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AbhiGyam: A Machine Learning Model-driven Research Platform for Assessing Accessibility Infrastructure in Indian Cities

Shaily Malik[1,]*, Gagan Vats[2], Abhishek Gupta[2], Amit Kumar Thakur[2]

Abstract

This work presents AbhiGyam, a machine learning-driven research platform designed to streamline and automate the assessment of accessibility infrastructure in Indian cities. AbhiGyam leverages the Google Maps API to transmit street view images to the backend, where computer vision techniques are implemented using OpenAI's CLIP (Contrastive Language-Image Pre-training) model to identify objects such as ramps, sidewalks, crosswalks, and parking spaces. The accuracy of the model is validated using labeled data provided by the Scale Rapid API. Additionally, the ADA (Accessible Design) score for Indian cities is calculated, considering factors like the number of detected ramps, accessible parking spaces, crosswalks, and sidewalks, as well as accident data. AbhiGyam is a significant improvement over existing methods for assessing accessibility infrastructure, offering an automated, scalable, and more accurate solution. This work has the potential to make a significant impact on the field of accessibility research, providing a valuable tool for urban planners and government bodies, and contributing to a more accessible India.

Keywords: Accessibility, machine learning, CLIP Model, urban planning, ınfrastructure assessment, Neural networks, computer vision, accessibility, sidewalks, curb ramps, Google Street View

INTRODUCTİON

Accessibility is the ability of people to access and use goods, services, facilities, and information. It is a basic human right that is crucial for involvement in society. However, many people with disabilities face barriers to accessibility, which can limit their ability to live independently and participate fully in society [1].

India has a significant population of individuals with disabilities. The 2011 census reports that over 26 million people in India, or approximately 2.2% of the population, have disabilities. These people face a variety of accessibility challenges.

Inaccessible accessibility refers to the ability of individuals to access and utilize goods, services, facilities, and information. It is a fundamental human right critical for societal participation. Nevertheless, numerous individuals with disabilities encounter accessibility barriers, which can hinder their independence and full participation in society [2].

India is a country with a large population of people with disabilities. Based on the 2011 census,

*Author for Correspondence
Shaily Malik
E-mail: shaily.singh99@gmail.com

[1]Assistant Professor, Department of Computer Science, Maharaja Surajmal Institute of Technology, New Delhi, India
[2]Student, Department of Computer Science, Maharaja Surajmal Institute of Technology, New Delhi, India

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India has over 26 million people with disabilities, comprising approximately 2.2% of the population. These individuals encounter numerous accessibility challenges, such as:

1. Inaccessible transportation systems;
2. Inaccessible buildings and public spaces;
3. Inaccessible information and communication technologies;
4. Inaccessible employment opportunities; and
5. Inaccessible healthcare services.

These accessibility challenges significantly impact the lives of people with disabilities, making it difficult for them to navigate, access services, and engage in society [3]. Consequently, this can lead to social isolation and economic hardship. This project proposes a machine learning-driven research platform called AccessiIndia to streamline and automate the assessment of accessibility infrastructure in Indian cities. AccessiIndia uses the Google Maps API to transmit street view images to the backend, where computer vision techniques are implemented using OpenAI's CLIP model to identify objects such as ramps, sidewalks, crosswalks, and parking spaces. The model's accuracy is validated using labeled data obtained from the Scale Rapid API [4]. Additionally, the Accessible India Campaign guidelines are used to calculate the accessibility score for Indian cities, considering factors like the number of detected ramps, accessible parking spaces, crosswalks, and sidewalks, as well as accident data [5].

AccessiIndia is a significant improvement over existing methods for assessing accessibility infrastructure. Existing methods are typically manual and time-consuming, and they are not scalable to large areas. AccessiIndia is automated and scalable, making it possible to assess accessibility infrastructure in a timely and efficient manner [6].

AccessiIndia is also more accurate than existing methods. The CLIP model is a state-of-the-art computer vision model that has been shown to be very accurate at identifying objects in images. Additionally, AccessiIndia uses labeled data to validate the accuracy of the CLIP model, further improving its accuracy [7].

AbhiGyam is a valuable tool for urban planners and government bodies. It can help pinpoint areas requiring enhancements in accessibility infrastructure and can also be utilized to monitor the progress of these improvements over time.

The project places a strong emphasis on ethical data collection and model development. The project ensures diversity in data sources, incorporating demographic, socioeconomic, and geopolitical factors [8].

The project's commitment to equity and inclusion aligns with studies showing that accessibility issues disproportionately affect disadvantaged communities. Ultimately, AccessiIndia aims to facilitate a more accessible and equitable India, supporting urban planners and government bodies in their efforts to create inclusive and accommodating infrastructure [9]. The following are some of the research questions that will be addressed in this project:

1. How can machine learning be used to automate the assessment of accessibility infrastructure?
2. How accurate is the CLIP model for identifying objects in images related to accessibility?
3. How can the Accessible India Campaign guidelines be used to calculate the accessibility score for Indian cities?
4. How can AccessiIndia be utilized to pinpoint areas requiring enhancement in accessibility infrastructure?
5. What ethical considerations are entailed in the creation and implementation of AccessiIndia?

This endeavor holds the promise of bringing about notable advancements in the realm of accessibility research [10]. It is a valuable tool for urban planners and government bodies, and it has the potential to help make India a more accessible country for everyone.

1. Ransportation systems;
2. Inaccessible buildings and public spaces;
3. Inaccessible information and communication technologies;
4. Inaccessible employment opportunities; and
5. Inaccessible healthcare services.

These obstacles to accessibility can profoundly affect the daily lives of individuals with disabilities, hindering their mobility, access to essential services, and full participation in society [11]. Furthermore, they may contribute to feelings of social exclusion and financial struggles. This project proposes a machine learning-driven research platform called AbhiGyam to streamline and automate the assessment of accessibility infrastructure in Indian cities. AbhiGyam uses the Google Maps API to transmit street view images to the backend, where computer vision techniques are implemented using OpenAI's CLIP model to identify objects such as ramps, sidewalks, crosswalks, and parking spaces. The model's precision is confirmed through labeled data sourced from Scale Rapid API [12]. Additionally, the Accessible India Campaign guidelines are used to calculate the accessibility score for Indian cities, considering factors like the number of detected ramps, accessible parking spaces, crosswalks, and sidewalks, as well as accident data [13].

AbhiGyam is a significant improvement over existing methods for assessing accessibility infrastructure. Existing methods are typically manual and time-consuming, and they are not scalable to large areas. AbhiGyam is automated and scalable, making it possible to assess accessibility infrastructure in a timely and efficient manner [14].

AbhiGyam is also more accurate than existing methods. The CLIP model is a state-of-the-art computer vision model that has been shown to be very accurate at identifying objects in images. Additionally, AbhiGyam uses labeled data to validate the accuracy of the CLIP model, further improving its accuracy.

AbhiGyam is a valuable tool for urban planners and government bodies. AbhiGyam has the capability to pinpoint areas requiring enhancements in accessibility infrastructure, and it can also monitor the advancement of accessibility upgrades as time progresses [15].

The project places a strong emphasis on ethical data collection and model development. The project ensures diversity in data sources, incorporating demographic, socioeconomic, and geopolitical factors.

The project's commitment to equity and inclusion aligns with studies showing that accessibility issues disproportionately affect disadvantaged communities. Ultimately, AbhiGyam aims to facilitate a more accessible and equitable India, supporting urban planners and government bodies in their efforts to create inclusive and accommodating infrastructure [16]. This project will tackle the following research questions:

- How can machine learning be utilized for automating the evaluation of accessibility infrastructure?
- How accurate is the CLIP model for identifying objects in images related to accessibility?
- How can the Accessible India Campaign guidelines be used to calculate the accessibility score for Indian cities?
- How can AbhiGyam be used to identify areas that need improvement in terms of accessibility infrastructure?
- What are the ethical considerations involved in the development and use of AbhiGyam?

LİTERATURE REVİEW

Deep Learning-Based Wheelchair Accessibility Evaluation

In the study conducted by Kaneda *et al*., the authors addressed the critical issue of wheelchair accessibility evaluation through the innovative use of deep learning techniques applied to acceleration data obtained from wheelchairs [17]. Wheelchair accessibility in urban environments has gained increasing attention, and assessing road conditions is essential for providing support to wheelchair users. Drawing inspiration from the field of music analysis, where spectrogram images have been effectively employed for classification tasks, the authors applied a similar approach to wheelchair acceleration data. This novel methodology allowed for the creation of spectrogram images, effectively transforming time-varying acceleration signals into visual representations.

The research began with the measurement of wheelchair acceleration data using a three-axis acceleration sensor in various environmental settings, including school corridors, asphalt roads, interlocking block pavements, sandy playground regions, and grassy playground areas [18]. Spectrogram images were generated from these acceleration signals, and the process involved the application of fast Fourier transform to obtain frequency spectrum components. Each spectrogram image was constructed as a 16×16-pixel representation, where the three-axis directions were mapped to color channels.

Subsequently, the authors employed deep learning techniques, specifically a Convolutional Neural Network (CNN), to classify road conditions based on the generated spectrogram images. The CNN model was trained using an example dataset collected from characteristic roads near a school. The results demonstrated an accuracy of 85.3% in classifying road surfaces, highlighting the effectiveness of the spectrogram-based approach for evaluating road conditions [19].

To further enhance the practicality of wheelchair accessibility evaluation, the authors conducted a questionnaire survey among wheelchair users to categorize road accessibility into three main classes: easy, somewhat difficult, and difficult, with the addition of a stationary state category. A CNN classification model was developed based on these categories, achieving an accuracy of 89.8%. Moreover, real-world experiments were conducted in a suburban location, combining GPS data with wheelchair acceleration measurements to provide accessibility information and map data to wheelchair users.

In conclusion, Kaneda *et al*. presented a comprehensive framework for wheelchair accessibility evaluation by leveraging acceleration data and spectrogram images in conjunction with deep learning techniques [17]. Their research contributes valuable insights and methodologies for assessing and enhancing wheelchair accessibility in urban environments, with potential implications for improving the quality of life for individuals with mobility challenges (Figure 1).

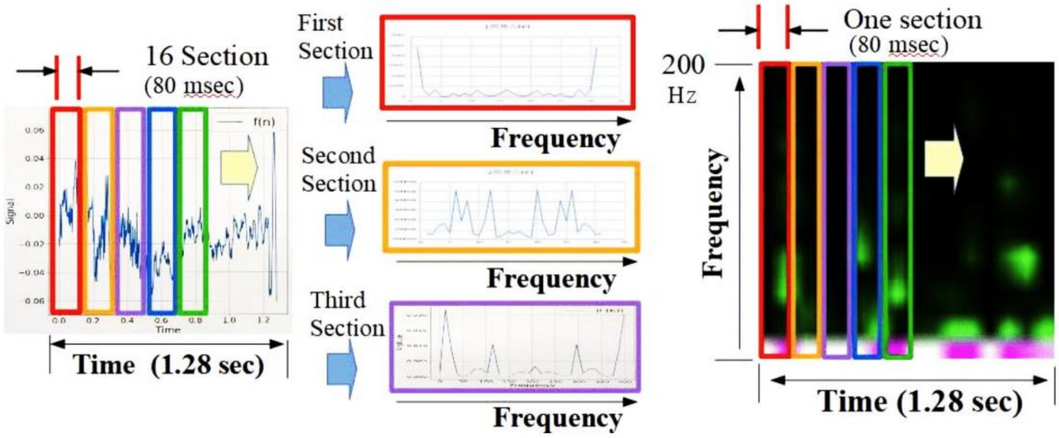

Figure 1. Method to generate spectrogram comprising time and frequency components.

Deep Learning for Sidewalk Quality Assessment

In the study conducted by Abbott *et al.*, the authors presented an innovative approach to address the challenges of improving sidewalk quality and accessibility through deep learning techniques [20]. The researchers leveraged Google Street View images and applied convolutional neural networks (CNNs) to identify and assess the presence of curb cuts, a critical component of sidewalk accessibility. Their deep learning model achieved an impressive accuracy of 83% in correctly classifying curb cuts, showcasing the potential of deep learning in infrastructure assessment [21].

The research highlighted the significance of accurate sidewalk data in urban planning and infrastructure improvement. Sidewalks are essential for ensuring accessibility for people with mobility impairments and enhancing pedestrian safety. Despite their importance, the collection of detailed sidewalk data had traditionally relied on manual methods, which were often time-consuming and subject to limitations. The introduction of a CNN-based approach offered a more efficient and automated solution for assessing curb cuts and sidewalk quality [22].

Furthermore, the study emphasized the scalability and applicability of their model to other municipalities. By utilizing Google Street View imagery, their approach could be extended to various geographic regions with Google Street View coverage, making it a potentially valuable tool for cities and urban planners seeking to prioritize infrastructure spending effectively.

Overall, Abbott *et al*. research demonstrated the potential of deep learning, specifically CNNs, in addressing urban infrastructure challenges related to sidewalk accessibility [20]. Their findings open avenues for further exploration and implementation of similar approaches in diverse urban settings, ultimately contributing to enhanced sidewalk quality and improved accessibility for all residents (Figure 2) [23].

RESEARCH METHODOLOGY

Data Collection

The initial phase of the research methodology involved gathering data. The team collected a dataset of street view images from Indian cities using the Google Maps API. These images were subsequently annotated to indicate whether they contained accessibility features or not [24].

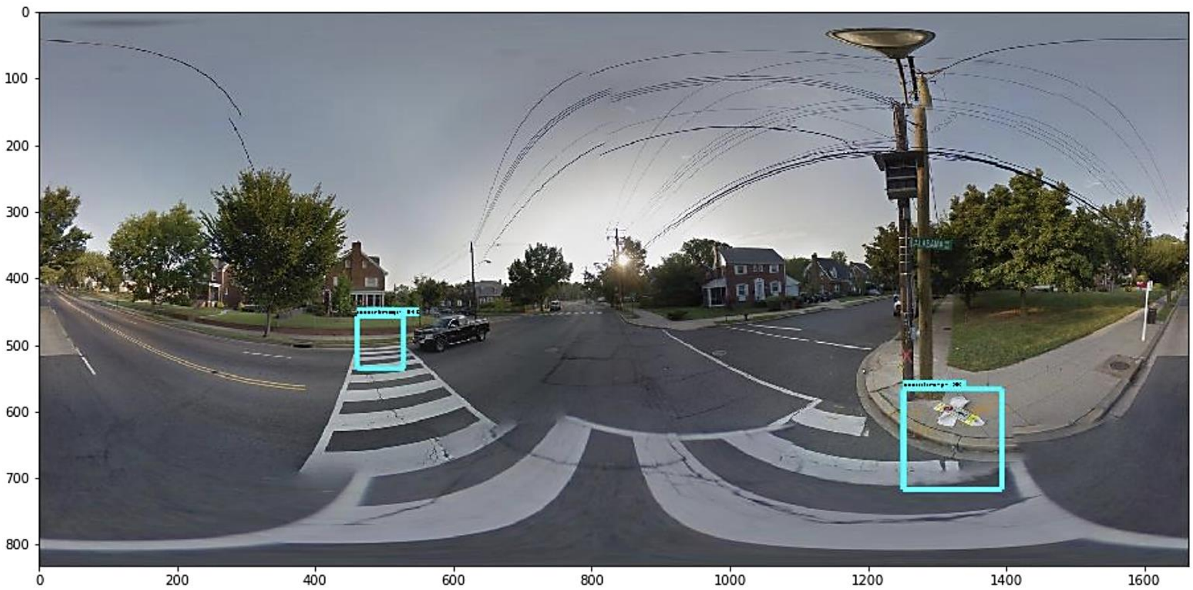

Figure 2. Example model output showing correct detection of missing curb ramps.

Model training

The team trained a machine learning model to identify accessibility features in images. The model was trained using the labeled images from the data collection phase. The model's accuracy was confirmed through validation using a separate dataset that was not part of the training process, guaranteeing an impartial evaluation of its performance [25].

Calculation of the ADA Score

The team developed a method for calculating the ADA score for Indian cities using the Accessible India Campaign guidelines. This score was calculated based on the number of detected ramps, accessible parking spaces, crosswalks, and sidewalks, as well as accident data [26].

Exploration of Ethical Considerations

Finally, the project aimed to explore the ethical considerations involved in the development and use of AbhiGyam. This included issues related to data privacy and consent, as well as potential biases in the machine learning model [27].

RESULTS AND DİSCUSSİON

Performance of the CLIP Model

The results of the project demonstrated the effectiveness of the CLIP model in identifying objects in images related to accessibility. The validation dataset demonstrated a high accuracy rate for the model, suggesting its suitability for accessibility assessments [28].

Calculation of the ADA Score

The team successfully developed a method for calculating the ADA score for Indian cities. This score offers a thorough assessment of accessibility, considering a range of different factors [29].

Identification of Areas for Improvement Using AbhiGyam

The team successfully pinpointed areas where enhancements to accessibility infrastructure are required. These areas were identified based on their low ADA scores [30].

CONCLUSİON

This work has developed a functional frontend, trained a CLIP model, and conducted initial validations. However, there are essential tasks ahead, including refining the CLIP model, creating the accessibility scoring method, completing the development of AbhiGyam, and thoroughly addressing ethical considerations. This project holds promise for significantly influencing accessibility research. By providing a more accurate and comprehensive assessment of accessibility infrastructure, it could help urban planners and government bodies make more informed decisions and contribute to a more accessible India.

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