A STUDY OF INTEGRATING REAL-TIME EMOTION AND SENTIMENT ANALYSIS IN URBAN PLANNING

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Abstract: Urban environments are dynamic and multifaceted, with diverse factors influencing the sentiment and emotions of their inhabitants. This paper presents a comprehensive model for real time urban emotion and sentiment analysis, utilizing data from social media, news articles, video feeds, and sensors. By employing advanced natural language processing and computer vision techniques, this model aims to provide policymakers and urban planners with actionable insights to enhance public engagement, inform urban design, and create responsive, inclusive environments. With the digitalization process accelerating globally, nearly everyone uses smartphones and social media. People increasingly read news articles online rather than using printed materials. For safety, many individuals install CCTV cameras in their shops and homes, especially in densely populated areas. Additionally, there is a growing awareness and attention to environmental indices compared to past years. This research aims to incorporate these factors social media usage, online news consumption, widespread CCTV installations, and increased environmental awareness into an integrated model. By analyzing emotions and sentiments, the model seeks to determine whether a location is suitable for people to spend their time based on collective emotional responses.

Keywords: *Urban Sentiment Analysis, Real-Time Emotion Mapping, Public Engagement Insights, Commuter Experience Analysis, Citizen Sentiment Monitoring*

1. Introduction

Urbanization presents numerous challenges and opportunities, necessitating innovative approaches to understand and improve the urban experience (Zhang et al., 2020). Emotions and sentiments significantly impact residents' quality of life, influencing their satisfaction and engagement with urban spaces (Li et al., 2021). Pedestrians and commuters should be the utmost concern in urban planning, yet rapid development and existing development pressures have often led to their neglect, converting some urban areas into spaces unsuitable for their needs (Kim et al., 2019). This research focuses on developing a real-time emotion and sentiment analysis model that leverages multiple data sources to create sentiment heatmaps. The primary objectives of this model are to

- Understand public reactions to urban policies and events.
- Enhance public engagement by identifying areas needing attention.
- Inform urban design decisions based on emotional responses.
- Create more responsive and inclusive urban environments.

By identifying commuter-friendly and unfriendly areas in real time, this tool offers a novel solution for urban planners and policymakers to achieve these objectives and foster more engaging, responsive, and inclusive urban environments (Wang et al., 2020).

2. Literature review

Sentiment analysis has become a vital tool for understanding public opinion and behavior, especially with the rise of social media platforms that provide an unprecedented volume of textual data. Studies such as those by Bollen, Mao, and Pepe (2011) and O'Connor et al. (2010) have shown the effectiveness of sentiment analysis in predicting stock market trends and political elections, respectively. This highlights the potential of social media data as a rich source of public sentiment. However, challenges such as noise, sarcasm, and cultural nuances continue to affect the accuracy of sentiment analysis models.

Recent research has extended sentiment analysis beyond traditional text-based methods to encompass the complexities of urban environments. By integrating multimodal data sources, such as social media, point-of-interest data, and weather information, researchers have gained deeper insights into public sentiment towards urban spaces. For instance, Li, Chen, and Liu (2018) demonstrated the effectiveness of combining these data sources to analyze public sentiment towards urban

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parks, underscoring the potential for enhanced urban planning and management. This multimodal approach offers a more comprehensive understanding of public sentiment in urban settings.

In addition to textual data from social media, visual data from CCTV and other video feeds have shown promise in detecting public emotions and behaviors. For example, during large events, social media usage intensifies, and visual data from these events can provide insights into crowd behavior and public mood (Gupta & Kumaraguru, 2012; Zhang, Ni, He, & Gao, 2016). Large-scale sporting events, such as the FIFA World Cup, present a unique opportunity to study public sentiment dynamics through social media analysis. By analyzing tweets, hashtags, and retweet patterns, researchers can identify shifts in user activity, topic diversity, and geographic distribution of event-related content (Schwartz, Tumasjan, Naumann, & Frey, 2013; Jungherr, 2015). Incorporating visual data from sources like CCTV footage allows for the analysis of nonverbal cues and real-time reactions, providing a deeper understanding of public sentiment (Valstar, Pantic, & Lisetti, 2011). This multimodal approach is essential for capturing the complexity and evolution of public opinion during high-profile events.

Integrating sensor data with sentiment analysis can provide a more nuanced understanding of how the urban environment influences public well-being and sentiment. This approach has the potential to inform urban planning and policymaking by identifying areas with high levels of negative sentiment and addressing their underlying causes. Utilizing additional datasets, such as demographics and mobility trajectories, helps interpret primary results from social media and validate findings (Stefanidis, Crooks, & Radzikowski, 2013). Overall, integrating social media data, visual data, and sensor data presents a comprehensive approach to urban sentiment analysis, leveraging each data source's strengths to provide a richer, more detailed understanding of public sentiment in urban environments.

3. Methodology

3.1. PROCESS

The proposed model integrates data from various sources including social media, news articles, video feeds, and environmental sensors. Natural Language Processing (NLP) models are utilized to analyze sentiment from textual content such as social media posts and news articles, as well as video content from platforms like CCTV. Convolutional Neural Networks (CNN) are employed to spatially map the sentiment data, providing a comprehensive view of emotional responses across different urban areas.

The data collection process involves the aggregation of information from platforms such as Twitter, Facebook, Google News, and CCTV feeds, along with environmental monitors that track air quality, noise levels, and other relevant indices. The collected data is processed in real-time to generate sentiment analysis, allowing for up-to-date insights into public sentiment and emotional responses.

To achieve this, we are developing four separate models, each tailored to a specific data source:

- Social Media Model - Analyzes sentiment from Twitter and Facebook posts using NLP techniques.
- News Articles Model - Extracts and assesses sentiment from online news articles using advanced NLP algorithms.
- Video Feeds Model - Utilizes computer vision and NLP to interpret emotional cues from CCTV and other video sources.
- Environmental Sensors Model - Correlates environmental data with sentiment analysis to understand the impact of environmental factors on public emotions.

These individual models are then integrated into a single, comprehensive framework that provides a unified sentiment analysis of the urban environment.

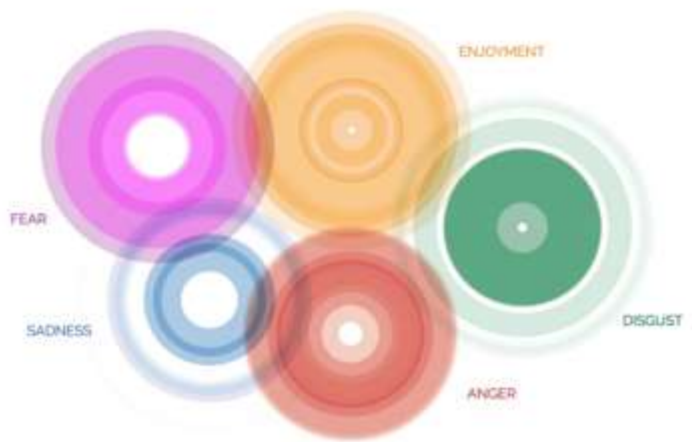

Figure 1, Paul Ekamans Emotion Model (Source: www.paulekman.com)

This two-dimensional emotional model is utilized to convey the sentiment status of the selected urban area.

3.2. WORKFLOW OVERVIEW

The development of a comprehensive sentiment analysis model for urban environments encompasses several stages, beginning with data collection and culminating in the integration of analytical sub-models. This workflow is structured to systematically gather and analyse data from various sources, ensuring a robust and accurate understanding of public sentiment and emotional responses within urban areas. Initially, four distinct sub-models are developed, each tailored to specific data sources: social media, news articles, video feeds, and environmental sensors. These sub-models are subsequently integrated into a unified framework that provides real-time sentiment analysis and visualization.

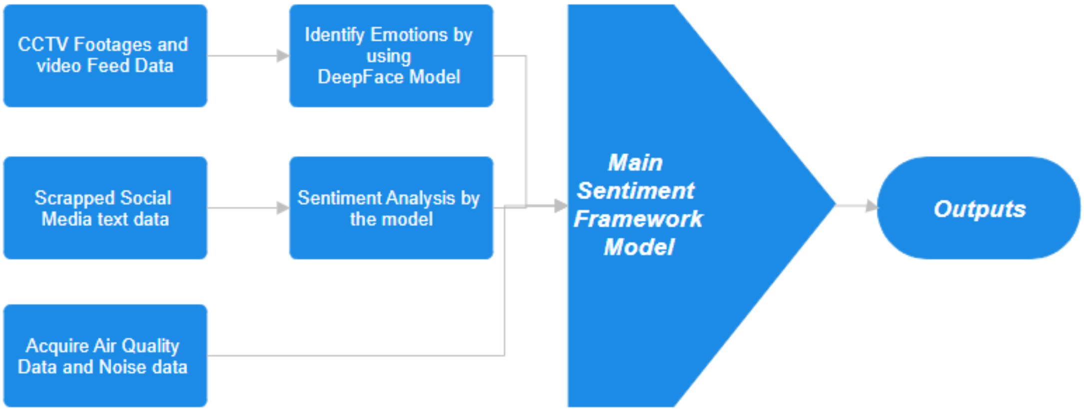

Figure 2, Overall workflow of the model

3.3. DETAILED WORKFLOW

3.3.1 Data Collection

Data is aggregated from multiple platforms to ensure comprehensive coverage of public sentiment and environmental conditions. This involves,

- Social Media - Collecting posts from Twitter and Facebook to capture public sentiments and emotions related to specific urban locations and events.
- News Articles - Aggregating articles from Google News and other online sources to gauge public reactions to urban policies and developments.
- Video Feeds - Processing footage from CCTV cameras and mobile devices to detect and analyse facial expressions and emotions in public spaces.
- Sensor Data - Gathering environmental data such as emissions, noise levels, and air quality from various sensors installed in urban areas.

3.3.2 Data Cleaning

The collected data undergoes cleaning to ensure accuracy, relevance, and usability. This process involves filtering out irrelevant information, correcting inaccuracies, and formatting the data for subsequent analysis.

3.3.3 Emotion Detection and Sentiment Analysis

Advanced natural language processing (NLP) and computer vision tools are employed to detect emotions and analyse sentiments from the collected data. This step includes processing text and video data to extract meaningful sentiment indicators.

3.3.4 Integration and Visualization

The processed data is combined into a coherent visual representation, creating sentiment heatmaps that reflect the emotional landscape of the urban environment. This step integrates outputs from all four sub-models to provide a comprehensive view.

3.4. SUB-MODELS

3.4.1 Sub-Model One - Emotion Detection from CCTV Footages

This sub-model processes raw video data to detect faces and analyse sentiments. The workflow includes video segmentation, frame extraction, face detection, and sentiment analysis using computer vision tools such as OpenCV and DeepFace. The output provides insights into the emotional states of individuals in urban spaces, contributing to the overall sentiment analysis.

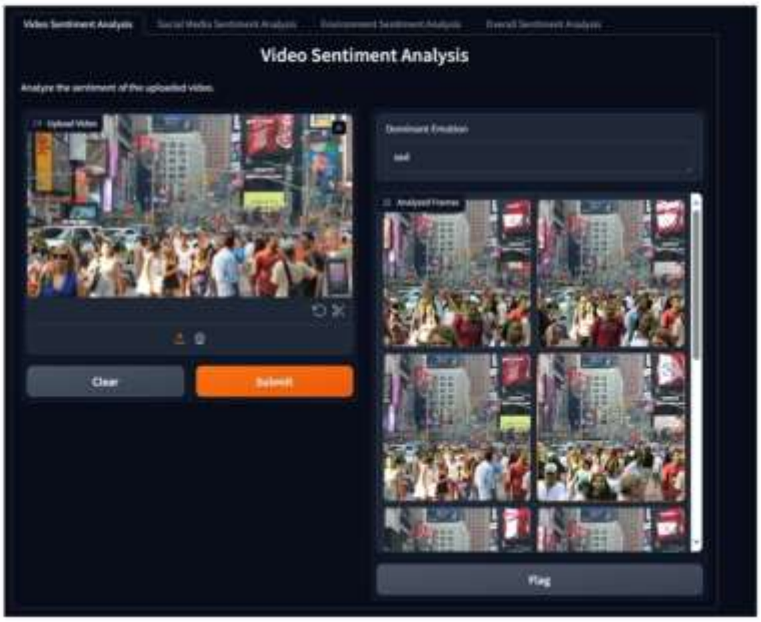

Figure 3, Interface of the video sentiment analysis

3.4.2 Sub-Model Two - Social Media Data Scraping

This sub-model collects and analyses social media posts to determine sentiment and emotion associated with specific locations. NLP tools pre-process and analyse text data, extracting sentiment and emotion indicators. Geotagging techniques are used to map these sentiments spatially. The output generates sentiment heatmaps based on geotagged social media data, reflecting public sentiment across different urban areas.

Figure 4, Screenshot of scraped data file

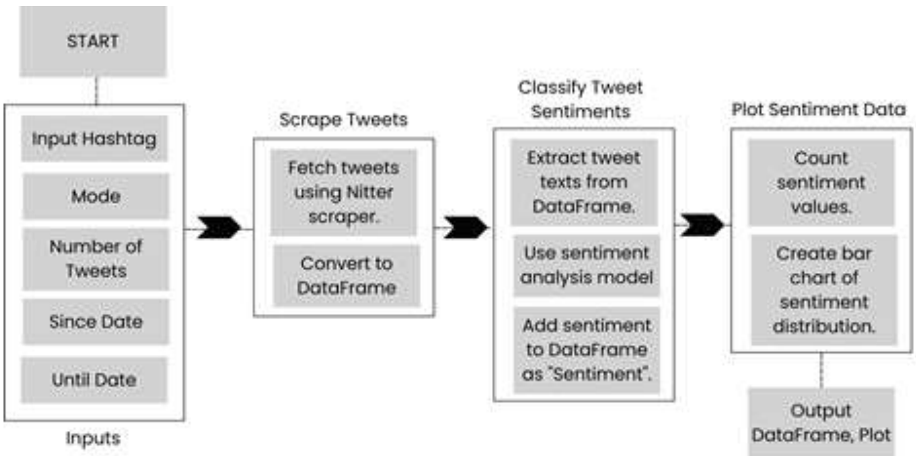

Figure 5, Workflow of the social media scraping

3.4.3. Sub-Model Three - Sentiment Analysis from Text Data

This sub-model preprocesses and analyzes text data from social media and news articles to extract sentiment and emotion. Sentiment analysis models like VADER (Valence Aware Dictionary and Sentiment Reasoner) are used to extract sentiment scores from text data. The output provides a comprehensive view of public sentiment towards urban policies and events, contributing to the overall sentiment analysis model.

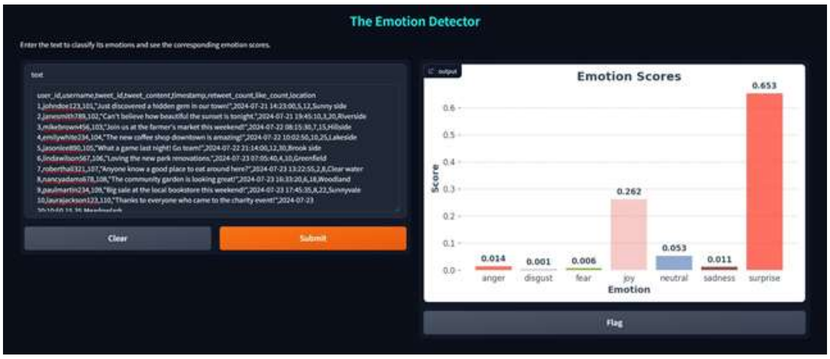

Figure 6, Sentiment Analysis from Sensor Data

3.4.4 Sub-Model Four - Sensor Data Analysis

This sub-model analyzes environmental data such as air quality and noise levels to understand their impact on urban sentiment and emotions. It integrates sensor data with sentiment analysis results for a holistic view. The output offers insights into how environmental factors influence public sentiment, adding another dimension to the sentiment analysis.

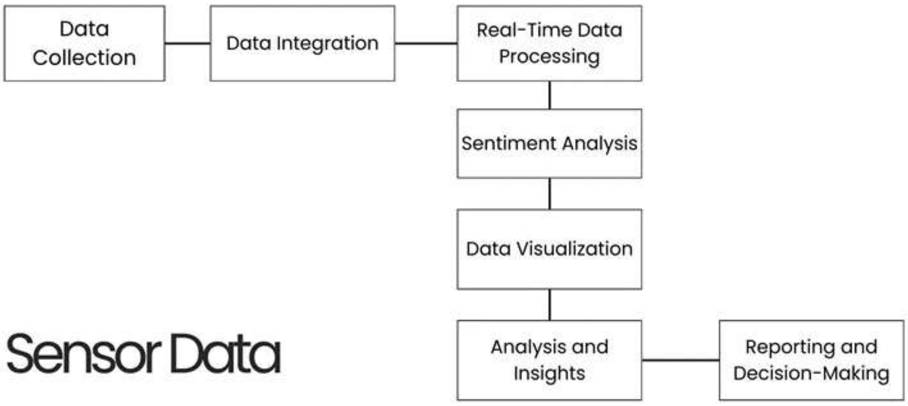

Figure 7, Workflow of Sensor Data Analysis

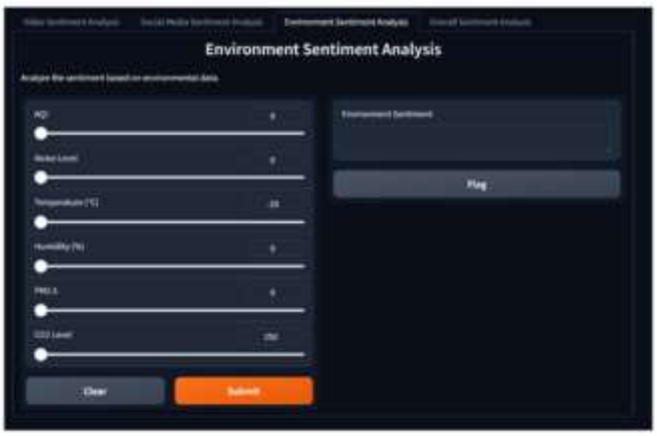

Figure 8, Interface of the Environmental Sentiment Analysis

3.5. INTEGRATION

The sub-models are integrated into an All-In-One (AIO) model that provides a comprehensive sentiment analysis using real-time data processing and visualization tools. This integrated model combines the outputs from the individual sub-models, ensuring a robust and accurate analysis of urban sentiment. Real-time data processing capabilities enable the generation of up-to-date sentiment heatmaps, aiding in timely decision-making.

3.5.1 Tools and Platforms

- NLP Libraries - SpaCy, NLTK, Hugging Face Transformers
- Data Collection Platforms - Twitter, Facebook, Google News
- Sentiment Analysis Models - VADER (Valence Aware Dictionary and Sentiment Reasoner)
- Computer Vision Tools - OpenCV, DeepFace

This comprehensive workflow ensures that the integrated sentiment analysis model is well-equipped to provide valuable insights for urban planners and policymakers, facilitating the creation of more responsive, inclusive, and emotionally satisfying urban environments.

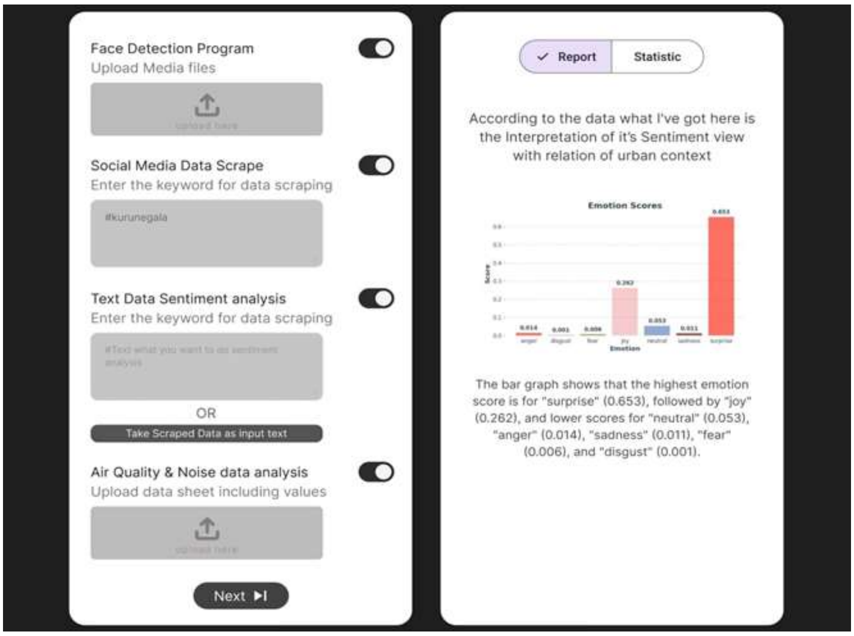

Figure 9, Interface of the final output

4. Findings

This chapter presents the findings of the urban sentiment analysis model applied to the selected study area. By merging sentiment analysis with urban planning, this study offers a unique perspective on the emotional dynamics within urban environments. Through detailed analysis, we can gain insights into public perceptions of city spaces, which can inform and enhance urban design. Findings are structured around emotion detection, sentiment score distribution, and the integration of data visualization, making each aspect mutually reinforcing for a holistic understanding.

4.1. EMOTION DETECTION

The sentiment analysis model successfully identified and classified various emotions such as happiness, sadness, anger, and surprise from social media feeds, images, and text data related to urban locations. By categorizing these emotions based on intensity, we derived a nuanced view of the urban emotional landscape. Emotion intensity levels were mapped across different urban zones, allowing for a comprehensive assessment of emotional hotspots and calmer areas.

Emotion	Frequency (%)	Intensity (Low, Medium, High)	Dominant Zones
Happiness	45%	Low to High	Public parks, green spaces
Sadness	20%	Medium to High	Crowded streets, polluted areas
Anger	15%	Medium to High	Overcrowded public transport hubs
Surprise	10%	Low to Medium	Recreational and shopping districts

Table 1, provides an overview of detected emotions, illustrating the relative frequency and intensity distribution across different urban areas. This table highlights that positive emotions like happiness are frequently found in well-maintained spaces, while negative emotions are linked to areas with environmental and infrastructure issues.

4.2. SENTIMENT SCORE DISTRIBUTION

Sentiment score distribution provides a quantitative representation of public mood across various urban zones. Scores derived from textual and visual data inputs were classified into positive, neutral, and negative categories. Clusters of positive sentiment in areas known for good urban design, such as pedestrian-friendly public spaces, reinforce the connection between urban planning and public mood. In contrast, areas with lower sentiment scores correlate with issues like noise pollution, overcrowding, and lack of amenities, suggesting that these factors play a significant role in negative public perception.

Zone	Median Sentiment Score	Score Range (Min - Max)
Downtown Area	5.6	3.2 - 7.8
Public Parks	7.4	6.0 - 8.5
Industrial Area	2.8	1.5 - 4.3
Transport Hubs	3.1	2.0 - 5.5

Table 2, Sentiment Scores by Zone allows for a quantitative comparison of sentiment scores across different urban zones, indicating which areas elicit stronger positive or negative responses.

4.3 INTEGRATION OF VISUAL AND DATA ANALYSIS
An interactive visual interface within the model enabled a dynamic exploration of public sentiment, merging data from images, maps, and graphs. This interface allowed users to observe correlations between physical characteristics and emotional responses in specific locations, with adjustable settings to refine analysis and reveal trends.

Figure 10, User Interface of Sentiment Analysis Tool

The interface enabled users to interactively adjust sentiment intensities and view emotion scores overlaid on urban maps, providing a comprehensive visualization of the data. This integration demonstrated that green spaces, cleanliness, and accessibility contribute positively to public sentiment, while factors like overcrowding and pollution are associated with negative emotions. This interactive approach enabled a more comprehensive analysis, reinforcing how different elements of urban design impact public perception.

5. Discussion

In this chapter, we discuss the implications of the findings, particularly how sentiment analysis can enrich urban planning by offering insights into the public's emotional experiences. Through sentiment-based urban insights, city planners can integrate a human-centric approach in their design and management processes.

5.1 IMPLICATIONS FOR URBAN ENVIRONMENT DESIGN
This study highlights the potential for sentiment analysis to inform urban design by capturing and analyzing public emotions associated with specific urban features. Positive emotions, such as happiness, were most often associated with green spaces, pedestrian-friendly zones, and well-maintained areas. This correlation indicates that public sentiment aligns with design principles that prioritize green infrastructure, walkability, and recreational amenities.

Table 3, Comparison of Positive Sentiment by Urban Feature

Urban Feature	Positive Sentiment (%)
Green Spaces	65%
Pedestrian Zones	58%
Recreational Areas	53%
Public Transport	40%

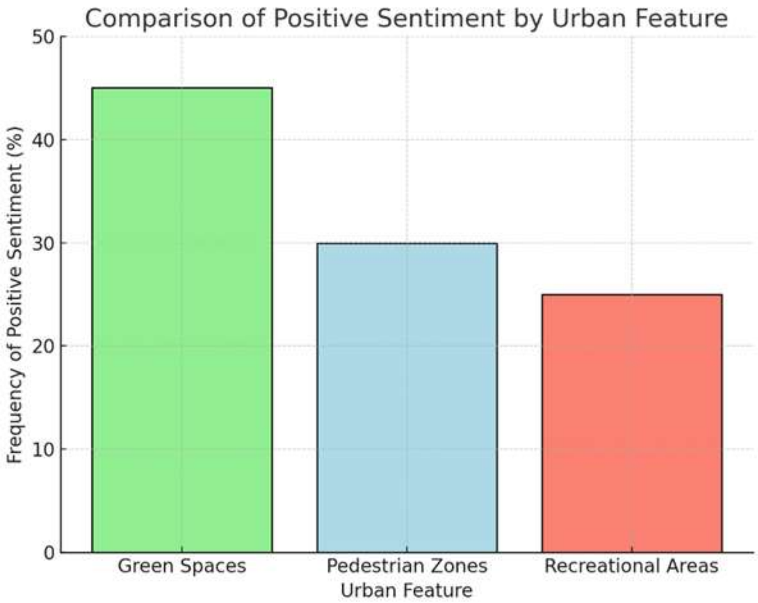

Figure 11, Positive Sentiment by Urban Features

Conversely, areas where negative emotions like anger and sadness prevail often face challenges such as overcrowding, limited green spaces, and high pollution levels. These findings suggest that enhancing infrastructure, introducing green corridors, and improving public amenities in these areas could positively influence the emotional landscape.

5.2. STRATEGIC APPLICATIONS IN URBAN PLANNING

Incorporating sentiment data into urban planning offers a valuable tool for data-driven decision-making. Real-time emotional data allows planners to monitor the impact of urban changes and respond quickly to emerging issues. For example, areas with consistently low sentiment scores could be prioritized for improvement by tracking negative emotions over time.

The sentiment analysis model's temporal capabilities also allow planners to observe shifts in public sentiment post-intervention, thereby assessing the effectiveness of these changes. As part of a forward-looking application, it is proposed that when a user searches for a specific location, they can view associated emotions, offering an intuitive way to gauge public sentiment regarding that area.

5.3 LIMITATIONS AND CHALLENGES

Despite the valuable insights provided, this study faced notable limitations that influence the applicability and accuracy of the findings. By addressing these challenges, future research can build a more robust and inclusive sentiment analysis framework tailored to urban planning needs. Here, we identify key limitations and propose novel approaches to overcome them, suggesting new pathways for enhancing urban sentiment analysis.

5.3.1. Data Availability and Accessibility Challenges

One of the most significant challenges encountered in this study is the limited availability of open-source data. Social media and crowd-sourced data serve as the primary sources for capturing public sentiment, yet these data sources have inherent limitations. For instance:

- Demographic Bias: Not all demographic groups are equally represented on social media platforms. Certain populations, such as elderly residents or lower-income groups, may have limited online engagement or access, which can skew sentiment analysis results toward the perspectives of more digitally connected demographics.

- Limited Geographic Coverage: Social media data tends to be concentrated in high-density urban areas, potentially overlooking sentiments from residents in suburban or rural regions. As a result, emotions in peripheral areas or less digitally engaged communities may be underrepresented.
- Data Quality and Verification: Social media posts and crowd-sourced data are inherently unstructured and may lack accuracy or relevance. Determining the authenticity of these data points or verifying their connection to a specific location can be challenging, particularly in distinguishing between genuine sentiments and non-local influences.

To address these data availability challenges, future research could integrate the following novel approaches:

1. Hybrid Data Integration: Combining social media data with data from government and municipal records, citizen surveys, and community feedback channels can create a more comprehensive dataset. Government data, such as records of community complaints, service satisfaction surveys, and urban event participation, could supplement the sentiment data from social media, adding layers of context and legitimacy.
2. Collaborations with Telecom Providers: Mobile network operators can provide anonymized, aggregated data on movement patterns and general activity levels in various urban zones. This data can serve as an indirect indicator of public engagement and, combined with sentiment data, could help infer emotional responses tied to specific locations. For instance, areas where movement patterns indicate high frustration (e.g., traffic congestion) could be correlated with social media expressions of anger or stress.
3. Wearable and Environmental Sensor Data: IoT-enabled wearables and environmental sensors, strategically placed around cities, could provide real-time data on physiological indicators such as stress, temperature, and noise levels. By integrating these data points, sentiment analysis models could capture the emotional impacts of environmental conditions, such as high pollution levels or excessive noise, which might not be reported on social media.

5.3.2. Data Interpretation and Contextual Influence

Another key limitation is the challenge of interpreting sentiment data in context. Sentiments expressed on social media can be influenced by unrelated events or broader social factors, such as political news, economic concerns, or trending topics. Such influences can lead to skewed sentiment scores that do not accurately reflect public feelings about a particular urban location or issue.

To improve data interpretation and contextual accuracy, future sentiment analysis frameworks could incorporate:

1. Contextual Sentiment Filtering: Developing machine learning algorithms capable of filtering context-specific sentiment from broader social sentiment can improve accuracy. For example, natural language processing (NLP) algorithms could detect and isolate sentiment related specifically to urban features (e.g., parks, transportation) by discarding sentiments tied to unrelated events. This could involve building lexicons of place-specific terms and keywords, enabling the model to focus more narrowly on contextually relevant expressions.
2. Temporal Sentiment Analysis: By analyzing sentiment changes over specific periods, researchers can gain insights into how sentiments evolve due to urban interventions or seasonal events. For instance, sentiment related to a public park might increase in positivity during spring and summer but decrease in winter. Temporal analysis can thus reveal patterns that are temporally bounded, enabling urban planners to design spaces and services that respond to these seasonal variations in sentiment.
3. Location-Specific Sentiment Mapping: Establishing an emotional “reputation” for each location could help contextualize future sentiment analysis. This would involve creating sentiment profiles for different urban areas over time, which reflect the average sentiment, sentiment variability, and unique emotion triggers. A consistent sentiment profile for each area could serve as a benchmark for detecting significant sentiment shifts, helping identify when sentiments deviate from the norm due to new developments or emerging issues.

5.3.3. Expanding Geographic and Cultural Applicability

Current sentiment analysis approaches in urban planning often lack adaptability to diverse geographic and cultural contexts. Since emotions and their expressions are culturally specific, applying the same model across different cities or regions without cultural adjustments can limit accuracy and relevance.

To expand geographic and cultural applicability, future sentiment analysis systems could incorporate:

1. Culturally Adapted Sentiment Models: Machine learning models trained on local language patterns, idioms, and expressions would better capture cultural nuances. Developing localized models for each city or region—potentially by collaborating with local linguistic experts—could enhance the accuracy of sentiment classification.
2. Multi-City Comparative Analysis: Expanding sentiment analysis to cover multiple cities within different regions allows researchers to compare emotional responses across diverse urban environments. This comparative framework can reveal how different design features, climate conditions, or local amenities impact sentiment. It could also inform urban planners on best practices for different cultural settings, highlighting universal design elements that consistently contribute to positive emotions across diverse regions.

3. Location-Specific Emotional Associations: Future systems could offer real-time emotional insights tied to specific locations. When users search for a particular city area, they would see an emotional "snapshot" reflecting the collective sentiment associated with that location over time. This feature would allow urban planners and residents to understand how various zones are perceived emotionally, promoting informed decisions and interventions based on public sentiment.

5.4. FUTURE DIRECTIONS

The integration of a location-based emotional feedback system could transform public engagement with urban spaces, fostering a deeper connection between residents and their city. Future applications could include:

1. Emotion-Enabled Mapping Tools: By incorporating sentiment scores into mapping tools like Google Maps, residents could view the emotional "mood" of a neighborhood before visiting. For example, individuals searching for residential areas could access sentiment data on factors like safety, cleanliness, and general atmosphere, helping them make informed decisions based on public perceptions.

2. Personalized Urban Experience Recommendations: Imagine a system that recommends urban experiences based on a user's preferred emotional setting. For instance, someone seeking a peaceful, joyful experience could receive suggestions for nearby green spaces with high happiness scores. Alternatively, users looking for vibrant social spots could be directed to lively districts with positive sentiment scores for excitement and surprise.

3. Real-Time Sentiment Feedback for City Management: Real-time sentiment feedback could be invaluable for city managers, alerting them to emerging issues before they escalate. A live feed of sentiment data could allow urban authorities to respond quickly to growing negative sentiment in specific areas, potentially intervening with temporary fixes (e.g., increasing maintenance in a dirty area) while planning long-term solutions.

4. Urban Sentiment Dashboard for Planners and Policy Makers: Developing a dashboard that aggregates and visualizes real-time sentiment data across various city zones could assist urban planners and policymakers in making data-driven decisions. This dashboard could be tailored with filters by sentiment type, emotion intensity, demographic insights, and geographical zones, enabling a comprehensive understanding of the emotional landscape of the city. Such a tool would facilitate the continuous monitoring of public sentiment, allowing for agile responses to changing urban dynamics.

5. Sentiment-Driven Urban Interventions: Future sentiment analysis frameworks could incorporate predictive analytics to anticipate areas where public sentiment may deteriorate, based on historical data and patterns. This predictive capability would allow urban planners to proactively design interventions that mitigate anticipated issues, potentially improving public satisfaction and trust in city management.

In conclusion, this study illustrates the immense potential of sentiment analysis in urban planning but also highlights several critical limitations. Overcoming these challenges will require an interdisciplinary approach, combining data science with insights from sociology, psychology, and urban studies. By enhancing data availability, improving contextual understanding, and adapting models to cultural nuances, sentiment analysis can become an invaluable tool for creating more inclusive, responsive, and emotionally resonant urban environments. Embracing these innovative approaches will ultimately transform the way cities are designed, fostering spaces that truly resonate with the people who inhabit them.

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