Traces of Joy: Exploring Urban Happiness through Machine Vision and Human Feeling

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Abstract

This study investigates whether urban happiness can be predicted from street-level visual and socioeconomic features. Using 28 happiness points identified by Drexel University students and approximately 40,000 sampling points across Philadelphia, we combine Google Street View imagery, semantic segmentation, and Census data within a Positive-Unlabeled (PU) Learning framework. Our model achieves an AUC of 0.968, revealing that building density and sky visibility positively predict happiness, while high owner-occupancy rates—contrary to conventional planning assumptions—show the strongest negative association. These findings suggest that "livability" and "happiness" may be distinct concepts, with implications for urban design that prioritizes vibrant, mixed-use environments over quiet residential suburbs.

1. Introduction

What makes a person truly happy? It might be a good night's sleep, a shared meal with friends, or simply standing in a place that feels right. The Swiss psychoanalyst Carl Jung wrote extensively about the relationship between our inner world and the external environment, suggesting that this connection is vital to psychological health (Jung, 1964). In simple terms, intricate neural pathways transform sensory input and cognitive processing into a direct and embodied awareness: I am happy here.

Across cultures and histories, "happy places" share certain universal features. They are often safe, aesthetically pleasing, socially engaging, and meaningful. While beauty and safety contribute to a sense of well-being, humanistic psychologists such as Abraham Maslow emphasized the deeper importance of belonging, social connection, and purpose (Maslow, 1954). Happiness, therefore, arises not merely from visual or material comfort, but from an interplay of physical, emotional, and social dimensions of place.

In Philadelphia—the city of brotherly love and sisterly affection—this connection between environment and emotion has recently taken tangible form through the work of psychology students at Drexel University's Happiness Lab (Stahl, 2025). In their participatory mapping project, 243 students identified local landmarks and hidden corners where they felt happiest. The resulting map curated 28 "happy places" across the city, ranging from small neighborhood parks to cozy cafés. Among them, the Cat Park on North Natrona Street was cherished for its quiet charm and friendly felines, while Mango Mango Desserts in Chinatown was celebrated for its bustling atmosphere and sweet delights. A student favorite, Maison Sweet on Chestnut Street, was described as "the kind of café where you might stay longer than planned" (Zillmer, 2025).

Building upon this psychological and experiential foundation, our project seeks to explore these patterns from a computational and visual perspective. Rather than relying solely on self-reported happiness, we aim to analyze how the physical appearance of streets—captured through street-view imagery—relates to the kinds of environments people describe as "happy places." Through this integration of psychological insight and data-driven urban analysis, the project aspires

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to reveal how the city's visual form mirrors its emotional landscape—and perhaps, to help uncover new happy places waiting to be found.

2. Methodology

2.1 Data Sources and Sampling Design

Our analysis integrates three primary data sources. First, we obtained Philadelphia's street centerline network from OpenDataPhilly to generate systematic sampling points at 200-meter intervals, yielding approximately 40,000 locations across the city. Second, we incorporated the 28 happiness points from the Drexel study as our positive samples. Third, we collected Census ACS 5-year estimates at the tract level to capture neighborhood socioeconomic context. Together, these points form a dataset that combines subjective emotional sites with objective, city-wide sampling.

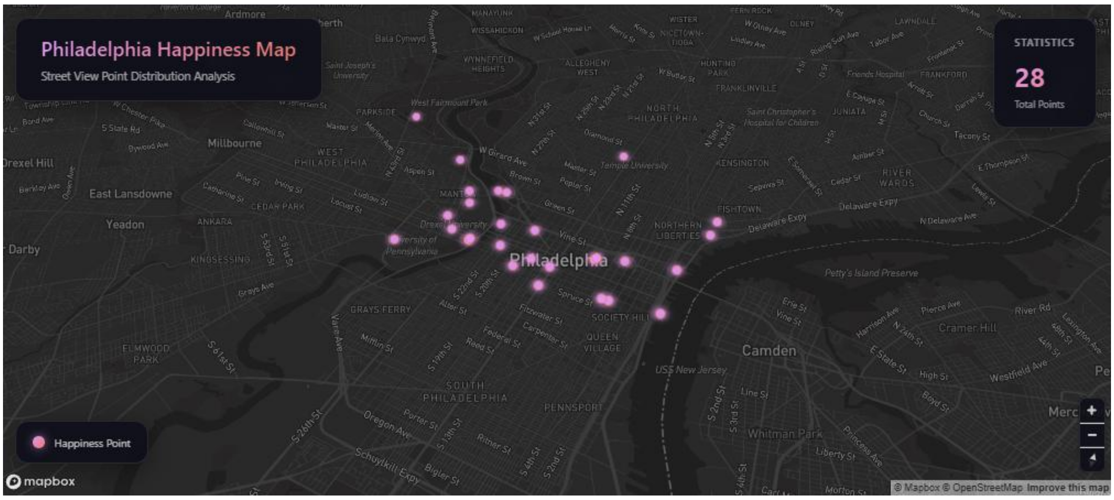

Figure 1. Spatial distribution of 28 happiness points across Philadelphia.

2.2 Street View Image Collection

For each sampling point, we queried the Google Street View API to obtain the nearest available panorama. Rather than using the standard API's resolution-limited output, we employed a tile-based download method that stitches 28 individual tiles (arranged in a 7×4 grid) into high-resolution panoramic images of 3,328×1,664 pixels. This approach captures the full 360° street environment, providing richer visual information for subsequent analysis. After filtering for coverage gaps, we retained imagery for approximately 95% of sampling points.

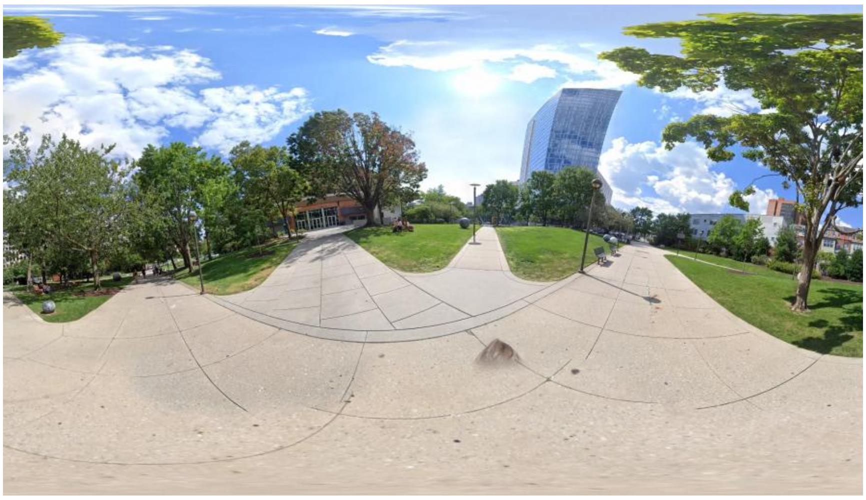

Figure 2. Example of a high-resolution Street View panorama (3,328×1,664 pixels) obtained via tile-based stitching.

2.3 Semantic Segmentation

Each image was analyzed using the SegFormer-B0 model pre-trained on the ADE20K dataset (Xie et al., 2021), which labels every pixel with a semantic category. The model recognizes 150 object categories including building, vegetation, sky, road, vehicle, and person. For each panorama, we extracted six visual features as pixel ratios: sky ratio (openness), Green View Index (vegetation coverage), building ratio, road ratio, vehicle ratio, and person ratio. Processing was conducted on a CUDA-enabled GPU, achieving throughput of approximately 2 images per second.

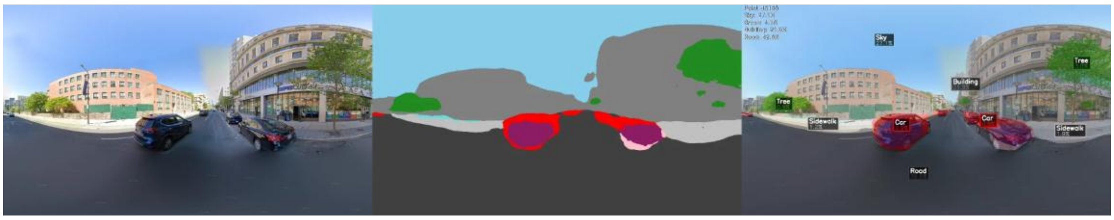

Figure 3. Semantic segmentation example: original Street View panorama (left), segmentation mask (middle), and labeled classification with urban element categories (right).

2.4 Census Data Integration

We performed spatial joins to associate each sampling point with its Census tract, incorporating seven socioeconomic variables: median household income, poverty rate, percentage with college education, racial composition (percent white), median age, home ownership rate, and unemployment rate. Combined with the six visual features, this yielded 13 predictors for modeling.

2.5 Positive-Unlabeled Learning

A key methodological challenge is that we only have confirmed "happy" locations—we lack labeled "unhappy" places. This is a classic Positive-Unlabeled (PU) learning problem (Bekker & Davis, 2020). Our approach proceeds in three steps: (1) compute the centroid of the 28 happiness points in standardized feature space and identify "reliable negatives" as the 30% of unlabeled points farthest from this centroid; (2) train Logistic Regression and Random Forest classifiers using 5-fold cross-validation; (3) apply the trained model to generate happiness probability scores for all 40,000 street locations.

3. Results

3.1 Model Performance

The Logistic Regression model achieved an AUC of 0.968 (±0.013), indicating excellent discriminative ability between happiness points and reliable negatives. Random Forest performed slightly lower at 0.939 (±0.045). The high AUC suggests that happiness points are systematically different from random street locations in measurable ways.

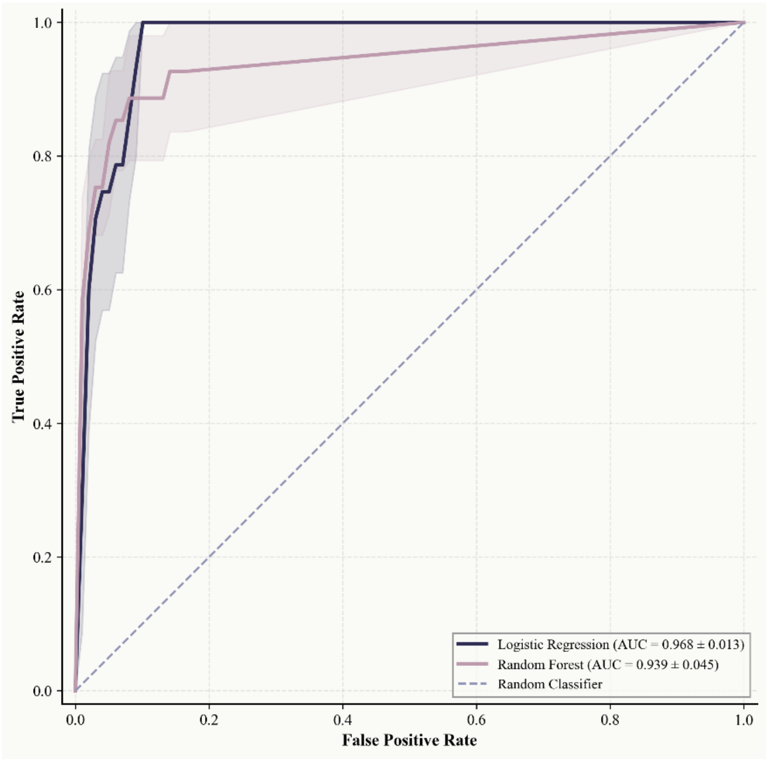

Figure 4. ROC curves showing model performance. Logistic Regression achieves AUC = 0.968; Random Forest achieves AUC = 0.939.

3.2 Feature Importance

Table 1 presents the standardized Logistic Regression coefficients. Building ratio emerged as the strongest positive predictor (+1.00), suggesting happiness points cluster in denser urban areas rather than sparse residential neighborhoods. Sky ratio (+0.58) and college education (+0.70) also showed positive effects—visible sky reduces feelings of confinement, while higher education levels may proxy for neighborhood amenities and maintenance.

Table 1. Logistic Regression Coefficients (Standardized).

Positive Factors	Coef.	Negative Factors	Coef.
Building ratio	+1.00	Owner occupancy	-2.10
College education (%)	+0.70	Poverty rate	-1.28
Sky ratio	+0.58	Road ratio	-1.23
Green View Index	+0.06	Vehicle ratio	-0.29

The most striking finding is the strong negative coefficient for owner occupancy (-2.10). This "Owner Occupancy Paradox" contradicts conventional planning wisdom that equates homeownership with neighborhood quality. We hypothesize that what makes a neighborhood good for living differs from what makes a place feel happy. High-ownership neighborhoods are typically quiet, safe, single-use residential areas—pleasant to live in, but not places you'd visit for joy. They're car-dependent, with few spontaneous social encounters. Happiness points, by contrast, cluster in mixed-use urban areas: walkable, with nearby amenities, active street life, and diverse activities.

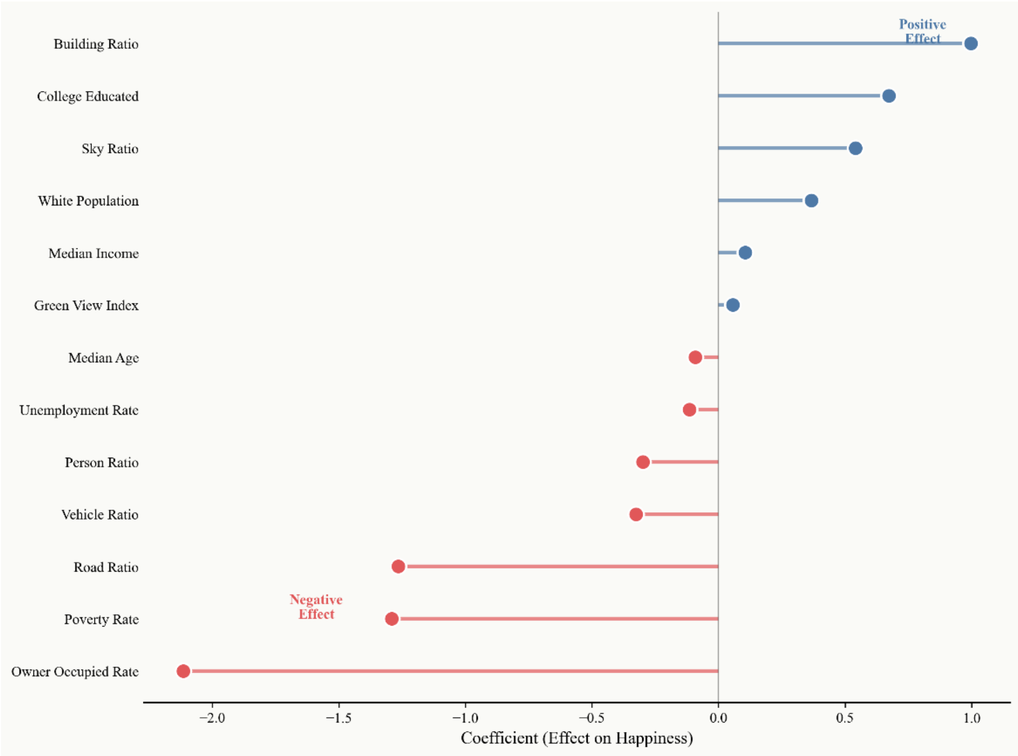

Figure 5. Feature coefficients from Logistic Regression. Green bars indicate positive predictors; red bars indicate negative predictors.

3.3 Spatial Patterns

Mapping predicted happiness scores across Philadelphia reveals a clear spatial structure. The highest scores concentrate in Center City, University City, Fairmount, and Northern Liberties—dense, mixed-use, walkable neighborhoods. Moderate scores appear in inner-ring neighborhoods with mixed uses. The lowest scores mark outer residential areas, industrial zones, and highway corridors. The happy places form a connected archipelago in the urban core, surrounded by a sea of lower-scoring residential and industrial areas.

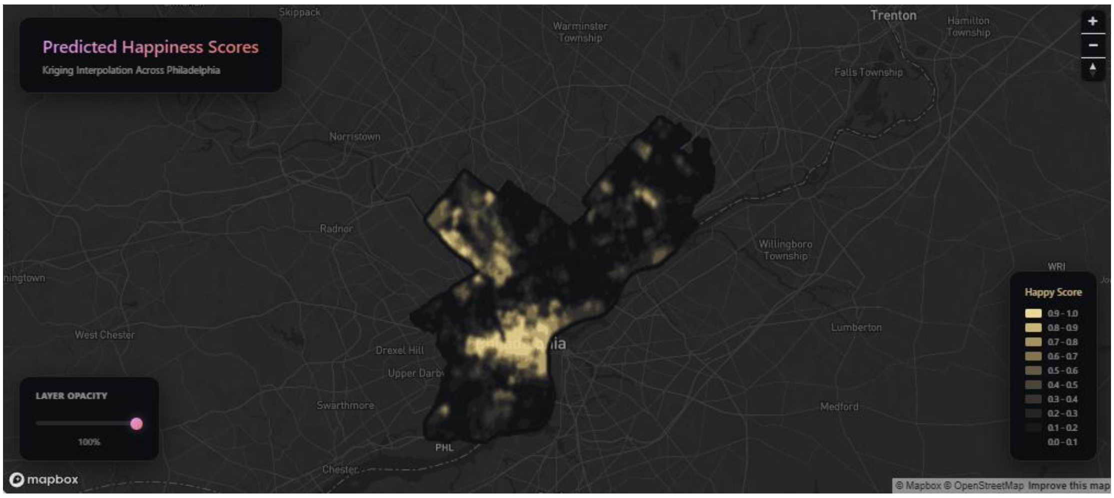

Figure 6. Predicted happiness scores across Philadelphia. Warmer colors indicate higher predicted happiness; cooler colors indicate lower scores.

4. Discussion

Strong model performance doesn't mean we've solved urban happiness. Several limitations deserve honest acknowledgment. With only 28 positive samples, statistical power is constrained—unusual characteristics of individual points may unduly influence results. Street View imagery cannot capture "secret gardens" where people actually feel happy: hidden courtyards, rooftop terraces, and tucked-away benches that don't appear in street-level panoramas. This proxy gap may explain why Green View Index shows such weak predictive power (+0.06)—the actual happy places might be far greener than what our imagery captures.

Census tract-level data averages over roughly 4,000 residents, missing within-neighborhood variation. Our model assumes happiness derives from measurable environmental and socioeconomic features. But some places are happy not because of what they look like, but because of what happened there. A nondescript bench where someone had their first kiss. An ordinary-looking café where friends gather every Sunday. A street corner that reminds someone of childhood. These places of memory can bring profound happiness despite being visually unremarkable. No amount of semantic segmentation can capture why a place matters to someone.

Our analysis also uses static data: street view images from a single moment, Census data averaged over five years. We miss seasonal variation—Philadelphia's Green View Index plummets in winter when deciduous trees are bare—and daily rhythms: the same plaza might feel vibrant on a Saturday afternoon and desolate on a Tuesday morning. Most importantly, this is a correlational study. We cannot claim that building density causes happiness. The relationship could be confounded, reversed, or more complex than linear models capture.

Future research could address the sample size limitation by adopting crowdsourced pairwise comparison methods. The MIT Place Pulse project (Dubey et al., 2016) collected over 1.1 million comparisons from 81,630 volunteers across 56 cities by presenting two street view images and asking "Which place looks safer?" or "Which place looks more beautiful?" A similar platform asking "Which place makes you feel happier?" could generate continuous happiness scores via the Elo rating system, yielding richer data than binary labels. Aggregating judgments from thousands of participants would also reduce individual bias and capture more generalizable perceptual patterns—moving from 28 students' memories toward a collective emotional geography of the city.

5. Conclusion

This study demonstrates how street-level imagery and machine learning can be combined to study urban emotion at a fine spatial scale. It extends psychological theories of place and well-being into a computational framework, transforming visual data into measurable indicators of how cities make people feel. Our key findings suggest that building density and sky visibility predict happiness, while road coverage and high owner-occupancy predict its absence. The Owner Occupancy Paradox highlights that "livability" and "happiness" may be distinct concepts.

For urban planners, these findings suggest several considerations: rethinking density to embrace mid-rise development that captures both urban vitality and psychological comfort; reducing car dominance through road diets and pedestrianization; addressing equity by investing in high-poverty neighborhoods; and embracing mixed-use zoning that allows retail, services, and housing together—creating "15-minute neighborhoods" where daily needs are within walking distance.

But we should be humble about what we've captured. Everyone living in Philadelphia has their own list of happy places, and there is never a single right answer to what happiness means. The Cat

Park with its friendly felines, the bustling atmosphere of Mango Mango Desserts, the cozy corner of Maison Sweet where you might stay longer than planned—these are not places we can fully quantify. A grandmother's kitchen. A spot by the river where someone proposed. The bench where you sat crying after a breakup and a stranger offered you a tissue.

Happiness is environmental, yes. But it's also biographical. Our models can find the patterns that connect happy places; they cannot explain why a particular place became your happy place. What we hope is that by mapping these patterns, we might help create more spaces where happiness can happen—even if we can't predict exactly who will find joy there, or why.

"A lot of things need fixing in Philly, but there are a lot of good things here."

References

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