Assessing Universal Accessibility of built environment though sentiment analysis at post-industrial disaster site – A case of UCIL, Bhopal, Madhya Pradesh

Kakoli Saha[1], Pavan Kumar C[2], Ratnesh Kerudkar[3]
[1] Department of Planning, School of planning and Architecture, Bhopal, Bhopal, 462030, India
kakolisaha@spabhopal.ac.in
[2],[3]Department of Computer Science and Engineering, IIIT Dharwad, Karnataka
pavan@iiitdwd.ac.in, 21bcs091@iiitdwd.ac.in

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Abstract

In 1969, Union Carbide India Limited (UCIL) established a pesticide plant in Bhopal, India. On December 3, 1984, a massive leak of over 40 tons of Methyl Isocyanate gas from the plant turned the city into a toxic gas chamber, causing one of the world's worst industrial disasters. An estimated 15,000 to 30,000 people lost their lives, and over 100,000 continue to suffer from chronic health issues. Decades later, the area around the UCIL site remains marked by environmental degradation, urban decay, and marginalization. This study focuses on assessing the universal accessibility of the built environment in the disaster-impacted zone using Sentiment Analysis. A study area was delineated around the UCIL site based on defined criteria and twenty-five landmarks were identified with study area. Google reviews were extracted for those landmarks and then filtered according to predefined universal accessibility key words. Selenium WebDriver, a robust browser automation tool, was employed to scrape reviews programmatically. After successfully collecting review data in CSV format, the next step was to analyze the sentiment of these reviews, particularly with respect to universal accessibility. For that purpose, the state-of-the-art Llama 7B natural language processing (NLP) model was utilized. The Llama model assess the sentiment of the reviews concerning accessibility features of the location. The model was instructed to assign a score between 0 and 1 for each review. The score of 0-0.4 represented the negative sentiment, while 0.5- 1 indicated the positive sentiment. The findings revealed that overall sentiment was negative in the study area with sentiment score not exceeding 0.23 for any landmark. The outcomes of sentiment analysis were cross validated using with GIS map. The results confirm the efficiency of the proposed method of Sentiment Analysis in Artificial Intelligence environment and need for such methods.

1. Introduction

In 1969, Union Carbide India Limited (UCIL) set up a plant to manufacture pesticide at Bhopal in India. On the early morning of December 3, 1984, Union Carbide India Ltd (UCIL) pesticide factory turned the city of Bhopal into a colossal gas chamber after leakage of more than 40 tons of Methyl Isocyanate gas. It was India's first major industrial disaster. Post-tragedy, the affected areas around the UCIL plant have faced significant challenges in terms of accessibility for people with disabilities, elderly citizens, and those affected by the health impacts of the gas leak. The overall urban mobility in areas near the tragedy site, is limited. Infrastructural deficiencies, poor public transportation, and lack of pedestrian-friendly spaces are prevalent. This paper focuses on universal accessibility assessment of the study area delineated around UCIL site from the perspective of mobility of persons with disability using Sentiment Analysis in Artificial Intelligence environment.

Sentiment analysis is a computational method used to identify and categorize the opinions expressed by an author in a specific text segment about the subject under discussion. Its primary goal is to measure the polarity and classify the tone conveyed in the text as positive, negative, or neutral. Prior to the development of sentiment analysis, companies relied on surveys or focus groups to gauge product reviews, which was both costly and time-consuming. With the rise of opinion sharing on social media platforms, sentiment analysis has emerged as a significant research field. Various techniques have been developed by researchers to use sentiment analysis for stock market prediction. Additionally, sentiment analysis plays a crucial role in forecasting election outcomes, making it a valuable tool for predicting political decisions.

Sentiment analysis can contribute to the education sector by enhancing teaching quality and boosting students' learning abilities. Additional applications include predicting box-office success, summarizing TV programs and news, and improving recommender systems, among others (Das et al. 2023). While some areas have been investigated, many more remain to be explored. This research marks the first instance of applying sentiment analysis to the field of universal accessibility in the built environment.

2.Background study

The Bhopal Gas Tragedy's huge human cost is highlighted by the combination of immediate deaths and long-term health problems. According to C. Sathyamala et al. (2009), official data indicate that there were roughly 2,500 deaths in the immediate aftermath, however other sources place the number between 3,000 and 10,000 deaths (Sriramachari & Chandra 2010). Cumulative estimates over time suggest that the gas exposure and its effects may have killed 15,000 to 30,000 people (Sriramachari & Chandra, 2010). Since 1985, as per survivor's and activist's organisation the number of people who have died subsequently were 20,000 (Sriramachari & Chandra, 2010). As far long-term impact is concerned, an estimated 100,000 people experienced persistent respiratory illnesses

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brought on by exposure. Furthermore, between 25% and 30% of survivors experienced mental and neurological disorders because of calamity. According to the Indian Council of Medical Research (ICMR), roughly 531,881 people, or 95% of the impacted population, suffered from a physical or mental health issue because of the chemical exposure. The total number of individuals affected by the disaster is staggering. Over 100,000 people are thought to have been hurt or disabled because of the catastrophe. Up to 587,000 people suffered from various negative effects. The number of compensation claims filed reached 554,895, reflecting the extensive impact on the community (Sriramachari & Chandra, 2010). Years following the tragedy, numerous families still live adjacent to the tall compound walls and barbed wire enclosing the abandoned Union Carbide plant, which has remained closed since the incident. Many of these slums and neighborhoods have been in place since before the plant was established, and additional settlements have since emerged on nearby abandoned lands. The residents of these areas continue to endure the consequences of the incident (Shrabana, 2018).

In this context, the need for assessing Universal Accessibility in the UCIL area, remains urgent. The traditional method to assess Universal Accessibility is physical auditing though purpose made audit checklists (Saha et al., 2020). The major drawback in this research is data update since data collection through physical visits at regular interval is both time consuming and costly affair. Sentiment analysis through Machine Learning (ML) technique can provide solution to this problem. Sentiment analysis refers to the automated process of extracting and evaluating subjective opinions about various aspects of an item or entity (Soleymani et. al., 2017). It is a machine learning technique that utilizes Natural Language Processing (NLP) to detect the emotions conveyed by the authors in a given text (Li et al., 2017). Initially, sentiment analysis was performed at the document level (Pang, 2004), followed by analysis at the sentence and phrase levels (Hua et al., 2004; Wilson et al., 2005). Sentiment analysis uses computational methods to identify and categorize the opinions expressed by an author in a specific portion of text concerning the subject on which the premise is based. Its primary aim is to measure the polarity and classify the tone conveyed by the author in a given text as positive, negative, or neutral. Many sentiment analysis methods heavily depend on a sentiment (or opinion) lexicon. This lexicon consists of a list of lexical features, such as words, that are typically classified based on their semantic orientation as either positive or negative (Liu, 2016). Numerous real-world applications depend on sentiment analysis for in-depth examination. Researchers have utilized it to identify trends in the stock market and cryptocurrencies by analyzing market sentiment (Das et. al., 2023). Recently, the healthcare sector has experienced a significant increase in the use of sentiment analysis applications, including customer opinion analysis (Ruffer et al. 2020; Park et al. 2020; Cortis and Davis 2021; Arora et al. 2021) and customer satisfaction analysis (Baashar et al. 2020; Miotto et al. 2018). Venkit et al. (2021) applied sentiment analysis to address the issue of discrimination against people with disabilities, PWD. Lomotey et al. (2025) applied Sentiment Analysis to Study Disability Discourse on social media. Disability and accessibility both arise from the interaction between individuals and their environment during the performance of certain activities (Lid and Solvang 2016). Bickenbach (2012) states that examining disability through the interaction between an individual's characteristics and environmental factors is an empirical approach. Aim of this research is to contribute to this empirical understanding using Sentiment Analysis techniques.

3. Need For a Universal Accessibility Assessment at UCIL Site, Bhopal City, Madhya Pradesh

Universal Accessibility originates from the concept of Universal Design (UD) (Lusher et al. 1989). Universal Design (UD) refers to the creation of products and environments that can be used by everyone to the maximum possible extent, without requiring adaptation or specialized design. The Universal Design India Principles include Equitable (*Saman*), Usable (*Sahaj*), Cultural (*Sanskritik*), Economy (*Sasta*), and Aesthetic (*Sundar*). The principles of Universal Design (UD) can be integrated into accessible built environments by involving people with disabilities as members of the planning team, incorporating barrier-free design in the planning process, and ensuring the provision of continuous paths of travel, among other measures.

Following the gas tragedy, Union Carbide ceased its operations in Bhopal but declined to remove the toxic residues from the site. A solar evaporation pond, located just beyond the factory grounds, served as a discharge site for the factory's waste. While the plant had to be erected by a river for the natural outlet for its waste, three ponds (Fig.2) were designed in the vicinity of *Khali* parade grounds, which were nowhere near enough to accommodate the factory's waste. The residue at the factory and contaminated ponds, continue to pollute the groundwater and soil. These chemicals will continue to linger in the environment and endanger residents for decades unless they are thoroughly cleared and the factory is decontaminated. There have been many non-governmental organizations that have successfully helped to rehabilitate the victims. These organizations provide health programmes, skill training, vocational education, economical support, and job opportunities for the victims of the tragedy. *Sambhavna Trust*- a clinic in Bhopal, led by Mr. Sarangi Satinath provides free traditional and western healthcare. They also conduct training programmes and traditional therapies for the victims. They emphasize on the participation of local communities and encourage them to form health communities in their respective neighborhoods. *Chingari* Rehabilitation Centre Led by Ms. Rashida Bai and Ms. Champadevi, who are also the victims of the tragedy, works primarily for congenitally disabled children born into the gas victim families in the slums of Bhopal. There are over 930 children enrolled with Chingari Trust as of 2022.

The Right of Persons with Disability (RPwD) Act, 2016, enacted by the Government of India, emphasizes that the built environment—including bus stops, railway stations, airports, roads, and all modes of transport—must conform to the prescribed standards of accessibility across various dimensions (Section 41 RPwD Act, 2016). Contrary to this, In urban Bhopal, 58% of persons with disabilities reported experiencing difficulties in accessing public transport, while 61% indicated challenges in accessing public buildings (NSS, 2018). The reported difficulties included the absence of ramps or lifts, challenges in opening doors, inadequate seating arrangements in waiting areas, difficulties at service counters, lack of accessible toilet facilities, and unavailability of clear signage for directions, instructions, or public announcements (NSS, 2018). The observations by NSS are also true for UCIL site as it is part of the urban Bhopal. In this background, Universal Accessibility assessment of the UCIL site is required to understand post disaster requirements. Since the Gas Tragedy affected areas beyond the UCIL factory site it was important to delineate a study area.

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4.Delineation of the study area

Bhopal is situated in the central Indian state of Madhya Pradesh (fig.1A). Established by Raja Bhoj of Parmar Dynasty in 11th century, Bhopal is now the capital city of the state and the administrative headquarters of both Bhopal division and Bhopal District. During the Bhopal Gas Tragedy, the population of Bhopal Municipal Corporation was approximately 894,739 (Indian Census 1981). The city is divided into four distinct districts, classified according to its chronological evolution. The old, fortified part of the city, the new city starkly segregated by the VIP road, the administrative town lying in the South and Bairagarh- a township occupied by refugees. However, the Union Carbide factory is located farther toward the northern edge of the city (fig.1B).

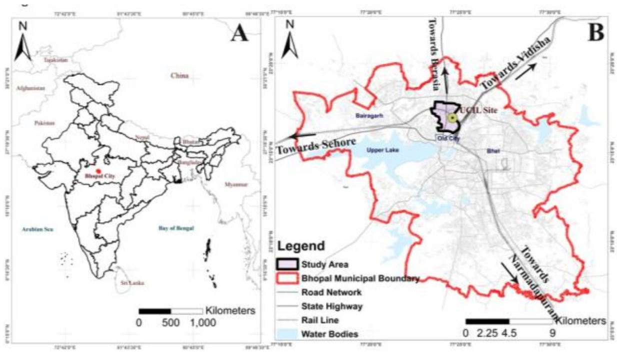

Figure 1. A. Bhopal city in India, B. Location of UCIL site and study area in Bhopal

A few housing colonies and slums exist within a kilometer radius of the abandoned factory, which continue to face the adverse effects of its radiating pollutants. For delineating the study area following criteria was set such as, a) Activity & Connectivity- Based on traffic flow and key interaction nodes; b) Accessibility & Boundaries- Major roads provide access and define impacted areas (fig.2A); c) Based on the intensity of gas exposure- determined by the direction in which the gas dispersed, following the prevailing wind patterns during the incident. The affected area due to gas leakage can be categorized into three zones such as: Zone I (e.g., within 500m), closest to the plant, was the most severely affected, with the highest concentration of gas leading to numerous deaths and acute health impacts. These areas included JP Nagar, Chola Basti and Kainchi Chola. Zone II (500m -1 km) experienced moderate exposure, resulting in serious but less fatal health issues. The areas that were affected comparatively less, included Ibrahim Ganj, Railway Colony, Nariyal Kheda. Zone III (1-1.5 km), being the farthest, had limited exposure with relatively minor health effects (fig2A); d) Social economic disparity along with developmental differences within the various areas around the UCIL site. Based on these criteria, an area covering 5.7sqkm surrounding the Union Carbide Factory was chosen for the study (fig.2B).

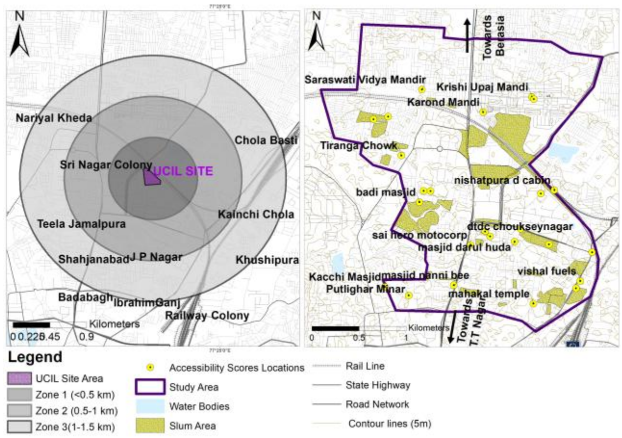

Figure 2. A. Zones of influence, B. Delineated study area

5. Methodology For the Sentiment Analysis

Social media is expanding rapidly, with millions of users posting reviews on various platforms each day. To analyze these reviews, sentiment analysis can be employed. In this research, the data collection started with analyzing and evaluating programming languages like Python for web scraping based on their support for tools such as Selenium, BeautifulSoup, or Scrapy, and one is finalized based on extensive community support and ease of use. After careful comparison Python was chosen for its mature ecosystem, specifically Selenium for dynamic web scraping. Flow chart in Fig 3 provides detailed description of the methodology for sentiment analysis.

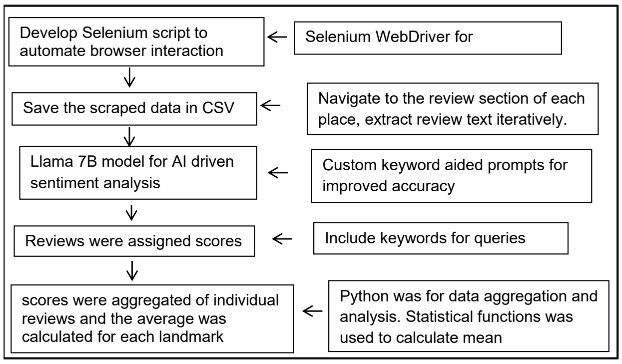

Figure3. Flow chart showing steps for Sentiment Analysis

5.1. Data Collection through web scrapping social media reviews

Accurate and relevant data collection is a cornerstone of this research. Google Maps reviews for prominent locations in the study area surrounding UCIL factory were identified as a valuable source. Since google reviews cannot be extracted for any random buildings or roads, twenty-five landmarks within study area boundary were identified for which google reviews were available (fig.4). These landmarks include religious buildings (temples and masjids), community halls, educational institutes, hostels, shops, traffic nodes, weekly wholesale market (*mandi*) UCIL factory precinct (fig. 4). Due to variations in built types, these landmarks represent overall characteristics of built environment in the study area. Total 1009 reviews were extracted spanning over the period of last eight years.

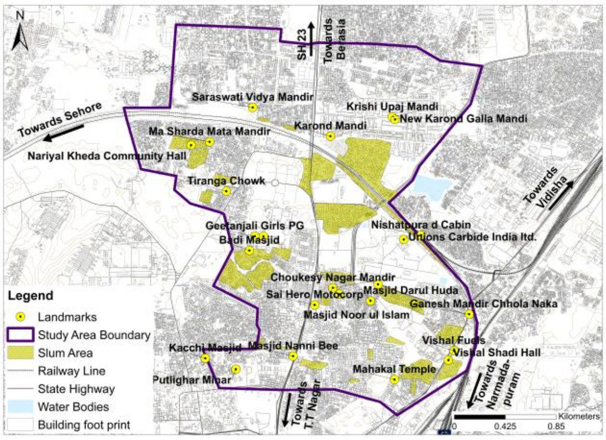

Figure 4. Location of landmarks within study area

To facilitate web scrapping, Selenium WebDriver, a robust browser automation tool, was employed to scrape reviews programmatically. The process began by configuring Selenium to interact with the Google Maps search interface. Search queries for specific locations were automatically input into the search box, and the resulting links to location pages were extracted using dynamic DOM selectors. Selenium then navigated to each location's page, accessed the reviews section, and triggered infinite scrolling to load all available reviews.

Once the reviews were fully loaded, Selenium iteratively captured all the review text. This information was stored in a structured format and exported to a CSV file using Python's csv library, enabling easy analysis. Despite its effectiveness, the process faced inherent limitations. Google Maps restricts the number of reviews visible via scrolling, which led to incomplete data for locations with a large volume of reviews. Additionally, the dynamic and asynchronous nature of Google Maps' interface required careful handling, increasing the complexity and runtime of the scraping task (Policies for Places API). Selenium WebDriver demonstrated remarkable robustness throughout this process. Its ability to simulate user interactions with high precision, execute JavaScript, and handle dynamically loaded content made it an ideal tool for navigating Google Maps. The cross-browser compatibility of Selenium and its extensive API for fine-grained control over browser actions further underscored its versatility. Although the limitations of Google Maps posed challenges, Selenium's powerful capabilities ensured an efficient and organized data collection workflow, providing critical data for the research.

5.2. Sentiment Analysis using Llama 7B Model

After successfully collecting review data in CSV format, the next step was to analyze the sentiment of these reviews, particularly with respect to universal accessibility. To achieve this, the state-of-the-art Llama 7B natural language processing (NLP) model was utilized. The Llama 7B model, known for its efficiency in processing and generating text, was locally deployed on a system, requiring approximately 14 GB of memory to operate. This local setup ensured greater control over the analysis process and minimized reliance on external APIs, enhancing privacy and data security. The sentiment analysis process involved generating prompts tailored to each review. For every review extracted from the CSV file, keywords related to universal accessibility such as 'Cognitive Impaired', 'Blind, Elderly', 'Hearing Impaired', 'Limb', 'Wheel Chair', 'Disabilities', 'Accessible Toilet', 'Handicap', 'Signage', 'Braille', 'Seating Area', 'Kerb ramps', 'Ramps', 'Walks and Paths', 'Lift', 'Tactile Guiding & warning blocks', 'Barriers and hazards', 'Handrails', 'Levelled parking', 'Non-slippery parking' were appended, followed by a specific question asking the Llama model to assess the sentiment of the review concerning accessibility features of the location. This method ensured the analysis remained focused on the research objective and accounted for nuanced aspects of accessibility mentioned in the reviews. The prompt generation process was automated and looped through all the reviews, enabling seamless analysis across a large dataset. The Llama model's output for each review was then stored alongside the corresponding review in a structured format, facilitating further analysis. This approach allowed the extraction of actionable insights regarding how users perceived the accessibility of various locations, providing valuable data to inform accessibility improvements. The combination of advanced NLP capabilities of the Llama 7B model and a robust prompt design ensured a thorough and contextually aware sentiment analysis process.

5.3. Calculating the Average Accessibility Score for each Location

To quantitatively compare the universal accessibility of different locations, an average accessibility score was calculated for each location. After completing the sentiment analysis, the reviews and their associated sentiments were leveraged to derive a numerical score reflecting the accessibility of each location. This was achieved using an additional prompt with the Llama 7B model, which instructed the model to assign a score between 0 and 1 for each review. Precisely, this prompt included the review, sentiment analysis, relevant keywords and the prompt that instructed the model to give a score between 0 and 1 representing the universal accessibility based on the review, sentiment analysis and relevant keywords. The score of 0 represented the worst level of accessibility, while 1 indicated the best. For each review, the Llama model analyzed the compiled prompt and provided an accessibility score. These scores were then aggregated for each location, and the average was calculated using the following formula:

$$Average\ Score = \frac{\sum_{i=1}^{n} score_i}{n}$$

Here, $score_i$ represents the accessibility score for the i^{th} review, and n is the total number of reviews for that location. This approach ensured that the score for each location was based on a holistic analysis of all its reviews, providing a reliable metric for comparison. Score 0-0.4 represents negative sentiment and score above 0.4 represents positive sentiment.

To visualize the results and facilitate effective analysis, a bar graph was plotted to highlight the relative differences in the average accessibility scores across landmarks (Fig.5). This graphical representation made it easier to identify trends and outliers, offering insights into which locations were perceived as more or less accessible. This data-driven approach enabled a clear and structured assessment of universal accessibility across various locations. According to fig.5, the average accessibility score of the twenty-five landmarks ranges from 0.07 to 0.2 Since 0-0.4 signifies negative sentiment (section 5.2) it can be inferred that overall sentiment about universal accessibility status of the study area is negative. Among landmarks, *Nishatpura d cabin* scored highest (0.2) the UCIL factory site scored lowest (0.07) (fig.5). Detailed investigation reveals that lack of accessibility parameters like Signage, Seating Area, Kerb Ramp, Lift, Toilet etc. contributed low accessibility scores in the study area. The output of sentiment analysis was further cross validated with GIS maps.

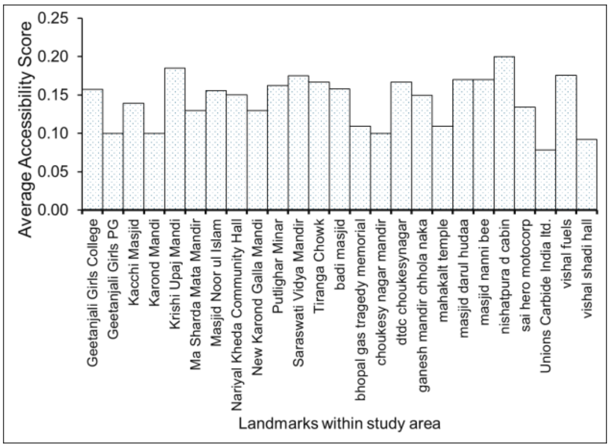

Figure 5. Landmark wise Average Accessibility Score

6.GIS analysis

The methodology for GIS mapping of Universal Accessibility is described in detail in Saha et al., 2020. The method has three steps such as: 1) Formulating checklists for auditing - the authors developed the Checklists for auditing using secondary sources (Saha et al., 2020); 2) Auditing the Universal Accessibility - An accessibility audit was conducted on the identified landmarks using a specially designed checklist; 3) Geospatial analysis – A geospatial analysis was used to develop a map depicting the hierarchy of universal accessibility zones in the study area. Details of the methodology described in a flow chart (Fig.6).

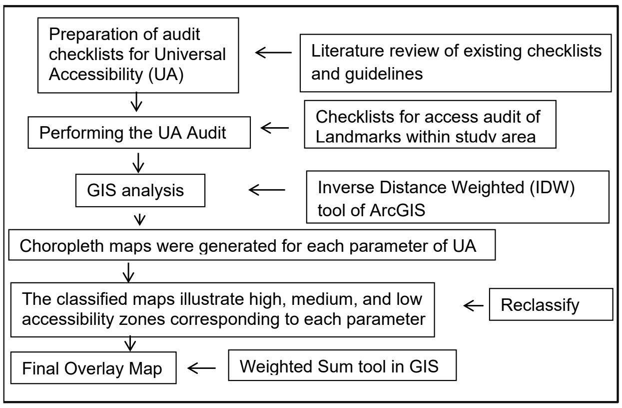

Figure 6. Flow chart showing steps of GIS analysis

6.1. Formulating Checklists for Auditing

The methodology for preparing a universal accessibility audit checklist is described in detail in Saha et al. (2020). Relevant guidelines and checklists such as *Access-improving the accessibility of historic buildings and places* (2011), *Code of Practice-on Accessibility of Public Services and Information provided by Public Bodie (2006)*; *Access Improving to Heritage Buildings*; *Accessible Route in Historical Cities (2011)* by National Disability Authority, Dublin, Ireland; *Harmonized Guidelines* (2016) published by Govt. of India were referenced for developing checklists for auditing. The checklists considered eight major disabilities such as Cognitive Impaired, Complete Blindness, Elderly, Hearing Impaired, Limb, Partial Blind, Speech Impaired, Persons in Wheelchair based on Indian guidelines namely the Barrier Free Guidelines (1998), Harmonised Guidelines (2016), CPWD Guidelines (2019), and the Revised Harmonised Guidelines (2021). The existing checklist has parameters like ‘Signages’, ‘Kerb Ramps’, ‘Tactile Guiding and Warning Blocks’, ‘Reservation and Information Counters’, ‘Toilet Facility’, ‘Platforms (bus stop)’, ‘Seating Area’, ‘Walks and Paths’, ‘Stairs’, ‘Lifts.’ Each parameter includes five to thirty sub-parameters. The checklist is used to audit the universal accessibility status of UCIL sites through physical survey.

6.2. Checklists based Universal Accessibility Survey

It is challenging for a non-disabled person to fully understand the intrinsic mobility support requirements of a person with a disability. A group of students assisting with the survey received initial training on universal accessibility and universal access auditing. Students were introduced to Epicollect5, a free mobile and web application designed for GIS compatible data collection (Epicollect 5 User guide). Projects for the UCIL study area were created within the application using the ‘Form Builder’ tool, with the audit checklists incorporated directly into the app. The students installed the Epicollect5 app on their smartphones and collected data at the designated landmarks. They assigned numeric values to each parameter during data collection. For example, a value of 1 was assigned if a sub-parameter was fully present, 0.5 if it was partially present, and 0 if it was absent. After completion of data collection, the data is downloaded in.csv format. Subsequently, the total value for each main parameter was calculated, followed by the determination of the relative percentage scores.

6.3. Preparation of weighted overlay map

The relative percentages were subsequently appended to the attribute table of the point shapefile. Choropleth maps for each parameter were generated using the Inverse Distance Weighted (IDW) tool in ArcGIS. The IDW tool creates an interpolated surface from points using the Inverse Distance Weighted technique (ArcGIS Desktop Help). The weight is inversely proportional to distance, meaning that nearby data points exert the greatest influence, resulting in a surface with greater detail and less smoothness. In IDW map of any parameter, higher values indicate that the high accessibility status of that parameter. The IDW map was subsequently reclassified using the ‘Reclassify’ tool in ArcMap (fig.7). The classified maps were subsequently input into the Weighted Sum tool, an ArcGIS geoprocessing function that overlays multiple raster layers, multiplying each by its assigned weight before summing them. Weights were assigned to individual layers of the accessibility parameters based on expert opinions. The group of experts consisted of academicians and stakeholders. Fig.8 shows the final weighted overlay map.

7. Discussion and conclusion

According to the sentiment analysis, overall sentiment about universal accessibility status of UCIL study area is negative as the average aggregate score is less than 0.4 (refer section 5.3). Between the landmarks, *Nishatpura d cabin* scored highest (0.2) and the UCIL factory site scored lowest (0.07). Fig.7 shows that *Nishatpura d cabin* falls within zone of medium accessibility for parameters like ‘Walks and Pathways’, ‘Stairs’, ‘Tactile Guiding and Warning Blocks’ which explains its highest score among all landmarks. It falls within zone of lowest accessibility in rest of the parameters (fig.7). The second highest score (0.18) was obtained by *Krishi Upaj Mandi* (weekly wholesale market). It is falling within zone of medium accessibility for parameters like ‘Kerb Ramp’and ‘Signages.’ On the other hand, UCIL factory site is falling within low accessibility zone in all accessibility parameters except 'Tactile Guiding and Warning Blocks.' The newly constructed bus stop equipped with tactile guiding and warning blocks and handrails in nearby vicinity boost the accessibility of the landmark in the said parameter

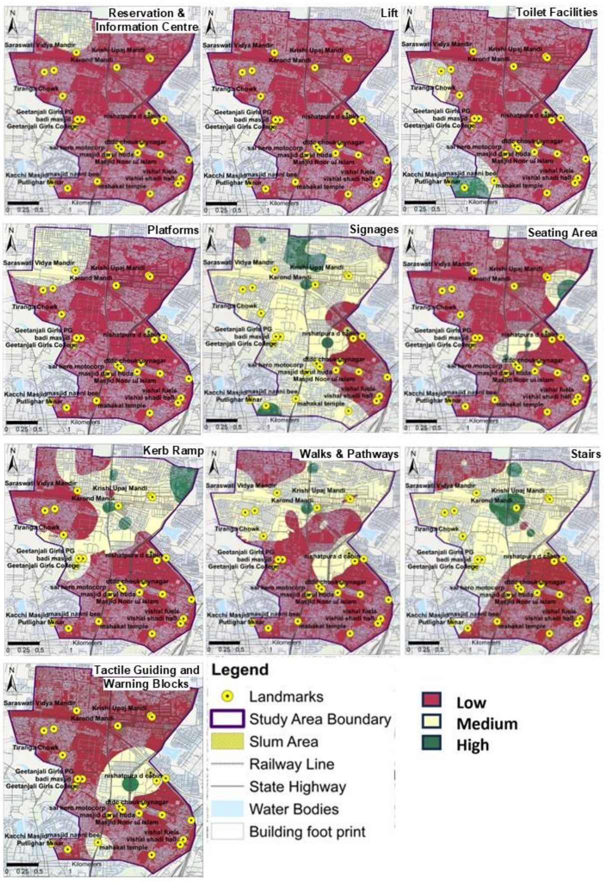

Figure 7. Reclassified map for each parameter

The final weighted overlay map (fig.8) shows that none of the landmarks falls within zone of high accessibility. A few landmarks such as weekly wholesale markets (*Karond Mandi, Krishi Upaj Mandi*), a religious building (*Ma Sharda Mata Mandir*), a school (*Saraswati Vidya Mandir*), a community hall (*Nariyal Kheda* Community Hall) fall within the zone of medium accessibility (fig 8). Sporadic presence of accessibility parameters like 'Sidewalk and Paths', 'Kerb Ramp,' 'Signages', 'Stair' (fig.8) is the reason behind this.

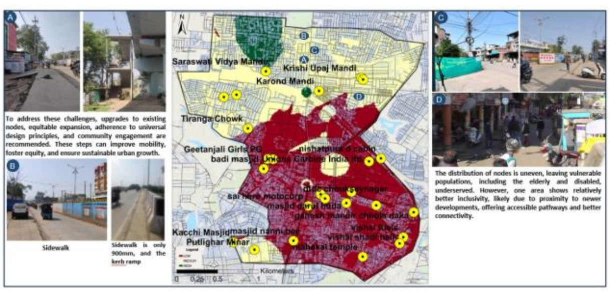

Figure 8. Weighted overlay map and corresponding photographs for the Study Area.

Rest of the nineteen landmarks fall within the zone of low accessibility (fig8). It confirms the overall negative sentiment regarding Universal Accessibility in the study area. The above discussion confirms that forty years after Bhopal Gas Tragedy, the affected areas around the UCIL plant are still facing significant challenges in terms of accessibility for people with disabilities, elderly citizens, and those affected by the health impacts of the gas leak. In this area, the physical and social infrastructure is degraded. It is essential to study the lived experiences of residents in these areas to identify specific barriers they face and find practical solutions that can be implemented in the city's planning and development processes. For that purpose, constant monitoring of the built environment is needed which is both time consuming and costly affair. The proposed method of Sentiment Analysis of built environment from social media review may offer solution to this problem. The major advantage of the proposed method is to get up-to-date information about the universal accessibility status of the same sites. The method has the potential to capture not only the existing built environment accessibility but the usability also. The positive outcome of cross validation with GIS maps proofs the efficiency of the proposed technique for sentiment analysis.
Universal accessibility for persons with disabilities during and after a disaster is a matter of rights, not charity. Persons with disabilities should no longer be expected to 'adapt' themselves to accommodate societal convenience. A significant amount of disability is not due to functional impairment, but rather due to environmental factors like built environment designs. The proposed method may significantly contribute to that process. Though the method is applied for a post- industrial disaster site, it has the potential to be applied in sites affected by other type of disasters.

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