Smart Cities and Sustainable Development: Global Scenario

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Smart Cities and Sustainable Development: Global Scenario

Abstract

The construction of Intelligent cities is a broad, international strategy that each country is implementing in response to the current issues of climate change, global warming, and the carbon emission age. Utilising data coming out of several sources is a huge source of inspiration for exploring potentials that are still unexplored in the Virtual-physical world of multiple dimensions. Even in terms of ethics, artificial intelligence has the ability to expedite the global process for reaping rewards. The focus on how Intelligent cities are categorised globally according to predetermined criteria is encouraging for implementing changes that will make the combination of sustainability and Intelligent cities a logical and consistent strategy. Progress in creating Intelligent cities can be made possible by the proportionate development of artificial intelligence. The 'democratisation' of this new technology should centre on investigating novel applications of artificial intelligence. This article discusses the tabular presentation and discussion of the Intelligent City Index (INTELLIGENT CITY METRIC) 2024 result-based rating of 142 cities across 72 nations. In addition to going over a few topics related to sustainability and Intelligent cities, this chapter offers an example of how to apply a few regression machine learning algorithms from UCI repository database

Keywords: Durability, Artificial Intelligence, Data Analytics, Cyber world and virtualSecurity, Intelligent City

Introduction

"A smart city is where traditional networks and services are made more efficient using digital solutions to benefit its inhabitants and business. A smart city goes beyond the use of digital technologies for better resource use and less emissions." European Commission, on Smart City [1].

"Smart Cities focus on their most pressing needs and the greatest opportunities to improve lives. They tap a range of approaches - digital and information technologies, urban planning best practices, public-private partnerships, and policy change - to make a difference. They always put people first." What is a Smart City [2]

What is an Intelligent City 2?

Utilising formerly unheard-of technical innovations like artificial intelligence systems, the Internet of Things, and big data is the core of the Intelligent city lifestyle. The objectives are to optimise the use of available resources, reduce energy use and waste, create an atmosphere that stimulates innovation and creativity, and raise people's standard of living by reducing living costs and making things easier and safer 3.

When governments refer to any feature as "Intelligent," they are referring to the way that technology interacts with physical space. This includes technological advancements that facilitate system learning and the integration of ICT infrastructure through the use of virtual cloud platforms. The term "Intelligent city" originated from the concept of "Intelligent growth," which first emerged in the 1980s with the rise of the New Urbanism movement. New Urbanism attempted to improve the thinking of the 1970s, a decade of superhighways and urban sprawl, with its communitarian principles of improving urban living through limited land usage and challenging developmental concepts influenced by the automotive, real estate, and oil sectors. The emergence of the Intelligent city movement was made possible by the technological boom of the 1990s and the ideas of New Urbanism. 2004 saw the first-ever "Intelligent City Summit" take place during a conference in Toronto, Ontario, Canada. The goal of a Intelligent state or city is to give its citizens and visitors the best possible quality of life. Frameworks that provide the best possible quality of life include the Kyoto Protocol, the Europe 2020 policy, and the IBM Intelligent planet. Using enhanced ICT and Internet of Things technology, cities in the Americas, Europe, Asia, and the African Union are putting Intelligent city projects into action to raise the standard of living for their residents. Using Intelligent city infrastructure 4 is one way to provide equitable distribution of public services across several access points, including senior living communities, libraries, post offices, schools, and other public spaces.

In an Intelligent city, people employ digital technology to connect, protect, and enhance their quality of life. IoT sensors, security cameras, social media, and other inputs function as a nervous system that provides citizens and the city manager with constant information so they can make informed decisions 5. As demonstrated by the Global Center's launch of a Intelligent city program, creating inclusive, livable, and sustainable urban areas is a top development goal from the UN's standpoint. Intelligent cities improve the urban environment via the use of innovation and technology, leading to a greater standard of life, more prosperity and sustainability, and more engaged and empowered citizens. The Global Centre is situated in Singapore, a leading Intelligent city that has received numerous awards. A major factor in improving lifestyles and means of subsistence is digitalisation 6.

NIST's (2018) USA frameworks for Intelligent cities include requirements for interoperability, composability, and harmonisation, among other things. "Interoperability" refers to the ability of several systems and components to work together, even when components are combined and replaced from different sources. Diverse stakeholders possess distinct "concerns," all of which need to be addressed by particular technology. Each of these problems—like timing accuracy, Virtualsecurity, or communications—represents an additional interoperability component. "Composability" refers to the ability to add new functionality without compromising system advancement and integration. Getting these functional features gradually would be better than rebuilding or re-engineering the entire system. The process of achieving interoperability between systems and technologies—even when they appear to be incompatible at first—is known as "harmonisation." These technologies may come from different industries (public safety, transportation, energy, etc.) or may have been developed in accordance with different standards from different standards development bodies. Harmonising the different needs might lead to the production of complementary and interoperable solutions. Without harmonisation, the other two goals of the framework—composability and interoperability—cannot be accomplished.

[7].

Elements of an Intelligent city

In his work, Anthopoulos (2015) 8 discussed various widely used architectures as well as a general multi-tier ICT architecture that included UN-Habitat's five-layered key performance metrics. As comparable layers, there is the natural environment, hard infrastructure (based on ICT and not), services, and soft infrastructures. The environment, mobility, economics, people, living, and governance are the elements of an Intelligent city, according to many researchers 9 and sub-areas of the Intelligent city concept, each containing four clusters viz. urban logistics, Intelligent technologies, socioeconomic factors, and environmental factors. Furthermore, the results of their literature review pointed to a research gap, suggesting that a more thorough and varied vision of the future must better integrate the Intelligent city concept. By providing creative solutions to persistent problems like pollution, traffic jams, and energy waste, Intelligent city adoption can improve people's quality of life 3. Academic classification of Intelligent cities: Intelligent technology, Intelligent infrastructure, Intelligent economy and policy, Intelligent sustainability, and Intelligent health (Stubinger et al., 10). Fairness, self-governance, individual welfare, and meeting fundamental human needs are all included in the social dimension.

The economic dimension, on the other hand, is concerned with the variety and strength of metropolitan economies. According to this research, social justice, economic dynamism, resource conservation, and good quality of life may all be successfully attained in an urban setting when these goals are met. In literature on Intelligent cities, the idea of urban sustainability is frequently covered. But it's crucial to ascertain how much and in what detail this idea is covered in order to comprehend Intelligent cities 11. The well-received Intelligent city boasts infrastructures, living lab initiatives, open data, newly offered citizen services, Intelligent district components, and Intelligent city initiative management[12].

Global Ecosystem of Intelligent Cities

Based on a set of predetermined criteria, the worldwide Intelligent city is categorised by the IMD Intelligent City Index (INTELLIGENT CITY METRIC). For comparison, it makes use of the ranks, rating, structure, and ranking from the prior year, which shows any shift in ranking from the current one. Table 1-13 presents the INTELLIGENT CITY METRIC 2024 Results for the top 5 rated cities, encompassing 142 cities across 72 global countries. To obtain a rapid overview, a few short tabular form representations were created using the results that IMD published. Figures 1 through 4 and Table 2 exhibit them, accordingly.

Table 1: Intelligent city rankings

Abu Dhabi	AxesSubplot(0.125,0.125;0.775x0.755)
Amsterdam	AxesSubplot(0.125,0.125;0.775x0.755)
Auckland	AxesSubplot(0.125,0.125;0.775x0.755)
Beijing	AxesSubplot(0.125,0.125;0.775x0.755)
Berlin	AxesSubplot(0.125,0.125;0.775x0.755)
Bilbao	AxesSubplot(0.125,0.125;0.775x0.755)
Boston	AxesSubplot(0.125,0.125;0.775x0.755)
Bratislava	AxesSubplot(0.125,0.125;0.775x0.755)
Brisbane	AxesSubplot(0.125,0.125;0.775x0.755)
Brussels	AxesSubplot(0.125,0.125;0.775x0.755)

Busan	AxesSubplot(0.125,0.125;0.775x0.755)
Canberra	AxesSubplot(0.125,0.125;0.775x0.755)
Copenhagen	AxesSubplot(0.125,0.125;0.775x0.755)

Table 2 provides a rankings group list based on the INTELLIGENT CITY METRICES 2024 results for quick comparison purposes.

Table 2: Groupby column of Smart City 2024 rating, corresponding ranks, name of the INTELLIGENT CITY METRICES latest year data

City	Smart City Rank 2024	Smart City Rating 2024	
Abu Dhabi	10	BB	1
Amsterdam	18	A	1
Auckland	31	BBB	1
Beijing	13	BB	1
Berlin	37	BBB	1
Bilbao	29	BBB	1
Boston	36	BBB	1
Bratislava	56	BBB	1
Brisbane	30	A	1
Brussels	40	BBB	1
Busan	45	BB	1
Canberra	3	AA	1
Copenhagen	6	AA	1
Denver	66	BBB	1
Doha	48	B	1
Dubai	12	BB	1
Dusseldorf	44	BB	1
Geneva	4	AAA	1
Gothenburg	39	A	1
Guangzhou	65	CCC	1
Hamburg	14	BBB	1
Hangzhou	64	CCC	1
Hanover	53	BB	1
Helsinki	9	AA	1
Hong Kong	20	A	1
Jeddah	55	B	1
Lausanne	7	AA	1
Ljubljana	32	BBB	1
London	8	A	1
Luxembourg	27	BBB	1
Lyon	61	BB	1
Madrid	35	BB	1
Mecca	52	B	1
Melbourne	33	A	1
Munich	21	A	1

Nanjing	62	CCC	1
New York	34	BB	1
Oslo	2	AA	1
Ottawa	46	BBB	1
Paris	49	BBB	1
Prague	15	A	1
Reykjavik	26	BBB	1
Riga	59	BB	1
Riyadh	25	B	1
Rotterdam	41	A	1
Seattle	63	BB	1
Seoul	17	AA	1
Shanghai	19	BB	1
Shenzhen	60	CCC	1
Singapore	5	A	1
Stockholm	11	A	1
Sydney	22	A	1
Taipei City	16	A	1
Tallinn	24	BBB	1
The Hague	42	A	1
Tianjin	54	BB	1
Toronto	51	BBB	1
Vancouver	43	BBB	1
Vienna	23	AA	1
Vilnius	47	BBB	1
Warsaw	38	BBB	1
Washington D.C.	50	BB	1
Wellington	28	BBB	1
Zaragoza	57	CCC	1
Zhuhai	58	CCC	1
Zurich	1	AAA	1

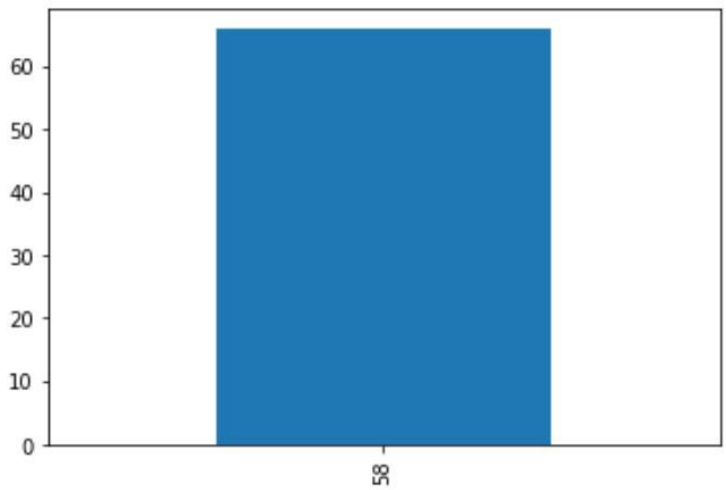

Figure 1: As per INTELLIGENT CITY METRICES data I

Fig 1 depicts the ratings counts based on Technology 2024 on the different types respectively, fig 2 provides the ratings count based on 2024 criteria.

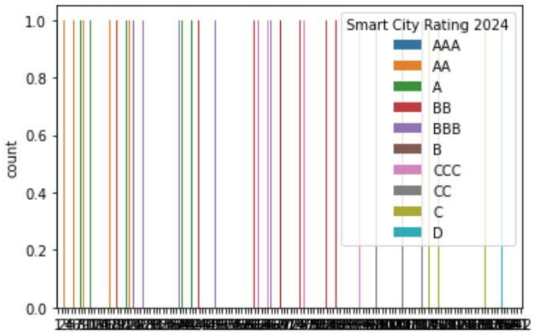

Figure 2: as per INTELLIGENT CITY METRICES data II

Fig 3 depicts the bar chart of city raking counts in each category.

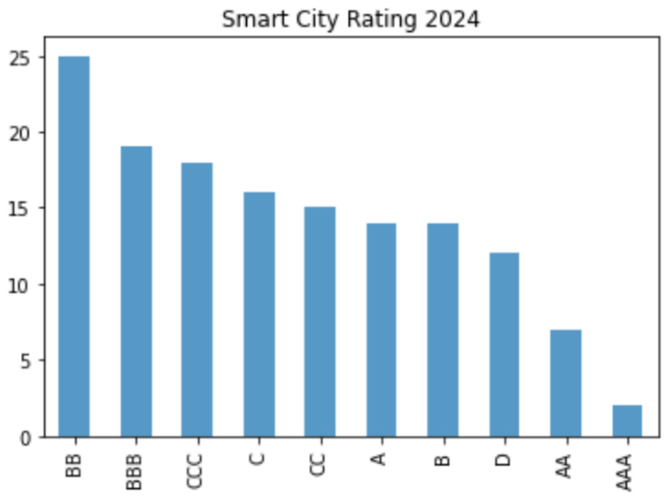

Figure 3: The smart city rating 2024 bar chart based on INTELLIGENT CITY METRICES data

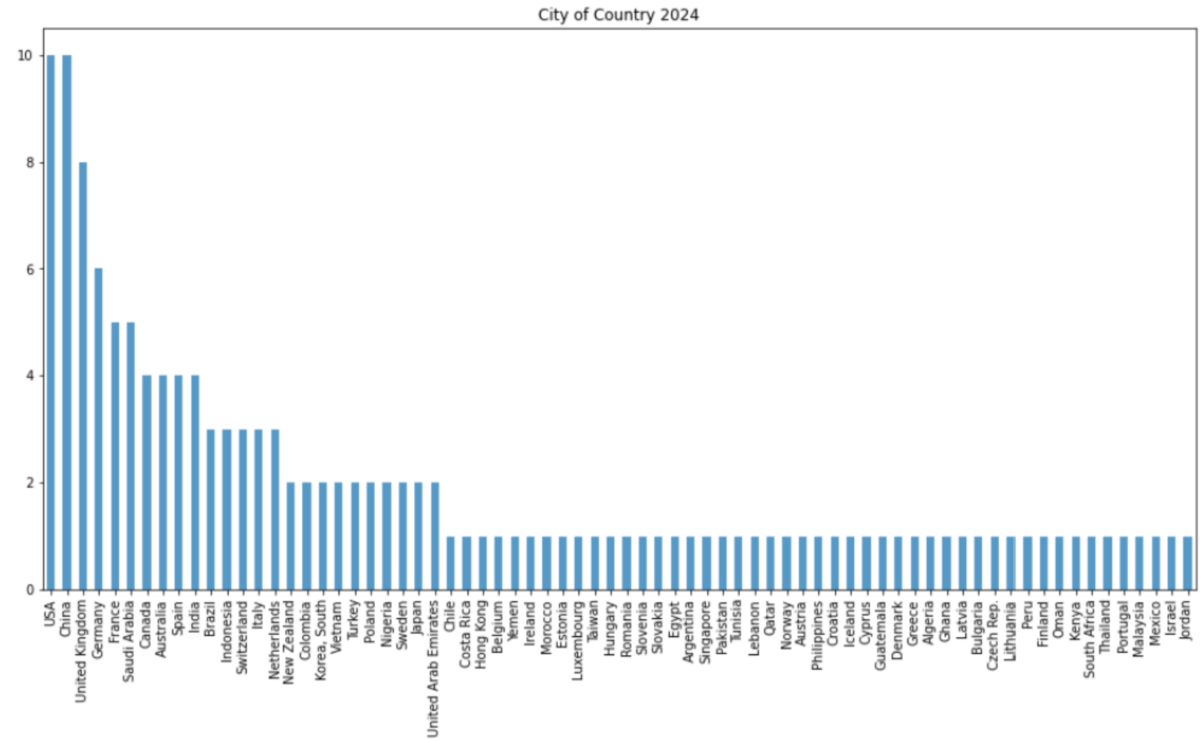

Figure 4: The INTELLIGENT CITY METRIC data bar chart of the corresponding nations

The INTELLIGENT CITY METRIC 2024 country list, which includes several of the list's cities, is shown in Fig 4. With ten cities apiece, the United States and obviously share the top spot. With eight cities, the North American city comes in second, followed by another European city with six cities.

It is renowned for using its integrative frameworks 14 and is ranked 71 in INTELLIGENT CITY METRIC 2024. The city project was organised around five axes: 1) open data; 2) Intelligent lighting; 3) social innovation; 4) alliance-building between research centres, universities, private and public partners; and 5) providing "Intelligent services" based on ICT 15. These initiatives were outlined by the City Council in 2010. has made significant progress towards becoming a Intelligent city. Furthermore, the case is especially significant due to its clear tendency in terms of municipal policies and reforms to become a well-known Intelligent City in Europe. As a result, assessing the Intelligent City initiative will shed light on 's current urban policies as well as their future course 12.

Central American country takes pride in having its own "blue zone," which is among the healthiest and longest-living regions on Earth 16. The capital city of San Jose is ranked 125th in the INTELLIGENT CITY METRIC 2024. According to The Independent, a UK news outlet, is recognised as the ninth healthiest of 17 countries. As part of the Real Estate Portfolio, 's first urban mixed-use development is Intelligent building(fig. 5). They construct a residential neighbourhood in Avenida Escazú that enhances well-being through distinctive urban experiences 18. Nevertheless, these creations demonstrate a creative approach to the global community's goal of a Intelligent city. They create living communities for the good of people and the environment, as their website states.

In order to guarantee minimal carbon emissions, electric vehicles—including buses—are commonplace in . However, some places have also seen the introduction of buses with electric overhead lines (Fig. 6). has a lengthy history of electric buses, dating back to the 1920s, according to BBC news websites 19. A medium Chinese City, the provincial capital of A similar another medium Chinese City, runs modern buses on a dedicated track with an overhead electric line. A medium Chinese City is ranked 64 in the 2024 INTELLIGENT CITY METRIC rating.

Figure 5: Latin American City, the capital of a small nation, is home to many dwellers, a Intelligent building. is one of the healthiest countries in the world.

Figure 6: In A medium Chinese City, the provincial capital of A similar another medium Chinese City, , green development ecosystem for sustainable development

Durability

Regardless of its level of technological sophistication, a city is considered Intelligent if its public organisations and public officials are able to create, implement, and assess a strategy and involve citizens and other stakeholders in its growth. This entails developing a city model that common people and other stakeholders co-conceive and co-implement 14. The United Nations (UN) 2030 Agenda for Sustainable Development is a global plan for peace and prosperity that aims to benefit both the environment and humankind in the present and the future. It was adopted by all UN Member States in 2015. The 17 Sustainable Development Goals (DEVELOPMENT CRITERIAs) are the focal point of the program; they represent an urgent call to action for global cooperation from both developed and developing countries. They understand the need to address poverty and other forms of deprivation at the same time as they put policies in place to improve education and health, reduce inequality, spur economic growth, fight climate change, and protect our forests and oceans 20.

Sachs and colleagues conducted research that built upon earlier findings from The World in 2050 program. These findings suggested six DEVELOPMENT CRITERIA Transformations as essential elements for accomplishing the Sustainable Development Goals (DEVELOPMENT CRITERIAs). The digital revolution for sustainable development 21 is one of the six areas of focus for sustainable development, along with education, gender, and inequality; (2) health, well-being, and demography; (3) energy decarbonisation and sustainable industry; (4) sustainable food, land, water, and seas; and (5) sustainable cities and communities. Interestingly, the use of these fields directly contributes to the thriving success of Intelligent cities. One of the main forces behind the DEVELOPMENT CRITERIAs is the development of knowledge and capability, and big data and a data-driven approach are emerging as important enablers for the years to come 22.

The Chinese province of A similar another medium Chinese City's capital, A medium Chinese City, demonstrates how to apply ancient solutions to modern problems. One example is the implementation of the Intelligent mobility program, which includes a multipurpose electric boat on the Great Canal that can transport goods and passengers without causing traffic jams. Figure 7 shows this in action.

Figure 7: One of the major Intelligent Cities that is improving is A medium Chinese City, the capital of A similar another medium Chinese City province in the most emerging country with abundant robotics application in daily life

Figure 8: An ambulance's green corridor and green panoramic roadways in A medium Chinese City,

Artificial Intelligence cum machine learning

History

Because there is a wealth of real-world data, Arthur Samuel's work over the past few decades has generated a great deal of attention and investigation. Two interconnected problems are at the heart of machine learning: (1) How can computer systems be designed to automatically improve with use? What fundamental ideas in computation, information theory, statistics, and learning apply to all learning systems, including those in computers, people, and organisations? Since it is still seen as relatively young, it advances quickly in many sectors.

Machine learning is typically seen as a subset of artificial intelligence, while deep learning is a further subset, as illustrated in Figure 9. Artificial intelligence is a general word.

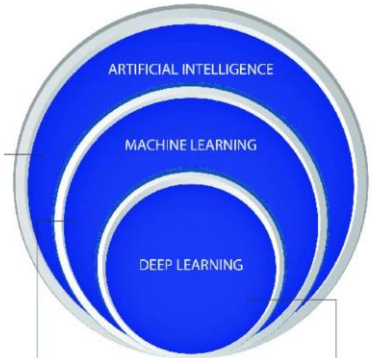

Figure 9: Artificial intelligence-machine learning and deep learning Venn diagram

Machine Learning Types

In supervised learning, an algorithm creates a function that maps inputs to intended outputs. The challenges of supervised learning are commonly referred to as the "classification problem." Through analysis of many input-output examples of the function, the learner is supposed to understand the behaviour of a function that transforms a vector to one of several classes.

When labelled examples are not available, unsupervised learning is used, which entails replicating a set of inputs.

Using both labelled and unlabelled samples, semi-supervised learning builds a suitable function or classifier.

An algorithmic method for teaching an algorithm to make judgements by observing and interacting with the outside environment is called reinforcement learning. Every activity generates an environment response, which then feeds back into the learning process.

Types of Supervised Learning

Regression and classification types comprise supervised classifications.

Regression

Numerical forecasts employ various techniques, including polynomial, linear, and sophisticated methods like Lasso and Ridge regression, to anticipate continuous target variables.

Grouping

k-nearest neighbour (kNN) 25, 26, Support vector machine (SVM) 27, Navies Bayes, Logistic Regression, etc. Decision tree 23, Random Forest 24, kNN

Types of Unsupervised Learning

K-means, k-mode, k-median, Principal Component Analysis (PCA), Hierarchical, and Independent Component Analysis (ICA) are some of the clustering techniques.

Learning via Reinforcement

Early Virtualnetics was the source of reinforcement learning, which has since been impacted by computer Intelligent City Metricence, psychology, neurology, and statistics. The fields of artificial intelligence and machine learning have demonstrated a notable and swift interest in this subject matter in recent decades 28. Using a system of rewards and penalties to train agents without providing clear instructions on how to perform the task, this strategy is known as enticing promise. Examples of these kinds of learning applications are robotics and autonomous vehicles.

In-depth education

Multiple processing layer computational models can obtain data representations at varying levels of abstraction thanks to deep learning. The state of progress in a number of other fields, including speech recognition, visual object recognition, item identification, drug development, and genomics, has significantly increased thanks to these methodologies. Deep learning makes use of the backpropagation approach to suggest changes to a machine's internal parameters that determine the representation of each layer by referencing the representation of the layer before it. This makes it possible for deep learning to uncover complex structures within large datasets. Recurrent neural networks have made it possible to analyse sequential data, including voice and text. Deep convolutional neural networks, on the other hand, have advanced significantly in the processing of speech, audio, pictures, and videos 29.

Scholars and professionals frequently utilise a few well-liked deep learning algorithms: Convolutional Neural Networks (CNN) 30, Long Short-Term Memory (LSTM) 31, Stacked LSTM 32, Gated Recurrent Unit (GRU) 33, and Bidirectional LSTM 34. However, the research community is also introducing a plethora of alternative deep learning techniques.

Analysis of Time Series Data

As data is essential to comprehending the Intelligent city ecosystem in a realistic manner, so too is open-source data. From a data analytics perspective, Christelle et al. examined the open data paradigm of Intelligent cities from 2015 to 2022 43. They show the following aspects of Intelligent cities: Intelligent living, governance, economy, people, environment, and mobility. Access to data, even if it is open source, is an essential requirement for study, particularly in terms of direction for the future.

Using Intelligent cars is part of Intelligent mobility. Nonetheless, traffic is equally important from the perspectives of time management, traffic congestion, and ease of movement in an intelligent city. For exploratory data analytics purposes, a typical use case of A significant European City, , which ranks 83 in INTELLIGENT CITY METRIC 2024, using traffic data 44 that is available in the UCI machine learning repository and was collected by TRAFFIC OPERATOR using the pandas open-source Python library 45 and a data frame in the Google Colab environment 46, 47, is provided below (EDA).

Dates of the data are 04-10-2016 through 19-12-2016. The original traffic data from A significant European City, UK, as seen in tables 3 and 4, is 35717 rows and eight columns of attributes after post-preprocessing. Any missing value treatment and the addition of derived data based on the datetime column in the day, weekday, month, and year were part of the data pre-processing. For the goal of improved data visualisation analytics, the occupancy column has also been driven to another % occupancy column. Nine properties are now displayed in the pre-processed dataset, as table 3 and table 4 below illustrate the top and bottom five rows, respectively:

An Application of Intelligent City Information

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Table 3: The top 5 rows of the dataset as in the pandas data frame post-pre-processing

Sl No.	SystemCodeNumber	Capacity	Occupancy	LastUpdated	Occupancy%	month	year	weekday	day	hour
0	0.997661	1	0.998816	0.998285	0.99498	0.991395	0.979759	0.96816	0.953796	0.931311
1	0.994058	0.998816	1	0.999912	0.998261	0.995644	0.985493	0.974441	0.960137	0.937874
2	0.993096	0.998285	0.999912	1	0.998816	0.996489	0.986801	0.975927	0.961675	0.939369
3	0.988202	0.99498	0.998261	0.998816	1	0.999209	0.992016	0.982195	0.968332	0.945713
4	0.983715	0.991395	0.995644	0.996489	0.999209	1	0.995497	0.986862	0.97357	0.950607

Table 4: The bottom five rows of the dataset, as in the pandas data frame post-pre-processing

Sl No.	SystemCodeNumber	Capacity	Occupancy	LastUpdated	Occupancy%	month	year	weekday	day	hour
35712	0.997661	1	0.998816	0.998285	0.99498	0.991395	0.979759	0.96816	0.953796	0.931311
35713	0.994058	0.998816	1	0.999912	0.998261	0.995644	0.985493	0.974441	0.960137	0.937874
35714	0.993096	0.998285	0.999912	1	0.998816	0.996489	0.986801	0.975927	0.961675	0.939369
35715	0.988202	0.99498	0.998261	0.998816	1	0.999209	0.992016	0.982195	0.968332	0.945713
35716	0.983715	0.991395	0.995644	0.996489	0.999209	1	0.995497	0.986862	0.97357	0.950607

The visual analytics are displayed in Fig 10 to 16 below. The systemCodeNumber categorical variable bar chart plot is depicted in Fig 10, which illustrates the type of car park used with the corresponding code provided by NCP, the car park operator. The occupancy vs occupancy percentage chart is provided in Fig 11, and Fig 12 depicts the capacity and occupancy chart. The occupancy bar chart for the hours of the day is provided in Fig 13, wherein the figure depicts car park occupancy from 7 hours in the morning to 16 hours in the afternoon, a generic trend in city car park occupancy. In the afternoon, 13 hours, the mode value is around 800 numbers, and the minimum occupancy in the morning, 7 hours, is around 250.

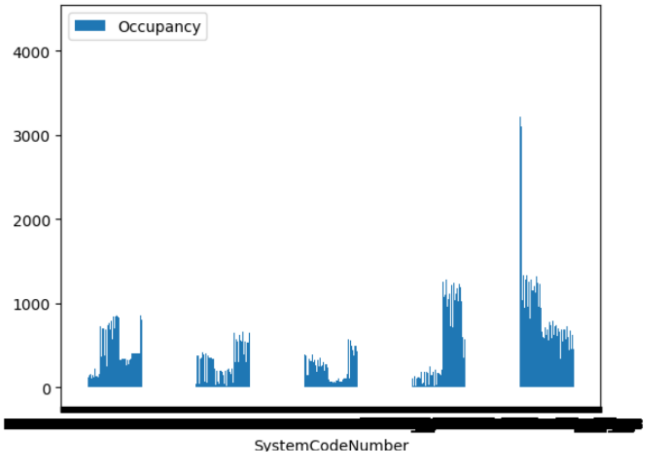

Figure 10: The systemCodeNumber columns

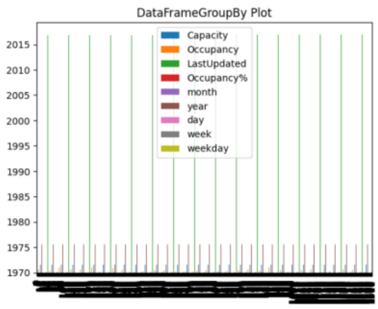

Figure 11: The dataframe groupby I plot

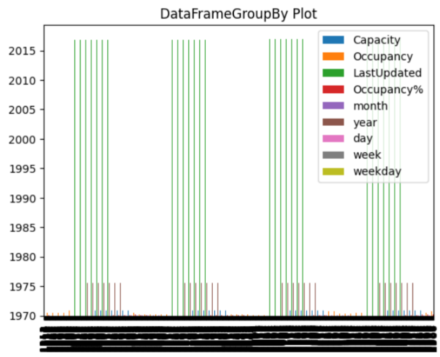

Figure 12: The dataframe groupby II plot

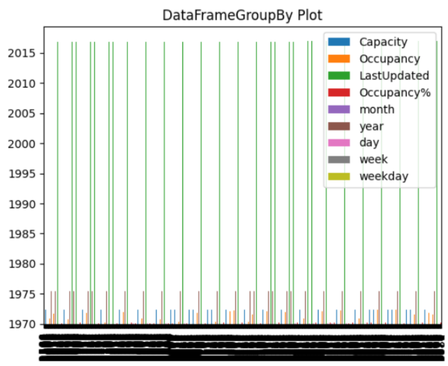

Figure 13: The different features-wise plot

Figure 14 depicts a two-month occupancy plot of the data provided, with an increasing trend, though single, apparently linear in Nature, for individual months rather than a generic trend for the total two months.

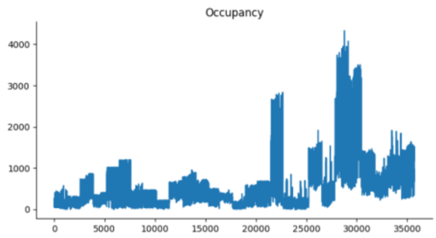

Figure 14: The occupancy density plot for the sample year

Figure 15 exhibits the occupancy line plot for the weekdays, which depicts the low occupancy on weekends compared to weekdays and weekdays.

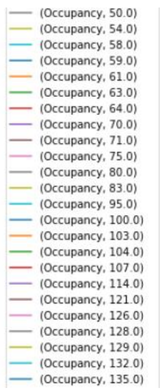

Figure 15: The plots for occupancy in different ranges

Fig 16 exhibits the occupancy plot for the entire month of 30 days, and it is for the different weekdays. Nonetheless, the pattern shows some variation, which is noticeable in Fig.

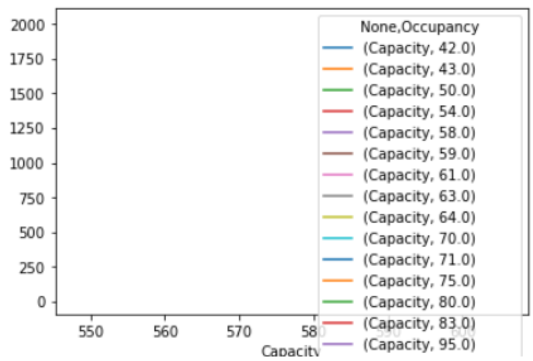

Figure 16: The capacity vs occupancy plot

As the dataset comprises both categorical and numerical variables, categorical ones are converted into numerical forms, and the correlation heatmap plot of all the variables is depicted in Fig 16. The correlation value explains the dependency of each variable with the others and provides a scope of inspection and gaining insight into the data, especially which data shows any trend of multi-co-linearity and thus enables to ponder the relevance of the variable to consider or discard concerning the target result cum meaningful information.

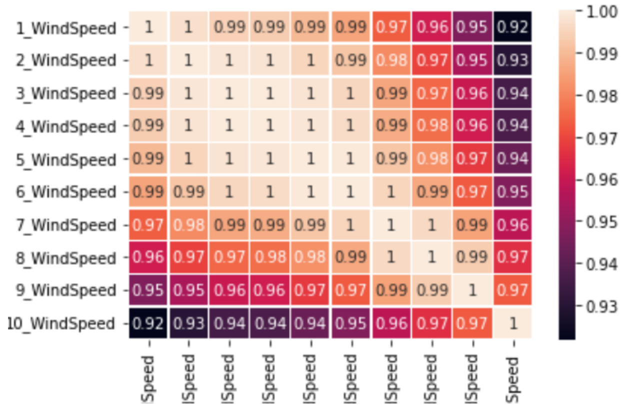

Figure 17: Correlation heatmap plot of the wind speed and direction dataset

Post data analytics of the City traffic dataset, the traffic occupancy dependency of any other variable has been investigated through the machine learning paradigm. The problem is a supervised technique of regression where any dependent variable relation with other independent variables can provide insight based on a data-driven approach. However, any relation with other variables should ideally be linear or non-linear, for which appropriate machine-learning techniques are available. Intelligent city metriceskit learns [48] library in Python has been used as a software resource to be run in a laboratory environment.

Table 5 provides a summary of linear regression, reflecting all the variables and their dependencies. Nonetheless, closer inspection suggests that the problem is unlikely to be of a linear regression kind; hence, a non-linear approach should also be undertaken for this dataset.

Table 5: Results of Regression Results

Apart from the linear regression method, support vector machine regressor, decision tree regressor, and random forest regressor have been used on the dataset for comparison of results purpose. From the results, it appeared by inspection that decision tree regressor and random forest regressor worked better than linear regression and support vector machine regressor algorithms. Table 6 compares decision tree and random forest regressor feature importance values wherein feature 0 appears significant compared to the other 31 features.

Table 6: Machine learning Algorithm and feature importance

Features- DTR - RFR		
Feature: n0	Score: 0.83392	Score: 0.71042
Feature: n1	Score: 0.01632	Score: 0.05079
Feature: n2	Score: 0.00100	Score: 0.03237
Feature: n3	Score: 0.11291	Score: 0.13125
Feature: n4	Score: 0.00000	Score: 0.00009
Feature: n5	Score: 0.00000	Score: 0.00067
Feature: n6	Score: 0.00201	Score: 0.00175
Feature: n7	Score: 0.00000	Score: 0.00163
Feature: n8	Score: 0.00000	Score: 0.00091
Feature: n9	Score: 0.00000	Score: 0.00024
Feature: n10	Score: 0.00000	Score: 0.00009

Feature: n11	Score: 0.00000	Score: 0.00002
Feature: n12	Score: 0.00000	Score: 0.00007
Feature: n13	Score: 0.00000	Score: 0.00064
Feature: n14	Score: 0.00000	Score: 0.00076
Feature: n15	Score: 0.00000	Score: 0.00033
Feature: n16	Score: 0.00000	Score: 0.00005
Feature: n17	Score: 0.00000	Score: 0.00055
Feature: n18	Score: 0.00000	Score: 0.00007
Feature: n19	Score: 0.00000	Score: 0.00010
Feature: n20	Score: 0.00000	Score: 0.00010
Feature: n21	Score: 0.00000	Score: 0.01374
Feature: n22	Score: 0.00000	Score: 0.00744
Feature: n23	Score: 0.00000	Score: 0.00059
Feature: n24	Score: 0.00000	Score: 0.00033
Feature: n25	Score: 0.00000	Score: 0.00221
Feature: n26	Score: 0.01477	Score: 0.01554
Feature: n27	Score: 0.00000	Score: 0.00899
Feature: n28	Score: 0.00019	Score: 0.01021
Feature: n29	Score: 0.00000	Score: 0.00022
Feature: n30	Score: 0.00000	Score: 0.00382
Feature: n31	Score: 0.01887	Score: 0.00371
Feature: n32	Score: 0.00000	Score: 0.00031

Table 7 depicts the R2 score of the training and testing datasets, which were split with a 70:30 ratio. The random forest technique yielded consistent and better results than support vector machines and decision tree regressors compared to the training and testing datasets.

Table 7: Performance metrics of different machine learning algorithms

Performance evaluated by Metrics	SVR	DTR	RFR
Coeff of determination Training	0.47	0.778	0.999
Coefficient of determination Testing	0.662	0.789	0.999

Aspects of Virtualsecurity in Intelligent Cities

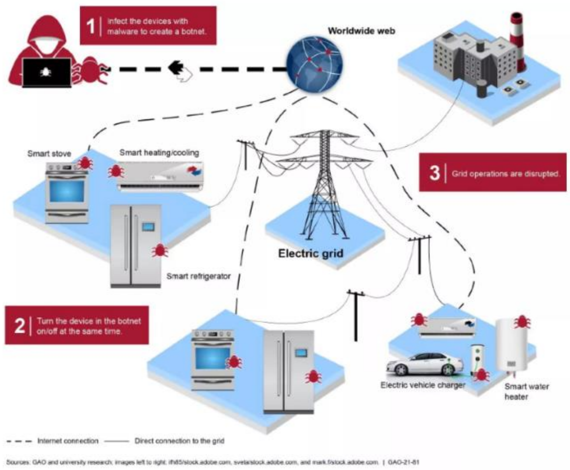

Figure 18: Invisible cyber attacker tends to target smart grid and smart city ecosystem and look for vulnerability

Security is addressed holistically in a Intelligent city by including all aspects of the city and integrating them into each of its component parts 49. By tying together Intelligent grids, electricity made Intelligent cities possible. On the other hand, Virtualcriminals, as seen in fig. 15, proactively search for openings. Intelligent grid development has accelerated recently due to technological advancements. The use of Intelligent grids has increased recently both in European nation and around the world, especially in critical infrastructures including energy systems, water, electricity, and natural gas. The importance of security concerns has increased in tandem with the surge in Intelligent grid implementation. Virtualsecurity attacks against these networks are becoming more frequent each year 50.

Cities that embrace Intelligent city planning also run the risk of facing more attacks from anonymous Virtualattackers operating in the virtual realm. The Intelligent city must also address the need to prevent hostile Virtualattackers from harming law-abiding inhabitants. Some of the most prevalent and Virtual security-sensitive elements of Intelligent cities are critical infrastructures, banking, healthcare, and public transportation. It's even thought that hackers are attempting to manipulate the e-vehicle charging gadget lately. Global positioning systems (GPS) 3, which are employed in practically all engineering and everyday applications nowadays, are one of the most sensitive fields. Many of these uses can be compromised by GPS spoofing.

Targeting Intelligent meters, artificial intelligence technologies, and the Internet of Things is also starting to become popular. Ullah et al. developed a Deep Reinforcement Learning (DRL) based method to thwart GPS jamming assaults against unmanned aerial vehicles (UAVs) in the air. Regardless of the channel type, UAV channel model, or jammer's geographic location, the suggested technique is meant to work. This method assesses the quality of UAV transmission in order to estimate the trajectory and power transmission level of UAVs. The results of the simulation show that the aforementioned method improves the mission-specific UAVs' 51 deployed Quality of Service (QoS). In their analysis of Virtualsecurity threats, Almeida et al. 49 created a Virtualsecurity cognitive map that included standards and laws, data privacy, network vulnerabilities, access restrictions, Internet of Things devices, and human behaviour. In 2023, the MITRE frameworks 52, which classify Virtualattack methods, methodologies, and procedures, introduced ATLAS 53, which outlines AI adversaries.

In Summary

Intelligent cities present a promising avenue for the progress of urban development. Using state-of-the-art technologies and data-centric solutions will help create more ecologically friendly societies in the face of growing metropolitan regions and complex issues 54. The two main forces behind sustainable Intelligent cities are energy decarbonisation and reduced carbon emissions. The basis of these is data generated, which British mathematician Clive Humby dubbed "the new oil" in 2006. To further investigate the data usage that the Virtual world is producing at an unprecedented rate these days, artificial intelligence is a crucial enabler for obtaining business intelligence of reality and efficacy. This chapter emphasised the potential application of artificial intelligence, however morally, to further investigate the advantages and provided a brief global scenario of the Intelligent city ecosystem. A significant European City, the second-biggest city in the UK, has also been described as a typical use case as a regression problem. Applying classification and clustering techniques to data from Intelligent cities generated by connecting to the internet is made possible by the data. The exponential growth of data coupled with its streaming across several Virtualspace devices and appropriate exploration of new paths of unrealised potential by users can revolutionise the Intelligent city paradigm on a global scale while maintaining local relevance.

Recognition

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