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# ARTIFICIAL INTELLIGENCE-BASED IDENTIFICATION OF SMART CITIES: A 200-CITY CLASSIFICATION FRAMEWORK FOR URBAN DEVELOPMENT, GOVERNANCE, AND SERVICE DELIVERY

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*The identification of smart cities remains a persistent challenge in urban research because city performance depends on the interaction of infrastructure quality, technological service delivery, governance capacity, and resident experience. This paper presents a structured, data-driven framework for classifying smart cities using artificial intelligence, with explicit relevance for urban development policy and comparative city assessment. The empirical design covers 200 cities worldwide and operationalizes smartness through 39 binary indicators organized under two pillars—Structures* ($n = 19$) *and Technologies* ($n = 20$)*—across five urban domains: health and safety, mobility, activities, opportunities, and governance. The dataset combines resident-based survey evidence for 147 cities, using 120 respondents per city, with documentary coding from online sources for 53 additional cities. Indicator values are converted into binary form using a 50% threshold, and cities exceeding 20 positive indicators are classified as smart. Four machine-learning classifiers—Artificial Neural Network (ANN), Random Forest (RF), Support Vector Machine (SVM), and XGBoost (XGB)—are evaluated on an 80/20 train–test split. The reported comparative accuracy profile shows strong predictive performance across all models, with ANN and RF reaching 97.5%, XGB 97.0%, and SVM 95.0%. Detailed test-set classification reports further indicate that RF and XGB achieve 0.97 accuracy, while ANN and SVM each achieve 0.95. Across the 200-city benchmark, 120 cities (60%) are classified as smart and 80 (40%) as non-smart. Feature-importance analysis shows that smart-city identification is most consistently associated with technological integration, transparent governance, resident feedback mechanisms, public-service digitization, sustainable waste management, and mobility efficiency. The findings demonstrate that artificial intelligence can provide a robust and interpretable framework for identifying smart cities and for informing urban planning, service modernization, and governance reform.*

*Index Terms* — smart cities; urban development; artificial intelligence; machine learning; city benchmarking; governance; urban services

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## INTRODUCTION

The concept of the smart city has evolved from a technology-centered ideal into a multidimensional framework that links digital capacity with governance, urban services, sustainability, and quality of life. Foundational scholarship emphasizes the role of information and communication technologies in improving urban efficiency, competitiveness, and livability, while later work has broadened the concept to include resilience, environmental performance, and citizen-centered governance [1, 2, 3, 4, 5]. For urban development research, this shift is especially important: a city is not meaningfully "smart" on the basis of technology alone, but through the extent to which technological systems improve infrastructure, public services, and civic interaction.

Despite the proliferation of smart-city indices, comparative assessment remains methodologically difficult. Many evaluation systems rely on heterogeneous indicators, varying data quality, and substantial expert judgment. These issues often limit cross-city comparability and hinder the translation of rankings into actionable urban policy. In response, data-driven approaches based on machine learning offer a promising alternative, as they can synthesize complex urban indicators, reduce manual subjectivity, and generate replicable classification frameworks [7].

This paper develops a manuscript suitable for a journal focused on urban development and smart cities by presenting a coherent, policy-relevant account of an artificial intelligence framework for identifying smart cities. The study uses a global 200-city benchmark structured around the IMD Smart City Index logic and demonstrates how machine learning can classify smart-city status while revealing the urban dimensions most strongly associated with that classification [6, 8, 9]. The topic falls squarely within the scope of urban development and smart-cities scholarship because it addresses comparative urban performance, infrastructure and service provision, governance quality, and evidence-based planning.

The central contribution lies in integrating multivariate urban indicators with machine-learning classification to create an objective and interpretable assessment structure. Rather than treating smartness as a purely rhetorical or branding category, the study operationalizes it through measurable structural and technological conditions. In doing so, it offers an analytic foundation for city benchmarking, strategic planning, and policy prioritization.

## MATERIALS AND METHODS

### *Research Design*

The analytical workflow follows four sequential stages: (1) selection of cities and indicators; (2) data organization and preprocessing; (3) machine-learning model training and testing; and (4) comparative interpretation of model performance and feature salience. This structure positions the study as both a methodological contribution and a practical tool for urban development assessment.

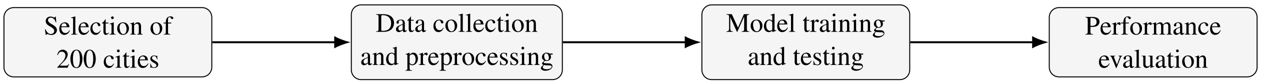

Figure 1: Workflow of the artificial intelligence framework for smart-city identification.

### *City Selection and Data Sources*

The study is grounded in the comparative logic of the IMD Smart City Index 2023, which assesses 141 cities using resident perceptions of infrastructure and technological services [8]. To create a broader and more analytically balanced benchmark, the dataset was expanded to 200 cities. This involved adding 59 cities, including locations that were deliberately not clearly identifiable as smart cities, in order to improve variation and support more objective classification.

The final 200-city dataset was assembled through two channels. First, 147 cities were represented using resident-perception data gathered through a 39-question survey, with 120 residents surveyed per city. Second, the remaining 53 cities were coded from relevant online information sources, including official city websites and related documentary materials. This mixed-source design was intended to improve dataset breadth while preserving the structure of the smart-city indicator framework [9, 10, 11].

For the survey-based component beyond the index-derived cities, resident responses were collected for six Moroccan cities—Casablanca, Fes, Marrakech, Tangier, Dakhla, and Laayoun—through anonymous online forms. These responses were aligned directly with the same 39 indicators used throughout the study.

### *Indicator Framework*

Smart-city status is modeled through 39 indicators grouped into two major pillars: Structures and Technologies. These indicators are further distributed across five substantive domains relevant to urban development: health and safety, mobility, activities, opportunities, and governance. Table 1 summarizes the architecture of the indicator system.

Table 1: Architecture of the 39-indicator smart-city framework.

| Pillar | Domain count | Indicator count | Illustrative examples |
|---|---|---|---|
| Structures | 5 | 19 | Basic sanitation, recycling, public safety, medical services, public transport, green spaces, school access, local-government transparency |
| Technologies | 5 | 20 | Online city-maintenance reporting, civic apps, CCTV, online medical appointments, mobility apps, e-ticketing, online job access, online voting |

The structural pillar comprises 19 indicators: health and safety (6), mobility (2), activities (2), opportunities (5), and governance (4). The technological pillar comprises 20 indicators: health and safety (6), mobility (5), activities (1), opportunities (4), and governance (4). This two-pillar design captures both foundational urban conditions and the degree to which technology is embedded in everyday service delivery.

### *Data Processing and Target Definition*

All collected information was converted into a binary format to support consistent classification. For survey-derived indicators, responses below 50% were coded as 0, while responses greater than or equal to 50% were coded as 1. Documentary evidence for the 53 non-survey cities was similarly reduced to affirmative/negative indicator coding.

A target variable was then constructed to indicate whether a city qualifies as smart. Let

$$\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{i39}), \qquad x_{ij} \in \{0,1\}.$$

City $i$ is classified as smart when

$$y_i = \begin{cases} 1, & \text{if } \sum_{j=1}^{39} x_{ij} > 20, \\ 0, & \text{otherwise.} \end{cases}$$

Accordingly, a city must exceed 20 positive indicators out of 39 to receive a smart classification. This binary rule converts a complex multidimensional profile into a clear and reproducible classification target.

### *Machine-Learning Models*

Four supervised machine-learning classifiers were used:

1. Artificial Neural Network (ANN),
2. Random Forest (RF),
3. Support Vector Machine (SVM), and
4. XGBoost (XGB).

These models were selected to represent distinct learning logics: neural pattern recognition (ANN), ensemble tree-based classification (RF and XGB), and margin-based classification in high-dimensional space (SVM). The classification task is binary: smart versus non-smart city.

The analysis was implemented in Python 3 within Jupyter Notebook 6.5.2. Core tools included Pandas for data handling, Scikit-learn for preprocessing and evaluation, XGBoost for gradient boosting, Matplotlib for visualization, and Keras for neural-network training. Label encoding was used during preprocessing, and the dataset was divided into 80% training and 20% testing subsets to ensure out-of-sample evaluation.

## RESULTS

### *Dataset Composition and Smartness Distribution*

The 200-city benchmark produces a clearly differentiated outcome distribution. Of the 200 cities analyzed, 120 (60%) are classified as smart and 80 (40%) are classified as non-smart. This distribution supplies sufficient class variation for supervised learning while maintaining a reasonable balance between categories.

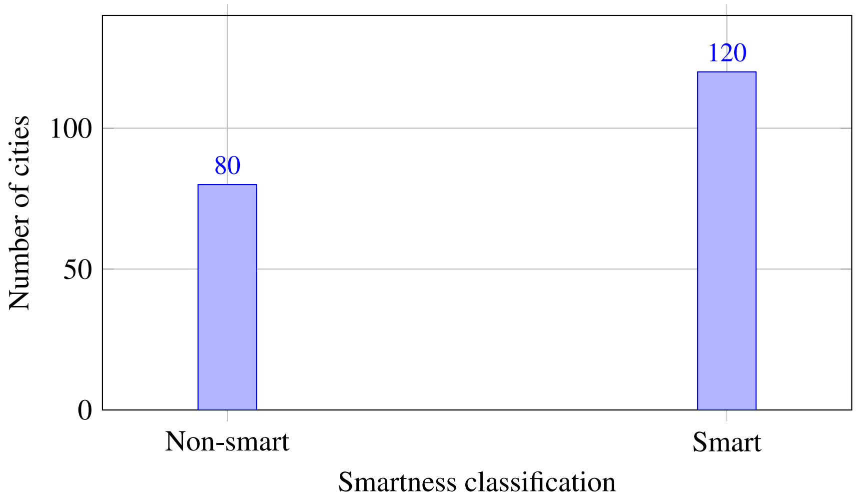

Figure 2: Distribution of smart and non-smart cities in the 200-city benchmark.

From an urban development perspective, this distribution is informative because it indicates that smart-city characteristics are present in a majority of the sample, but a substantial portion of cities still fall below the operational threshold. This reinforces the need for comparative frameworks that can distinguish between different patterns of urban performance.

*Comparative Classifier Performance*

The reported comparative accuracy plot shows that all four models perform strongly. ANN and RF achieve the highest reported overall accuracy at 97.5%, XGB follows closely at 97.0%, and SVM achieves 95.0%.

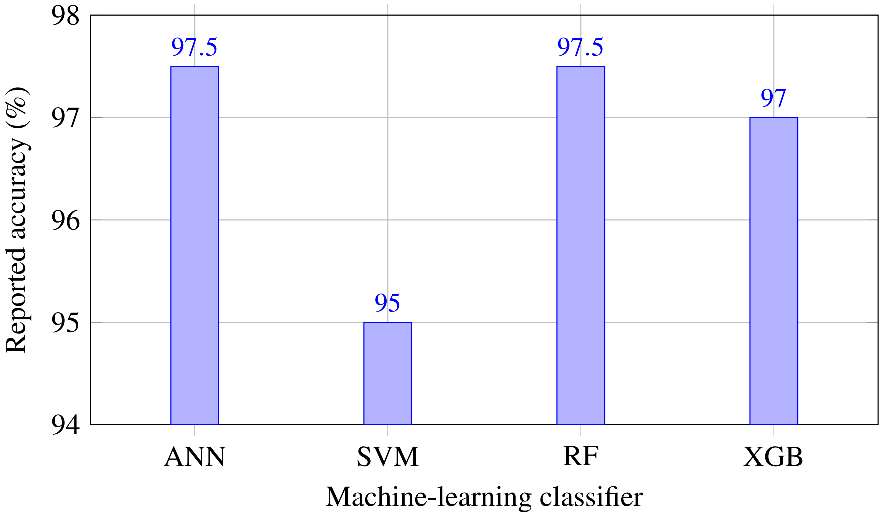

Figure 3: Reported comparative accuracy of the four machine-learning classifiers.

These results indicate that the 39-indicator framework contains a stable and learnable signal. For urban benchmarking, this is a significant finding: it suggests that smart-city status, when defined through transparent structural and technological criteria, can be identified with high reliability across distinct model families.

### *Detailed Test-Set Classification Reports*

Table 2 presents the detailed test-set performance metrics reported for each model. RF and XGB achieve 0.97 accuracy, while ANN and SVM each achieve 0.95. Across models, class-wise precision, recall, and F1-scores remain consistently high, indicating strong discrimination between smart and non-smart cities.

Table 2: Reported test-set classification metrics for the four models.

| Model | Accuracy | Class 0 (P/R/F1) | Class 1 (P/R/F1) | Test support |
|---|---|---|---|---|
| Random Forest | 0.97 | 1.00 / 0.94 / 0.97 | 0.96 / 1.00 / 0.98 | 40 |
| Artificial Neural Network | 0.95 | 1.00 / 0.88 / 0.94 | 0.92 / 1.00 / 0.96 | 40 |
| XGBoost | 0.97 | 1.00 / 0.94 / 0.97 | 0.96 / 1.00 / 0.98 | 40 |
| Support Vector Machine | 0.95 | 0.94 / 0.94 / 0.94 | 0.96 / 0.96 / 0.96 | 40 |

Random Forest performs especially well in balancing robustness and discrimination, while XGBoost delivers nearly identical test performance. ANN is notable for perfect precision on the non-smart class, and SVM maintains stable, well-balanced metrics across both classes. Taken together, the results show that no model performs poorly; instead, all four support the validity of the classification framework.

### *Substantive Indicators of Smart-City Status*

Beyond predictive accuracy, the study identifies a recurring set of indicators that help distinguish smart from non-smart cities. These indicators are substantively meaningful for urban development because they connect governance, service access, environmental management, and mobility.

Table 3: Representative high-importance indicators emphasized by each model.

| Model | Representative indicators emphasized in the model interpretation |
|---|---|
| Random Forest | Resident feedback on local government projects (SG19), accessible information on local-government decisions (SG16), recycling services (SH2), and satisfactory medical services (SH5) |
| Artificial Neural Network | Online voting to increase participation (TG18), resident participation in local decision-making (SG18), apps for locating parking spaces (TM8), recycling services (SH2), and air-quality management (SH4) |
| XGBoost | Resident feedback mechanisms (SG19), online medical appointment scheduling (TH6), online public-transport scheduling and ticketing (TM10), and online reporting for city maintenance (TH1) |
| Support Vector Machine | Recycling services (SH2), satisfactory public transport (SM8), green spaces (SA9), resident feedback (SG19), resident participation in governance (SG18), air-pollution monitoring apps (TH5), and online voting (TG18) |

The repeated appearance of governance indicators is particularly important. Feedback mechanisms, transparency, and participation are not peripheral variables; they are central to the classification of smart cities. Likewise, technological indicators tied to concrete services—medical appointments, transport ticketing, maintenance reporting, and civic interfaces—suggest that technology matters most when it improves daily urban functionality.

Environmental and livability indicators also remain prominent, especially recycling, air quality, medical services, green spaces, and public transport. This reinforces the argument that smart-city classification is not reducible to digital infrastructure alone; it emerges from the integration of technology with inclusive, sustainable, and service-oriented urban development.

## DISCUSSION

### *Relevance for Urban Development and Smart-City Research*

The manuscript contributes directly to urban development scholarship by demonstrating that smart-city identification can be structured through transparent urban indicators and evaluated using reproducible machine-learning methods. The combination of infrastructure, service, and governance variables ensures that the analysis remains grounded in city development rather than abstract computational performance.

This is especially relevant for journals focused on urban development and smart cities because the study links three essential concerns: first, how cities are comparatively assessed; second, which dimensions most strongly differentiate higher-performing urban systems; and third, how data-driven tools can support evidence-based planning. The framework therefore serves not only as a classification exercise, but also as a decision-support structure for policymakers, planners, and urban researchers.

### *Technological Integration as a Defining Driver*

A central finding is that technological capability is the most decisive differentiator between smart and non-smart cities. The consistent prominence of online civic participation, digital service interfaces, maintenance reporting systems, and mobility applications indicates that technology functions as a major driver of urban smartness when it is effectively integrated into public service systems.

This conclusion is important because it clarifies the meaning of technological advancement in the smart-city context. The key issue is not merely the presence of advanced systems, but the degree to which those systems are embedded in governance processes, health access, mobility management, and resident interaction. Cities that successfully digitize public-facing services appear more likely to satisfy the operational threshold for smart classification.

### *Governance, Sustainability, and Urban Livability*

Although technology is identified as a primary driver, the results also show that technological performance alone is insufficient. Governance and environmental service indicators appear repeatedly across all four models. Resident feedback, participation in local decision-making, accessible government information, recycling, public transport, and green-space quality all contribute materially to smart-city identification.

This pattern has two implications. First, it supports a broader understanding of smart urbanism in which civic responsiveness and sustainability are integral, not secondary. Second, it suggests that technologically ambitious cities may still fall short of smart-city classification if public services remain weak, governance is opaque, or livability conditions are poor. For urban development strategy, the path to smartness is therefore best understood as the co-development of infrastructure, service quality, environmental stewardship, and institutional trust.

### Planning Implications

The results have clear planning implications. Cities seeking to improve their smart-city standing should prioritize:

1. digital interfaces that reduce friction in public services, such as online scheduling, reporting, and e-ticketing;
2. governance reforms that increase transparency, participation, and resident feedback;
3. investments in basic urban services, including medical provision, waste management, and public transport; and
4. environmental and livability improvements that support long-term resilience and citizen well-being.

These priorities align strongly with the remit of urban development research because they connect digital modernization with institutional quality and quality-of-life outcomes.

### Limitations

Several limitations should be acknowledged. First, the binary encoding scheme necessarily compresses nuance by reducing indicator intensity to yes/no values. Second, the operational definition of smartness depends on a threshold rule ($> 20$ positive indicators), which is transparent and useful for classification but still represents a constructed decision rule rather than a natural category. Third, the data sources are mixed: while 147 cities are represented through resident-based survey evidence, 53 cities are coded through documentary review, which may introduce variation in source granularity. Fourth, the study provides high-quality comparative classification, but it does not estimate the cost, feasibility, or sequencing of interventions required for cities to improve their status.

These limitations do not undermine the usefulness of the framework, but they do indicate directions for further work, especially around richer scaling, cost-sensitive modeling, and longitudinal tracking of city transformation.

## CONCLUSION

This paper presents a clear and policy-relevant artificial intelligence framework for identifying smart cities through a 200-city benchmark organized around structural and technological indicators. By integrating 39 indicators across health and safety, mobility, activities, opportunities, and governance, the study demonstrates that smart-city classification can be undertaken with high predictive reliability. Across the reported results, all four machine-learning models perform strongly, with RF and XGB showing the strongest detailed test-set accuracy and ANN also performing at a very high level in the comparative assessment.

The substantive findings are equally important. Smart-city status is most strongly associated with technological integration that improves everyday urban services, but the analysis also shows that governance quality, resident participation, environmental management, medical services, and mobility performance remain central. In this sense, smartness is best understood as the practical convergence of technology, institutional responsiveness, and livable urban development.

For a journal concerned with urban development and smart cities, the manuscript offers a useful combination of methodological rigor and policy relevance. It demonstrates how machine learning can support comparative urban assessment while preserving interpretability and direct planning value. The resulting framework can inform city benchmarking, strategic prioritization, and future research on data-driven urban transformation.

## DATA AVAILABILITY STATEMENT

The study is based on a 200-city indicator framework compiled from resident-perception surveys and documentary coding aligned with the Smart City Index indicator logic. The empirical structure, variable design, and reported performance metrics are fully described in the manuscript.

## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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