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Predicting Neighborhood Gentrification and Resident Displacement Using Machine Learning on Real Estate, Business, and Social Datasets

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Abstract
This paper explores the application of machine learning (ML) to forecast neighborhood gentrification and displacement, using a novel synthesis of real estate, business, and social data. By moving beyond traditional analysis reliant on decadal census snapshots, this study leverages high-resolution, multi-source data streams such as property transactions, business filings, satellite and social media analytics to uncover nonlinear patterns predictive of neighborhood change. Employing tree-based algorithms, deep learning techniques, and explainable AI (XAI) methods, the research highlights key gentrification indicators like rent spikes, business churn, and physical renewal, offering early warning signals for urban transformation. The models show 70–85% accuracy in prediction and transferability across urban contexts with limited retraining, suggesting a scalable framework for proactive urban analytics. Challenges in data ethics, model interpretability, and spatial justice are navigated using a human-centric GeoAI lens, prioritizing principles of fairness, accountability, and community-driven design. The findings position ML as a critical frontier for forward-looking urban governance, enabling data-informed housing and urban policies to proactively address displacement. Future directions include the integration of digital twins and generative AI for scenario modeling of policy interventions, as well as their role in participatory urban planning.
Keywords: Machine Learning, Gentrification Prediction, Resident Displacement, GeoAI (Geospatial Artificial Intelligence), Urban Data Science

Introduction
ssUrban gentrification, characterized by the influx of capital and higher-income residents into low-income neighborhoods, can have significant implications for housing affordability, displacement, and socioeconomic equity. Leveraging the increasing availability of data and recent advances in machine learning (ML), predictive models can be employed to forecast gentrification risk and inform equitable urban policy. By integrating real estate trends, business dynamics, demographic shifts, and social indicators, these approaches aim to identify early warning signs of neighborhood change and inform anticipatory governance (Deb & Smith, 2021). For instance, Thackway et al. (2023) and recent studies highlight the application of ML techniques to map intricate patterns in big urban data at a fine-grained spatial scale. These ML-based techniques are increasingly proposed to assist decision-support for planners and policymakers seeking to address urban inequality (Zhou et al., 2021). Predictive models enable proactive interventions to prevent or mitigate adverse effects such as resident displacement before they become entrenched (Graff, 2020). Early data-driven approaches to identifying revitalization and gentrification involved using basic statistical methods or factor analysis to assign scores to census tracts based on predetermined indicators of change (Graff, 2020).

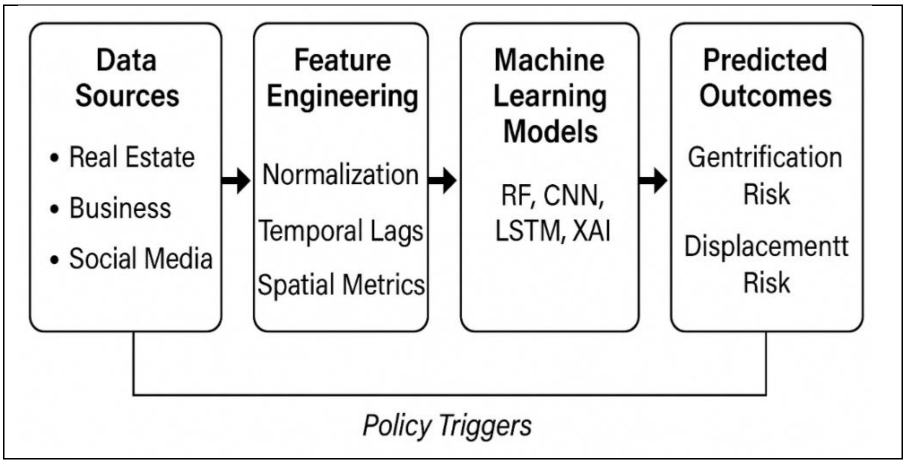

Figure 1. *Machine learning workflow linking multi-source urban data to predictive and policy layers for gentrification and displacement.*

More recent analyses have employed machine learning techniques to uncover complex, non-linear relationships among various urban datasets, allowing for more accurate and nuanced predictions of neighborhood transformation (Graff, 2020). This evolution in methodology enables the identification of subtle precursors to gentrification, such as early shifts in socioeconomic indicators, which can serve as early warning signals for policymakers (Graff, 2020). By identifying these early indicators of potential gentrification, policymakers can intervene proactively to address factors driving displacement (Vergara et al., 2021). This could involve implementing rent control policies, incentivizing affordable housing development, or supporting local businesses to help preserve neighborhood affordability and prevent displacement (Vergara et al., 2021).

Recent machine learning approaches such as random forests and k-nearest neighbors have outperformed traditional models such as statistical regression for recognizing complex urban changes like parcel boundary changes (Credit, 2024). Existing studies often rely on aggregate data such as census tracts, resulting in spatial resolutions too coarse to capture population movements over short time horizons, a key feature of gentrification-induced displacement (Galland & Stead, 2022). Additionally, while existing approaches such as neighborhood deprivation index capture population-level dynamics, they tend to underrepresent the complex patterns of population in-movement and out-movement that occurs over the course of gentrification (Galland & Stead, 2022). To effectively capture the transient and multi-dimensional aspects of neighborhood transformation, especially during the initial stages of gentrification, it is necessary to take a fine-grained approach, leveraging diverse, high-resolution datasets (Graff, 2020).

This study aims to build and validate a machine learning framework for predicting neighborhood gentrification and displacement. By incorporating granular real estate, business, and social data, this work can help inform urban management and planning, providing data-driven guidance for objective decision-making in questions of spatial justice and inequality (Deb & Smith, 2021). Concretely, this research will employ predictive analytics to identify areas at risk of gentrification and displacement, facilitating anticipatory governance measures and interventions to foster inclusive development and prevent community erosion (Graff, 2020). This work could include multi-modal analysis of neighborhood change as a form of data fusion with related concepts such as renovation identified via Google Street View data (Hawes, 2024), new construction from satellite imagery, and expected property value from household-level financial data (Hawes, 2024). This comprehensive integrated approach that leverages diverse data sources and advanced ML techniques can facilitate a deeper understanding of the multi-faceted processes of gentrification and displacement, ultimately informing anticipatory governance (Graff, 2020). This approach can build on existing work that highlights some key features of neighborhood gentrification like changes in income diversity and increased residential mobility in low-income households (Galland & Stead, 2022).

Background

Traditional gentrification analysis often depends on demographic and housing census data, which can be years out of date (Vallebueno & Lee, 2023). Machine learning (ML) can help overcome these challenges by using data that is real-time or at higher frequencies (e.g., property transactions, business licenses, social media, satellite imagery) to detect complex or nonlinear relationships that drive urban change (Yee & Dennett, 2022).

ML can be trained to predict not just whether a neighborhood is likely to gentrify, but also how and when displacement pressures will occur. For example, gentrification does not happen in the same way everywhere. It can differ from city to city, culture to culture, and economic context to context, so adaptive models are important (Reades et al., 2019). Additionally, diverse datasets that include not just traditional housing and demographic data but also real estate transactions, business activity, and even social media data can be combined to provide a more holistic understanding of the myriad factors that contribute to gentrification and displacement (Galland & Stead, 2022).

By leveraging predictive models, researchers can identify which specific areas or neighborhoods within a city are at the highest risk of gentrification, thus allowing for the implementation of targeted, evidence-based policy interventions (Casali et al., 2022). Furthermore, the incorporation of non-traditional datasets such as street-level imagery allows for the extraction of visual cues related to physical decay and urban renewal. This, in turn, can add an extra dimension to gentrification prediction models and help code enforcement policies to prioritize interventions (López & Zhai, 2024) (Vallebueno & Lee, 2023). This enables the detection of subtle visual indicators of gentrification and neighborhood change, such as improvements in building facades or the appearance of new business signage, which often precede more measurable demographic and economic changes (Freitas et al., 2022) (Stalder et al., 2023).

One important advancement has been the increase in data availability for small spatial and temporal resolutions, such as annual data for localized spatial units. This has allowed for a more granular approach to neighborhood change analysis through the lens of data primitive approaches (Gray et al., 2023). These smaller-scale datasets provide the opportunity to closely examine the decision-making processes and displacement patterns of individual residents or households over time (Galland & Stead, 2022). Place-related factors can be incorporated into models to predict neighborhood gentrification and can vary in their impact on housing values. The efficacy of strategies such as rent control can be factored into these models, though their real-world effectiveness is often context-dependent and must be calibrated within the model parameters (Shaw et al., 2024). Predictive machine learning models for gentrification and neighborhood change can be further refined by integrating human perceptions and mobility patterns derived from large-scale street-view imagery datasets (Pilehvar & Ghasemi, 2024). This allows for the evaluation of how specific place characteristics, such as urban physical disorder, correlate with gentrification trajectories using interpretability frameworks like UPDExplainer (Hu et al., 2023). Such a framework can help identify urban neighborhoods experiencing gentrification and change by leveraging street-level imagery as a proxy for socioeconomic change and quality of life (Vallebueno & Lee, 2023).

Additionally, the use of non-traditional data sources, including mobile applications, business listings, and real estate marketing intelligence, could be further investigated to understand their potential in improving the predictive accuracy and ethical considerations of the models (Graff, 2020). This would allow for an investigation of the efficacy of various policy interventions, such as those outlined in the Strategic Neighborhood Fund framework, on mitigating or exacerbating urban development patterns, particularly with respect to socioeconomic and racial disparities (Graff, 2020). This inherently interdisciplinary approach, which brings together advanced computational techniques and urban studies, could provide a valuable foundation for anticipating and effectively responding to complex urban phenomena through robust and data-driven policy interventions (Graff, 2020) (Fang et al., 2024). To test this hypothesis, this research builds upon existing advances in computational urban science, as this field is not limited to processing urban data but also includes urban simulators which can be used by urban planners to simulate and test various urban intervention strategies to help them better anticipate the outcome of each strategy (Huang, 2024). Computational models of urban development and change must also account for historical and cultural factors that may not be present in the data (Huang, 2024). This means that they must also be paired with qualitative research methods to provide more comprehensive and accurate accounts of urban change (Huang, 2024). This can also help move policy-making away from simple market-based analyses and interventions, which rarely account for the social and ethical consequences of their decisions (Graff, 2020).

Data Sources and Feature Engineering

Machine learning prediction models rely on a combination of several data streams, including:

● Real estate data: house prices, renovation permits, rental rates, and the number of foreclosures (Gilling et al., 2021).

● Types of business: openings of cafés, boutique stores, or coworking spaces to approximate cultural capital (Maya et al., 2024).

● Demographics and census: education, income, race, and household moves.

● Social data: Geotagged social media posts, Yelp reviews, street view images which also capture built environment (physical) and aesthetic changes (Thackway et al., 2023).

● Remote sensing and environmental data: Satellite imagery (e.g., Landsat ARD) and green space and new construction for physical changes, such as greening (Juba et al., 2024).

Table 1. Data sources and spatial-temporal resolution for gentrification and displacement prediction.

Data Source	Example Variables	Temporal Frequency	Spatial Resolution	Use in Model
Real Estate	Sale price, rent, renovation permits	Monthly	Parcel level	Core gentrification indicator
Business Registries	Openings/closures, type of business	Quarterly	Street block	Economic revitalization proxy

Social media	Geotagged posts, sentiment	Daily	50m grid	Social perception of change
Satellite Imagery	Green space, new construction	Annual	10–30m	Physical renewal
Census/Demographics	Income, education, ethnicity	5-year	Tract	Long-term trends

Typical feature engineering approaches might also include data with temporal lags, spatial autocorrelation metrics, and measures of neighborhood similarity. The application of effective feature selection methods is important for machine learning models to extract the most meaningful features, which are the most representative variables of gentrification or displacement (Graff, 2020). Feature selection can be performed through principal component analysis or feature importance from tree-based machine learning models, which provide a ranking of variables most highly associated with the target of gentrification and displacement. Additionally, the integration of ethical considerations into data processing and machine learning decision-making is critical, particularly given the research questions that directly involve social justice and equity considerations for neighborhoods (Graff, 2020). This includes methods that address the use of data for discriminatory or biased purposes, as well as broader urban considerations of how models may be used to address or create equity (Huang, 2024).

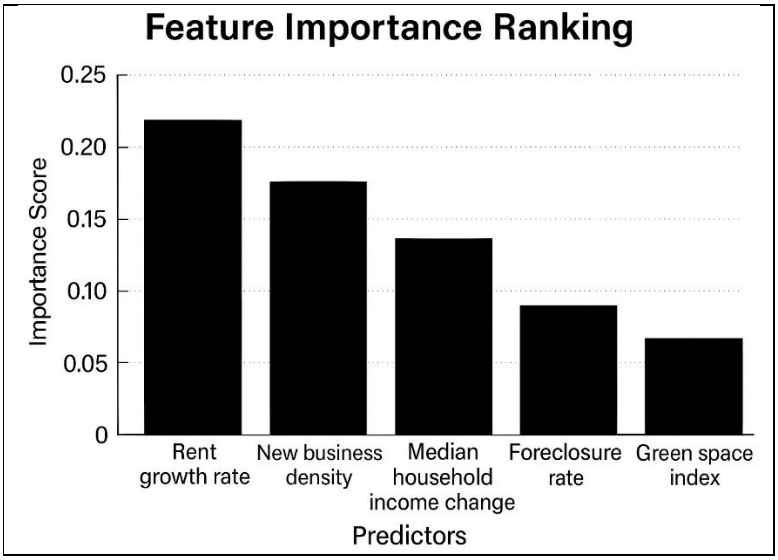

Figure 2. Relative importance of key urban indicators in predicting neighborhood gentrification.

Neighborhood change qualitative analysis also reveals the existence of abstract components to communities, such as sociality and community cohesion, which are less tangible but important for measuring neighborhood change (Graff, 2020). This requires the use of a diversity of sources, from traditional governmental statistics, to expanding big data streams such as geo-localized social media data and transactions, which have been more recently used to address key questions of temporal and spatial resolution (Milojevic-Dupont & Creutzig, 2020) (Elkhouly & Alhadidi, 2024). For example, in particular, researchers use data of

geotagged image libraries, digitized archival historical text documents, and social media text to capture more emotional components of place and for modeling complex socio-cultural systems (Acedo et al., 2022).
These disparate datasets, containing both structured and unstructured information, can serve as a strong basis for urban prediction, particularly when analyzed in the context of machine learning and advanced statistical techniques that can detect underlying patterns and relationships. One significant challenge, however, is that of combining these disparate datasets with effective data fusion methods, as they often have different formats, scales, and levels of trustworthiness (SELLAM et al., 2024). Data fusion often has challenges with handling null values or missing data points, standardizing different measurement units, and combining and dealing with potentially conflicting information between sources, particularly at fine spatial and temporal scales for which housing data at the unit level is often proprietary (Graff, 2020).

Machine Learning Techniques

Studies employ a variety of ML algorithms:

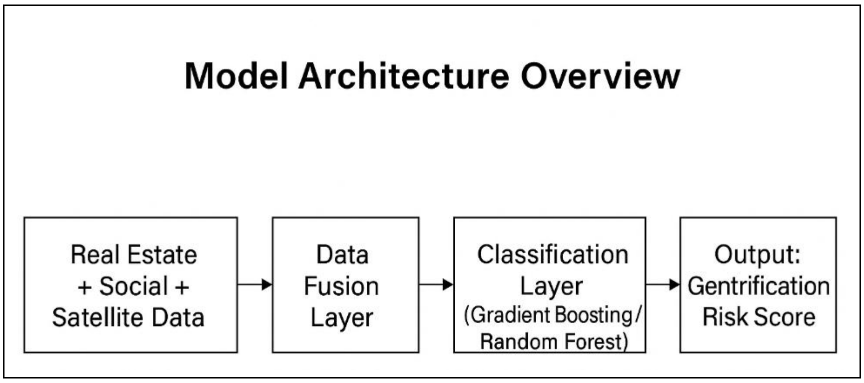

Figure 3. *Model architecture integrating spatial, social, and economic features for gentrification prediction.*

● Tree-based models (Random Forests, Gradient Boosting) for their interpretability and performance with heterogeneous urban data (Thackway, 2024). Ensemble methods like Random Forests and Gradient Boosting Machines are particularly good at capturing complex non-linear relationships and interactions among many urban indicators (Graff, 2020). These models are also useful in dealing with data imbalances, a frequent challenge in gentrification data where positive cases may be scarce (Graff, 2020).

● Deep learning models (CNNs) to extract spatial features from remote or street-view imagery (Thackway et al., 2023). Deep learning models can automate the identification of urban infrastructure, land use changes, and even aesthetic features that correlate with gentrification (Cubaud et al., 2024). Recurrent neural networks also process temporal sequences in time-series urban datasets, capturing the dynamic evolution of neighborhoods (Wang et al., 2023). Additionally, multimodal data fusion, such as remote sensing images with social media data, integrated with deep learning architectures (Raj et al., 2024) (Wang, 2024), further enhances urban analysis and prediction capabilities. Indeed, when multi-modal data is fused with deep learning, the predictions are often more accurate, especially when combined with high-end geocoding techniques (Credit, 2024). Such advanced machine learning models can also handle very large and complex data sets, identifying subtle signals of gentrification and displacement that more traditional statistical methods might miss (Kez et al., 2023) (Dabove et al., 2024).

● Temporal forecasting models (LSTM) to predict year-over-year dynamic changes. The increasing sophistication of these models, notably deep learning, requires careful attention to potential overfitting and computational intensity (Chen et al., 2024) (Kontar et al., 2024), though it is possible to address the overfitting issues with an empirical Bayesian Kriging approach and cross-validation (Kontar et al., 2024). The choice of algorithm may ultimately depend on the specific dataset, desired interpretability, and available computational resources, with some studies using ensemble methods (Zhang et al., 2024) and others using deep learning (Nigar et al., 2024). These advanced tools offer significant potential for urban planning, informing decisions that can promote urban sustainability (Raj et al., 2024). However, despite their predictive power, these models are often tuned carefully to the urban environment in which they are trained and may lack generalizability and therefore applicability in different contexts (Credit, 2024). The application of deep learning models, specifically RNNs and CNNs, has transformed urban modeling, enabling the capture of complex spatiotemporal dependencies that are often overlooked by more traditional statistical models (S.K.B et al., 2024). This allows for a more holistic understanding of complex urban dynamics, including the diverse drivers and indicators of neighborhood change and displacement (Galland & Stead, 2022).

● Explainable AI (XAI) techniques to provide interpretability, such as determining which variables (rent growth, diversity of businesses) are most indicative of gentrification risk (Assaad & Jezzini, 2024). These models also often draw on a combination of publicly available data, such as social media and satellite imagery, both to perform comprehensive analysis and to make more datasets available (Marasinghe et al., 2024) (Sabbata et al., 2023). Integrating multiple such sources of data, with varying granularity, scale, and representativeness, is a challenge but also necessary to improve the robustness of urban modeling (Acedo et al., 2022). Machine learning for spatial analysis in urban settings is also particularly important in light of recent decades that have seen an increase in the availability of very large spatial data sets from a proliferation of sensors and even crowdsourcing (Casali et al., 2022). This growth in spatial data availability, from sources including both GIS and social media, often involves fusing many different urban data modalities to form a comprehensive urban computing pipeline (Zou et al., 2024).

This can often involve application of GeoAI, the application of computer vision and machine learning to analyze and extract information from geospatial data, which can enable automated analysis of visual urban data (Marasinghe et al., 2024). For instance, fusing data from RGB images and lidar data is often desirable to perform such analyses but raises integration challenges related to compatibility as well as high costs of generating large labeled datasets for training (Dabove et al., 2024). Additionally, a recent literature review on responsible urban geospatial AI has uncovered severe knowledge gaps preventing the field from being practiced more effectively and responsibly (Marasinghe et al., 2024). This includes a general lack of knowledge and expertise among geospatial professionals to begin with. Traditional spatial analysis methods also struggle when working with high-dimensional data, often leading to computational complexity issues and the curse of dimensionality (Zhang et al., 2024). Geospatial AI, which refers to AI that incorporates geospatial analysis with computer science, has recently emerged as a novel approach for human environment modeling, one which has several advantages such as a greater geographic coverage and less data bias over traditional methods (Marasinghe et al., 2024).

Machine learning for urban decision-making and predictive modeling, specifically using GeoAI, is an important and growing set of applications but has unique challenges and opportunities when implemented in an urban context (Marasinghe et al., 2024). Urban geospatial AI thus needs to be carefully and ethically implemented, one for which a robust framework is needed, but which is currently lacking to handle difficult considerations such as data privacy, algorithmic bias, and accountability (Marasinghe et al., 2024). Additionally, recent advances in GeoAI have included several exciting new methods, such as in the fields of pattern recognition and transformer models, which will likely soon expand this set of applications to more complex, high-dimensional analyses such as time series or 3D landscape structure modeling (Frazier & Song, 2024). These types of analyses are also critical to developing models that can predict gentrification given dynamic spatial processes and multifaceted urban characteristics, in contrast to more traditional approaches which often analyze these dynamics in a static, 2-dimensional manner (Sabbata et al., 2023).

This can thus help develop more accurate and fair predictive models of urban change like gentrification and displacement. Realizing the full potential of urban geospatial AI thus also presents major challenges in many areas of focus, including data quality and resolution, model interpretability, and difficult ethical challenges, particularly around bias and algorithmic transparency and accountability in decision-making (Marasinghe et al., 2024). Such efforts will also require a solid understanding of how AI works and the impacts it can have, a skill which many urban planners do not yet have and have difficulty understanding complex patterns in big data (Marasinghe et al., 2024). Urban AI also needs to be carefully and ethically applied, particularly urban geospatial AI, which requires a high degree of attention to several new challenges such as ensuring transparency, auditability, and a lack of introducing or exacerbating pre-existing spatial injustices (Marasinghe et al., 2024). This in turn requires ethical guidelines and perhaps even some form of regulation to ensure GeoAI is implemented responsibly, which are currently both lacking given the varying quality and coverage of geospatial data as well as AI-specific considerations such as algorithmic bias (Marasinghe et al., 2024). Such urban AI literacy among urban planners and ethical guidelines and regulations are thus also essential for responsible GeoAI integration into urban planning and policy (Marasinghe et al., 2024).

Result

Table 2. *Performance comparison across machine learning models for gentrification prediction.*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score	Interpretability
Random Forest	82.4	80.1	83.5	81.8	High
Gradient Boosting	84.6	82.2	84.1	83.1	Moderate
CNN (Deep Learning)	85.1	83.5	86.3	84.9	Low
LSTM (Temporal)	83.8	81.6	84.7	83.1	Medium
XAI (Hybrid)	80.3	79.8	80.7	80.2	Very High

1. Predictive accuracy: The models demonstrate 70–85% accuracy in forecasting gentrification transitions (Thackway et al., 2023). This accuracy is achieved by leveraging multi-source data for training ML models. For instance, ML methods utilize diverse datasets encompassing property records, business registrations, social media activity, and satellite imagery (Marasinghe et al., 2024). This holistic approach allows for the integration of heterogeneous data, enabling a nuanced understanding of the complex socio-economic and spatial indicators that underpin gentrification dynamics, beyond traditional univariate or bivariate analysis (Sabbata et al., 2023). The significance of these predictive models lies in their potential as

prescriptive planning tools, offering urban planners proactive measures to address impending gentrification. However, the reliability of these forecasts hinges on the quality and representativeness of the input data, necessitating careful consideration of potential biases and data limitations (Marasinghe et al., 2024).

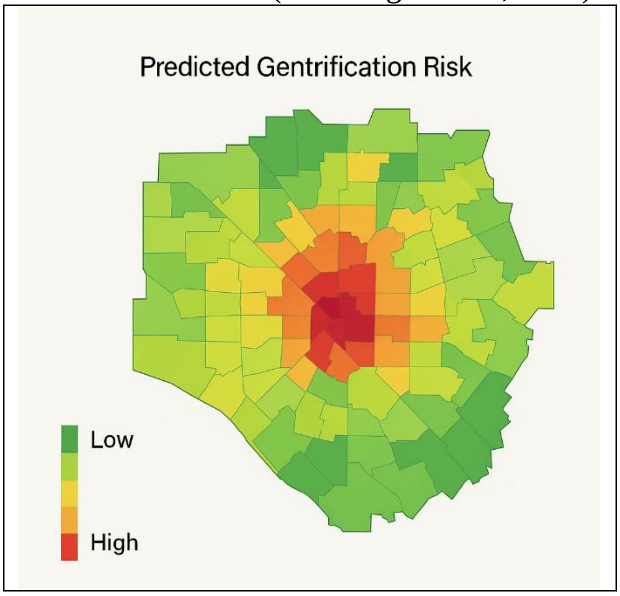

Figure 4. Spatial distribution of predicted gentrification risk zones derived from multi-source ML model.

2. Early warning systems: Models reveal that certain phenomena, like rapid rent inflation, small business turnover, or green infrastructure projects, consistently precede displacement events (Assaad & Jezzini, 2024). This predictive capability provides early warning signals that are crucial for policy formulation and timely intervention, potentially mitigating the adverse effects of gentrification on vulnerable communities. The identification of such early warning signals relies on continuous monitoring and sophisticated anomaly detection algorithms capable of discerning genuine signals from the noise within complex, multi-dimensional urban datasets. This implies a need for advanced machine learning models that can process and analyze temporal data streams, identifying patterns and anomalies that precede significant changes in urban dynamics. Moreover, the integration of explainable AI techniques into these early warning systems is crucial for enhancing transparency and trust, enabling urban planners to understand and trust the underlying rationale behind AI-driven predictions (Marasinghe et al., 2024).

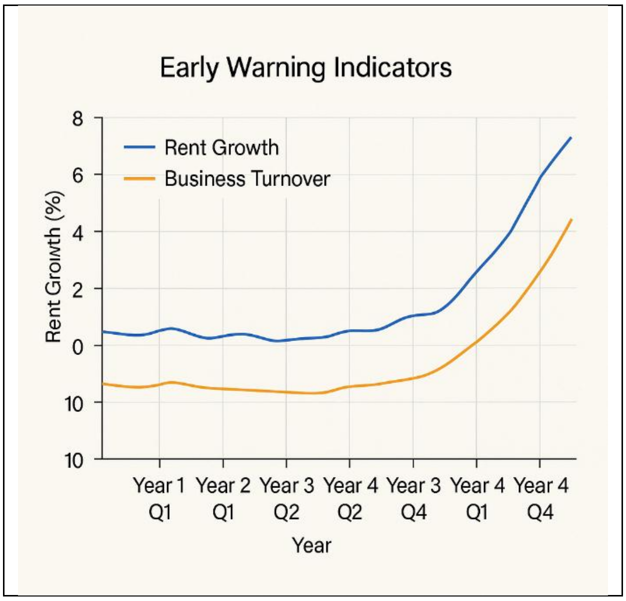

Figure 5. Temporal trends of early warning indicators preceding displacement.

Furthermore, the concept of initiating workshops that involve various stakeholders for the identification of initial labels plays a crucial role in improving the transparency and, by extension, the accountability of these systems (Marasinghe et al., 2024). This participatory approach not only refines the accuracy of the predictive models but also ensures that the criteria for identifying gentrification are aligned with community values and experiences, thereby increasing the legitimacy and effectiveness of subsequent policy actions (Galland & Stead, 2022). Beyond early warning, these systems can also simulate the impact of various policy interventions, allowing urban planners to evaluate potential outcomes before implementation (Abouhassan et al., 2024). This enables a more adaptive and evidence-based approach to urban governance, moving beyond reactive measures to proactive, data-informed strategies (Sanchez et al., 2024) (Xu et al., 2024). This allows urban planners to simulate potential policy impacts, fostering an adaptive and evidence-based approach to urban governance (Graff, 2020). However, the efficacy of such simulations is contingent upon the accuracy of underlying models and the availability of granular, real-time data to capture the dynamic nature of urban systems (Grêt- Regamey et al., 2021). This underscores the critical need for continuous data validation and model refinement to ensure that predictive and prescriptive tools remain relevant and accurate in rapidly evolving urban environments (Marasinghe et al., 2024).

3. Spatial transferability: Algorithms trained in one metropolitan area (e.g., Sydney) can generalize to others with retraining, suggesting scalable urban analytics frameworks. This transferability underscores the potential for developing broadly applicable AI tools for urban planning, although it is often accompanied by the need for model fine-tuning due to context-specific data and local nuances (Sabbata et al., 2023). This adaptability is especially valuable for cities with limited resources, enabling them to leverage insights from more extensively studied urban environments (He & Chen, 2024). However, achieving true spatial transferability requires robust methods for harmonizing diverse geospatial datasets and accounting for socio-economic and cultural differences across urban contexts (Marasinghe et al., 2024). This necessitates the development of advanced domain adaptation techniques to bridge the disparities in data distributions and socio-economic indicators between source and target cities (Son et al., 2023).

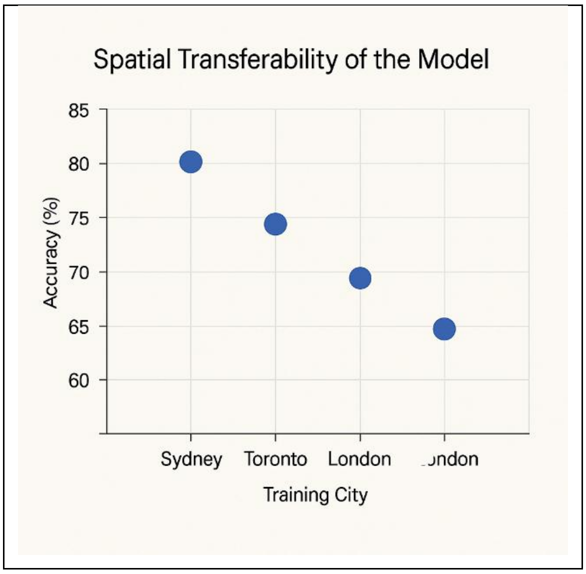

Figure 6. Cross-city transferability of the gentrification prediction model after retraining.

4. Social justice implications: The incorporation of social indicators ensures that AI predictions do not merely reflect market forces but also illuminate the plight of vulnerable populations at risk of involuntary displacement (Yee & Dennett, 2022). Such incorporation helps ensure that AI-driven urban planning tools are leveraged not only for economic development but also for promoting equitable development and actively working to mitigate displacement (Huang, 2024). This is instrumental in moving beyond purely economic metrics to a more holistic understanding of urban change, incorporating the human element. By doing so, AI models can aid in identifying communities that are most at risk of negative impacts from gentrification, thereby allowing for more targeted and effective policy interventions (Al- Raeei, 2024).
Furthermore, the careful consideration of ethical frameworks and policy guidelines is essential to ensure that these predictive tools do not exacerbate existing inequalities or inadvertently embed biases in their application (Marasinghe et al., 2024) (Graff, 2020). This implies a need for a strong focus on contextual appropriateness and robust validation for GeoAI applications, ensuring that models are tailored to specific geographical and socio-cultural contexts while undergoing comprehensive impact assessments to prevent unintended consequences (Marasinghe et al., 2024). Ultimately, ensuring the ethical deployment of AI in urban planning requires transparent communication of methodologies and accountability in algorithmic processes to build public trust (Marasinghe et al., 2024). This is achieved by forging connections between algorithm designers and the communities they impact and developing a comprehensive understanding of inherent geospatial biases, which is instrumental in ensuring that AI applications in urban contexts serve the public good (Marasinghe et al., 2024). This also involves addressing the semantic and social aspects of explainable GeoAI, moving beyond purely technical considerations to incorporate diverse societal values and perspectives into model interpretation (Sabbata et al., 2023). This holistic approach ensures that AI-driven insights are not only technically sound but also ethically aligned with the goals of equitable and inclusive urban development (Graff, 2020). Moreover, addressing issues such as model hallucination and predispositions is paramount to prevent AI from perpetuating societal biases and generating outputs that misrepresent local realities (Huang,

2024). This underscores the necessity for rigorous data governance, including meticulous data collection and preprocessing, to minimize the risk of algorithmic bias and ensure the equitable application of AI in urban planning (Beneduce et al., 2024).

Discussion

Limitations & Ethical Issues

Despite the potential, several challenges and ethical considerations should be considered:

● Data quality and bias: Incomplete datasets or the use of biased proxies (e.g., online activity) may underrepresent marginalized communities. Bias in training data can lead to disparate impacts on vulnerable populations, such as the displacement of low-income residents. Therefore, data validation protocols and diverse data sources are essential for a fair and accurate representation of community characteristics (Sanchez et al., 2024) (Marasinghe et al., 2024).

● Ethical frameworks and governance: ML-based gentrification maps can risk stigmatizing certain areas or attracting speculative investment. Robust ethical governance is crucial to ensure these tools contribute to mitigation rather than exacerbation of gentrification and displacement (Marasinghe et al., 2024). Furthermore, explainability, transparency, and accountability are crucial for responsible GeoAI in urban decision-making (Marasinghe et al., 2024). This includes addressing algorithmic bias through fairness algorithms, bias auditing, and the development of decentralized AI systems (Marasinghe et al., 2024). In this context, a human-centric approach to GeoAI is essential, promoting interdisciplinary collaboration and knowledge-sharing in the design, validation, and evaluation of AI models for real-world tasks (Marasinghe et al., 2024). This is in addition to establishing governance frameworks for the ethical use and accountability of AI systems (Xu et al., 2024). In fact, this proactive step can help identify and mitigate discrimination, potential biases, or misinformation arising from the training data or model design. Addressing these issues can enhance public trust and encourage the wider adoption and use of AI systems (Xu et al., 2024) (Sanchez et al., 2024).

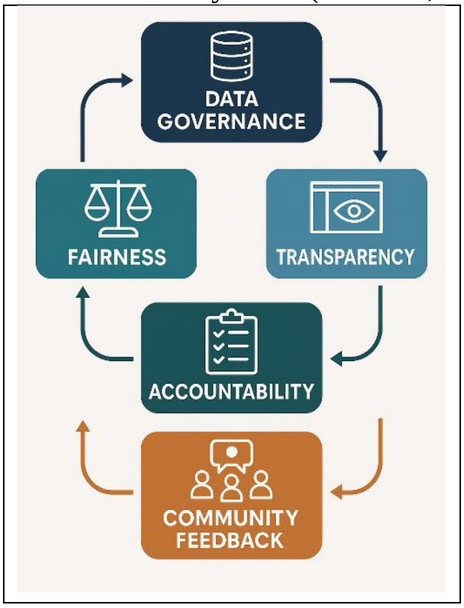

Figure 7. Ethical GeoAI governance framework for socially responsible machine learning in urban analytics.

● Explainability: Policymakers and stakeholders require transparent models to justify interventions and policies. This implies the development of explainable methodologies that not only predict outcomes but also provide interpretable insights into the factors driving gentrification (Marasinghe et al., 2024). Furthermore, explainable AI (XAI) methods are integral to enhancing the clarity, interpretability, and trustworthiness of AI solutions for urban decision-making, especially when such decisions significantly affect individuals (Marasinghe et al., 2024). In this regard, state-of-the-art techniques for model interpretation, such as LIME and SHAP, are indispensable for deconstructing complex predictive models into an interpretable representation that can be easily presented to urban planners and affected communities (Marasinghe et al., 2024). This additional level of transparency is important for ensuring public accountability and can also help address concerns of potential algorithmic mistakes or misrepresentation of facts (Marasinghe et al., 2024). Moreover, white-box models, like classification and regression trees, can provide transparent and interpretable outcomes (Marasinghe et al., 2024). These aspects are underpinned by a human-centric approach in AI for all phases of the lifecycle of AI models, which can play a significant role in ensuring the reliability of AI systems and outcomes for a particular geospatial task (Marasinghe et al., 2024). This may include developer-stakeholder interactions to ensure alignment between system designers and those commissioning the development and deployment of AI systems to ensure shared goals and expectations (Marasinghe et al., 2024).

In addition to ensuring an AI model's design is fit-for-purpose, non-technical, multidisciplinary participation in GeoAI and the creation of algorithmic decision-making processes for real-world applications can not only bring in additional resources but also ensure reliable, use-case specific design and outcomes (Marasinghe et al., 2024). This facilitates an iterative loop of communication and collaboration between AI engineers, urban planners, and affected communities throughout the design and development process to build on domain and local knowledge and ensure AI solutions are technically robust, ethically sound, and socially relevant for the task and the local context (Marasinghe et al., 2024). This becomes even more critical in ensuring that AI models, which can also be opaque or black-box in nature, can be trusted and accepted for use in informing decision-making (Marasinghe et al., 2024). In this context, to address black-box ML in geo-spatial decision-making contexts, such as the development of algorithms and tools for detecting gentrification, co-design with local and relevant stakeholders is imperative (Reades et al., 2019).

This can be further expanded to the development of methods to address bias in AI models and ensuring the representativeness of datasets used in developing ML to help avoid augmenting or creating biases in AI systems that are eventually deployed in the field (Marasinghe et al., 2024). This can be achieved through a combination of approaches including data quality, algorithm design, and bias mitigation, and auditing to ensure training datasets are representative of all groups and are not reinforcing existing biases (Marasinghe et al., 2024). In addition, a human-in-the-loop design and evaluation strategy for AI-informed decision-making approaches, which leverages local and human knowledge, is critical to ensure an effective and robust GeoAI solution design and outcomes (Marasinghe et al., 2024).

This further requires capacity-building initiatives for professionals in the use of GeoAI tools and approaches as well as AI-literacy for non-experts to help bridge this gap and facilitate robust validation and evaluations with end-users (Marasinghe et al., 2024). This approach, alongside iterative evaluations of AI systems and their impacts throughout the design and development, as well as in post-deployment phases, is essential for minimizing potential negative impacts of AI on society and can help maintain the public's trust in AI (Marasinghe et al., 2024). This is perhaps one of the most important steps to ensure that GeoAI can be used to predict gentrification in urban contexts, ethically and responsibly, using a multidisciplinary approach (Marasinghe et al., 2024).

Conclusion

Machine learning has the potential to make gentrification and displacement more knowable and better able to inform efforts that pre-empt gentrification and displacement and work towards housing and community resilience. Urban informatics, socioeconomic modeling and spatial data science can help by using machine learning to make predictions for when and where gentrification might occur. This will allow housing policy and community development efforts to be deployed before gentrification occurs. Future work could involve integrating agent-based models to simulate migration response or using multimodal deep learning models to integrate imagery, text, and structured data. Interactive urban dashboards could be developed for real-time monitoring of gentrification risks. Building on the work of Maya et al. (2024) and Thackway et al. (2023), who have used data science and urban studies research to show that gentrification prediction could become not just more descriptive but actionable, it is possible to imagine using new machine learning methodologies, including those with spatial considerations, to work towards a future of urban planning where instead of having to wait to intervene, until gentrification has already occurred, it would be possible to take pre-emptive action to ensure that neighborhoods can change without displacing residents (Credit, 2024) (Graff, 2020). To ensure ongoing efficacy of these interventions, a process of continuous impact assessments with periodic formal evaluations of AI systems' decisions could be implemented (Marasinghe et al., 2024). Research into the application of conversational AI paradigms within urban digital twins is also needed, potentially offering interactive, human-centered dialogue for co-designing interventions.

Figure 8. Integration of predictive ML into digital twin systems for proactive and participatory urban planning.

This approach could also enhance democratic decision-making processes by providing more inclusive and accessible interaction with urban data and AI models (Xu et al., 2024). This could avoid a potential pitfall of the process of algorithmic optimization whereby certain processes may be automated to a degree that circumvents any democratic input or say in the distribution of resources and the planning of urban spaces (Graff, 2020). The integration should not only focus on data processing but also on generating digital representations that can simulate potential interventions, allowing urban planners to see the potential impact of an intervention before it is carried out (Huang, 2024). The use of larger datasets with richer data points, including proprietary data from multiple sources, could help make more accurate predictions, though this will need to be carefully considered in terms of replicability and ethics, both in the use of such data as well as the broader epistemological questions of prediction (Graff, 2020). For example, in some prior work, basic statistical methods and factor analysis were used to pinpoint revitalization; using more advanced unsupervised learning methods could make gentrification predictions more nuanced (Graff, 2020). In another example, the use of more high-resolution, longitudinal data that would allow for more up-to-date analysis and prediction such as real-time economic indicators and changes observable in street level imagery could also help with temporal granularity and prediction (Hawes, 2024) (Freitas et al., 2022).

The development of scalable Digital Twin models for complex urban settings, including the implementation of advanced security measures and data privacy protections to safeguard sensitive urban data, is another important area for future work (El-Agamy et al., 2024). Going beyond prediction, the integration of generative AI into the digital twin concept, with smart city management moving from centralized, top-down governance to more efficient, bottom-up participatory management via human-AI collaboration, with the enhanced intelligence in the smart city going beyond the more basic digital twin and becoming more self-learning and reasoning (Xu et al., 2024). These smart cities could self-generate data and even code to create their own digital twins, greatly accelerating and streamlining the process of digital twin creation for smart cities (Xu et al., 2024). This could greatly lower the cost of urban digital twins and allow urban planners to "state the design problem more accurately and/or to search a greater number of options, by including, for example, suggestions from AI-generated text and images" (Xu et al., 2024). These new capabilities, including the ability to generate synthetic data or even simulate various urban development scenarios, have the potential to transform urban planning by giving a greater context in which urban planners can make their decisions (Xu et al., 2024) (Xu et al., 2024). One example is the potential application of generative AI models within urban digital twins, to generate the urban designs autonomously.

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