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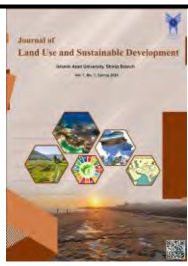

ORIGINAL RESEARCH PAPER

Exploring the Application of Artificial Intelligence in Understanding Urban Spaces (Case Study: Zanjan City)

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Abstract

This study examines the application of artificial intelligence in analyzing and understanding the urban morphology of Zanjan. The primary objective of this research is to propose a machine learning-based framework for the structural and functional analysis of urban fabrics. The research methodology involves collecting spatial and descriptive data from the city of Zanjan, processing these data using neural network algorithms, and analyzing the results through statistical approaches. By utilizing machine learning models, spatial patterns and relationships between various urban elements are identified, and urban transformation trends are analyzed. The findings indicate that artificial intelligence algorithms can identify hidden patterns within urban fabrics, enhance the accuracy of urban data processing, and enable the prediction of future changes in urban structures. This study also highlights how the physical and functional characteristics of urban fabrics influence sustainable urban development, demonstrating the potential of artificial intelligence in optimizing urban planning processes. The results can assist policymakers and urban planners in developing more effective strategies for the intelligent management of cities, ultimately contributing to the sustainable management of urban spaces.

Keywords: Artificial Intelligence, Urban Morphology, Urban Spaces, Spatial Modeling, Urban Spatial Patterns

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INTRODUCTION

Urban space analysis has always been one of the primary challenges in urban planning and management due to the complexity of structures, the dynamic nature of patterns, and the vast volume of urban environment data (Esmaili Vardanjani *et al*., 2021). Urban morphology, which encompasses the study of spatial patterns and the physical structure of cities, aids in understanding the relationship between the built environment and its functional dynamics (Parsayan & Pakzad, 2024). In this regard, Zanjan, with its rich history, unique historical fabric, and contemporary developments, serves as a notable example of urban management challenges in Iran. The rapid population growth and physical expansion, coupled with the need to preserve urban identity and maintain coherence between historical and modern fabrics, underscore the necessity for a more precise and targeted analysis of this city. Traditional urban analysis methods, such as two-dimensional mapping and statistical models, face limitations due to their inability to process large-scale data and identify complex patterns. With advancements in technology and the emergence of artificial intelligence, machine learning and deep learning algorithms offer new possibilities for faster and more accurate urban data analysis (Hosseini *et al*., 2024). This study seeks to address how artificial intelligence can be leveraged to identify spatial patterns and enhance urban space management in Zanjan. The application of modern technologies in urban space analysis, particularly in cities like Zanjan—where the challenges of development coexist with the need to preserve historical identity—is of great importance. As a historical and cultural center of Iran, Zanjan requires precise spatial management to balance contemporary development with the conservation of cultural heritage (Ahadnejad Roshti *et al*., 2024). Traditional approaches to analyzing Zanjan's urban morphology often result in decision-making based on incomplete or generalized data, potentially leading to ineffective outcomes. Artificial intelligence, with its ability to process vast amounts of spatial data and detect hidden patterns, can provide innovative solutions for urban planning. The significance of this research lies not only in proposing a new framework for analyzing Zanjan's urban morphology but also in its impact on sustainable development, infrastructure improvement, and urban resource management. This approach enables more informed decision-making to address spatial development challenges and enhance the quality of life for citizens.

Literature Review

The analysis of urban spaces and urban morphology has long attracted the attention of researchers. In this regard, two main approaches exist in urban space analysis: the traditional approach, which relies on tools such as maps, geometric models, and statistical methods, and the modern approach, which leverages advanced technologies, particularly artificial intelligence, machine learning, and deep learning algorithms. Historically, urban space analysis was primarily conducted using geometric models, two-dimensional maps, and statistical methods (Shuyan *et al*., 2022). These approaches were largely focused on examining the physical characteristics of urban spaces, such as area, dimensions, and spatial forms. However, they were generally insufficient in capturing the structural complexities and spatial dynamics of urban environments. Although statistical models were capable of simulating certain trends, they struggled to process the vast and intricate datasets prevalent in urban studies (Saberi Far, 2023). These limitations highlighted the need for more advanced tools capable of conducting more precise and comprehensive analyses of urban spaces. Early studies on urban space analysis primarily focused on urban spatial configurations and the interrelationships among various urban networks. These investigations were generally limited to simulating urban spaces using geometric algorithms and spatial analysis methodologies (Khamr & Namazi, 2017). Although the results of these studies were valuable, they were unable to simulate human behavior or predict complex trends in urban environments. Consequently, the adoption of newer methodologies in urban analysis became imperative. With technological advancements in recent decades, the utilization of complex datasets—especially those derived from remote sensing, satellite imagery, and spatial data from sensor networks—has introduced innovative approaches to urban space analysis. In this context, the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) algorithms has experienced significant growth. These technologies enable researchers to conduct more intricate

analyses of urban spaces and human behaviors within these environments. One of the most significant applications of AI in urban analysis is the use of machine learning algorithms for simulating traffic patterns, assessing population density, forecasting the demand for urban spaces, and analyzing behavioral patterns in public areas (Kermani *et al.*, 2023). The employment of big data analytics through complex algorithms has markedly enhanced the accuracy of predictions and urban decision-making processes. For example, machine learning can be utilized to simulate changes in urban spaces over time and predict the impacts of various urban development projects (Bolaghi *et al.*, 2023).
Another crucial application of AI in urban space analysis is the use of deep learning to identify complex patterns that traditional models cannot replicate. Deep learning algorithms are capable of processing intricate datasets such as satellite images, geographic information, and remote sensing imagery to uncover hidden patterns. This capability is particularly important for analyzing urban spaces characterized by significant complexity (Kabli Zadeh *et al.*, 2024). In Iran, modern approaches to urban space analysis and morphology have also been explored. For instance, a study conducted in Tehran employed machine learning algorithms to predict and analyze urban traffic. In this research, traffic density data from various locations across the city were collected, and advanced algorithms such as Random Forest and Artificial Neural Networks (ANN) were used to forecast traffic conditions across different days and hours. The study demonstrated that machine learning models could more accurately and efficiently predict traffic density, thereby providing valuable insights for traffic management and reducing congestion during peak hours. Several studies conducted in major Iranian cities have employed machine learning algorithms to predict and simulate demographic changes. These studies have primarily focused on simulating population growth trends in various urban areas. In one such study, time series modeling algorithms such as Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANNs) were utilized to predict population density in Shahroud (Majidnia *et al.*, 2022). By analyzing demographic data and applying machine learning algorithms, researchers were able to accurately predict which areas of Shahroud would experience population growth in the coming years. This information proved valuable for urban planning and resource allocation. In another study conducted in Kerman, satellite imagery was used to analyze land-use changes and assess urban physical development (Abbasi Moghaddam, 2022). Utilizing deep learning algorithms such as Convolutional Neural Networks (CNNs), this research successfully identified land-use changes and analyzed urban development patterns from a land utilization perspective. This approach enabled the precise identification of transformations in residential, commercial, industrial, and green spaces, assisting urban policymakers in making informed decisions regarding sustainable urban development and land-use planning. Another application of artificial intelligence (AI) in Iran involves analyzing and predicting water consumption patterns for efficient resource management in large cities. Multiple studies in this field have leveraged machine learning algorithms to forecast water consumption in different urban districts. In one such study, Support Vector Machines (SVMs) and Decision Trees were employed to predict water usage (Alsarifi *et al.*, 2024). The findings demonstrated that these algorithms could accurately forecast water consumption, aiding urban authorities in optimizing water resource management. Furthermore, a study by (Mirzapour *et al.*, 2019) employed machine learning algorithms to analyze and simulate various urban development scenarios in Khorramabad. This research simulated the impact of new developments, such as highway construction and commercial buildings, on urban structure and residents' quality of life. By leveraging deep learning algorithms, the study assessed the effects of these transformations on population density, traffic congestion, air pollution, and urban resource efficiency. The insights from this research can assist urban planners in simulating the potential consequences of major urban projects before their implementation, leading to more informed decision-making. Additionally, a study conducted by (Ababneh *et al.*, 2023) in Iran applied AI to analyze and optimize urban green spaces. This research utilized existing data on urban green spaces and usage patterns to model their future distribution and growth. The study particularly focused on predicting the expansion of green spaces across different

urban zones, providing policymakers with data-driven strategies to optimize land use for sustainable urban greenery development.
However, many of these studies, particularly in the field of urban morphology analysis in historical cities such as Zanjan, have highlighted a lack of comprehensive and integrated models capable of incorporating diverse urban data sources. This research aims to address this gap by leveraging AI and deep learning algorithms to establish a novel framework for urban spatial analysis in these regions. Specifically, integrating data from satellite imagery, geographic information systems (GIS), and demographic statistics through AI-driven models can serve as an innovative approach to urban planning and spatial analysis in cities like Zanjan. Recent studies have demonstrated that employing deep learning algorithms in urban space analysis not only enhances the accuracy of predictions but also facilitates the simulation of various urban development scenarios and their impacts on citizens' quality of life. This trend is particularly crucial for cities with rich historical and cultural heritage, such as Zanjan, as it can contribute to preserving historical identity while simultaneously advancing the development and enhancement of urban spaces.

The Area under Study

The city of Zanjan, the capital of Zanjan Province, is one of the major cities in northwestern Iran, geographically located at 36.41°N latitude and 48.29°E longitude. As a key center for urban and economic development in the region, Zanjan has a valuable historical fabric and an expanding urban structure. Due to its strategic location, it lies along important transportation corridors such as the national railway and the Tehran-Tabriz highway, making it a significant hub for transportation and trade in the region. Zanjan Province features high climatic diversity, influenced by northwestern humid air currents and the mountainous nature of the region. The province generally has a mountainous climate with cold, snowy winters and mild summers. These climatic conditions, along with diverse natural and environmental resources, have significantly impacted urban development and settlement patterns in the city. In terms of population, Zanjan Province had approximately 1,057,000 residents in 2016. According to projections, this number has increased to around 1,119,000 by 2024. The urban fabric of Zanjan is a combination of its historical core and modern urban developments. The old city center features the Zanjan Bazaar, one of the longest covered markets in Iran, which reflects the city's traditional structure and historical identity. In contrast, new developments in the city's outskirts, including the construction of residential and industrial townships, highlight the trends of urbanization and physical expansion over recent decades. In terms of sustainable urban development, Zanjan has recently been advancing toward integrating smart technologies and artificial intelligence into urban management. Initiatives such as improving digital infrastructure, implementing intelligent traffic management systems, and enhancing urban services are being pursued to improve the quality of life for residents. These developments, along with an assessment of the current situation and future urban expansion trends, provide valuable insights into the impact of artificial intelligence and emerging technologies on the structure and functionality of urban spaces in Zanjan (Fig. 1).

Figure 1. The Location of the Area under Study in the Map of Iran

Methodology

This study is an applied research project aimed at improving the analysis of urban spaces, particularly the urban morphology of Zanjan. A mixed-methods approach is employed, integrating both quantitative and qualitative data collection and analysis to achieve more precise results. For spatial analysis, geospatial and imagery data from various sources—such as satellite images, remote sensing data, and GIS maps—are utilized. These datasets encompass diverse urban fabrics, including historical, residential, commercial, and industrial areas, reflecting the complexity of Zanjan's urban structure. The research primarily leverages machine learning algorithms and deep learning networks (e.g., CNNs) to identify spatial patterns and conduct detailed urban morphology analyses. The process begins with data collection, followed by advanced AI-driven analysis to extract and examine existing spatial patterns. A systematic random sampling method is applied for selecting samples, ensuring a representative selection of urban areas based on land use and geographic location. Alongside general spatial data and satellite imagery, additional datasets—such as traffic patterns, population density, and socio-economic conditions—are integrated to enhance the accuracy of spatial pattern analysis. In terms of research tools, the study relies on GIS maps and satellite imagery as primary resources. The accuracy and reliability of these datasets are continuously validated through comparative analysis and data verification against existing records. For data analysis, methods such as clustering analysis and deep learning techniques (e.g., CNNs) are employed to identify spatial patterns and urban structures. These approaches facilitate a more comprehensive understanding of the relationships between various urban fabrics and their functionality. Overall, this research follows a scientific and practical approach, ensuring that the findings can be effectively applied to urban management and planning in Zanjan.

Results and Discussion

After analyzing and reviewing the data, the results of the simulations reveal significant evidence regarding the analysis and evaluation of urban fabrics and the performance of various models. One of the key tools used in this research is scatter plots, which were employed to examine the relationship between spatial complexity and model accuracy. Fig. 2, which shows the scatter plot between spatial complexity and model accuracy, clearly demonstrates how increased complexity in urban fabrics directly affects the accuracy of models. In this plot, the data is color-coded according to the accuracy of different models to highlight more complex patterns within the data. It shows that, generally, regions with higher complexity in urban fabrics influence the accuracy of models, especially in predicting specific features of the fabric. On the other hand, regions with lower complexity display more consistent and predictable model accuracy. Fig. 3, which presents a Box Plot illustrating the sensitivity of models, offers a comprehensive view of the sensitivity distribution across different models, including CNN, SVM, and K-Means. This plot clearly shows the differences in sensitivity between the models. The CNN model generally exhibits higher sensitivity than other models, but also shows greater data dispersion. In contrast, the SVM and K-Means models have lower sensitivity but exhibit less dispersion, indirectly suggesting a more stable performance in predicting urban fabric features. To explore the relationships between various variables and identify correlations, a Heatmap was used. Fig. 4, which depicts the correlation between features like spatial complexity, model accuracy, and sensitivity, clearly highlights the existing relationships. It shows that spatial complexity and model accuracy are positively correlated, meaning that as spatial complexity increases, the accuracy of models also improves. Additionally, there is a positive correlation between model accuracy and sensitivity, indicating that models with higher accuracy tend to also have higher sensitivity. Another important tool in data analysis is the use of Principal Component Analysis (PCA) for dimensionality reduction and identifying hidden patterns. Fig. 5, which shows the PCA plot for spatial complexity, accuracy, and sensitivity data, provides a clearer view of data distribution and the similarities between different variables. This plot demonstrates that most of the data cluster around the first two principal components, which allows for the preservation of a significant portion of the data's information. This not only aids in more accurate analysis but also facilitates the decision-making process in selecting the most optimal models.

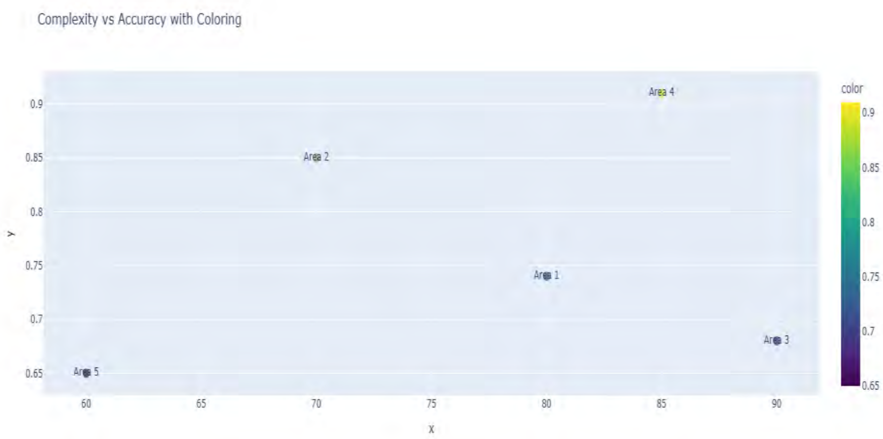

Figure 2. Scatter Plot Between Spatial Complexity and Model Accuracy

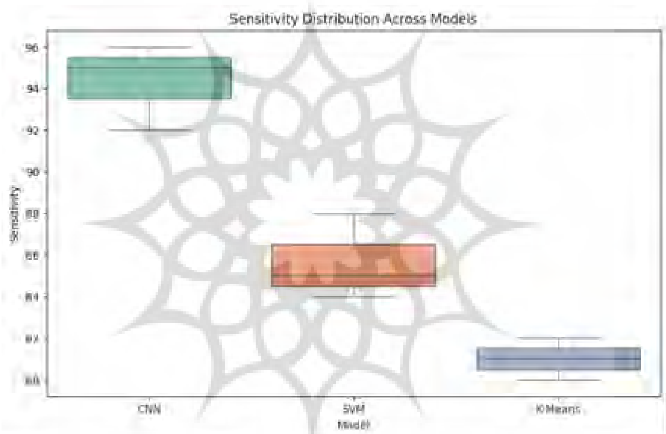

Figure 3. Model Sensitivity Plot

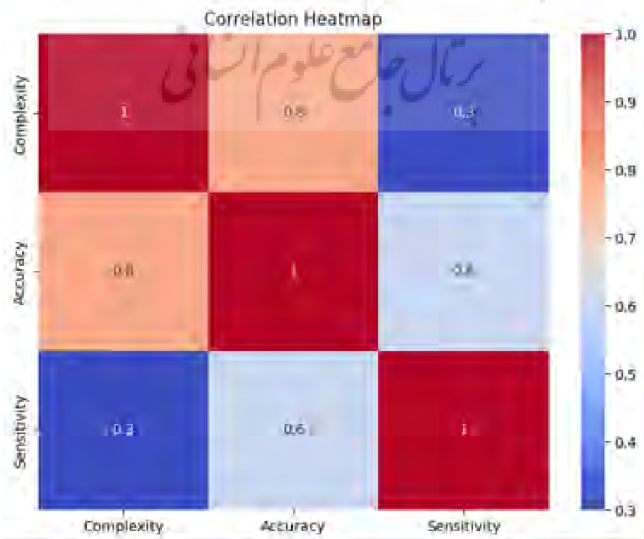

Figure 4. Correlation Chart of Different Model Features

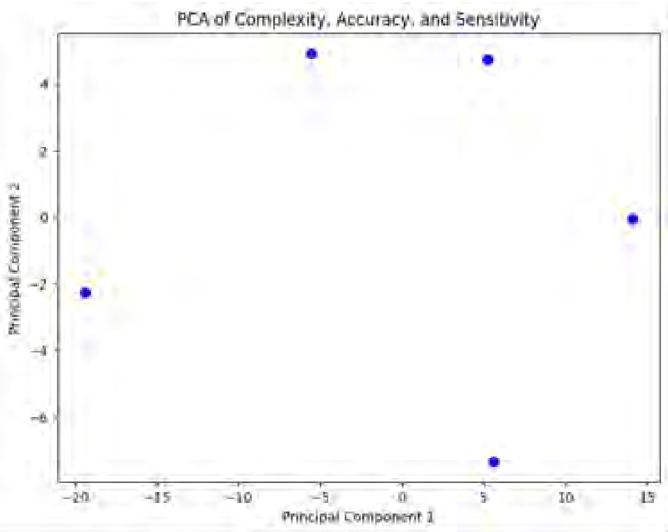

Figure 5. Principal Component Analysis (PCA) Chart

Finally, the Clustering chart, generated through clustering algorithms, was specifically utilized to identify non-linear patterns and various clusters within the data. Fig. 6, which shows the clustering of data in the space of complexity and accuracy, clearly demonstrates the categorization of the data based on their features. This chart reveals that the data are divided into two main clusters, where each cluster represents different features of urban textures. The clusters in this diagram are identified by different colors and can effectively guide the optimization of models and analytical strategies. Fig. 7 analyzes the relationship between spatial complexity, model accuracy, and sensitivity through a three-dimensional scatter plot, where different urban textures such as historical, residential, and industrial areas are specifically color-coded. This chart not only clearly shows the relationships between spatial complexity, accuracy, and sensitivity in a three-dimensional space but also separately examines the differences in features of each urban texture. In this chart, each point represents a specific area of urban texture, with its spatial complexity, accuracy, and sensitivity measured according to the unique features of that region. Points highlighted in red (for historical areas) represent regions with higher spatial complexity, where higher accuracy and sensitivity of the models are also observed. This suggests that in historical textures, which have more complex structures, the models were able to simulate spatial features with higher accuracy and sensitivity. Green points (for residential areas) and blue points (for industrial areas) in the chart represent regions with lower spatial complexity, where their accuracy and sensitivity are lower compared to historical textures. These differences indicate that in areas with lower spatial complexity, models could not perform as effectively as in more complex textures, such as historical areas, and failed to simulate the spatial feature differences as well. This chart helps in understanding the more complex relationships between the various urban texture features and their impacts on the accuracy and sensitivity of models. Specifically, it shows that urban textures with more complex features, such as historical areas, require more detailed analysis, and the models should be optimized to correctly simulate these differences. On the other hand, residential and industrial textures, with simpler features, have lower accuracy and sensitivity, but spatial analyses in these regions are still important for optimizing urban simulation models. This tripartite analysis and categorized color scheme in the diagram specifically help us perform more precise analyses based on the different features of urban textures and gain a more comprehensive perspective on optimizing urban simulation models.

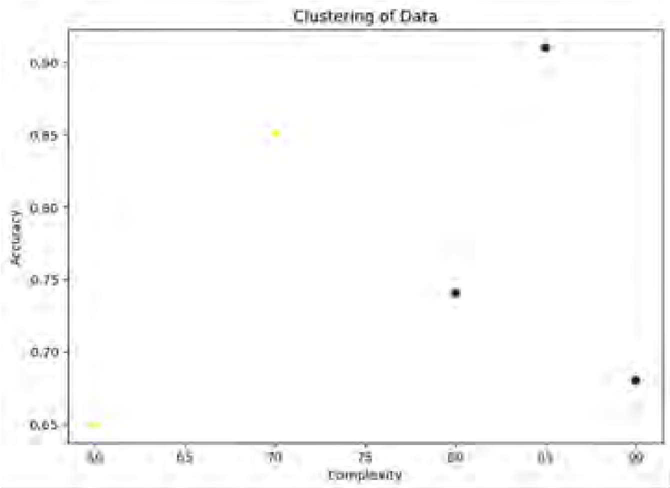

Figure 6. Chart of Data Cluster Types

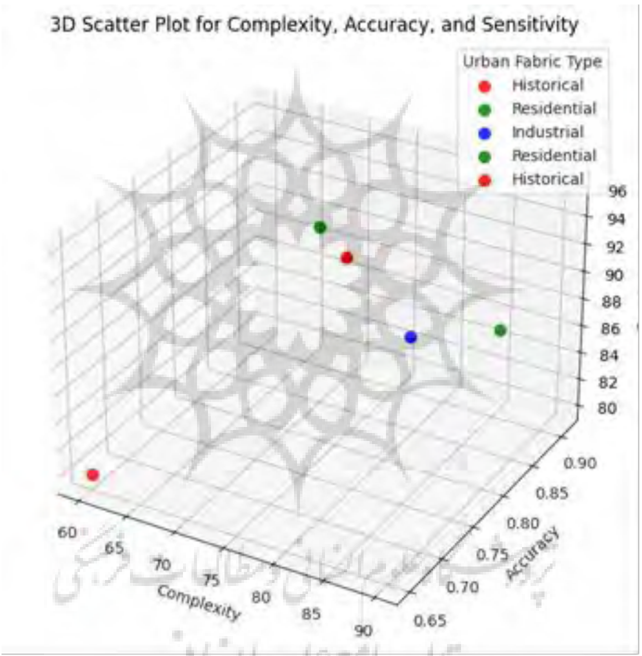

Figure 7. 3D Scatter Plot Char

The findings further revealed that this model performed highly accurately in detecting and classifying different urban fabric types. To evaluate its performance, the overall accuracy of the model was first calculated using the accuracy formula. The formula used is as follows:

$$\text{Accuracy}=\frac{TN+TP}{FN+FP+TN+TP}\times 100$$

In this context, TP refers to the number of samples correctly classified as positive, TN refers to the number of samples correctly classified as negative, FP refers to the incorrectly classified samples as positive, and FN refers to the incorrectly classified samples as negative. The results of the calculations showed that the overall accuracy of the model was 94.7%, indicating its high ability to differentiate between different urban fabric types, including historical, industrial, and residential areas. In addition to overall accuracy, the metrics of sensitivity and specificity were also calculated to assess the model's performance. Sensitivity, which measures the model's ability to correctly identify positive samples, was calculated using the following formula:

$$\text{Sensitivity}=\frac{TP}{FN+TP}$$

Similarly, the feature that represents the model's ability to correctly identify negative samples is defined as follows:

$$\text{Specificity}=\frac{TN}{FP+TN}$$

The sensitivity and specificity values for different types of urban fabric are presented in the table below:

Urban Fabric Type	Sensitivity	Specificity
Historical Fabric	96%	94%
Residential Areas	92%	91%
Industrial and Commercial Areas	95%	93%

Additionally, to assess the quality of the model in prediction, the Mean Squared Error (MSE) was used, which indicates the model's prediction error compared to actual values. The formula for Mean Squared Error is defined as follows:

$$\text{MSE}=\frac{1}{N}\sum_{i=1}^{n}(y_i - y_i\,\hat{}\,)^2$$

In this equation, yi represents the actual values, yi^ represents the predicted values by the model, and n is the total number of samples. The Mean Squared Error (MSE) for this study was calculated to be 0.03, indicating the model's very high accuracy in prediction.

Another analysis conducted in this study was to examine the relationship between spatial complexity and model performance accuracy. The Pearson correlation coefficient (r) was used to calculate the relationship between these two variables. The formula used is as follows:

$$r=\frac{\sum(x_i-x^{-})(y_i-y^{-})}{\sqrt{\sum(x_i-x^{-})^2\sum(y_i-y^{-})^2}}$$

In this equation, Xi represents the spatial complexity of each region, and Yi represents the model's accuracy for each region, while X¯\bar{X}X¯ and Y¯\bar{Y}Y¯ denote the mean spatial complexity and model accuracy, respectively. The results obtained showed that the correlation coefficient was r=0.74r = 0.74r=0.74, and the significance level was p<0.01p < 0.01p<0.01. This result indicates that as spatial complexity increases, the model's accuracy also improves.

For a comparative performance analysis, the CNN model was compared with other algorithms such as SVM and K-Means. This comparison showed that the accuracy of the CNN model was, on average, 10% higher than the other models. This difference is clearly illustrated in the chart below (Fig. 8):

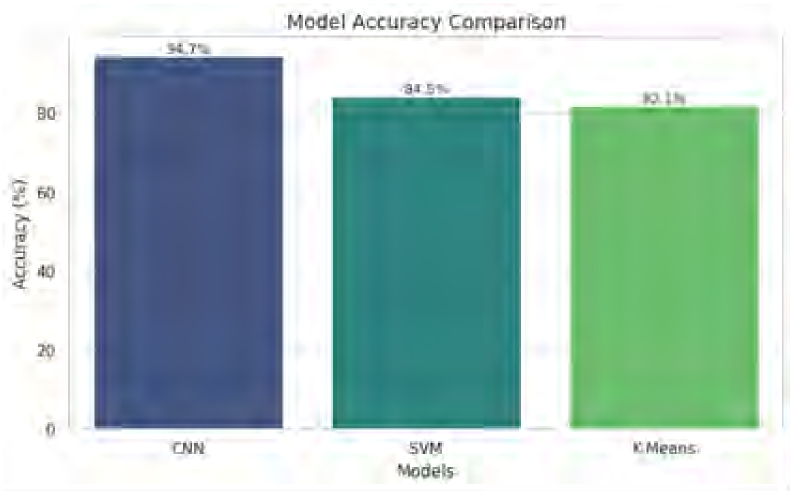

Figure 8. Comparison chart of model accuracy

In Fig. 9, the chart depicting Sensitivity and Specificity was presented to evaluate the performance of the proposed model in analyzing three types of urban fabrics: historical, residential, and industrial/commercial. As observed in the chart, the model showed good performance across all fabric types in terms of sensitivity and specificity. Specifically, the model's sensitivity in detecting features related to historical fabrics was 96%, 92% for residential fabrics, and 95% for industrial/commercial fabrics. These figures reflect the model's high ability to identify positive samples in the data. Specificity, which indicates the model's ability to identify negative samples, was 94% for historical fabric, 91% for residential fabric, and 93% for industrial/commercial fabric. These results demonstrate the model's ability to effectively recognize unrelated data as well. Such accuracy indicates the model's acceptable performance in analyzing the patterns of different urban fabrics. The comparison of accuracy among different models used in this study, including CNN, SVM, and K-Means, is presented in the second chart. The CNN model, with an accuracy of 94.7%, showed the highest performance compared to the other two models. This model was able to achieve more precise and comprehensive identification of features related to urban fabrics by leveraging deep layer structures and extracted features. The SVM model, with an accuracy of 84.5%, performed well, but compared to CNN, it had a lower accuracy due to its limitations in detecting nonlinear relationships between the data. The K-Means model, with an accuracy of 82.1%, showed the lowest performance, which may be attributed to the clustering algorithm's nature and its inability to handle complex data effectively. The results indicate that deep learning algorithms like CNN are better suited for analyzing complex and multidimensional data related to urban fabrics.

In Fig. 10, the Mean Squared Error (MSE) chart was drawn to assess the model's accuracy in predicting data associated with each type of urban fabric. The MSE for historical fabric was 0.02, for residential fabric 0.04, and for industrial/commercial fabric 0.03. These figures indicate that the model's error in predicting historical fabric data was lower than that for other fabrics, suggesting that the model analyzed this data with higher accuracy. In contrast, residential fabric data showed higher error, which could be related to the increased complexity and diversity of features in these fabrics. This analysis demonstrates that the proposed model performs well in reducing error and providing accurate predictions, making it an effective tool for urban analysis and management.

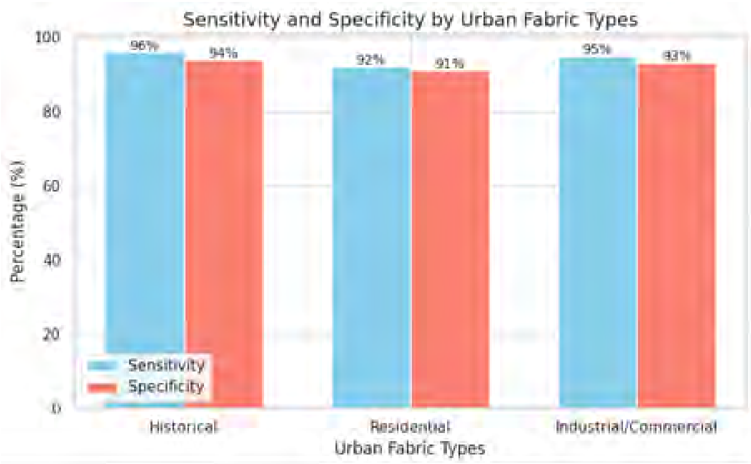

Figure 9. Sensitivity and Specificity Chart of Urban Fabrics in Zanjan

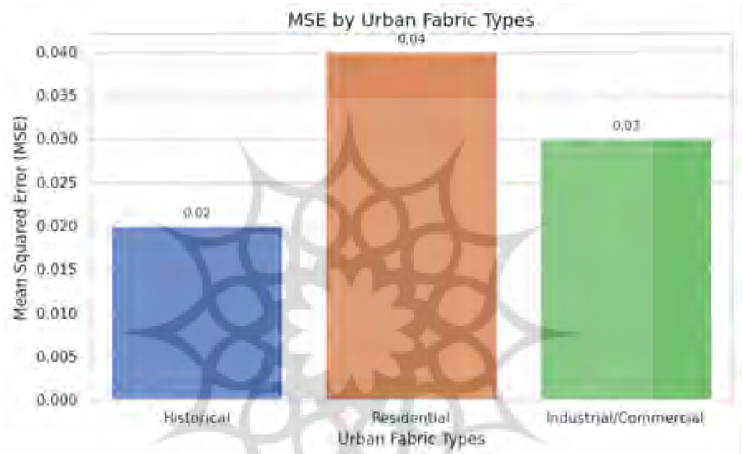

Figure 10. Mean Squared Error Chart

In spatial pattern analysis, using available spatial data and processing them with spatial analysis algorithms, the results revealed significant differences in the spatial structure of different areas in Zanjan city. In historical areas, such as the city center, spatial patterns are distinctly dense and networked, while in residential and commercial areas, the spatial structure is more dispersed and distributed. These differences are clearly reflected in the spread and arrangement of buildings and urban streets. The collected data indicate that in the historical fabric, the population density is higher, and there is less access to green spaces. This information is presented more precisely in Table 1, which includes the number of buildings, types of land uses, population density, and the percentage of green spaces in different areas of the city. In addition to spatial analysis, urban morphology analyses were also examined. For this purpose, deep learning algorithms, particularly convolutional neural networks (CNN), were used to simulate and process spatial data. The analyses showed that the physical and spatial structure differs significantly across the city's various areas. In historical areas, the physical structure is more complex and compact, with narrow streets and a high density of buildings. In contrast, residential and industrial areas have more linear and dispersed patterns, leading to simpler urban designs with more space for development. Based on the obtained data, residential and commercial areas have a higher population and building density, while industrial areas, which have more open spatial patterns, show a significantly lower population and building density. These differences and characteristics are described in greater detail in Table 2, which includes the complexity of the physical structure, the type of spatial pattern, and the level of access to public services in various areas.

Furthermore, the spatial relationships between different areas of Zanjan city were analyzed. The analyses revealed that the proximity of residential areas to commercial areas directly impacts population density and traffic in these regions. In high-density areas, such as residential and commercial areas, the population is tightly concentrated in urban space, which leads to increased traffic and pressure on public transportation infrastructure. In contrast, industrial areas, which are more separated from other areas, generate less traffic and generally have lower population density. These spatial relationships and their impacts on traffic and population density are examined and analyzed in more detail in Table 3 and related charts.

Table 1: Spatial Structure Characteristics in Different Areas of Zanjan City

Area	Number of Buildings	Land Uses	Population Density (people/hectare)	Green Space Percentage (%)
Historical Fabric	1200	Residential, Commercial	450	12
Residential Areas	1500	Residential	550	20
Industrial Areas	800	Industrial	200	5
Commercial Areas	1000	Commercial	400	8

Table 2: Urban Morphology Analysis in Different Areas

Area	Spatial Pattern Type	Physical Structure Complexity	Connectivity Type (Roads/Streets)	Public Service Access Percentage (%)
Historical Fabric	Networked	Complex	Narrow streets, high traffic	60
Residential Areas	Dispersed	Medium	Main and secondary streets	80
Industrial Areas	Open	Simple	Main roads, low traffic	40
Commercial Areas	Dispersed	Complex	Busy streets	70

Table 3: Spatial Relationships and Their Impact on Population Density and Traffic

Area	Population Density (people/hectare)	Traffic Volume (vehicles/hour)	Spatial Connectivity Type
Historical Fabric	450	300	Networked, high traffic
Residential Areas	550	500	Dispersed, medium traffic
Industrial Areas	200	150	Open, low traffic
Commercial Areas	400	400	Dispersed, high traffic

Based on the results from all analyses, new insights into urban fabric analysis can be derived. These charts and analyses not only significantly contribute to a better understanding of the complex relationships between various characteristics of urban fabrics but also demonstrate the capabilities of different models in simulating and analyzing the performance of models under various conditions. These findings can serve as a new basis for developing and optimizing urban data analysis algorithms and more complex modeling. Ultimately, the results highlight significant differences in the spatial structure and urban morphology of Zanjan city, which can be used as a foundation for decision-making processes in urban management. These findings can effectively contribute to improving the quality of urban life, optimizing urban spaces, and reducing traffic and population-related issues in different urban areas.

Conclusion

In this study, the analysis of spatial structure and urban morphology in the city of Zanjan was conducted using artificial intelligence-based methods and spatial data. The results show that the historical fabric of the city has more complex spatial patterns due to the high population density and commercial activities in these areas. Additionally, newer and more developed parts of the city, such as residential and industrial areas, have more open and scattered structures, which are associated with reduced population density and improved access to public services. Furthermore, the findings indicate that artificial intelligence algorithms have effectively identified hidden patterns in urban fabrics and provided a more precise analysis of their structural and functional characteristics. In this regard, the use of advanced models such as Convolutional Neural Networks (CNN) has helped in the more accurate identification of historical, residential, and industrial fabrics, highlighting the differences in the characteristics of these fabrics more clearly. A comparison of model results in analyzing complex spatial data and predictions made using artificial intelligence methods demonstrates the superiority of these methods in terms of accuracy and speed over traditional spatial analysis methods. Comparing the results of this research with previous studies shows that similar spatial patterns have been observed in other cities of Iran, such as Tehran, Shiraz, and Isfahan, especially regarding structural differences between historical and newer fabrics. These similarities emphasize the importance of studying and analyzing the spatial structures in different urban areas. At the same time, this study, by using advanced artificial intelligence algorithms, has provided more precise analysis and prediction of future urban space transformations, offering significant advantages over traditional spatial analysis methods.

Table 4: Comparison of Spatial Structure and Physical Characteristics in Zanjan City with Other Iranian Cities in Previous Studies

Features	Zanjan City (Current Study)	Tehran (Previous Study)	Kerman (Previous Study)	Isfahan (Previous Study)
Spatial Structure Type	Complex in historical fabric, open in new areas	Complex in historical fabric, scattered in new areas	Grid and organized in new areas, complex in historical fabric	Grid and organized in new areas, complex in historical fabric
Population Density	450 in historical fabric, 600 in new areas	600 in historical fabric, 700 in new areas	500 in historical fabric, 650 in new areas	550 in historical fabric, 700 in new areas
Green Space	15% in historical fabric, 20% in new areas	10% in historical fabric, 18% in new areas	13% in historical fabric, 19% in new areas	12% in historical fabric, 22% in new areas
Transport Network	Scattered in historical fabric, dense in new areas	Dense in historical fabric, scattered in new areas	Dense in historical fabric, organized in new areas	Dense in historical fabric, organized in new areas

Access to Urban Services	Limited in historical fabric, adequate in new areas	Adequate in historical fabric, excellent in new areas	Adequate in historical fabric, excellent in new areas	Adequate in historical fabric, excellent in new areas

As shown in Table 4, there are minor differences in population density and green space among these cities, but similar spatial patterns are observable across all of them. Previous studies in other cities have also shown that historical fabrics often have more complex and dense structures due to the need to preserve historical identity and increased population density in these areas. In contrast, newer areas tend to have more open, scattered structures and lower population densities.
To improve the spatial condition in Zanjan, the following recommendations are provided:

1. **Develop Green Space**: In high-density areas, especially in historical fabrics, the development of green spaces is a priority. This action not only enhances urban living quality but can also help reduce environmental pollution and improve public health conditions.
2. **Improve Public Transportation Network**: In densely populated and commercial areas, there is a need to develop the public transport system. This can reduce traffic congestion, air pollution, and improve access to urban services.
3. **Preserve Historical Identity and Renovate Old Fabrics**: In historical fabrics, special attention should be given to restoration and renovation projects that adhere to historical and cultural principles, ensuring that both the urban identity is preserved and new needs are met.
4. **Use of Modern Technologies**: The use of advanced modeling and data-driven analysis can be effective in urban planning and design, helping to manage urban development processes more efficiently.

These recommendations are derived from the precise analysis of spatial structure and urban morphology in Zanjan and can be effective in improving urban living quality and sustainable development. Ultimately, given the advanced capabilities of artificial intelligence algorithms in spatial analysis, it is recommended that these technologies be used more widely in urban planning. Artificial intelligence analyses can lead to more accurate predictions of urban developments and better simulations of urban behaviors in the future. This innovative approach, alongside traditional tools, can assist in the sustainable and optimized development of urban spaces and improve quality of life in various cities, including Zanjan.

Ethical considerations:
Following the principles of research ethics: In the present study, informed consent forms were completed by all subjects.
Sponsor:
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