where functions and operation of a sensor are no longer required, now predictable parameters are used to power the machine to either irrigate or not using machine learning and AI tools. This was presented in section 4. As the volume of data generated globally continues to grow, the use of data as an energy source will likely become more widespread in the future. However, there are also several challenges associated with this approach, such as the high computational power required to transform data into energy. Despite these challenges, using data as an energy source has several promising applications, including powering self-driving cars, drones, and other autonomous machines.

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