Journal of Cleaner Production 378 (2022) 134203

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Urban resilience and livability performance of European smart cities: A novel machine learning approach

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A R T I C L E I N F O

Handling Editor: Maria Teresa Moreira

Keywords:
City resilience
Machine learning
Predictive model
Smart cities
Urban livability

A B S T R A C T

Smart cities are centres of economic opulence and hope for standardized living. Understanding the shades of urban resilience and livability in smart city models is of paramount importance. This study presents a novel two-stage data-driven framework combining a multivariate metric-distance analysis with machine learning (ML) techniques for resilience and livability assessment of smart cities. A longitudinal dataset for 35 top-ranked European smart cities from 2015 till 2020 applied as the case study under the proposed framework. Initially, a metric distance-based weighting approach is used to weight the indicators and quantify the scores across each aspect under city resilience and urban livability. The key aspects under city resilience include social, economic, infrastructure and built environment and, institutional resilience, while under urban livability, the aspects include accessibility, community well-being, and economic vibrancy. Fuzzy c-means clustering as an unsupervised machine learning technique is used to sort smart cities based on the degree of performance. In addition, an intelligent approach is presented for the prediction of the degree of livability, resilience, and aggregate performance of smart cities based on various supervised ML techniques. Classification models such as Naïve Bayes, k-nearest neighbors (kNN), support vector machine (SVM), Classification and Regression Tree (CART) and, ensemble models including Random Forest (RF) and Gradient Boosting machine (GBM) were used. Three coefficients (accuracy, Cohen's Kappa (κ) and average area under the precision-recall curve (AUC-PR)) along with confusion matrix were used to appraise the performance of the classifier ML models. The results revealed GBM as the best classification and predictive model for the resilience, livability, and aggregate performance assessment. The study also revealed Copenhagen, Geneva, Stockholm, Munich, Helsinki, Vienna, London, Oslo, Zurich, and Amsterdam as the smart cities that co-create resilience and livability in their development model with superior performance.

1. Introduction

1.1. Overview

With an estimated population growth of 6.7 billion in cities globally by 2050, multifaceted intelligent urban systems form the norm (Sun et al., 2020). In the midst of unfettered urban flux, Laissez-faire urbanization has drenched the leapfrogging possibilities of smart solutions and digital intelligent platforms to turn cities into more liveable units thus, failing to offer a dignified standard of living to the urban inhabitants (Calzada, 2017). Digital solutions provide opportunities for development, at the same time pave ways for abuse and entail a litany of challenges (DeRolph et al., 2019). The use of smart technologies in cities have intensified beyond borders of utilitarianism to the extent of implying pressure on infrastructure (Lee et al., 2021). When rethinking strategic autonomy in the digital era, smarter cities, a paradigm beyond smart cities framed to optimize challenges, present a mesmeric case in tremendously ameliorating interconnectivity with less focus on creating value for urban inhabitants (Boykova et al., 2016). These smarter cities are moving up the ladder of digital development where techno-centricity takes the driver's seat (Yigitcanlar and Lee, 2014). Digital solutions in cities scale with users (Hatuka and Zur, 2020). However, embarking on technological development beyond a point where technology has met the user requirement, involves risk. Despite

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https://doi.org/10.1016/j.jclepro.2022.134203
Received 20 November 2021; Received in revised form 3 September 2022; Accepted 16 September 2022
Available online 10 October 2022
0959-6526/

smart technologies being a prerequisite in intuitively bridging gaps and concerns of urban inhabitants, the bureaucratic barriers have led to an uncoordinated drive for the technologies to scale when attempting to engage city residents for these technologies to work (Ramboll, 2020). Smart city experience of today focus on city dwellers as a means for testing smart solutions with less concern being paid on their values, beliefs, and livability (Mouratidis, 2021). When scaling technological developments within the urban context, the concept of livability requires special attention, as people and their interactions are the key drivers for technologies to find their application in the smart ecosystem (Sutriadi and Noviansyah, 2021). To continue, without human settlements, cities don't exist and thus focusing on the concerns of city residents and including the dimensions of people and communities with economic and environment pillars when addressing the concept of smart city is crucial for sustainable outcomes. However, being smart and sustainable too cannot fully improve all the key "quality-of-life" aspects and foster livability (Yigitcanlar and Lee, 2014).

The concept of livability can transform intelligent units into habitable spaces (Pan et al., 2021). However, techno-centric development must not only focus on livability as the soul to an endurable unit, but also on the ability of a city to rebound post stress, thus offering a dignified standard of living to the urban inhabitants. Cities are often vulnerable to unexpected predicaments such as economic upheaval, anthropogenic disruptions, climate change, geopolitical instability, public health crisis, and diplomatic embargos (Ukkusuri et al., 2021). Smart cities of today despite realizing the importance of resilience are no exception to these uncertainties. The Covid-19 outbreak in Wuhan, central China is a classic exhibition of insufficient city resilience (Chu et al., 2021). The Covid-19 pandemic has left lime lighted questions on urban resilience and livability of tech-driven smart cities around the globe (Feng et al., 2022). The pandemic paradigm has left opportunities for smart, sustainable, and mega-cities to optimize urban systems to cope with future external disruptions for a sustainable, liveable, and resilient habitable unit. Thus, it is seen that the failure of holistic thinking in optimizing development challenges has resulted in sceptics raising concerns on whether the aspiring smarter cities of today or the cities that claim to be smart and sustainable hold a striking balance between livability and resilience. Thus, the central agenda when making incremental technological improvements in smart and sustainable cities must include the traditional involvement of people and strategies to address the challenges in an urban scale; in short, resilience and livability. Thus, co-creating livability and resilience in cities to scale artificial intelligence (AI) solutions in a sustainable manner has become a top priority. It is incredibly important to explore and understand how smart cities address the concept of resilience and livability and to what extent ranked smart cities address these paradigms in planning for next generation cities. It is unclear so as to, 'Where does the world cities that are smart, smarter, and smart-sustainable fall within the dimensions of resilience and livability?'

1.2. Research significance and objectives

Smart cities are complex urban ecological systems built to optimize challenges and improve the residents quality of life with the ubiquitous use of data (Alsarayreh et al., 2020; Shehab et al., 2021; Kutty et al., 2022). However, the vision of smart cities goes beyond the use of information and communication technologies (ICT) for better resource use and fewer emissions for most (see: Albino et al., 2015; Mohanty et al., 2016; Akande et al., 2019; Sharifi, 2019). While, it means smarter urban transport networks, upgraded water supply and waste disposal facilities and more efficient ways to light and heat buildings for some (see: Ahvenniemi et al., 2017; IEEE, 2022). It also means a more interactive and responsive city administration, safer public spaces, capacity to absorb, recover and prepare for future shocks and, meeting the needs of an aging population for others (see: UNESC, 2016; ITU, 2016). Despite the literature explaining the concept of smart cities abundantly, with the concept expanding over the years, currently there is still not yet a common and acceptable definition for the smart city concept (Arafah, and Winarso, 2017). To support the implementation of the multifarious smart city concept, it is crucial to measure the performance of cities with the aim to historically document their strengths and weaknesses, for the scope of future improvements and to inform interested stakeholders about the level achieved in different target goals. Smart city assessment tools and models present city-rankings, revealing the best (and the worst) places for certain activities, which is pointed out by literature to be a central instrument for assessing the attractiveness of urban regions. Several smart city assessment tools and frameworks exist such as the smart ranking systems developed by the University of Vienna, the Intelligent Community Forum's Smart21 communities, the Global Power City Index, the Smarter Cities Ranking, the World's Smartest Cities, the IBM Smart City, and the McKinsey Global Institute rankings (Albino et al., 2015). However, an exhaustive overview of the frameworks, rating systems, and number of indicators, for the aforementioned smart city assessment tools and models, conducted by Albino et al. (2015), revealed a lack of thematic focus on the multi-dimensional concept of the expanding smart city concept and the omission of the indicator typologies. 43 indicator frameworks were scanned for indicators that could be related to the CITYkeys pre-selected subthemes and thus potentially be used for the CITYkeys framework. Based on this inventory analyzed by Neumann et al. (2015), it is reported that in general terms, the analyzed frameworks suggested that the availability of the key performance indicators (KPIs) were saturated. It also reported the following gaps in terms of the indicator availability: multilevel governance and economic vibrancy, education, employment, scalability, accessibility, and replicability. The report suggests that there was a significant variation in the coverage of different sub-themes, including for instance the "energy and mitigation" and "environment" sub-themes (Neumann et al., 2015). To continue, there have also been several approaches to standardize the indicators from which the frameworks or rankings can provide an assessment for smart city implementation. Recently, Huovila et al. (2019) provided a quite extensive comparative analysis of existing standardized indicators for smart city assessment. The analysis provided by Huovila et al. (2019) indicated that there is a lack of balance between the different indicators, namely between the indicators related to sustainability and smartness. There is also a strong emphasis on the smartness indicators (ISO-37120:2018, 2018; Sharifi, 2019). Huovila et al. (2019) affirms that International Organization for Standardization (ISO), European Telecommunications Standards Institute (ETSI), and Sustainable Development Goal 11 are well documented, but the International Trade Union (ITU) standards have a short definition of the indicators. The well-known indicator sets proposed by the ITU under the 'United 4 Sustainable Smart City' (U4SSC) initiative to shape future cities focus only on integrating sustainability with smartness under the dimensions: Economy, Environmental and, Society and Culture (ITU, 2016). Despite targeting the soul agenda of urban smartness and sustainability, the initiative promises on making future cities more resilient. However, the indicators under U4SSC fails to address urban resilience in depth across multiple dimensions of resilience.

Thus, it is seen that many of the existing smart city assessment frameworks and tools are mainly used for promotional purposes and very few for an evaluation of what actually should be done in order to increase the performance of future developments in terms of resilience and livability along with urban smartness. When a city is planned to be smart, it is a must to prepare the city to be resilient at all times (Arafah and Winarso, 2017). Further, to mitigate the negative effects of urbanization in cities, it is an essential target of sustainable smart cities to transform dwelling units into livable spaces (i.e., urban livability) - a concept clearly underrepresented in the smart city frameworks analyzed (Benita et al., 2021). Thus, envisioned to discretely answer the call of improved local livability and susceptance to unexpected predicaments, it is seen that the effective implementation of city resilience and urban livability face numerous obstacles. A recent review published by

Ramirez Lopez and Grijalba Castro (2021) on resilience in smart cities revealed a lack of integrity in practically addressing the multi-dimensional facets of city resilience, where a biocentric vision of territorial urban planning and capacity building is undertaken than a human centric approach to better living. Similarly, a review conducted by Paul and Sen (2020) revealed that the developed western cities that often act as benchmarks for Dickenson cities account the livability from a physical aspect (such as mobility options, transit-oriented design, and fiscal supremacies) than from a socio-economic perspective. It is to note that, shocks are meant to occur within cities that are termed smart, but to what speed can the cities rebound to their natural state is a question that institutions and policy makers must answer to better protect cities when under chaos. This requires a standardized lens for city leaders to analyse the resilience capacity to position adaptation to unexpected predicaments and livability frame of reference to envision a human centric development targeted for better living standards.

In vain, the livability and resilience paradigm have been used interchangeably in several contexts targeting the soul agenda; quality of life with a smart growth strategy to rebound post-stress. Given the intrinsic element of kinship between urban resilience and livability, it is crucial for planners and policy makers to analyse these paradigms under a generalized frame of reference tailored across multiple aspects. Thus, investigating smart city development from a broader strategic vision in light of resilience capacity and livability is crucial. For the same, several assessment approaches exist such as the non-parametric optimization based techniques like the data envelopment analysis, composite index based scoring, GIS and remote sensing based assessments and many more. Machine learning (ML), a subset of artificial intelligence (AI) has recently gained immense attention owing to its ability to effectively determine the relationship between the input features and the response variable (s) in a complex system (Wakjira et al. 2021, 2022; Hwang et al., 2021). Despite their great capability, machine learning models are rarely applied in the field of resilience and livability assessments in an urban scale. In this research, a large dataset of smart cities has been collected and used to propose a novel machine learning based framework for the assessment of resilience and livability of smart cities. Several machine learning classification and predictive models are built to understand the level of resilience and livability of smart cities based on a pre-defined set of indicators under multiple aspects. Thus, the ML algorithms would predict whether a city/smart city with specific ranking is resilient, livable and whether or not they co-create resilience and livability in their urban development model. To this end, this research targets to achieve the following objectives as to;

a) Present a novel two-stage framework combining metric-distance based multivariate analysis with machine learning techniques for the assessment of urban livability and resilience of smart cities based on various influential indicators.
b) Conduct a comprehensive assessment of city resilience and livability of 35 leading European smart cities as the case to identify their coping capacities based on their clustered performance as high, medium, and low.
c) Predict the degree of livability and resilience, as categorical variables, based on the values of the indicators under each aspect of resilience and livability using machine learning classifiers.
d) Compare and select the best classifiers based on coefficients such as model accuracy and precision to predict the degree of aggregate performance as the classification output.

2. Background review

2.1. The evolution of urban resilience and livability

Ecological modernization and socio-biophysical uncertainties in cities have raised consensus of urban planners in the opinion to include the concepts of livability and resilience in the existing development model. Since the classical era, Aristotle in his best-known work Ēthika Nikomacheia mentions the term “Eudaimonia” which means living a reconciled life (Yu, 2001). American psychologist Carol Ryff in 1989 extended Aristotle’s Eudemonic well-being of what she regarded as psychological well-being under: autonomy, personal growth, self-acceptance, sense of purpose in life, environmental mastery and positive relations with others (Ryff, 1989). Thus, livability is known from ancient time dating back to Plato and Aristotle, with a plethora of conceptualization at different period of time. The late 1960s and 1970s saw the emergence of livability with The Electors Action Movement (TEAM) in Vancouver, as a people-centric concept to the then existing growth-centred approach on the economy. Geographer David Lay argued on the existing livability approach of late 1970s as a discursive approach to showcase political power amidst the quality-of-life proposition (Lay, 1980). In 1981, Donald Appleyard, an American landscaper, introduced livability in the field of urban planning and design for the first time through his book ‘Liveable streets, protected neighbourhoods’. Appleyard et al. (1981) characterised livability as an unmeasurable definition to the quality of life through urban redevelopment plans, focusing on the infrastructure and transportation sector. Appleyard mentions that cities have different stage of attractiveness and thus different stage of livability. A Liveable city is one where people aspire to live and can afford to live (Newman, 1999). The late 1990s′ in the view of scholars was an era that focused on livability discourse as a means to address the concerns of the elite class and nobles; a neo-liberal agenda (Uitermark, 2009). The 21st century saw the use of livability as an integrative concept that connected human values with the social environment, rather than a profit-centred development agenda. Brenner et al. (2009) in his publication ‘Cities for People, Not for Profit’, exemplifies livability as “an alternative, post-capitalist form of urbanization.” There are many criteria that define livability of a city, where the criteria defining livability is either objective or subjective to an individual’s personality, culture, national background, traditions, and expectations. Dutch sociologists Tonkens and Constandse however argues on the objective notion of livability in cities, as it rips human-centric urbanization with the division of functionalism on cities, thus tarnishing the social fabric of community-living (Kaal, 2011). Thus, livability in modern era is a malleable concept translated into spatial levels to add quality to human lives, conceptualized under diverse contexts (Higgs et al., 2019).

Livability is obtained by re-creating small neighbourhoods so-called new urban villages with an eye to combat unprecedented urbanization (Weichselgartner and Kelman, 2014; Benita et al., 2021). These so-called urban villages are a part of complex ecological systems that are susceptible to several shocks and operate under numerous exogenous and endogenous uncertainties. Dealing with uncertainties is crucial for cities to thrive when attempting to recover from adversity (Nitschke et al., 2021). Building resilience in ecological systems is a vital endeavour towards reducing the exposure to extreme events and peace-building in city (Sanchez et al., 2018). Etymologically the word “resilience” originates from the Latin word “resilio”, meaning “to-bounce back” (Manyena et al., 2011). Resilience planning dates back to the ancient era, long since the Romans in 4th Century BC built the *Cloaca Maxima* sewer pipeline; a flood resilient sewerage network system (Galderisi et al., 2020). Resilient studies focus on understanding a systems performance pre and post disruptive events (Hudec et al., 2018). Reggiani et al. (2015) identifies resilience as; the ability of a regional system to return to equilibria post disruption (engineering resilience), or the extent to which urban systems can handle chronic stresses and shocks (ecological resilience). Martin (2012) recognizes adaptive resilience as the ability of a system to reorganize post stress to facilitate system operation through endless change and reduced recursion of shocks. While Lagravinese (2015) defines economic resilience as an adaptive capacity of regions/local areas to resist recessionary shocks. Socio-ecological resilience as identified by Rodin (2014), recognizes urban system as a nonlinear system susceptible to change in an evolutionary pattern. The fact that cities are socio-ecological systems, which feature dynamic interactions across time and space, implies that the adaptive approach to resilience can provide a more suitable theoretical basis for conceptualizing urban resilience (Sharifi and Yamagata, 2016). To achieve, maintain, and strengthen these abilities, any urban system should entail the following criteria: robustness, stability, flexibility, resourcefulness, coordination capacity, redundancy, diversity, foresight capacity, independence, connectivity and interdependence, collaboration capacity, agility, adaptability, self-organization, creativity and innovation, efficiency, and equity (Sharifi and Yamagata, 2016). A detailed explanation to these criteria can be found in Sharifi and Yamagata (2014, 2016). The degree of resilience can support explanations on why some regions are capable to withstand stress and the reason some adversely affected regions recover in a relatively brief period of time post disaster compared to other regions. When thinking about these criteria as the base of urban resilience system, it should not be forgotten that synergies and trade-offs exist between some of them. For instance, improving redundancy may have adverse implications for efficiency of the system. Or a balance point between independence and connectivity may differ from one context to another and, generally, finding balance between these two may turn out to be challenging (Sharifi and Yamagata, 2016). Thus, the concept of urban resilience and livability is multi-dimensional and does not hold a 'fixed boundary' in terms of its definition and interpretation.

2.2. Are smart cities addressing resilience and livability?

Transforming a city into being smart with the use of innovative technologies is vital and inseparable to achieve better living standards for urban residents (Mdari et al., 2022). Smart cities are vessels of intelligence and an efficient incubator of empowered spaces which clearly holds tight the importance of the themes: intelligence, well-being, resilience, and spatial development (Rios, 2012). Although these concepts are of high importance, they are addressed only marginally by several authors in their proposed definitions of the smart city. Livable cities shape residents to be better citizens, intelligent scientists, potential workforce, effective policy reformers and better enablers of smart services (Kutty et al., 2020; Kutty et al., 2020a). While resilient cities act as shields against undesirable externalities by working in 'smarter ways' with relentless focus on civic life and communities' adaptive capacities (Patel and Nosal, 2016). Thus, an intimate philosophical kinship exist between these paradigms. In vain, livability and resilience paradigm have been used interchangeably in several context targeting the soul agenda; quality of life with a smart growth strategy.

Despite philosophical kinship between both the paradigms, their application has spanned across diverse dimensions specific to social needs and diverse functionalism of cities. Although the objectives remain same, i.e., to enhance quality of living and provide a sustainable way of life to the inhabitants, most cities have diversified this objective to attain city specific goals to meet the needs of city dwellers. The Russian capital city Moscow addresses the bedeviled road traffic congestion issues by initiating alternative mobility plans and implementing intelligent transport systems (a clear example of pan-city development) geared at delivering a sustainable mode of work and life to the citizens (Golubchikov and Thornbush, 2020; Danilina and Slepnev, 2018; Chudiniva and Afonina, 2018). In Jaffa-Tel Aviv, the smart city practice is viewed as an ideal strategy to tackle the prevailing challenges of education, health, sanitation, and culture to promote sustainable development and community well-being (Toch and Feder, 2016). In the case of Singapore, the smart city program focuses on big data by implementing a nationwide network of digital sensors intended to provide city officials with real-time information on the happenings of the city by gathering, allocating, analyzing, and interpreting the data with the sole objective of transforming the country into an intelligent nation (Shamsuzzoha et al., 2021). Thus, offering a dignified standard of living to the citizens through smart practices. While the Msheireb downtown smart city project in Doha, Qatar which is an urban regenerative development program built with a strong and unique Qatari identity complementing Islamic architectural language aims at delivering a better and a greener standard of living to its citizens and expat community (Kucukvar et al., 2021; Sharif and Pokharel, 2021). The city intends to practice green transportation system by adopting zero emission mobility-electric tram system (Kucukvar et al., 2022; Kutty et al., 2020b). In addition, it also focuses on another important goal, which is to transmit knowledge and diversify the broadband connectivity. This initiative would aid the community to attract foreign investments into their market thus helping in boosting the smart economy with a touch of livability (Ringel, 2021). To understand the vulnerability of smart city development to climate change, nature based-solutions are integrated with built-up spaces to improve livability under the Smart City Mission in Bhubaneshwar, India (Pandey, 2021). Livability conditions were assessed in the city of Bhopal, India for smart mobility services based on socio-economic profiling (Chatterjee et al., 2020). Administrators in the city of Bhopal believe smart transportation as a measure to integrate community needs for economic and social development. Thus, a smart city can be viewed as a multi-objective concept tailored to achieve livability.

Reconfiguring urban development in light of sustainability requires integrating resilient features with digitalized smart solutions (Shmelev, 2016). The existing research on the urban resilience framework is mainly divided into two directions. One is a comprehensive resilience framework research based on multiple dimensions. The Rockefeller Foundation and ARUP proposed the city resilience framework (CRF) in 2014, which includes Health & Wellbeing, Economy & Society, Infrastructure & Environment and Leadership & Strategy (Arup and Rockefeller Foundation, 2014). Cutter et al. (2008) developed the disaster resilience of place (DROP) and baseline resilience indicators for communities (BRIC) to provide the baseline of measuring community resilience from the perspective of community capital. Jabareen (2013) attempted to establish a multidisciplinary conceptual framework to support urban resilience, thus proposing the resilient city planning framework (RCPF). Moreover, the disaster resilience scorecard developed by UNISDR assessed community resilience from the perspective of ten key tasks of disaster prevention and mitigation (UNISDR, 2004). A quick risk evaluation tool developed by UNISDR assessed community resilience from the perspective of required abilities to cope with common disasters derived from the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR, 2014). The other direction is an urban resilience framework based on specific risks or a single system. A resilience-based ontology was structured to assess and elaborate the real time data streams from smart city technologies in the city of Florence, Italy under the RESOLUTE project (Bellini et al., 2017). A real-time assessment of dynamic resilience of smart infrastructures was made possible through the Smart Resilience Project (SRP) by constructing a benchmarking matrix, the "resilience cube" (Jovanovic et al., 2019). The impact of critical infrastructure retrofits; smart rainwater harvesting mechanism on urban resilience was studied by Oberascher et al. (2021). To understand the impact of smart city development on urban resilience in China, Zhou et al. (2021) constructed an urban resilience model, where policy performance was assessed using the PSM-DID approach. While, based on the geomorphological characteristics, a mixed approach using machine learning (ML) classifiers and GIS was used to identify the hotspot areas prone to flood in Lisbon city, Portugal by Motta et al. (2021). A flood risk index was then constructed for the city within every 100 $m3$ *cell.* To improve the power distribution network resilience in Milan, Italy, Bosisio et al. (2021) used ML with GIS algorithm to understand the surges in the network under variable load conditions.

2.3. Bringing machine learning to smart city research

Machine learning (ML) is a hypernym term that encompasses several tools and techniques to explicitly perform tasks based on self-learning and adapting to patterns on their own (Alpaydin, 2020; Abdella et al., 2020). ML models assist in understanding system behaviours by executing functions through learned trends and patterns rather than any predefined set of procedural codes (Abdella et al., 2021). ML techniques also play a significant role in the areas that aim to foster smartness and sustainability from a city level perspective. Majumdar et al. (2021) used ML approaches to predict the congestion propagations on road networks using a LSTM network architecture based on motor vehicle speed data. A univariate and multivariate predictive model was built, and the predictive accuracy of the models were estimated. Wang and Gohary (2017) proposed several data-driven predictive models to understand the level of building energy in terms of consumption for smart infrastructures. Here, prediction using the smart metrices from historic data, along with feature selection identifying the required data quantity were based on ML algorithms. While, LASSO algorithm dealt with feature selection, three ML techniques were used for model implementation and testing. Nutkiewicz et al. (2017) combined data driven machine learning model with an energy simulation model to address the influence of transition spaces on building energy usage. The integrated model provided recommendations in addressing sustainable practises at the building design, management, and energy utilization phases. Li et al. (2019) developed and implemented an improved deep machine learning model by integrating genetic algorithms (GAs) and the extended Kalman filter (EKF) for effective computation, prediction, and accuracy of infrastructure smartness. This modified deep belief network (DBN) was trained using a back-propagation algorithm (BP-DBN), or new algorithm based on EKF. Gómez et al. (2020) used supervised modelling to develop a sustainability category forecasting framework to assess the comprehensive community perspective at micro territorial levels. The decision-making model used ML tools such as decision trees (DT), support vector machines (SVM), and artificial neural networks (ANN) to develop a sustainabile development index (SDI). Considering time dimensionality, Sehovac et al. (2019) developed a novel energy load forecasting method integrating RNN with Sequence-to-Sequence (S2S) deep learning algorithm. Two S2S models namely Gated Recurrent Unit (GRU) and LSTM were used to test electrical data consumed by a single building level post-smart retrofits at different forecasting lengths.

2.4. Research novelty and state-of-the art

It is seen that urban resilience and livability paradigms share multidimensionality (Bruzzone et al., 2021). Most of the existing resilience framework do not address socioecological and multi-dimensional facets of city resilience (Zhou et al., 2021). Indeed, most of the urban resilience assessments focus on addressing risk-specific events including natural calamities like flood, earthquake etc. with mere consideration of social connectivity, institutional resilience, and infrastructural aspects. Similarly, the current livability indices address quality of life from a materialistic point of view, ignoring well-being and other social aspects. The well-known Economist Intelligence Unit (EIU) 'Global Livability Index' (GLI) fails in addressing many environmental factors such as the access of green urban areas, sports, and recreational facilities, population claiming to suffer from noise pollution and, to what extend the citizens are active in the city (O'Sullivan, 2020).

In addition, most of the studies have used ML techniques to understand the smartness of cities across each Giffinger's dimensions with relatively no studies focusing on the use of ML techniques to understand resilience and livability in smart cities as a joint analysis. To continue, none of the studies have attempted to capture resilience and livability using ML techniques from a broader picture including a mix of materialistic and socio-economic conditions, political commitments, and resident engagement all under an indicandum. The use of ML classifiers in predicting the degree of resilience and livability of smart cities across a broad spectrum of themes is unique. Furthermore, the subjective weights assigned to indicators often increases uncertainty in the scores analyzed (Becker et al., 2017; Gan et al., 2017). Similarly, the use of equal weights for indicators ignores the relative importance and trade-offs between the indicators used in the assessment process (Paracchini et al., 2008; Greco et al., 2019). Composite indices developed by international organizations and institutions choose simplicity as the best methodological option. The current existing livability indices such as the OECD 'Better Life Index' and the EIU Global Livability Index, which act as the 'best' among many existing performance assessment frameworks for livability are all based on equal weights assigned to each indicator, dimensions, and sub-dimensions. Similarly, the well-established Arup 'City Resilience Framework' uses expert-based weights for all the indicators, aspects, and sub-aspects within the framework to construct a composite index to quantify resilience. Research has it that, unbiased and credible weighting schemes can deliver impressive gains in classification accuracy, while offering greater transparency, interpretability, and robustness (Card et al., 2019). Thus, to this end, this research attempts to close the prevailing knowledge gaps by proposing a novel two-stage joint assessment framework for resilience and livability assessment with several novel elements within as follows;

a) First of its kind joint analysis in smart cities using machine learning techniques that considers the intricate facet of connectivity lodged in the urban resilience and livability concepts for smart cities.
b) The livability assessment presented in this research includes a mix of materialistic and socio-economic conditions that intertwine each other to support the multidimensional perspective of livability; a unique approach least applied to the current existing livability frameworks.
c) The urban resilience indicators chosen for the assessment is unique in its ability to access the potential response capacity of city from a multi-dimensional perspective that includes political commitments and resident engagement.
d) An unbiased novel weighting scheme based on the relative metric-distance with reference to a benchmark entity being processed in the observed set is used to score and rank the performance of smart cities under multiple aspects of the resilience and livability framework.

3. Methodology

Integrated approaches can appear to be overly complex, however offers ways to resolve vagueness and uncertainties. The current study proposes a novel two-stage assessment framework combining multivariate analysis and various machine learning models for the first time to thoroughly investigate the resilience and livability of smart cities over time using a set of indicators. For this purpose, 35 leading European smart cities were chosen as the case study with data spanning across 2015 till 2020. To build consensus on the weights assigned to indicators, it is important to use concrete methods that remove subjective preferences unlike the most commonly sought equal weights and expert-based weights. For the same, in stage 1, a novel metric-distance based weighting and scoring approach is used initially to assign weights to all the indicators and obtain desired scores for each aspect under resilience (social, economic, infrastructure and built environment and, institutional resilience) and livability (accessibility, community well-being and economic vibrancy). In stage 2, two types of data-driven analysis are performed namely; clustering as one of the unsupervised machine learning technique and classification, a supervised ML technique. The Fuzzy c-means clustering algorithm as a simple clustering technique is used to identify the optimum number of clusters and label the smart cities to different clusters based on their performance as high, medium, and low. The classification techniques, Naïve Bayes, k-nearest neighbor (kNN), support Vector Machine (SVM), Classification and regression tree (CART), Random Forest (RF), and Gradient Boosting Machine (GBM) are used to predict the level of livability and resilience of smart cities, as categorical variables, based on the values of the indicators under each aspect of resilience and livability. A total of 68 indicators (30 livability indicators and 38 resilience indicators) were used in computing the aggregate performance and building predictive models. The schematics of the machine learning techniques and proposed model in this study is shown in Fig. 1.

3.1. Research data and description

In this study, 35 top ranked European smart cities selected as per the ranks published in the IMD-SUTD Smart City Index 2020 were chosen to study the resilience and livability performance of smart cities. The Smart City Index 2020 ranks cities based on economic and technological data, as well as by their citizens' perceptions of how "smart" their cities are. Due to these cities covering nearly three-quarter of the list of top 50 leading global smart cities, the sample size is fairly large for the results to be economically extrapolated to a global level when understanding resilience and livability in the current smart city development models. For the purpose of the present study, it is important to establish a working definition of livability and resilience in the context of smart cities. Livability describes the frame conditions of a decent life for all the inhabitants of cities, regions and communities including their physical and mental wellbeing. Livability is based on the principles of sustainability and smartness and thus is sensitive to nature and the protection of its resource. As a special focus to improve livability in smart territories, we consider three prime aspects that are relevant to livability namely; accessibility (Ziemke et al., 2018), community well-being (Phillips et al., 2014; Chao et al., 2017), and economic vibrancy (Schnitzler and Shmelev, 2019). Accessibility is that aspect which aims to create an urban environment that all citizens have easy access to urban services, as accessibility reflects the quality of an urban environment; Planning for community wellbeing means identifying strategies and actions that will help people live healthy, happy, and fulfilled lives; Economic vibrancy is the characteristics of an economy that is vibrant and continuously contributing to the health and well-being of people and communities by providing economic security and access to opportunities. While resilience describes the vulnerability of a city to various shocks and disturbances from the outside world and itself. Thus, resilience assessment in smart cities helps in understanding and thus guiding the future of the city with the concept of adaptability. We consider the fact that the resilience of a system depends on the resilience of sub-systems, which comprise infrastructure and built environment resilience (Masoomi, and van de Lindt, 2019), institutional resilience (Guiraudon, 2014), economic resilience (Williams and Vorley, 2014; Bastaminia et al., 2017) and social resilience (Säumel et al., 2019; Copeland et al., 2020). Social resilience is a function that involves demographic characteristics and people's ability to acquire resources; economic resilience refers to the economic vitality of a local community and the diversity of the economic environment, which can ultimately be attributed to ensuring the stability of residents' livelihoods; institutional resilience refers to the region has extensive disaster experience, disaster reduction planning and resources, including local government efforts to increase disaster awareness and residents' disaster preparedness; infrastructure resilience refers to the ability of a community to recover from and respond to disasters and infrastructure damage. To continue, a core component of completing a resilience and livability assessment is identifying the initial indicators to assess resilience and livability and measure their progress over time. However, the indicators are not conceived as a defined set of measurements but rather as a guide to understanding and strengthening resilience and livability in cities that are claimed to be smart. The main purpose of the indicators is to assist communities in developing livability/resilience-strengthening strategies that encourage innovation, socio-ecosystem protection, and beneficial interactions across several urban aspects relevant to resilience and livability. While there are no cardinal rules or set procedures to be followed in selecting indicators, all the indicators for this study were selected from the existing literature on resilience and livability across multiple aspects (see Table S1 and Table S2) according to whether or not they are relevant to the issue they are intended to describe, thus helping maximize the usefulness of the information for decision-making. All the data for each indicator across years from 2015 till 2020 were collected from the city statistics database of European commission (https://ec.europa.eu/eurostat/web/cities/data/database) and the OECD regional and cities statistics (https://stats.oecd.org/). The indicators and aspects selected for urban livability and city resilience along with their desirability values are presented in Table S1 and S2 (Appendix A), respectively. A correlation matrix is often used to summarize data, as an input into a more advanced analysis, and as a diagnostic for advanced analyses. The correlation matrix, which shows the correlation coefficients between the indicators under various aspects of urban livability and city resilience used in the study is shown in Figs. 2 and 3, respectively. This matrix is symmetrical, with the same correlation shown above the main diagonal being a mirror image of the values below the main diagonal. Table S3 and Table S4 in appendix present the descriptive statistics of all the urban livability and city resilience indicators for the average annual data (see Fig. 3).

3.2. Non-dimensional normalization

Multi-criteria performance indicators have different measuring units (Abdella et al., 2019). To remove the variability and achieve dimensional consistency, all these compound indicators must be normalized (Abdella et al., 2017). Research has shown that normalizing data before evaluating it on classifiers impact the classification performance (Quackenbush, 2002). Several data normalization techniques exist in literature such as; linear scaling (Latha and Thangasamy, 2011), median-MAD normalization (Eesa and Arabo, 2017) clipping (Choi et al., 2016), z-score (Saranya and Manikandan, 2013), log scaling (Shier, 2004), Double-sigmoid (Jain et al., 2005), Tan-h normalization (Farmanbar and Toygar, 2016) and many more. Some of these normalization techniques have been used and tested for accuracy by many researchers for the improvement of the classification performance in the area of machine learning. However, these pre-processing methods cannot be generalized, and no method has yet been claimed to be superior to the other (Singh and Singh, 2020). That being said, Min-max [0, 1] normalization method was reported the best when compared to some existing normalization methods (e.g., z-score, tanh, Quadric-Line-Quadric, mean-centred, Sigmoidal, and decimal scaling) for the classification of data on SVM (Lin et al., 2008), Induction Decision Tree classifier (Al-Shalabi and Shaaban, 2006), k-NN (Su et al., 2016), Probabilistic Neural Network (Kadir et al., 2013) and XGBoost (Borkin et al., 2019) classifiers. Thus, in this study, in the data pre-processing stage, the linear min-max scaling, a common data normalization technique is used, which when applied to data belonging to various field has shown significant accuracy on the classification performance. The overall indicator-matrix in time $t, t+1, \ldots, t+N$, denoted by $X^{k}_{ijt,t+1\ \ldots\ t\ +\ N}$, when considering the ith indicator column under the *k*th aspect for the *j*th smart city under study is as shown below:

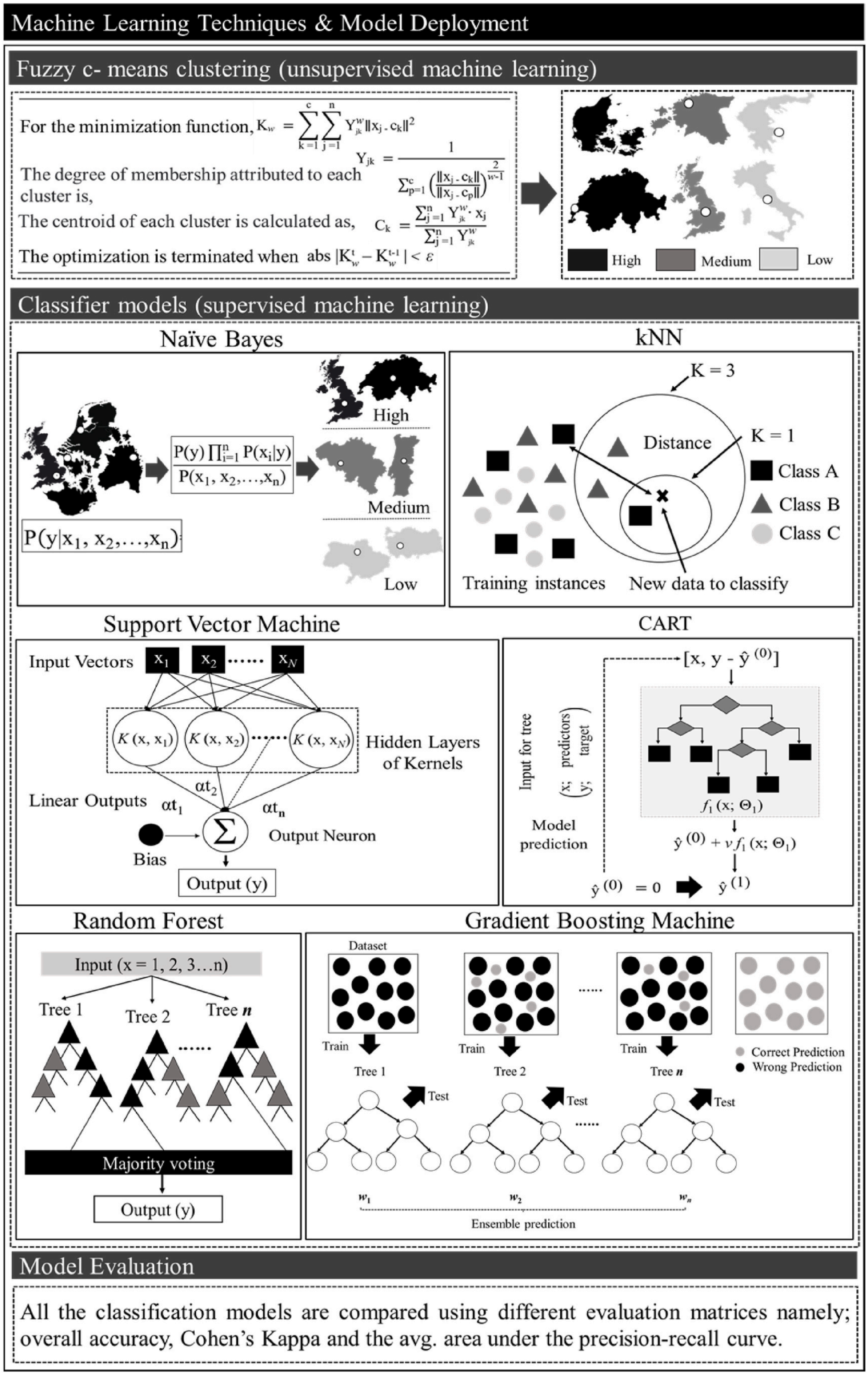


Fig. 1. Proposed machine learning techniques for the resilience and livability assessment of smart cities.

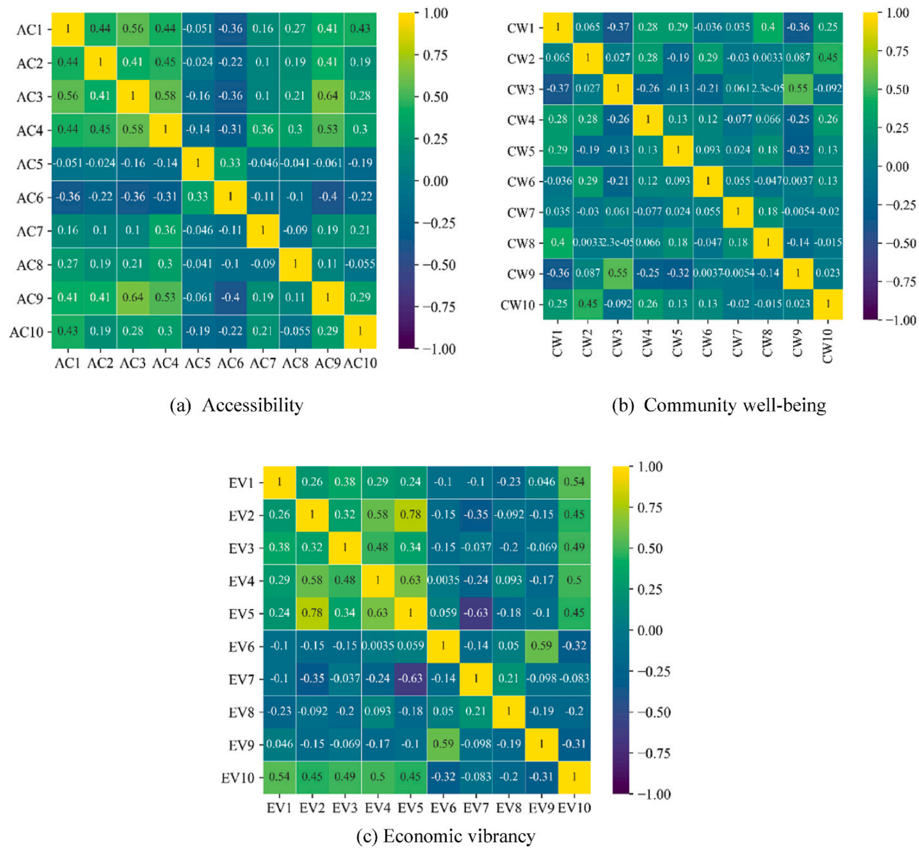


Fig. 2. Correlation matrix for all the indicators under each aspect of urban livability.

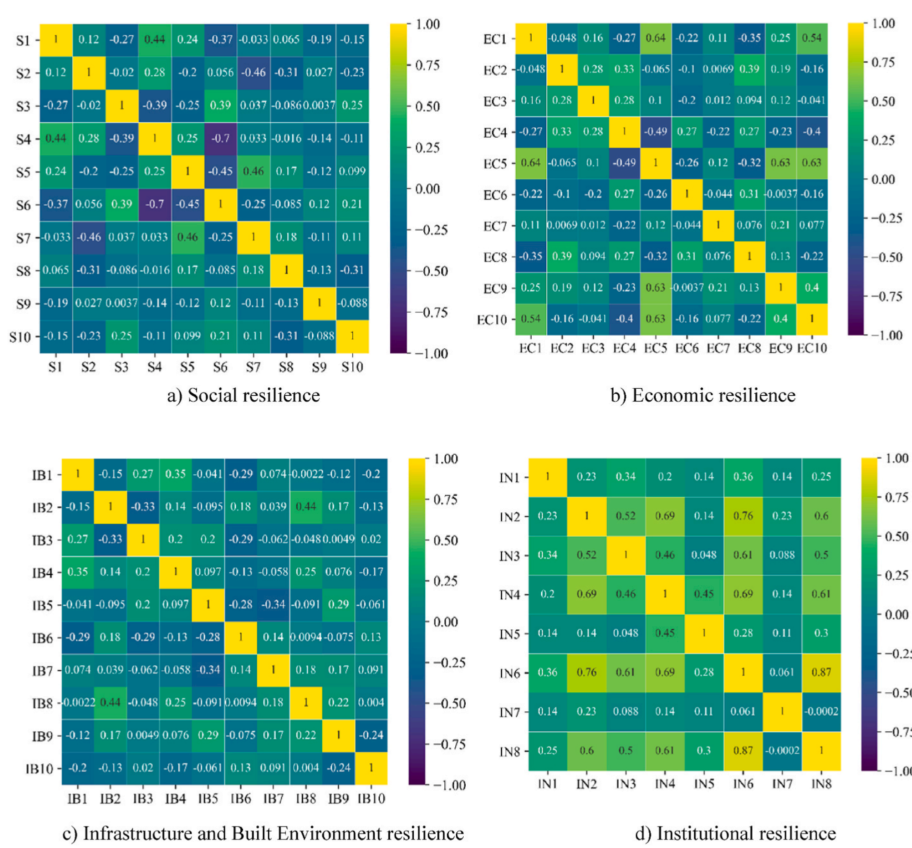


Fig. 3. Correlation matrix for all the indicators under each aspect of urban resilience.

$$X^{k}_{ijt,t+1\ldots t+N}=\begin{bmatrix} Xk11t & Xk11t+1 & \ldots & Xk11t+N & Xk21t & Xk21t+1 & \ldots & Xk21t+N & \ldots & Xkm1t & Xkm1t+1 & \ldots & Xkm1t+N \\ Xk12t & Xk12t+1 & \ldots & Xk12t+N & Xk22t & Xk22t+1 & \ldots & Xk22t+N & \ldots & Xkm2t & Xkm2t+1 & \ldots & Xkm2t+N \\ Xk13t & Xk13t+1 & \ldots & Xk13t+N & Xk23t & Xk23t+1 & \ldots & Xk23t+N & \ldots & Xkm3t & Xkm3t+1 & \ldots & Xkm3t+N \\ \vdots & \vdots & \ldots & \vdots & \vdots & \vdots & \ldots & \vdots & \ldots & \vdots & \vdots & \ldots & \vdots \\ Xk1nt & Xk1nt+1 & \ldots & Xk1nt+N & Xk2nt & Xk2nt+1 & \ldots & Xk2nt+N & \ldots & Xkmnt & Xkmnt+1 & \ldots & Xkmnt+N \end{bmatrix}$$

where i = 1,2,3 .... m; j = 1,2,3 ... ***n*** and; X^{k}_{ijt}, X^{k}_{ijt+1}, and X^{k}_{ijt+N} represent the ith indicator column under the kth aspect over time t, t+1, and t + N, respectively for the jth smart city considered for the assessment. Initially, the indicators are categorized based on the degree of desirability i.e., on how an indicator would contribute to the outcome of the phenomenon to be estimated (see Table S1 and Table S2). If the indicator value contributes in a positive manner to the desired outcome, it is ascribed as a positive-indicator (e.g., in the selected city resilience indicators, the indicator "span of bicycle network per km^2" has 'positive' desirability). Other else, the indicator is attributed as a negative-indicator (e.g., the indicator "Percentage of population with no access to health insurance coverage" has 'negative' desirability among the other urban livability indicators).

The normalized scores for the positive-indicators are calculated using Eq. (1):

$$X^{k}_{ijs}=k+\frac{\left(X^{k}_{ijs}-Min^{k}_{js}\right)(K_1-k_0)}{\left(Max^{k}_{js}-Min^{k}_{js}\right)};\forall s=t,t+1,\ldots,t+N \tag{1}$$

where Min^{k}_{js} and Max^{k}_{js} are the minimum and maximum values of the jth smart city under the kth aspect for over the respective time 's'. Eq. (1) is further modified to find the normalized scores of the negative-indicators (i.e., to reverse the desirability on the normalized score) as shown in Eq. (2);

$$X^{k}_{ijs}=k+\frac{\left(Min^{k}_{js}-X^{k}_{ijs}\right)(k_0-K_1)}{\left(Max^{k}_{js}-Min^{k}_{js}\right)};\forall s=t,t+1,\ldots,t+N \tag{2}$$

K_1 with an assigned value of 1 is the upper bound, while k_0 with an assigned value of 0 is the lower bound of the normalized data set. Assigning 1 and 0 to the upper and lower bound respectively can give a range of unit length to the resulting normalized scores.

3.3. Metric-distance based weighting and scoring

Multi-criteria performance assessment combines numerous heterogenous indicators across several aspects in a standardized manner to a single synthetic score that explains the behaviour of the phenomenon to be measured. In this step, we propose a novel three-step multivariate metric-distance based approach to weight the indicators and obtain a homogenized score for each aspect under city resilience and urban livability.

First, for a selected set of standardized indicators, $X^{k}_{ij}=\left[X^{k}_{1j},\ X^{k}_{2j},\ \ldots,\ X^{k}_{mj}\right]$ determined to represent the decision-making entities (in this case, European smart cities), the metric distance of a homogenous decision-making entity $\boldsymbol{e_u}=(X^{k}_{1u},\ X^{k}_{2u},\ \ldots,\ X^{k}_{mu})$ with respect to a benchmark entity $\boldsymbol{e_v}=(X^{k}_{1v}, X^{k}_{2v};\ \ldots, X^{k}_{mv})$ is calculated using Eq. (3) as;

$$D(v,u)=\sum_{i=1}^{m}\frac{|d_i(v,u)|}{\sigma(X^{k}_{i})}\prod_{\hat{j}=1}^{i-1}\left(1-R_{\hat{j}i}\right) \tag{3}$$

where, $R_{\hat{j}i}$ is the partial correlation coefficient between X^{k}_{i} and $X^{k}_{j}\ |\ (i>\hat{j})$; $\sigma(X^{k}_{i})$ is the standard deviation of X^{k}_{i}, and $d_i\ (v,u)$ is the distance between the values of indicator X^{k}_{iu} and X^{k}_{iv} (i.e., discriminate effect), which is obtained using Eq. (4) as:

$$d_i\ (v,u)=x^{k}_{iv}-x^{k}_{iu}, i\in\{1,2,\ldots,m\} \tag{4}$$

To rule out the presence of negative correlation and negative partial correlation coefficient, Eq. (3) is further modified to form Eq. (5) as:

$$D^2(v,u)=\sum_{i=1}^{m}\frac{\left|d^2_i\ (v,u)\right|}{\sigma^2\ (X^{k}_{i})}\prod_{\hat{j}=1}^{i-1}\left(1-R^2_{\hat{j}i}\right) \tag{5}$$

Second, adequate weights are assigned to each independent variable (indicators). For the same, the stability of each indicator in the overall-indicator matrix is looked into by determining the Pearson correlation (r) between the calculated metric distances and the indicators. The proposed metric-distance approach assigns importance to each indicator based on the empirical Pearson's correlation, rather than subjective weights. Furthermore, the calculated metric-distance values and each indicator in the overall-indicator matrix are continuous variables, thus making bivariate correlation a suitable approach for the analysis. In this step, the new weight (w_i) is assigned to each indicator (using Eq. (6)) established by weighting the Pearson's r, i.e., the values of the correlation coefficients are divided by the aggregate correlations; where $\sum \boldsymbol{w_i}=1$.

$$w_i=\frac{r_i}{\sum_{i=1}^{m}r_i},\forall i=1,2,\ldots,m \tag{6}$$

$\boldsymbol{r_i}$ is the bivariate correlation between the calculated metric-distance value and the value of the i^{th} indicator. $\sum_{i=1}^{m}r_i$ is the sum of all Pearson's correlation coefficients between the indicators and the obtained metric-distance value. It is to note that, to calculate the metric-distance, a fictive decision-making entity with minimum values for each of the indicators in the indicator-matrix is utilized as the benchmark entity, since the metric-distance values in the "n-dimensional space" for other entities is calculated based on the distance from the benchmark entity.

Third, the composite score (S_j) for each entity (i.e., smart city) under the respective aspect is obtained by following the aggregation process in Eq. (7) as:

$$S_j=\sum_{i=1}^{m}w_i x^{k}_{ij} \tag{7}$$

3.4. Fuzzy c-means clustering

Fuzzy c-means algorithm is an unsupervised fuzzy partitioning technique used first by Dunn (1973) to partition a dataset X into fuzzy groups as outputs with a certain degree of membership. The membership matrix $[Y_{jk}]_{(c\bullet n)}$ indicates the degree of membership of the j^{th} smart city to the k^{th} fuzzy cluster as in Eq. (8), where $Y_{jk}\in[0,1]$.

$$M_f(Y)=\left\{\begin{array}{l|l} Y\in R^{c.n} & \displaystyle\sum_{k=1}^{c}Y_{jk}=1;\ 0<\sum_{j=1}^{n}Y_{jk}<n \\ & Y_{jk}\in[0,1];\ 1\le k\le c;\ 1\le j\le n \end{array}\right\} \tag{8}$$

Accordingly, with random value initialization of Y_{jk}, Eq. (9) iteratively minimizes the objective function:

$$K_w = \sum_{k=1}^{c}\sum_{j=1}^{n} Y_{jk}^{w} \parallel x_j - c_k \parallel^2$$

where, $\{c_k\}_{k=1}^{c}$ represents the centroids of 'c' fuzzy clusters, 'w' is a weighting exponent on the membership matrix highlighting the degree of fuzziness in the classification output with $1< w <\infty$, and $\| \cdot \|$ is the Euclidean p-norm of x_j and c_k in $\mathbb{R}^n$.

The degree of fuzzy membership attributed to each cluster, at every iteration, starting from random 'c' cluster centroids is calculated using Eq. (10) as follows;

$$Y_{jk} = \frac{1}{\sum_{p=1}^{c}\left(\frac{\|x_j - c_k\|}{\|x_j - c_p\|}\right)^{\frac{2}{w-1}}} \tag{10}$$

According to the fuzzy membership values, the centroid of each cluster is then computed using Eq. (11) as follows;

$$C_k = \frac{\sum_{j=1}^{n} Y_{jk}^{w} \cdot x_j}{\sum_{j=1}^{n} Y_{jk}^{w}} \tag{11}$$

The iterative optimization is terminated on satisfying the condition in Eq. (12) i.e., when the centroid of each cluster remains the same.

$$\left|K_w^t - K_w^{t-1} < \varepsilon\right| \tag{12}$$

3.5. Classification predictive models

A total of six classification algorithms are then examined in this study to propose the best predictive model with the highest predictive performance/accuracy for resilience, livability, and aggregate performance of smart cities.

3.5.1. Naïve Bayes

Naïve Bayes classifier is a supervised learning algorithm that is based on Bayes' theorem with a strong (naïve) independence assumption between the input features. This assumption enables the multiplication of the conditional probabilities to determine the response variable. Given a class variable y based on n input features $\{x_i\}_{i=1}^{n}$, the Bayes' theorem states (see Eq. (13)) as:

$$P(y|x_1, x_2, \ldots, x_n) = \frac{P(y)P(x_1, x_2, \ldots, x_n|y)}{P(x_1, x_2, \ldots, x_n)} = \frac{P(y)\prod_{i=1}^{n} P(x_i|y)}{P(x_1, x_2, \ldots, x_n)} \tag{13}$$

3.5.2. k-nearest neighbor

K-nearest neighbors (KNN) is a non-parametric machine learning algorithm that uses the observations of K nearest neighbors to make predictions. It can be used for both regression and classification problems. Given a training dataset $(X, Y) = \{(x_i, y_i)\}_{i=1}^{n}$, where X is the input variables and Y is a class label, kNN estimates the conditional probability of Y given X and groups an observation to the class with the highest probability. Given a positive integer q, the KNN algorithm first identifies q observations that are closest to a test observation x and estimates the conditional probability of observation x to be in class e as in Eq. (14):

$$p_k(X) = \frac{1}{q}\sum_{i\,\varepsilon\, N_q} I(y_i = e) \tag{14}$$

where N_q is the set of q observations closest to a test observation and $I(y_i = e)$ is an indicator variable equal to unity if a given observation (x_i, y_i) is in class e and zero otherwise.

3.5.3. Support vector machine

Support vector machine (SVM) is a popular supervised ML algorithm that can be used for classification as well as regression problems. The goal of SVM is to map the input data into high-dimensional space where they can be linearly separable by implementing kernel function. Given a training dataset $\{(x_i, y_i)\}_{i=1}^{N}$, the objective of SVM is to find a classification rule to predict the label of the response variable by solving the following the optimization problem in Eq. (15):

$$\min_{W,b,\xi} \frac{1}{2}W^2 + C\sum_{i=1}^{N}\xi_i \tag{15}$$

$$\text{subject to}: \; y_i\left(W^T\varphi(x_i) + b\right) \geq 1 - \xi_i, \forall i \tag{16}$$

$$\xi_i \geq 0, \forall i \tag{17}$$

where $C > 0$ is a regularization parameter introduced to penalize the misclassified points via the slack variables ξ_i, b is the intercept, and W is the weight.

The solution to the optimization problem in Eq. (15) through Eq. (17) is given by Eq. (18) as follows:

$$\sum_{i\varepsilon\, SV} y_i\alpha_i K(x_i, x) + b \tag{18}$$

where $K(x_i, x)$ is the kernel function, SV denotes support vectors, which are subsets of training data points, and α_i is Lagrange multiplier.

The four popular kernel types include linear kernel, polynomial kernel, hyperbolic tangent (sigmoid) kernel, and radial basis function (RBF).

3.5.4. Classification and Regression Tree (CART)

Classification and regression tree (CART) also referred to as decision tree is a set of non-parametric supervised learning algorithms that can be used for both classification and regression predictive modelling problems by learning a simple tree model (Breiman et al., 1984). The CART method splits the feature space into multiple smaller disjoint regions with similar response values using a set of rules to predict a class label (in classification) and value (in regression) of the response variable. Each internal node in CART specifies a test on an attribute of the data, while each branch represents the test output. The root node, which is the topmost node in CART denotes the most relevant feature, while the leaf node or terminal node provides the predicted class label. Given training dataset of N size, the algorithm firstly partitions the predictors space into D disjoint regions: $\{R_1, R_2, \ldots, R_D\}$ based on the Gini Index (Alpaydin, 2020). In the next step, tree pruning is performed to reduce overfitting. The performance of the CART model can be optimized by tuning its hyperparameters including the maximum depth of the tree, minimum number of samples required to split an internal node, and minimum number of samples required to be at a leaf/terminal node.

3.5.5. Ensemble models: Random forest, gradient boosting

Ensemble models are supervised machine learning paradigm that integrate multiple single learners (a.k.a. base learners or weak learners) into one model to reduce variance error, bias, and produce a strong model with enhanced generalization capability and superior performance (Breiman et al., 1984). The most popular type of meta-algorithms that combine base learners are bootstrap aggregation (bagging) (Breiman, 1996) and boosting (Sutton, 2005) ensembles. In bagging ensemble (e.g., random forest), multiple base learners are trained independently in parallel on a different bootstrap sample, while in boosting ensemble (e.g., gradient boosting) the base models are trained sequentially.

As its name suggests, random forest (RF) is a forest of randomly created CART models. Each decision tree predictor in the RF algorithm uses bootstrap samples, which are samples drawn from the original dataset with replacement. Moreover, random subsets of input features are considered when splitting nodes in the decision tree on the best split among a random subset of the features selected at every node (Svetnik et al., 2003). The split at each node is performed in two steps. Firstly, a random subset of input features is selected from the bootstrap sample (Svetnik et al., 2003). The best subset feature is then selected to perform

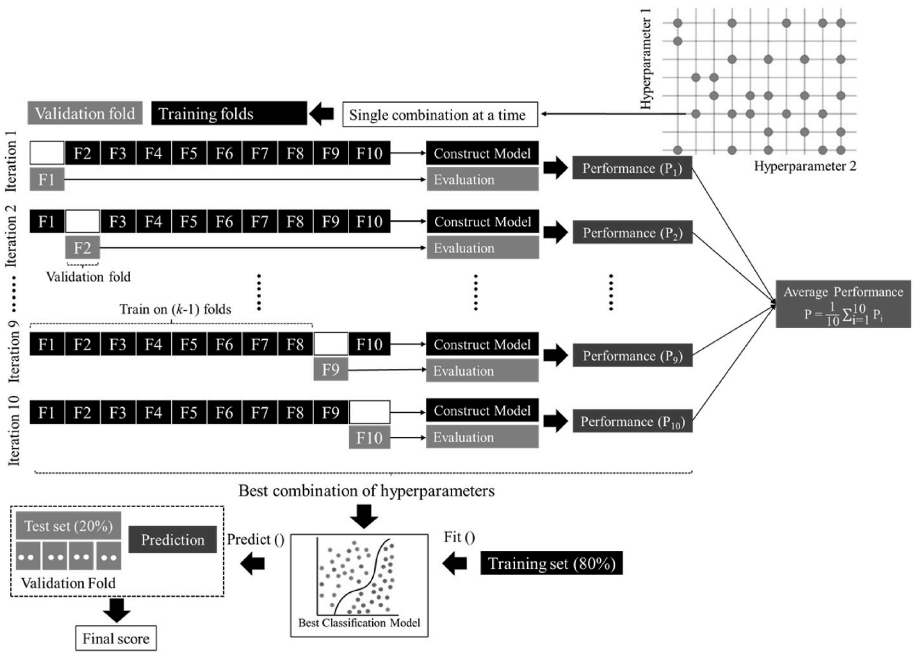


Fig. 4. 10-fold cross validation with grid search for hyperparameter tuning.

the decision split at each node of a decision tree (Svetnik et al., 2003). Each tree predictor outputs a class prediction, then the final prediction of the RF classifier is taken as the class with the most votes. Similarly, gradient boosting machine (GBM) is a powerful boosting algorithm, which combines a sequence of weak learners to generate an additive model whose performance is significantly enhanced compared to the base learners (Bishop, 2006). In the first step, equal weight is assigned to each data point. In the subsequent steps, the model is retrained by assigning more weight to the observations that were incorrectly classified by the base learner in the previous step. In each step, the GBM

Table 1
Resilience performance for all the 35 smart cities across each aspect of urban resilience for the average data over time 2015–2020.

Smart Cities	S^1	Rank	EC^2	Rank	IB^3	Rank	IN^4	Rank
Brussels	0.7190	13	0.7469	19	0.6268	19	0.6490	13
Sofia	0.4215	31	0.6144	28	0.5665	25	0.2782	32
Prague	0.6951	15	0.8338	14	0.6928	13	0.4078	27
Copenhagen	0.8258	8	0.9754	3	0.9554	1	0.8224	2
Munich	0.7469	10	0.8937	8	0.7168	8	0.5941	17
Tallinn	0.7414	11	0.8700	9	0.6575	16	0.6215	15
Dublin	0.6158	19	0.5958	32	0.6840	15	0.6956	9
Athens	0.2534	33	0.6114	29	0.5872	21	0.5633	18
Bilbao	0.6491	18	0.6421	25	0.6962	9	0.5497	19
Lyon	0.5846	20	0.7783	18	0.6961	10	0.6610	11
Dusseldorf	0.4961	26	0.7122	23	0.5092	28	0.3881	30
Bologna	0.5437	23	0.6053	31	0.4949	32	0.3292	31
Hamburg	0.6979	14	0.7003	24	0.5019	29	0.6506	12
St. Petersburg	0.4545	27	0.7883	17	0.6293	18	0.5463	20
Marseille	0.5460	22	0.8040	16	0.6437	17	0.5974	16
Geneva	0.8376	7	0.8274	15	0.8698	2	0.8136	5
Budapest	0.5662	21	0.7422	20	0.6010	20	0.4833	24
Manchester	0.8748	4	0.7242	22	0.6892	14	0.5049	22
Amsterdam	0.8965	1	0.9459	4	0.8388	3	0.7907	6
Vienna	0.8586	6	0.8431	12	0.7860	4	0.6467	14
Warsaw	0.5163	25	0.8384	13	0.4679	33	0.4495	25
Lisbon	0.4402	30	0.7280	21	0.5678	24	0.4449	26
Bucharest	0.4534	28	0.6320	26	0.4979	30	0.2253	34
Krakow	0.6574	17	0.9099	5	0.4954	31	0.4955	23
Bratislava	0.5275	24	0.6106	30	0.5862	22	0.3914	29
Helsinki	0.6749	16	0.9033	6	0.7820	5	0.6883	10
Stockholm	0.8634	5	1.0009	1	0.7511	6	0.8171	4
London	0.8757	3	0.8562	11	0.6960	11	0.8184	3
Zaragoza	0.7200	12	0.8563	10	0.7341	7	0.7257	8
Oslo	0.7992	9	0.9826	2	0.5791	23	0.8924	1
Zurich	0.8873	2	0.9019	7	0.6956	12	0.7901	7
Moscow	0.3697	32	0.4339	33	0.5313	27	0.4015	28
Kiev	0.0978	35	0.2879	35	0.2841	35	0.2518	33
Rome	0.4418	29	0.6197	27	0.5404	26	0.5443	21
Ankara	0.1529	34	0.3669	34	0.3172	34	0.1120	35

S^1: Social; EC^2: Economic; IB^3: Infrastructure and Built Environment; IN^4: Institutional.

introduces a base learner (decision tree) to overcome the shortcomings of the existing base learner(s). The learning rate controls how hard each base learner attempts to correct the errors of the previous learner in the sequence.

3.6. Hyperparameter optimization

The predictive performance of the ML model is highly dependent on the values of its hyperparameters which are the parameters that control the learning process of the model (Abdella et al., 2021). Hence, it is crucial to explore the combination of the hyperparameters that produce the best model. In the current study, a tuning technique known as grid search, that exhaustively searches the optimum values of hyperparameters considering all possible combinations of user-specified hyperparameters was used to optimize the hyperparameters, as shown in Fig. 4. Besides, standard k-fold cross-validation is used to overcome the problem of overfitting (Abdella and Shaaban, 2021). The k-fold cross-validation is performed in the following procedures: (a) split the training dataset into k equal parts, (b) use $k-1$ parts to train the model and the remaining one part to validate the model, (c) repeat step (b) until each part is used for both the training and validation set, and (d) finally compute the performance of the model as the average performance of the k estimations. Grid search is combined with 10-fold cross-validation ($k = 10$) in this study to optimize the hyperparameters of the classification algorithms, as shown in Fig. 4.

Table 2
Livability performance for all the 35 smart cities across each aspect of urban livability for the average data over time 2015–2020.

Smart Cities	AC[1]	Rank	CWB[2]	Rank	EV[3]	Rank
Brussels	0.8187	15	0.3404	17	0.4963	18
Sofia	0.4115	32	0.3585	15	0.3558	29
Prague	0.6835	21	0.3836	12	0.5506	13
Copenhagen	0.9416	8	0.3588	14	0.6308	9
Munich	0.9508	6	0.3382	18	0.8656	1
Tallinn	0.5179	30	0.2349	28	0.4911	19
Dublin	0.8671	11	0.4511	8	0.4660	21
Athens	0.2344	35	0.1672	31	0.1204	34
Bilbao	0.8172	16	0.3186	22	0.4575	23
Lyon	0.8339	14	0.3899	11	0.5363	14
Dusseldorf	0.6874	20	0.3976	10	0.2740	31
Bologna	0.6150	26	0.2452	27	0.3249	30
Hamburg	0.8149	17	0.2178	29	0.4342	25
St. Petersburg	0.6044	27	0.1469	33	0.4634	22
Marseille	0.6286	25	0.1683	30	0.4793	20
Geneva	1.0721	1	0.3012	25	0.6195	10
Budapest	0.6814	22	0.3285	20	0.4966	17
Manchester	0.9429	7	0.3098	23	0.6660	7
Amsterdam	0.9776	4	0.5017	5	0.6942	4
Vienna	0.8617	12	0.3022	24	0.6631	8
Warsaw	0.6510	23	0.5417	4	0.4297	26
Lisbon	0.7045	19	0.3460	16	0.5071	16
Bucharest	0.3394	34	0.1393	34	0.3812	27
Krakow	0.7255	18	0.3201	21	0.5110	15
Bratislava	0.5851	28	0.1552	32	0.4379	24
Helsinki	0.8544	13	0.3330	19	0.5690	11
Stockholm	0.9807	3	0.4963	6	0.6774	5
London	1.0271	2	0.6389	2	0.7699	2
Zaragoza	0.8830	9	0.3731	13	0.5558	12
Oslo	0.9756	5	0.4457	9	0.6729	6
Zurich	0.8812	10	0.6867	1	0.7220	3
Moscow	0.5780	29	0.4782	7	0.3562	28
Kiev	0.4468	31	0.6047	3	0.0823	35
Rome	0.6416	24	0.2754	26	0.1976	33
Ankara	0.3659	33	0.1241	35	0.2466	32

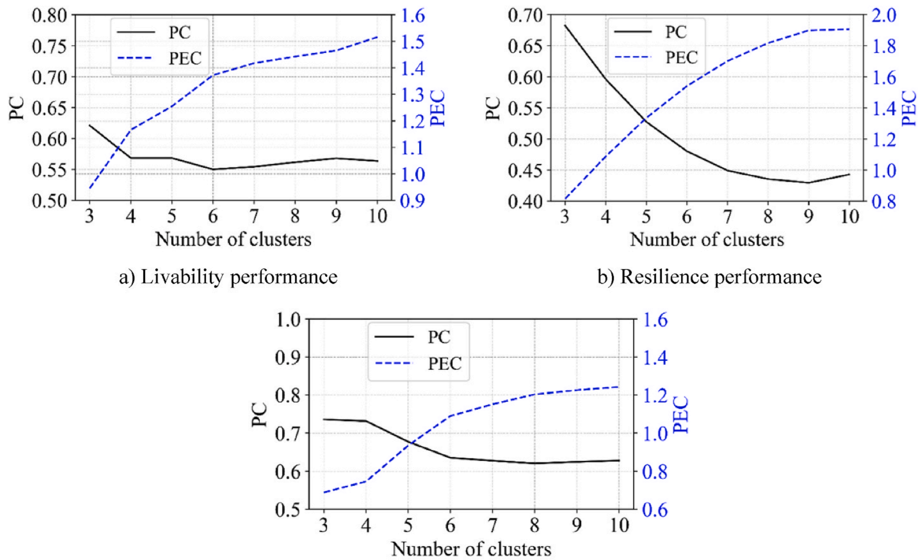
AC[1]: Accessibility; CWB[2]: Community well-being; EV[3]: Economic vibrancy.

4. Results and discussion

4.1. Scoring and performance assessment

In this section, we assess the resilience capacity, livability, and then estimate the aggregate performance of all the 35 European smart cities to address the research question on to what level the smart cities of today co-create resilience and livability in their development model. For the same, scores across each aspect under resilience and livability were calculated using the novel three-step multivariate metric-distance based approach proposed in section 3.3 through Eqs. (3)–(7), to weight the indicators and obtain a homogenized score for each aspect under city resilience and urban livability and presented in Table 1 and Table 2, respectively. It is seen that, when understanding social resilience, Amsterdam is the most socially resilient smart city with a performance score (S_s) of 0.8965, followed by Zurich (S_s = 0. 8873) and London (S_s = 0. 8757) in the 2nd and 3rd place, respectively. However, Kiev, Ankara, and Athens are most vulnerable to social upheavals in city, which is evident from the significantly low social resilience performance of 0.0978 (rank = 35), 0.1529 (rank = 34) and, 0.2534 (rank = 33), respectively. Under economic resilience, Stockholm, Oslo, and Copenhagen with a score of 1.0009, 0.9826, and 0.9754 perform significantly well and are ranked 1st, 2nd' and 3rd, respectively in the order of their economic resilience. While the least resilient smart city to economic shocks is the Ukrainian city of Kiev (S_{EC} = 0.2879). The second to the least resilient city is Ankara (S_{EC} = 0.3669, rank = 34) followed by Moscow (S_{EC} = 0.4339, rank = 33). Kiev still remains the least resilient city under the infrastructure and build environment aspect with a score (S_{IB}) of 0.2841. This translates the fact that, Kiev despite being a well-established east European smart city, the ability to absorb, and recover from the escalating climate change, disaster and environment related risks is relatively low. The same is true in the case of Ankara (S_{IB} = 0.3172, rank = 34) and Warsaw (S_{IB} = 0.4679, rank 33) as well. On the contrary, the capital of Denmark, Copenhagen has well designed infrastructural resilience in their planning model, which is well reflected in their performance (S_{IB} = 0.9554, rank = 1). Along with Copenhagen stands Geneva and Amsterdam are in the 2nd and 3rd place, respectively under the same aspect. It is seen that Oslo is the most efficient smart city in terms of enforcing normative practices in adverse operating environments with an institutional resilience score (S_{IN}) of 0.8924. While Copenhagen with a score of 0.8224 and the English city of London (S_{IN} = 0.8184) also adopt well to changing conditions and thus, institutionally resilient with ranks 2nd and 3rd, respectively. On the other hand, Ankara (S_{IN} = 0.1120, rank = 35), Bucharest (S_{IN} = 0.2253, rank = 34), and Kiev (S_{IN} = 0.2518, rank = 33) pose insufficient institutional resilience relative to the existing smart cities.

When studying urban livability of smart cities, it is seen that Geneva follows an inclusive urban development pattern with better access to facilities for its people. This is well evident when observing the accessibility score (S_{AC} = 1.0721) of the 'peace capital' of world under the said dimension. London (S_{AC} = 1.0271, rank = 2) and Stockholm (S_{AC} = 0.9807, rank = 3) are no exception for people to get around and live in the city. On the contrary, Athens with a score of 0.2344 is ranked the least accessible smart city followed by Bucharest (S_{AC} = 0.3394, rank = 34) and the Turkish city of Ankara (S_{AC} = 0.3659, rank = 33). Under the community well-being aspect, the north central Swiss state of Zurich is the best performing smart city with a score S_{CWB} = 0.6867. London continues its reign as the 2nd best liveable smart city (S_{CWB} = 0.6389) committed to build a community with lifelong wellness along with Kiev ranked the 3rd (S_{CWB} = 0.6047). However, Ankara (S_{CWB} = 0.1241) remains the least liveable city followed by Bucharest (S_{CWB} = 0.1393) and St. Petersburg (S_{CWB} = 0.1469) under the community well-being aspect. A well-orchestrated response towards economic vibrancy is seen in the case of Munich with a score (S_{EV}) of 0.8656. London (S_{EV} = 0.7699; rank = 2) and Zurich (S_{EV} = 0.7220; rank = 3) are no far behind in realizing urban vibrancy in their planning model. While Kiev with a



a) Livability performance

b) Resilience performance

c) Aggregate performance

Fig. 5. Variation of performance measures with the number of clusters.

performance score of 0.0823 is ranked the least economically vibrant smart city, followed by Athens ($S_{EV} = 0.1204$; rank = 34) and Rome ($S_{EV} = 0.1976$; rank = 33).

4.2. Clustered performance assessment

As discussed in section 3.4, Fuzzy c-means algorithm is used to cluster the smart cities based on the scores obtained under each aspect of livability and resilience. The number of clusters considered were within the range of $[3, 10]$, and the optimum number of clusters were determined using two performance measures: namely, partition coefficient (PE) and partition entropy coefficient (PEC). The maximum value of PEC and the minimum value of PE corresponds to a good partition. The results of fuzzy c-means suggested that the optimum number of clusters corresponds to three, as can be observed in Fig. 5(a)–5(c) showing the distribution of PEC and PE with the number of clusters for livability, resilience, and aggregate performance, respectively.

Fig. 6(a)–6(c) shows the results of fuzzy c-means cluster analysis using the optimum number of clusters for urban livability, city resilience, and aggregate performance, respectively as high, medium, or low. As can be observed in these figures, most of the smart cities fall under the medium level of livability (43%), while 31% and 26% of the smart cities fall under high and low levels of livability, respectively. With regard to the resilience level, the majority of the smart cities (51%) fall under the medium level of resilience, while 40% and 9% of the smart cities fall under the high and low levels of resilience, respectively. In Fig. 6(a), Copenhagen, Geneva, Amsterdam, Stockholm, London, Vienna, Manchester, Munich, Zaragoza, Oslo, and Zurich were grouped under the high livability performance class. However, all these smart cities remained unchanged with smart cities such as Lyon, Tallinn and Helsinki newly added to the high performing category while clustering cities based on resilience (Fig. 6(b)). When attempting to understand the smart cities that co-create resilience and livability together in their development model, it is seen that, all the smart cities that are under the high livability performing class remains the same except for Manchester being replaced by the Finnish city of Helsinki. It is seen that Bologna, Sofia, Athens, St. Petersburg, Bratislava, Bucharest, Kiev, Rome, and Ankara fall under the low performance cluster for livability. When taking a look into the smart cities classed under the aggregate category, we can see that St. Petersburg is pushed to the medium performance class while Moscow is added to the low performance cluster. All the other smart cities under the low livability performance cluster remains same in the low aggregate performance cluster, Fig. 6(c). While Kiev and Ankara remain in the low performance class in all the three assessments conducted with Moscow added to the list under resilience. The trend in performance of each of the European smart cities under livability, resilience, and aggregate categorization over time from 2015 till 2020 are shown in Fig. 7(a)–(c), respectively.

4.3. Classification models

Different ML algorithms were trained on the annual data for the smart cities (a total of 210 data points) to predict the level (high, medium, or low) of livability and resilience of the smart cities based on the values for the indicators under each aspect. Besides, ML-based models were proposed to predict the level of aggregate performance of smart cities based on the values for the indicators under the livability and resilience aspects. To assess the degree of livability of smart cities, the indicators under each aspect of livability, namely; accessibility, community well-being, and economic vibrancy (a total of 10 indicators for each aspect) were considered as input features. Thus, the input vector for the assessment of livability level comprised 30 predictors. Similarly, for resilience level, the indicators related to social resilience, economic resilience, infrastructure and built environment, and institutional resilience (a total of 38 indicators) were used as predictors that determined the response variable, namely, the level of resilience. The dataset was split into train and test sets that comprised of 80% and 20% of the complete dataset, respectively. The optimized hyperparameters for each model is presented in Table 3.

To compare the classification models, the coefficients namely; overall accuracy (ACC), Cohen's Kappa (κ), and the average area under the precision-recall curve (AUC-PR) were used. Table 4 through Table 6 presents the accuracy, Cohen's Kappa, and average AUC-PR of each model on the training and test datasets. Among the single models, CART showed the highest performance in predicting the level of livability in smart cities on the training dataset (95% accuracy), however, it showed low performance on the test dataset (78% accuracy). Similarly, despite a perfect agreement and an excellent level precision in the training group of the model created by CART ($\kappa = 0.926$; AUC-PR = 0.979), the resulting value showed only a moderate agreement ($\kappa = 0.471$) and marginal precision (AUC-PR = 0.642) in the testing group. These results show the low generalization ability of a single CART model. As listed in

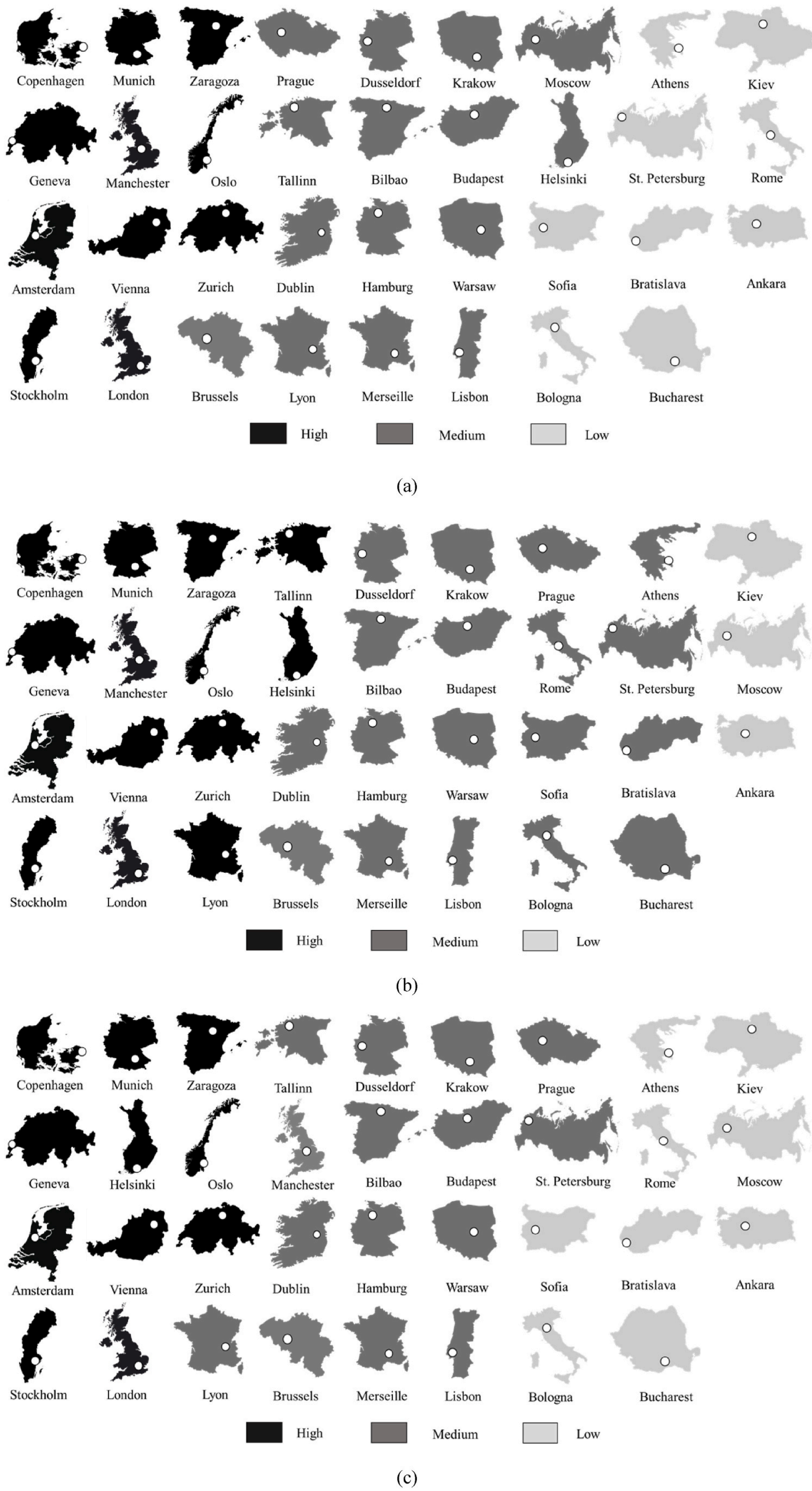
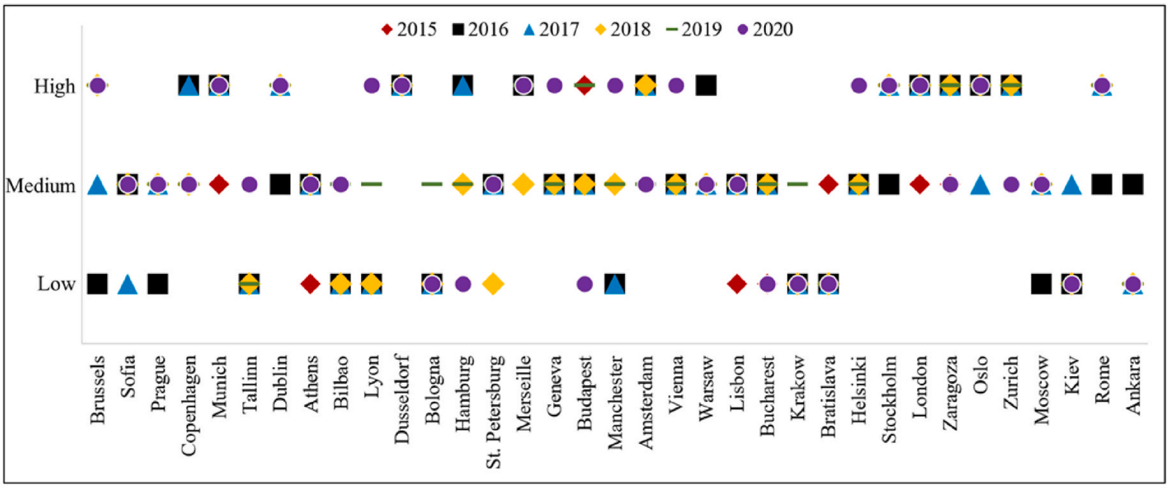
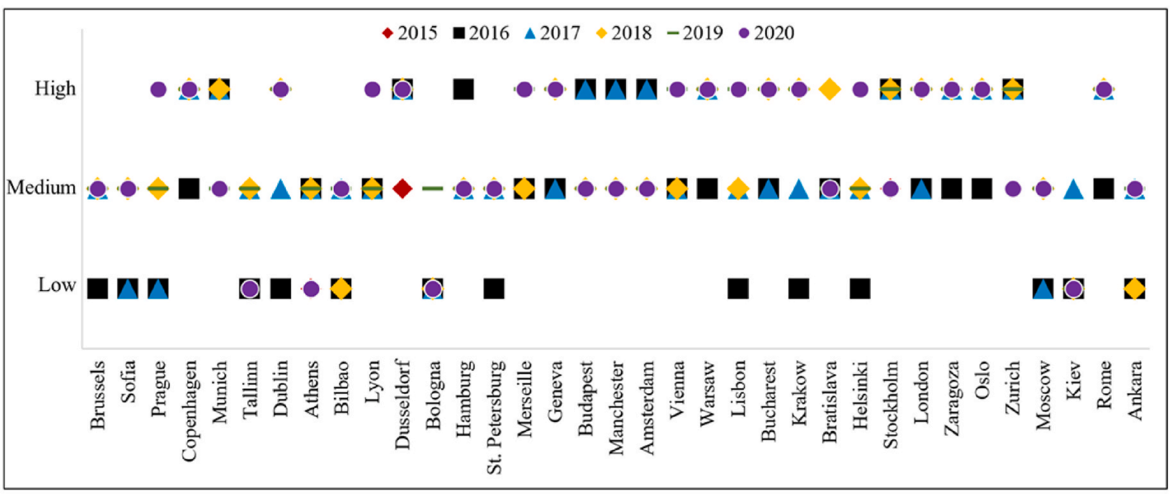


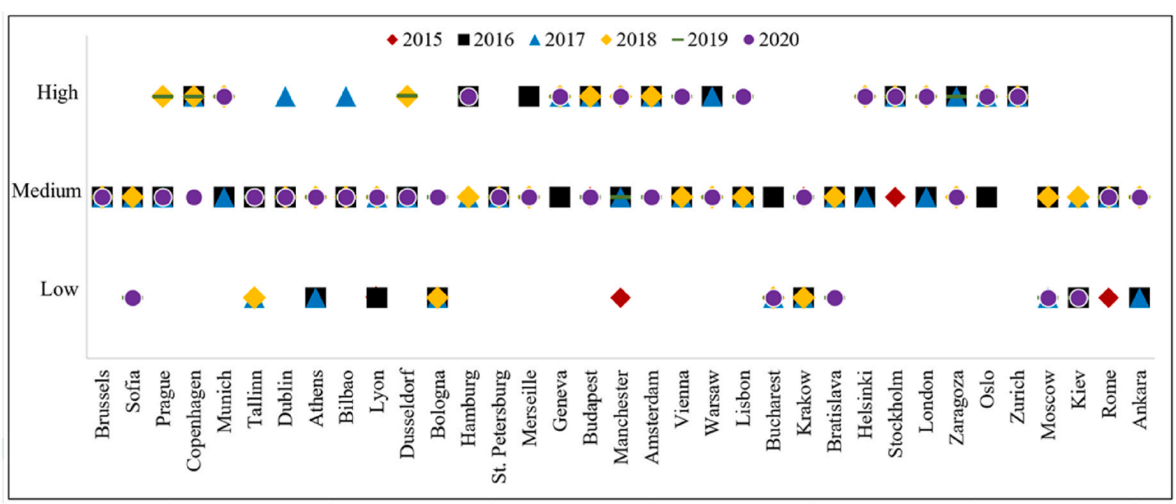
Fig. 6. Distribution of the smart cities based on the level of (a) livability (b) resilience (c) aggregate performance.



(a) Livability



(b) Resilience



(c) Aggregate performance

Fig. 7. Progressive performance of smart cities over time (2015–2020) categorized into high, medium, and low.

Table 3
Optimal values for the hyper-parameters of the ML models.

Model	Hyper-parameters	Optimal values		
		Livability	Resilience	Aggregate
kNN	k	12	11	15
CART	Maximum depth	4	7	7
SVM	Kernel	poly	poly	poly
	C	0.01	0.01	0.1
RF	Number of estimators	13	50	14
	Maximum depth	4	9	4
	Minimum sample split	2	2	2
	Minimum sample leaf	1	1	1
	Maximum features	auto	auto	auto
GB	Number of estimators	10	5	3
	Maximum depth	3	10	3
	Learning rate	0.05	0.2	0.5
	Maximum features	sqrt	sqrt	sqrt

Table 4
Performance of different models in predicting livability level.

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.85	0.76	0.761	0.595	0.931	0.792
kNN	0.85	0.88	0.759	0.793	0.910	0.910
SVM	0.90	0.83	0.843	0.714	0.990	0.936
CART	0.95	0.78	0.926	0.471	0.979	0.642
RF	0.99	0.88	0.982	0.795	0.999	0.907
GBM	0.97	0.95	0.954	0.916	0.996	0.960

Table 5
Performance of different models in predicting resilience level.

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.82	0.73	0.722	0.565	0.901	0.800
kNN	0.79	0.76	0.683	0.607	0.880	0.850
SVM	0.85	0.80	0.775	0.681	0.961	0.916
CART	0.98	0.85	0.973	0.792	0.991	0.812
RF	1.00	0.90	1.000	0.837	1.000	0.909
GBM	1.00	0.93	1.000	0.877	1.000	0.954

Table 6
Performance of different models in predicting aggregate performance level.

Model	Accuracy		Cohen's Kappa		Average AUCPR	
	Train set	Test set	Train set	Test set	Train set	Test set
Naïve Bayes	0.89	0.73	0.835	0.543	0.961	0.751
kNN	0.80	0.78	0.681	0.623	0.882	0.877
SVM	0.99	0.76	0.991	0.578	0.999	0.932
CART	0.99	0.76	1.000	0.292	1.000	0.502
RF	0.98	0.85	0.972	0.733	0.999	0.896
GBM	0.99	0.90	0.991	0.816	1.000	0.913

Tables 4 and 5, the ensemble models showed higher accuracy compared to the single models. Among all models, the GBM model showed the most accurate prediction on the test dataset (95% accuracy), while the Naïve Bayes model showed the least predicted performance on the test dataset. Similarly, the GBM showed the best performance in predicting the level of resilience on the training dataset (ACC = 1.00, $\kappa = 1.00$, AUC-PR = 1.00). The accuracy of the GBM model in predicting the degree of resilience was 93% on the test dataset compared to 90%, 85%, 80%, 76%, and 73% for RF, CART, SVM, kNN, and Naïve Bayes, respectively, as listed in Table 5. Random forest is the second-best model in predicting the level of livability and resilience of the smart cities, as listed in Tables 4 and 5. The predictive accuracies of the ML algorithms for aggregate performance level are listed in Table 6. The Naïve Bayes classifier showed the least performance on the test set, as listed in Table 6. The GBM exhibited the highest performance with accuracies of 99% and 90% on the training and test sets, respectively. Similarly, in the training group, the GBM model exhibited a strong agreement (κ = 0.991) and a superior level of precision (AUC-PR = 1.00). Similarly, it showed the highest AUC-PR value of 0.913 and Cohen's Kappa κ value of 0.816 in the testing group. Precision-recall curve based on the test dataset for livability, resilience and aggregate performance is shown in Figures S1(a)–(c), respectively. For brevity, the precision-recall curve based on the train dataset is shown in Figures S2(a)–(c) (SI file).

The performance of the ensemble models, particularly, RF and GBM models, is further investigated with the aid of a confusion matrix, which is a table presenting the actual level versus the predicted level of livability, resilience, and aggregate performance of smart cities. Other performance metrics include recall and precision. Precision refers to the percentage of the correctly predicted level of livability or resilience of the smart cities by the ML model. In addition, the actual livability/resilience/aggregate performance level that are correctly predicted by the algorithm is recall. Fig. 8(a)-8(d) show the confusion matrix for the level of livability on both the train and test sets using the RF and GBM models, while Fig. 9(a)-9(d) show the confusion matrix using the RF and GBM for the resilience level of the smart cities. In these figures, the diagonal elements show the number of correctly predicted livability/resilience levels along with recall in percentage. The proposed GBM showed high precision, recall, and accuracy in identifying the level of livability and resilience of the smart cities, as shown in Fig. 8(a)-8(d) and Fig. 9(a)-9(d), respectively. Fig. 10(a)-10(d) show the confusion matrix for aggregate performance level based on the proposed RF and GBM models, where AP stands for aggregate performance. As can be observed in these figures, the proposed GBM model showed high accuracy, recall, and precision in predicting the aggregate performance level for the smart cities on both the training and test sets. Thus, it can be concluded that the proposed GBM can effectively be used to predict the level of livability, resilience, and aggregate performance of future smart cities. Fig. 11(a)-(c) show the Spider diagram denoting the balanced accuracy (ACC), precision (AUC-PR), and agreement (κ) on the classification outputs for all the different classifiers to establish resilience, livability, and aggregate performance assessment. Furthermore, to enhance the use-case of the machine learning models discussed, a suit of computational ML models as a web-based application to predict the level of resilience and livability for any unknown smart city (X) under respective aspects of resilience and livability is created. The data-driven web-based application contains two main layers namely; Back-end and Front-end. Back-end or data access layer contains machine-learning models for analyzing the data inputs to each aspects under resilience and livability. Front-end contains the web-based link (assessable via mobile and web browser), which acts as the interface the decision maker will use to make predictions on whether a respective smart city is high, medium or low performing in terms of resilience and livability (Web application link: https://appsmartcity.herokuapp.com/).

5. Conclusion

This study proposed a novel two-stage assessment framework combining metric distance-based multivariate analysis and numerous machine learning models for the first time to thoroughly investigate the resilience and livability of smart cities for a selected set of indicators over time. The metric-distance based multivariate analysis includes a novel weighting approach to weight indicators and obtain the composite scores for each aspect under the resilience and livability paradigm. The rationale behind the proposed weighting scheme is "weights based on the correlation matrix." The new weighting scheme is unbiased in the sense that it is data-driven, and that no expert opinion has been included in the weighting process. Fuzzy c-means clustering as an unsupervised partitioning algorithm with six supervised classification techniques

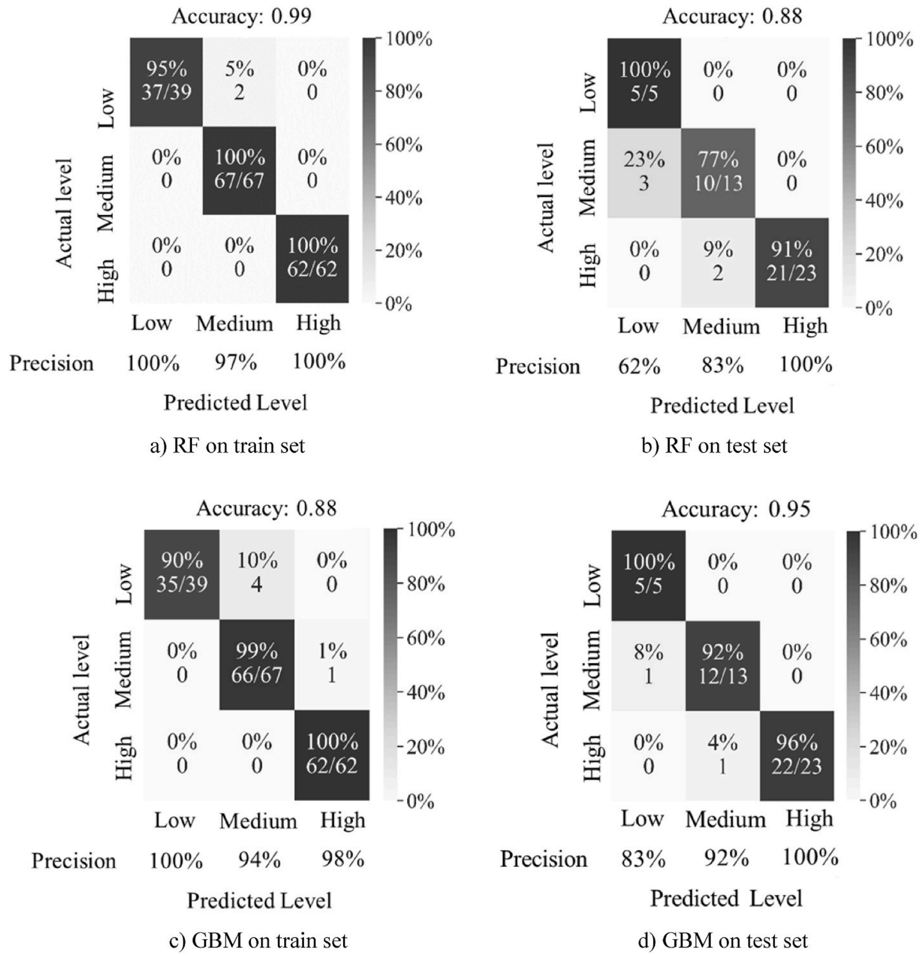


Fig. 8. Confusion matrix of RF classifier on (a) train set and (b) test set, and GBM classifier on (c) train set and (d) test set for livability level.

formed the basis of the 2-stage framework. Thirty-five (35) top-ranked European smart cities were taken as the case to study the co-creation of resilience and livability in the current existing development models of smart cities using the proposed framework. The metric distance based multivariate analysis used to score and rank the smart cities helps in understanding the composite performance of cities under the respective aspects of resilience and livability for a defined set of indicators. Such an approach can help smart cities to progressively monitor their performance over time. The results of the multivariate analysis revealed only 31% of the smart cities as high performing in terms of both resilience and livability. While 43% of smart cities marginally co-create resilience and livability in their smart development models, nearly 26% of smart cities need to make considerable improvements in moving from the low performing to the high performing class while structuring smart city policies. Different machine learning classifiers were used in the study to predict the level of resilience, livability, and aggregate performance. Parameters such as ACC, Kappa (κ), and AUC-PR were used to identify the quality and predictive capacity of each model. The models which showed the highest value across each parameter was selected as the best quality model. The comparison of different classifiers revealed the proposed GBM classifier as the most accurate classifier model that can be used to predict the level of livability, resilience, and aggregate performance of future smart cities. It is seen that ensemble modelling delivers accurate and superior predictive models over any single learning model. This is attributed to the reduced error variance and limited dispersion of model forecasts using ensemble models. Further, the proposed web-based application as a use-case to predict the level of resilience and livability of an unknown city (X) can help decision makers and urban planners with less knowledge in machine learning and statistical techniques to conduct predictions with ease for informed decision making.

The vision for realizing a fully resilient and livable city is ambitious indeed - but, it is attainable. The city's ability to innovate and incorporate new ideas about its infrastructure shows that it's becoming a more resilient city. The authors admit that no one city is successful in all the aspects, some cities are displaying innovation in a few, leading to their categorization as high performing. It is believed that these competitive cities creates large markets; acts like a magnet to attract investments, knowledge, talent, skills, and management; and generates new ideas, well-paying jobs, economic opportunities, and wealth. The authors exemplify the importance in creating liveable and resilient smart cities with a citizen centric approach. Least liveable and resilient cities can learn from the success stories and custom-made initiatives of the best performing smart cities that are livable and resilient. The authors further bring in possible perspectives to broaden the understanding on how each of these smart cities have landed under respective categorization. The success mantra of each high performing city was attributed to their unique urban development model. Zurich has initiated several projects that placed the financial capital of Switzerland under a high performing category such as their long-term goal to becoming a 2000-W society by 2050. Another project was the Green City Zurich project that aims to preserve and increase all green spaces. These difficult goals are feasible when their government allocates investment funds, focuses on energy efficiency, renewable sources, and increasing the public's awareness on sustainability. While, the English capital, London has initiated several new projects such as the London Datastore, which is free open data access, that brings information to the public and engages with new users. In addition, the city is currently pursuing a

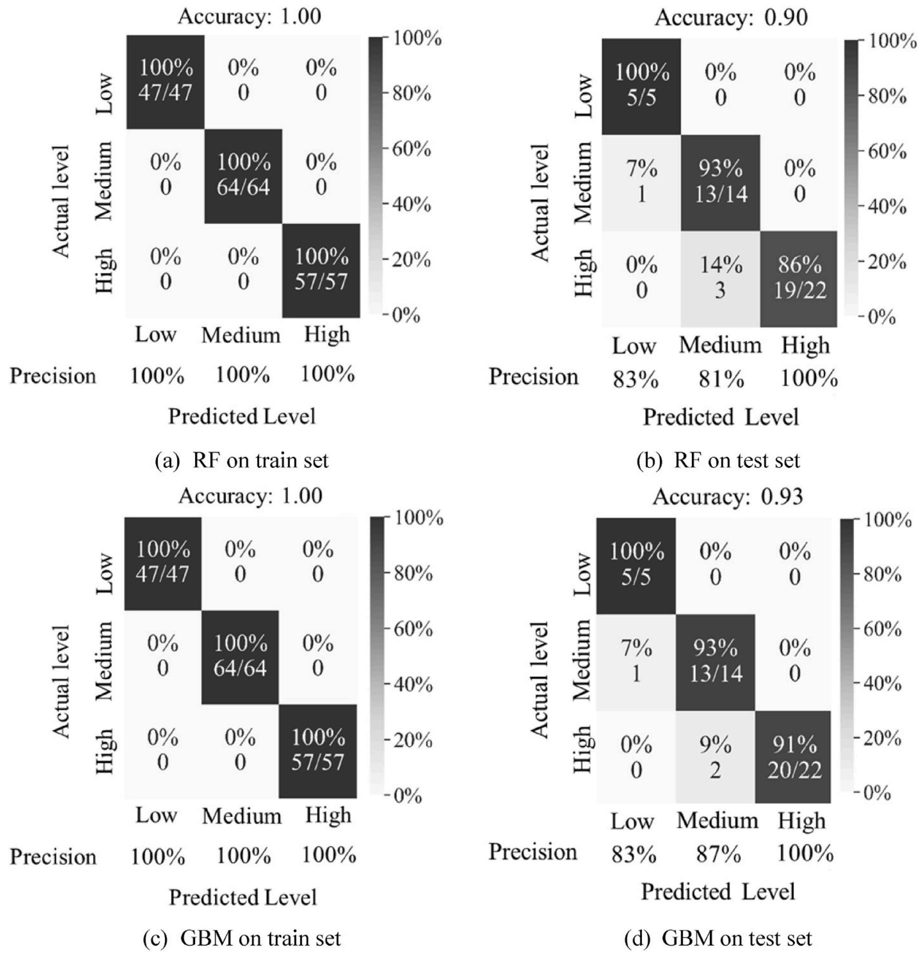
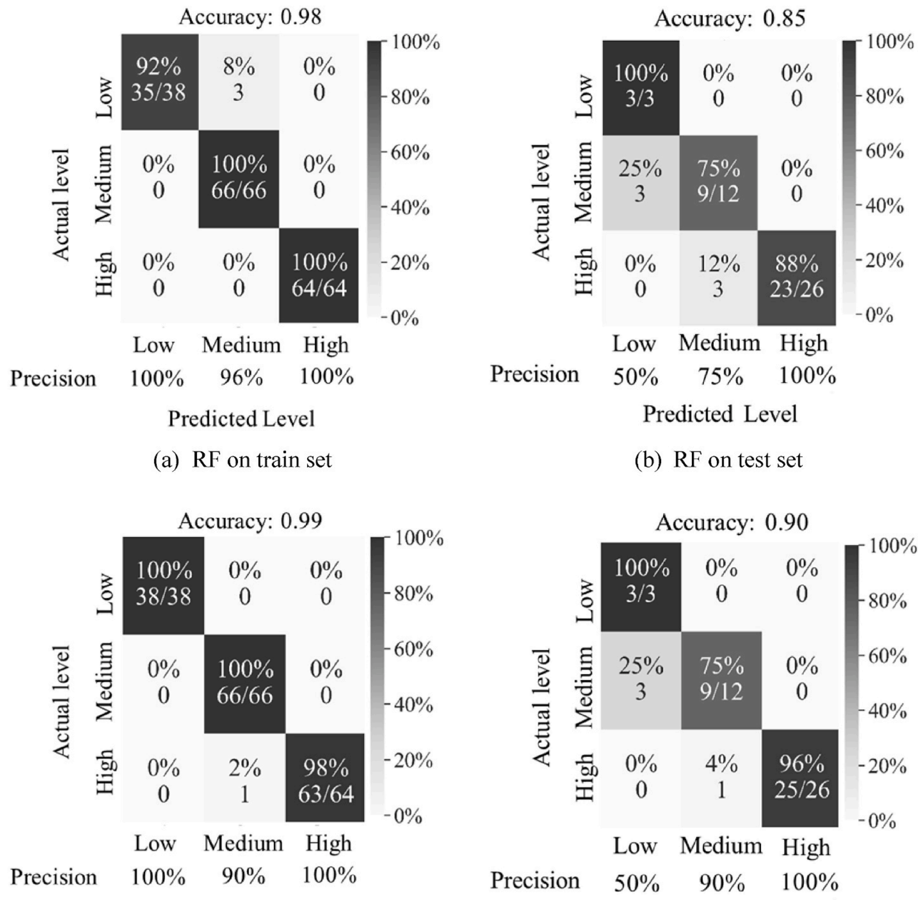


Fig. 9. Confusion matrix of RF classifier on (a) train set and (b) test set, and GBM classifier on (c) train set and (d) test set for resilience level.

"Low Carbon Capital" strategy to reduce carbon emissions by 60% by 2025 against the 1990 levels, to strengthen the environmental resilience. Through the insertion of city traffic sensors, parking sensors, and alternative modes of transportation, the city can significantly reduce wasted time and achieve these environmental goals. On the other hand, the city of Copenhagen has not only a 'smart plan' but is already well ahead with the investments to implement it. The City of Copenhagen has invested 34 million Euros in new streetlights and more than DKK 100 million (EUR 13 million) in new traffic lights and intelligent traffic management (Bjørner, 2021). This means that the City of Copenhagen can now promise cyclists and bus passengers that by 2023 they will have their travel time reduced by 10 percent while the travel time for motorists will stay the same. Copenhagen has also maintained a strategy focused on adapting public spaces, fostering renewable energies and the rationalization of cleaner mobility. The authorities intend to neutralize 100% of the city's polluting emissions by 2025, while considering that its urban population of 1.3 million will increase by 20% (Copenhagen Cleantech Cluster, 2012). The city of Amsterdam has installed sensor-based smart meters in its buildings to reduce its carbon footprint, allowing inhabitants to track their personal energy usage in real time. Installing "smart work centres" and "co-working spaces" throughout the city has also been shown to reduce daily commuting emissions. By operating heating, cooling, and lighting based on occupancy, sensors put in public venues can assist in preventing energy wastage. While, the Norwegian capital city, Oslo has seeked to expedite the switch to "zero emissions" automobiles by allowing them to use bus lanes for free parking and lower fees. Liveable smart city activities include electric bus trials, zero-emission construction sites, retrofitting existing buildings with sensors or Building Management Systems, and the creation of circular waste management and green energy systems, to name a few. Moreover, cities can use commonly available indexes to benchmark themselves on competitiveness, such as the Global Competitiveness (GC) index and the Ease of Doing Business (EDB) index. The authors further emphasize on promoting circular economy practices to reduce the reliance on scarce resources, thus increasing the economic resilience. For example, a wastewater treatment plant could become a resource generator providing electricity and manure from digested sludge as well as treated effluent for irrigation and industry. Zurich, Geneva, Oslo and Trondheim are great benchmarks to such practices. To mainstream resilience principles, city governing authorities must develop and incorporate in its operations crosscutting and sector-specific resilience standards and guidelines for project design, implementation, infrastructure delivery, and operation and management of assets and services.

Furthermore, the authors recommend taking a closer look into every aspect of the growth puzzle to transform smart cities to smarter, resilient, liveable, and sustainable dwelling units. The success of Copenhagen, Geneva, Stockholm, Munich, Helsinki, Vienna, London, Oslo, Zurich, and Amsterdam, as revealed in the current assessment in co-creating livability and resilience into their development model, can be attributed to their people centric initiatives to apprehend the standard of living. The authors further present some success stories from European member states that well addresses several aspects of resilience and livability as benchmark cases for upcoming futuristic cities. The well-integrated bicycle lanes in the unified metropolitan regions of Amsterdam and Copenhagen have brought cycling as a social activity than a means to commute around the streets (aspects: community well-being, infrastructure and built environment) (Pucher and Buehler, 2008).



(a) RF on train set (b) RF on test set

(c) GBM on train set (d) GBM on test set

Fig. 10. Confusion matrix of RF classifier on (a) train set and (b) test set, and GBM classifier on (c) train set and (d) test set for aggregate performance (AP) level.

The Tour de Force initiative by the Danes and the Dutch Cycling Embassy (DCE) have created a liveable culture among people to adopt a healthy style of living through cycling practice, resulting in improved quality of public spaces, social benefits in terms of the total urban kilometres travelled within the cities, increased activity rate of youth population, improved accessibility, and reduced impact on the overall carbon emissions (Darity Jr et al., 2015; Pucher et al., 2021). Similarly, the Cultural and Creative Cities (CCC) initiative ensures socio-economic vitality and cultural engagement through job creation and innovation in cities, an important parameter for resilient and liveable cities (aspects: social resilience, economic resilience and, economic vibrancy) (UNESCO, & World Bank. 2021). High performing cities like Geneva, Stockholm, London, and Zurich are a part of this initiative since 2015 thus, pointing out the success mantra in their performance. The 'Cultural Heritage in Action' (CHA) programs (see: https://culturalheritageinaction.eu/) adopted by cities of Eindhoven, Helsinki, Amsterdam, and Munich have resulted in establishing a balance in smart targeted growth and resilience by bringing cultural investments into the lives of citizens (aspects: community well-being, social resilience). With highest density of electric car users on road, Oslo's success in strategizing the ambitious 'Climate and Energy Initiative' across the years from 2015 till 2020 as reported by the GREENGOV research project has resulted in socio-economic and environmental resilience. The Economic Resilience Initiative, a part of the joined-up EU response to the challenges posed by forced displacement and migration, and implemented in close cooperation with EU member states, the European Commission, donors, and other partners is another success story to enhance resilience in cities. Such are many among the few examples that least performing smart cities can take a look into to slide in improvements to their existing smart growth agenda.

It is certainly sensible to think that decision makers may want to assess different compensation indices to different indicators, or to compensate differently, for example, among single indicators of a family or among the families themselves. It is that, sometimes the indicator sets proposed here within, used in evaluating the urban resilience and livability, fail to fall in line with the city goals. This can, for instance, contribute to poor evaluation of future smart city developments in light of resilience and livability, that are evaluated according to indicators that have nothing to do with what was idealized by the city managers or planners. For the same, it is recommended to add custom indicators in conjunction with the plans and projects of a city. Improving inclusive growth with a structured institutional framework is what is recommended by the authors. The European smart cities loose the shared growth agenda while competing for stronger growth. This is well evident in the case of German smart cities like Munich, Dusseldorf, and Hamburg. Munich has pushed its boundaries over the years to reach top rank in addressing resilience and livability paradigms while, Dusseldorf and Hamburg remain under marginal performance with less growth seen over the years. The reason attributed for the same can be the fragmented jurisdictional structure prevalent in the German state, which is evident from the ranking of these cities under the institutional resilience and economic vibrancy aspects in this study. The authors highlight that shared growth must also focus across the regions within countries, while most often it is seen only among the population. The growth has to be strong, shared, and resilient, as to which the future research direction should focus. To continue, it is important to note that networks with

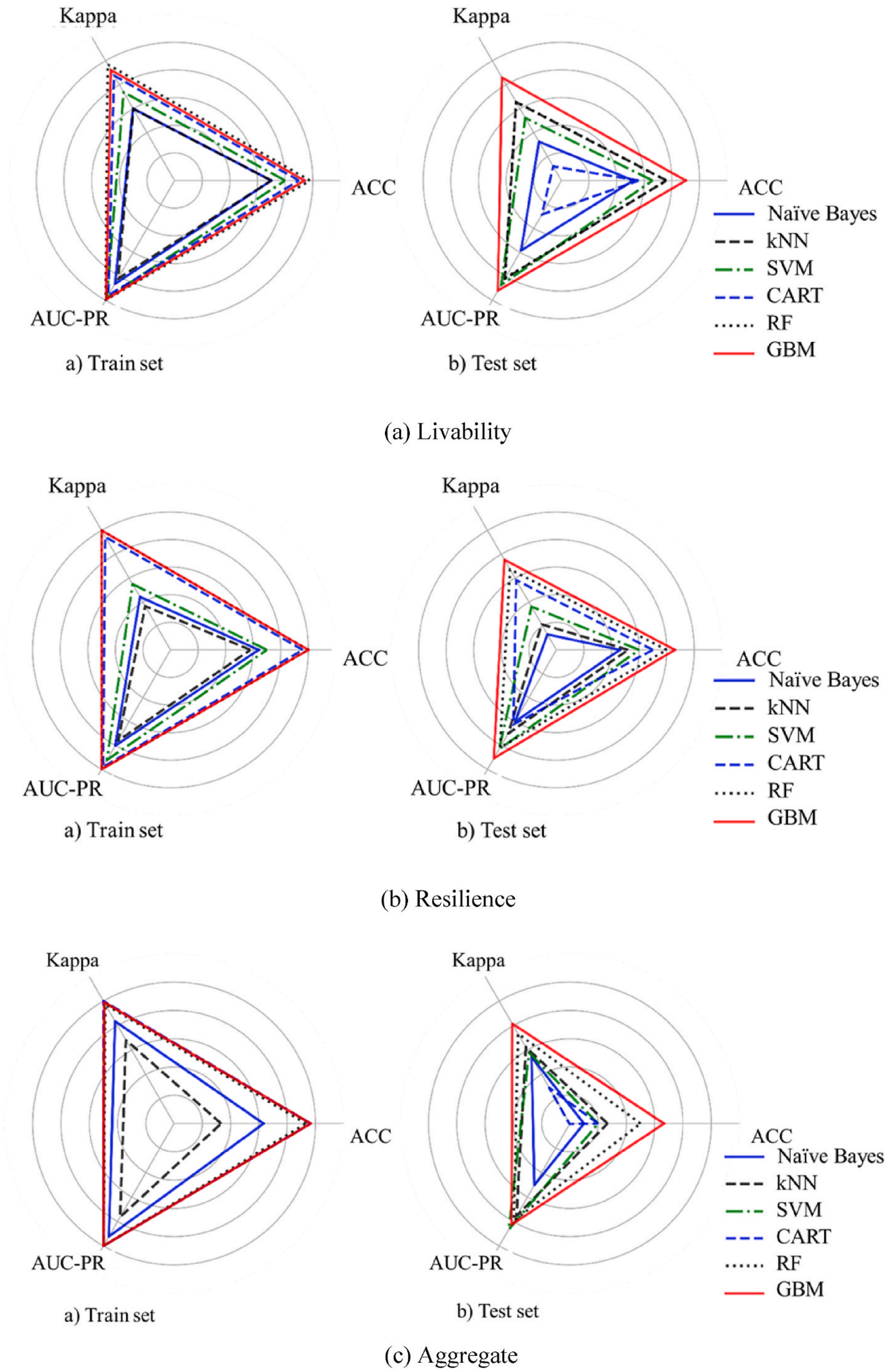


Fig. 11. Spider diagram denoting the balanced accuracy (ACC), AUC-PR, and the agreement (κ) on the classification outputs for different classifiers.

greater generalization are less interpretable. In real time, a classifier model should not only care about the accuracy but also about how certain the prediction is. High epistemic uncertainty can arise in models where there are few or no observations for training. Epistemic uncertainty is due to limited data and knowledge. Given enough training samples, epistemic uncertainty will decrease. Practitioners must seek better interpretability to build more robust models that are resistant to uncertainties. Thus, the authors recommend using model-agnostics such as LIME, Surrogate models, and Shapley values to explain what different classifiers are doing so as to improve the model interpretability. Furthermore, the proposed multivariate metric-distance based approach allows comparing observations and provides a mathematical structure to analyse the results through a metric, except when there are collinearity problems among single indicators. More specifically, the coefficient of determination R^2 only detects the linear correlations between single indicators. From a methodological point, the multivariate adaptive regression splines (MARS) as a non-parametric method that extends the model by looking for non-linear interactions between the single indicators and the composite indicator is recommended. Further, the authors recommend using an iterative procedure to the proposed metric-distance based weighting scheme which revises the indicators under each aspect based on the highest average spelled coefficient, so as to achieve a model with best quality.

CRediT authorship contribution statement

Adeeb A. Kutty: conceptualization- methodology-formal analysis-writing original draft-writing review editing. **Tadesse G. Wakjira:** methodology-software-data curation-formal analysis-writing original draft-visualization. **Murat Kucukvar:** methodology-writing original draft-conceptualization-supervision-project administration. **Galal M. Abdella:** investigation-validation-resources-supervision. **Nuri C. Onat:** validation-writing review editing-resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jclepro.2022.134203.

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