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Building an AI-powered platform to identify safety risks in urban design

Gerard Jover Pujol

Abstract- The configuration of street networks has a significant impact on public health, including the prevalence of crime and sexual harassment in public spaces. Therefore, policymakers and urban planners must identify specific characteristics of the built environment associated with higher rates of harassment to design safer and more inclusive public spaces that promote gender equality and support the full participation of all individuals in urban life. While urban developers have tools to evaluate other factors such as mobility or visibility, there is a lack of software when it comes to safety evaluation. The motivation behind this project is the need for effective tools that empower urban designers and developers to evaluate safety in their designs. This paper introduces the UrbView project, which aims to develop an AI-powered platform for identifying safety risks in urban design.
At the end of this project the platform will present a simple but robust base so that the services can continuously evolve and improve by iterating over the AI model with better technologies and more data.
Keywords- Intelligent systems, safety, urban design, street network configuration, public health, artificial intelligence, satellite imagery, data pipeline, microservices, cloud.

Resum- La configuració de les xarxes de carrers té un impacte important en la salut pública, inclosa la prevalença de la delinqüència i l'assetjament sexual a l'espai públic. Per tant, els responsables polítics i els planificadors urbans han d'identificar característiques específiques de l'entorn construït associades a taxes més altes d'assetjament per dissenyar espais públics més segurs i inclusius que promoguin la igualtat de gènere i donin suport a la plena participació de totes les persones en la vida urbana. Si bé els desenvolupadors urbans tenen eines per avaluar altres factors com ara la mobilitat o la visibilitat, hi ha una manca de programari pel que fa a l'avaluació de la seguretat. La motivació d'aquest projecte és la necessitat d'eines efectives que permetin als dissenyadors i promotors urbans avaluar la seguretat en els seus dissenys. Aquest treball presenta el projecte UrbView, que té com a objectiu desenvolupar una plataforma impulsada per IA per identificar riscos de seguretat en el disseny urbà.
Al final d'aquest projecte, la plataforma presentarà una base senzilla però robusta perquè els serveis puguin evolucionar i millorar contínuament iterant sobre el model d'IA amb millors tecnologies i més dades.
Paraules clau- Sistemes intel·ligents, seguretat, disseny urbà, configuració de xarxes de carrers, salut pública, intel·ligència artificial, imatges per satèl·lit, pipeline de dades, microserveis, núvol.

1 Introduction

The configuration of a street network has a significant impact on various aspects of urban life, including transportation, economic activity, and social interactions [1]. However, an often-overlooked aspect of street network configuration is its influence on public health. Recent research has demonstrated that how a street network is designed can have a significant impact on the health outcomes of individuals living in urban areas [2]. According to urban planning experts, there is a lack of technological tools that enable urban planners/designers to incorporate a social perspective regarding gender equity and crime prevention in their designs/plans. This project intends to incorporate crime and sexual harassment prevention in the urban planning process by providing services based on artificial intelligence technology.

• Contact email: gerard.jover2000@gmail.com
• Authorized work by: Felipe Lumbreras (DCC)
• Course 2022/23

1.1 Crime

Research has shown that crime can have a significant impact on public health, including physical and psychological health outcomes [3]. Victims of violent crime may suffer from long-term mental health issues such as anxiety, depression, and post-traumatic stress disorder (PTSD) [4]. In addition, crime can lead to increased stress levels and reduced social cohesion within communities, creating a sense of fear and mistrust.

Urban planners have a crucial role to play in addressing safety and security concerns in urban areas. According to research by Olojede and colleagues [5], incorporating features such as improved lighting, surveillance systems, and safe routes into public space designs can significantly reduce crime rates. Moreover, urban planners have the ability to encourage social interaction and community engagement, which plays a vital role in fostering trust and developing a collective sense of responsibility for safety and security.

Having tools to evaluate their designs is essential for urban planners to determine the effectiveness of their safety measures. They can use data on crime rates and public health outcomes to inform their decisions and make adjustments to their designs as needed. With the right tools and strategies, urban planners can create environments that promote safety, health, and well-being for all citizens.

1.2 Sexual harassment

Sexual harassment continues to be a prevalent problem faced by women and other marginalized groups within urban areas. Despite numerous studies highlighting the hostile environments experienced by women, limited research has explored the concrete connection between sexual harassment and the layout of the street network.

According to research conducted by Mohamed et al. [6], suggests that harassment incidents occur more frequently on street segments with high volumes of foot traffic and a lack of visibility and spatial accessibility, amongst other characteristics. These findings indicate that certain public spaces are more prone to sexual harassment, hindering women's freedom of movement and participation in urban life. Women may avoid certain areas or change their behavior to avoid unwanted attention, such as choosing to travel by car instead of walking or running errands during less busy times of day. These behaviors have significant impacts on their quality of life and sense of safety in the city.

Furthermore, sexual harassment can limit women's access to employment, education, and other opportunities. Women may be discouraged from pursuing certain careers or activities that require them to navigate public spaces where they are vulnerable to harassment, contributing to gender inequalities in the workforce and other areas of life. Urban planners and designers can play a critical role in addressing these issues by incorporating crime and sexual harassment prevention into their designs/plans. This includes features such as improved lighting, surveillance systems, and safe pedestrian routes that prioritize safety and security, as well as promoting social interaction and community engagement to build trust and reduce the risk of crime [7].

Therefore, understanding the factors that contribute to sexual harassment in public spaces, including the configuration of the street network, is crucial. Policymakers and urban planners must identify specific characteristics of the built environment that are associated with higher rates of harassment to design safer and more inclusive public spaces that promote gender equality and support the full participation of all individuals in urban life.

2 MOTIVATION

The motivation behind the UrbView [8] project emerges from the urgent need for effective tools that empower urban designers and developers to evaluate safety in their designs. While numerous factors are carefully considered during the selection of urban designs, the aspect of safety has often been overlooked due to the lack of suitable tools developed thus far.

Our project aims to address this critical gap by introducing revolutionary technology that assists urban planners and architects in identifying high-risk crime areas. UrbView goes beyond conventional approaches by providing innovative solutions that equip professionals with the necessary tools to mitigate risk factors and foster the creation of safer, more interconnected urban environments. By leveraging our innovative solution, we not only enhance the safety of existing and future city designs but also contribute to optimizing public transportation planning.

3 OBJECTIVE

This project has two main goals:

- Building a centralized platform that consolidates data on urban design and public health, and provides users with services to evaluate the design and safety of cities.
- Develop an initial algorithm that can assess urban designs and offer valuable insights to the users.

Here below are listed the specific proposals to create the platform and build the AI-based algorithm fore evaluation:

- Build the data producer pipeline to transform data from different sources into our custom format.
- Create a storage for our file data such as images or metadata files.
- Define and create a database to store the ingested data.
- Explore the data generated and study what transformations and algorithms can be used.
- Build an environment based on PyTorch and Hydra to make traceable experiments.
- Train and evaluate with different approaches to obtain the best possible model.
- Create an endpoint that performs inference from new coordinates.
- Build the front-end of the platform that allows users to interact with the services and trigger our endpoints.

Note that the primary focus of this project is constructing the platform. Although the development of the AI model is also an objective, it is not the primary goal. Instead, we aim to create an initial solution that can serve as a foundation for future iterations and enhancements. The emphasis is on building a robust platform that can evolve with future developments and improvements.

3.1 Methodology and Planification

For this project, the Kanban method was chosen as the primary methodology for software development. Kanban is an Agile methodology that emphasizes continuous delivery, flexibility, and collaboration. It is based on a visual board that represents the workflow, with each step of the process represented by a column. Each work item is then moved from one column to the next as it progresses through the different stages. This method allows for real-time tracking of progress and makes it easy to identify bottlenecks or areas for improvement.

Azure DevOps [9] was used, which provides powerful tools such as the board for managing agile projects. This allowed me to create and manage work items such as product backlog items (PBI) and pull requests (PR). By linking PRs to PBIs on the board, I was able to easily track the progress and visualize the status of individual features.

4 Related Work

This section reviews the current state-of-the-art in two areas relevant to the development of an AI-powered platform for identifying safety risks in urban design. The first section discusses cloud microservices architecture and the Azure platform, while the second section examines recent advances in AI algorithms for urban planning using computer vision and deep learning.

4.1 Platform

Cloud computing has emerged as an essential technology for managing large-scale data and computation in various domains. Microservices architecture is a software design approach that focuses on developing small, independent, and loosely coupled services that can work together to provide complex functionality. Azure is a cloud platform provided by Microsoft that offers a comprehensive set of cloud services, including compute, storage, networking, and AI/ML.

Azure provides various tools and services to develop and deploy microservices-based applications. Some of the services we will be using for the development of the services are:

- Azure Machine Learning [10] empowers data scientists and developers to build, deploy, and manage high-quality models faster and with confidence. It accelerates the time it takes to achieve results by offering machine learning operations (MLOps), seamless integration with open-source tools, and a comprehensive suite of integrated tools. This reliable platform is specifically designed to support responsible AI applications within the field of machine learning.

- Azure Functions [11] is a serverless compute service that allows developers to build and run event-driven applications.

- Blob Storage [12] is a cloud-based storage service that grants users the ability to store and manage unstructured data, such as images, videos or documents. It provides a highly scalable and durable solution for handling substantial volumes of data.

The platform will leverage the cloud microservices architecture and the Azure platform. Our two main storage services will be a Blob Storage for unstructured data and a database for structured data to centralize of the information gathered from different sources. All the research stage will be based on the Azure ML environment, which will allow use to work with our stored data and use the computing resources to create get the best models. Finally, we will use Endpoints to trigger the different functionalities of our data pipeline, from data generation to inference.

4.2 Services

Urban planning requires the analysis of large amounts of data from various sources, including satellite imagery, street-level photos, coordinate system information files and many others. Computer vision and deep learning techniques have been recognized as a powerful tools for analyzing urban planning data, as mentioned by Xu et al. [13], who used deep learning techniques to extract information from street view images for urban sustainability analysis.

Recent advances in deep learning have led to significant improvements in various computer vision tasks in the field of urban planning. A great example of AI-powered solution for urban planning is the "Space Syntax" project developed by researchers at University College London [14]. This project used deep learning algorithms to analyze street-level images and map the spatial structure of urban environments. The project allowed urban planners to understand the relationship between spatial design and the use of space as well as longer term social outcomes.

The platform presented in this project will leverage computer vision and deep learning techniques to analyze various types of urban data, but for an initial approach that simplifies the complexity of covering all possible sources of data this project will work with satellite imagery. Our intelligent system will use a classification AI model to label street designs as safe or not safe, which will allow our different services to make petitions to the model when necessary and then present the results in a format that provides value to the users.

5 Development

5.1 Data

The Free To Be project is a social initiative that seeks to challenge gender stereotypes and promote gender equality among marginalized groups. It consists of a crow-mapping tool developed with CrowdSpot for girls and young women to share their experiences and help decision-makers to respond to the issue.

The project built a platform dedicated to uncovering and sharing the real stories of women, aiming to bring these narratives to the attention of individuals in positions of power to advocate for meaningful change. The main feature was an interactive map where girls and women could mark locations with pins, expressing their positive or negative experiences. This included places they loved, avoided, felt safe in, and areas that could be improved.

After a successful pilot in Melbourne in 2016, an enhanced version of the crowd-mapping tool was launched in five cities across five continents. In 2018, Free to Be expanded its reach to Sydney, Delhi, Kampala, Lima, and Madrid. The platform provided a platform for young women in these cities to identify and share their experiences in public spaces, pinpointing areas that made them feel uneasy or scared, as well as spaces where they felt happy and safe.

The dataset[1] used for this project consists of approximately 14,000 samples from Delhi (India), each of which includes coordinates paired with descriptions of experiences, along with a classification of whether the experience was considered to be a good or bad one.

Fig. 1: Example of different images generated from Delhi coordinates using Google Maps API.

The dataset offers valuable insights into the experiences of women and their subjective perceptions. This uniqueness enables us to incorporate qualitative information into the model learning process. Through analysis of the dataset, we can develop a deeper understanding of the factors that contribute to positive experiences for women and identify specific areas that require further attention to promote gender equality.

In the development of the AI solution, the initial approach chosen for the solution focused only on image data for binary classification. Qualitative data was not considered in this particular stage. However, it is acknowledged that incorporating qualitative data in future iterations of the AI component could lead to more robust decision-making. By integrating qualitative data, a text-retrieval approach could be employed to extract meaningful insights from the data.

5.2 Infrastructure

5.2.1 Design

The main motivations behind the design are:

- Create a very simple system that can evolve easily.
- Keep the data centralized.
- Process automation and AI integration in the data life-cycle.
- Use a microservices architecture based on the cloud.

The entire architecture has been designed following a logical layer approach. Every layer represents a specific part of the data journey. The different layers are described conceptually in the following sections.

Key decision points during the architecture design were:

- Custom data models oriented to the solutions.
- Simple and manageable data workflow.
- Minimization of different technologies.
- Central database engine.

The design of the architecture is completely extensible using a loosely coupled architecture, which guarantees the ability to add new components with flexibility.

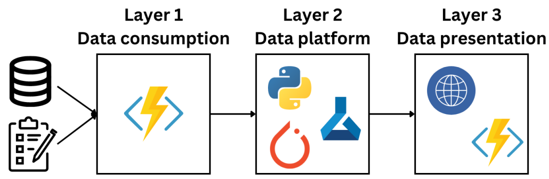

Fig. 2: Diagram of the logical architecture and it's components.

5.2.2 Data consumption

The data consumption corresponds to the layer 1 of our architecture shown in figure 2, and is the first step of our data pipeline, a fundamental element for our data processing as it is the one who is responsible of ingesting external data and converting it into a format useful for the company.

For the case of use of this project, two main workflows have been implemented:

1. The first data generation workflow allows us to store individual documents into our centralized blob storage. As explained later in 5.4.2, one of our services will allow users to input coordinates paired with experiences, which will trigger this workflow and store the result according to our data model.

2. The second data generation workflow consists of a function which converts coordinates into samples composed of images paired with metadata, which will be stored in the platform storage and used as the input data to train our model. This first workflow uses the Google Maps API to generate the images and extract the corresponding metadata from a given coordinate, and allows us to export to the storage we define. The id of the samples generated contained some metadata such as the city and country, but was unique as it used uuid4 to generate a random identifier.

In the Azure environment, Azure Functions is a serverless solution that allows you to write less code, maintain less infrastructure, and save on costs. Instead of worrying about deploying and maintaining servers, the cloud infrastructure provides all the up-to-date resources needed to keep your applications running.

We defined our workflows as endpoints triggered by an HTTP trigger, which will allow the front-end of our services to send POST petitions that will triggers the ingestion of the new data into our platform.

[1] *Crowdspot*, (n.d.). Free to Be Delhi Archive. Retrieved from https://crowdspot.carto.com/datasets.

5.2.3 Data platform

The data platform corresponds to the layer 2 of our architecture shown in figure 2, and is where all the data processing and algorithms will be computed. Conceptually, this layers is the one in charge of transforming the data to obtain the maximum value out of it.

Our environment will work with Python as the main language for data manipulation, and Pytorch will be used as the framework for developing and deploying AI solutions.

Within this layer we also include our framework for fast experiment iteration, which will allow to easily train and evaluate new AI models, track results and use cloud virtual machines for faster computation.

5.2.4 Experiment framework

PyTorch Lightning [15] is a lightweight PyTorch wrapper that simplifies the process of training deep learning models. It provides a high-level interface for defining models, optimizing hyperparameters, and tracking experiments. By using PyTorch Lightning, researchers can focus on the model design, rather than the training loop.

Hydra [16] is a configuration management tool that simplifies the process of defining and managing complex configuration setups. It allows for the separation of the configuration logic from the application logic, making it easier to experiment with different hyperparameters and configurations.

The experiment framework developed for this project combines PyTorch Lightning and Hydra to provide a streamlined and efficient approach to deep learning experimentation. The framework allows for the creation of configuration files that define the hyperparameters and settings for each experiment. These configurations can be easily modified and tracked, allowing for rapid iteration and experimentation.

The framework also includes automatic logging of experiment metrics using Weights and Biases [17], making it easy to monitor the progress of each experiment. Additionally, the framework provides an interface for automatically saving and loading models, making it easy to continue training from a previous checkpoint.

Fig. 3: Example of mertics comparison from multiple experiments using Weights and Biases.

5.2.5 Model endpoint

Azure Machine Learning provides an easy-to-use and scalable platform for building and deploying machine learning models. One key feature of AzureML is the ability to create endpoints, which are RESTful APIs that can be used to interact with deployed models. Endpoints enable users to quickly and easily deploy and manage models in a production environment, making it easy to perform real-time inference on new data.

When deploying a model as an endpoint in AzureML, users can choose to include model checkpoints as part of the deployment. Model checkpoints are saved versions of the trained model that can be used to perform inference without having to retrain the model from scratch. This can be especially useful for models that take a long time to train, or for applications where real-time inference is required.

AzureML endpoints can be configured to use model checkpoints for inference by loading the checkpoint during the endpoint initialization process. Once the checkpoint is loaded, the endpoint can use it to perform inference on new data in real-time. This enables users to quickly and easily deploy and manage models, without the need for time-consuming retraining.

By using this framework and Azure Machine Learning SDK, we are capable of running experiments in the cloud with powerful machines. The trained models can then replace the current AI model deployed to improve the results of our inference system while not needing to change anything in the architecture.

5.2.6 Storage

When our platform consumes new data as coordinates with text and sentiment classification, the documents get stored in the CosmoDB, a NoSQL database provided by Azure. This database defines a contract to which all new sources of data need to be transformed before inserting it.

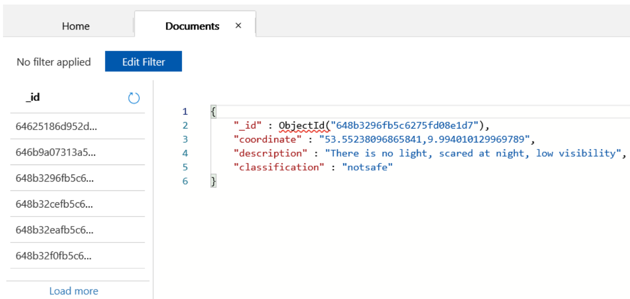

Fig. 4: Example of a document in CosmoDB explorer.

To train our model in the cloud it is necessary to generate a dataset of images from the given coordinates in our CosmoDB. These files will be stored in an Azure Blob Storage to which the hosted machines will have access during training.

The folder structure is organized based on the input type, and each sample is defined as an image–metadata pair with the same identifier but different extension (.png and .json, respectively).

5.2.7 Data presentation

Finally, the data presentation corresponds to the layer 3 of our architecture shown in figure 2, and is where all the processed data in presented to the user in a way that can provide value.

Similar to how the data ingestion layer works, this last layer is based too in Azure Functions and endpoints that user will trigger when using the different services.

5.2.8 Front-End

The front-end of our application is built using a combination of Flask, HTML, CSS, and JavaScript. Each of these technologies serves a specific purpose in creating a user-friendly interface. The Flask framework enables the development of the web application, while HTML is used for structuring the content and CSS for styling and visual enhancements. JavaScript is utilized to add interactivity and dynamic functionality to the front-end.

The front-end components are designed to interact with various Azure Functions endpoints, establishing communication between the user interface and the back-end functionalities.

The user interface elements have been designed by the graphic design company, Raw Studio Picture [18], based in Hamburg. Over multiple meetings the usability and product feeling have been discussed in order to come up with the most appealing results possible.

5.3 AI Algorithm

In order to develop our intelligent system, an AI component was created and deployed. Although the primary focus of the project is not on building a highly robust AI model, experiments were conducted using a simple initial approach to establish a foundation upon which further improvements could be made. The aim of these experiments was to lay the groundwork for future enhancements and iterations of the AI model, allowing for the development of a more sophisticated and effective solution.

The initial approach consisted of a binary classification problem. The aim of the task is to classify street network designs as either “good” or “bad”. To achieve this, a ResNet50 model that has been pretrained on ImageNet dataset was used. The ResNet50 model is a deep neural network architecture that has shown excellent performance in image classification tasks, and is often used for an initial experiment.

Our dataset contains 14k samples, with the “bad” class being the majority at 60%, and the “good” class being the minority at 40%. Class imbalance can be a problem in machine learning tasks, as it can result in a biased model that favors the majority class.

The input to our AI algorithm is an image generated by our data generator pipeline. The output of our model is a binary classification of “good” or “bad” based on the street network design. This output will enable us to evaluate the performance of our algorithm and determine its effectiveness in classifying street network designs.

5.3.1 PoC

In order to evaluate the effectiveness of our approach, we conducted a proof-of-concept (PoC) experiment using a simple baseline model. The purpose of this experiment was to obtain initial results and determine whether our approach was on the right track.

We trained the model on our dataset and evaluated its performance using standard classification metrics such as accuracy and F1-score. The results obtained from this experiment served as a baseline for our subsequent experiments.

Our initial baseline consisted of:

- Pretrained ResNet50 with ImageNet weights.
- Binary classification.
- Cross entropy loss.
- Learning rate of 1e-3 using Adam optimizer.
- ReduceLROnPlateau scheduler.
- No data augmentation.
- Batch size of 64.
- Train/validation split of 80%/20%.

In addition, we conducted a comparison between two types of input images: those obtained from OpenStreetMap and those obtained from Google Maps. Our hypothesis posited that the street network is associated with the perception of safety among citizens. This proof-of-concept (PoC) aimed to validate whether the street patterns alone are sufficient or if other elements are also correlated with this subjective sensation.

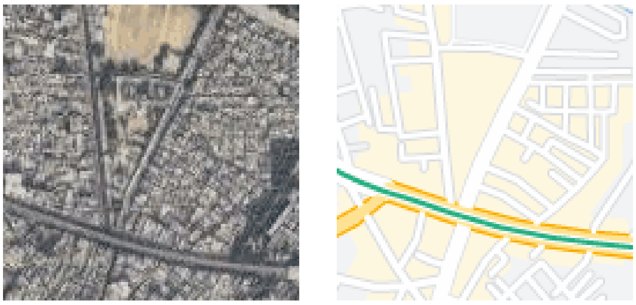

Fig. 5: Comparison of two images from Google Maps (left) and Open Street Map (right) given a same coordinate.

TABLE 1: VALIDATION RESULTS OF THE POC EXPERIMENT FOR OPENSTREETMAP AND GOOGLE MAPS.

Metrics	**Results**	
	OpenStreetMap	**Google Maps**
Accuracy	62.75%	66.46%
F1-score	56.78%	55.04%

For the metrics of the table the best results from multiple experiments were selected.

The first column of the table 1 presents the results of the PoC experiment conducted using OpenStreetMap data. On the validation set, the accuracy reached 62.75%, with an F1-score of 56.78%.

The second column of the same table displays the results of the PoC experiment using Google Maps data. The validation set, the accuracy was 66.46%, accompanied by an F1-score of 55.04%.

Comparing the two tables, it can be observed that the PoC results slightly differed between the two datasets. In terms of accuracy, the Google Maps data outperformed the OpenStreetMap data in validation set. However, when considering the F1-score, the Open STreet Map data achieved a higher score on the validation set.

While the results of the PoC are not exceptionally high, with a best validation accuracy of 66.46% and a best validation F1-score of 55.04%, they do indicate that the approach has potential and can be further optimized.

We can also stick to Google Maps as our source of data, as it has proven to achieve better results than Open Street Map images.

5.3.2 More research

Improving the results of the project posed several challenges, which necessitated strategic decisions. These challenges are as follows:

- Limited Sample Size: The task at hand faced the limitation of having a small number of samples available for analysis. This scarcity of data posed a challenge in achieving robust and accurate results.

- Unbalanced Data: The data provided for the project exhibited an imbalanced distribution, with approximately 60% labeled as “bad” and 40% labeled as ”good.” This data imbalance can affect the model’s ability to effectively learn and generalize patterns from the dataset.

- Resource and Time Constraints: Another challenge was the limited availability of resources and time. These constraints had an impact on the extent of experimentation and the complexity of the approaches that could be implemented within the given project timeframe.

To address these challenges, a new baseline approach was designed. The initial baseline comprised the following components:

- Pretrained ResNet50 with ImageNet Weights: Leveraging a pretrained model, specifically ResNet50, that had been trained on the ImageNet dataset. This choice was made because ImageNet contains satellite images, which align with the nature of the project’s data. Utilizing a pretrained model allows the baseline to benefit from the already learned features relevant to the task.

- Weighted Cross Entropy Loss: To account for the data imbalance, a weighted cross entropy loss function was employed. This technique assigns higher weights to the underrepresented class (in this case, the “bad” class), enabling the model to give more attention to the minority class during training.

- Data Augmentation: Data augmentation techniques, including rotations, flips, and random noise generation, were implemented to artificially increase the size and diversity of the dataset. This augmentation strategy aimed to mitigate the limited sample size challenge and enhance the model’s ability to generalize.

Additionally, experiments were conducted involving fine-tuning and transfer learning. These techniques allow the model to adapt and learn from the specific task at hand, leveraging the knowledge and features extracted from the pretrained ResNet50 model.

By making these strategic decisions, the project aimed to overcome the challenges posed by limited data, data imbalance, and resource constraints, thereby laying the foundation for improved results and performance in the subsequent stages.

5.3.3 Final model

The final results of the experiments are presented in the table 2.

TABLE 2: VALIDATION RESULTS OF THE EXPERIMENT USING FINETUNING AND TRANSFER LEARNING.

Metrics	**Results**	
	Finetuning	**Transfer Learning**
Accuracy	67.02%	66.22%
F1-score	56.33%	54.87%

First column from table 2 provides the results obtained through the fine-tuning approach. The model achieved an accuracy of 67.02% on the train set, with an F1-score of 56.33%.

The second column of the table shows the results obtained through the transfer learning approach. In this case, the model achieved an accuracy of 66.22% on the train set, with an F1-score of 54.87%.

These results allow the performance of the models trained using different techniques to be compared. It is observed that the fine-tuning approach yielded slightly higher accuracy and F1-scores compared to the transfer learning approach. However, it is important to note that both approaches demonstrated promising results, achieving reasonably high accuracy and F1-scores on the validation set given the simple approach used and the lack of data.

5.4 Services

This section focuses on the development of services aimed at evaluating the design of street networks using our algorithm. The purpose of these features is to equip urban designers with robust tools that enable them to comprehensively assess the safety and efficiency of street networks. By leveraging our algorithm, these services offer valuable insights and analysis to inform decision-making in urban design processes.

The user interface has been crafted using HTML, CSS, and JavaScript, providing an intuitive and visually appealing design. HTML forms and elements have been utilized to capture user inputs and display relevant information, while CSS styling has been applied to ensure consistency, responsiveness, and an engaging user experience across different devices and screen sizes.

The integration of Python, Flask, HTML, CSS, and JavaScript has empowered us to create a robust and user-friendly portal that seamlessly interacts with the backend services. This combination of technologies ensures a smooth and intuitive user experience, enabling users to access and utilize the Spot Review, Danger Map, Plan Evaluation, and Public Transport Graph services efficiently and effectively.

5.4.1 Portal

The main portal of our platform provides users with access to four distinct services: Spot Review, Danger Map, Plan Evaluation, and Public Transport Graph. Each of these services offers unique functionalities, catering to different aspects of user needs.

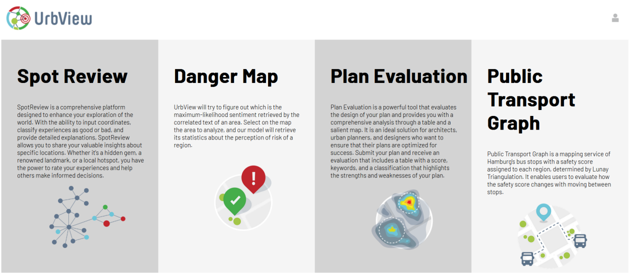

Fig. 6: Portal interface showing all the services available.

5.4.2 Spot Review

Spot Review is an interactive app designed to share experiences and sensations of spots in your city. With the ability to input coordinates, classify experiences as good or bad, and provide detailed explanations, Spot Review allows users to share valuable insights about specific locations.

This service is not thought as part of the tools for urban designers or planners, but as a possible source of data for the platform to improve the AI models which require tons of samples.

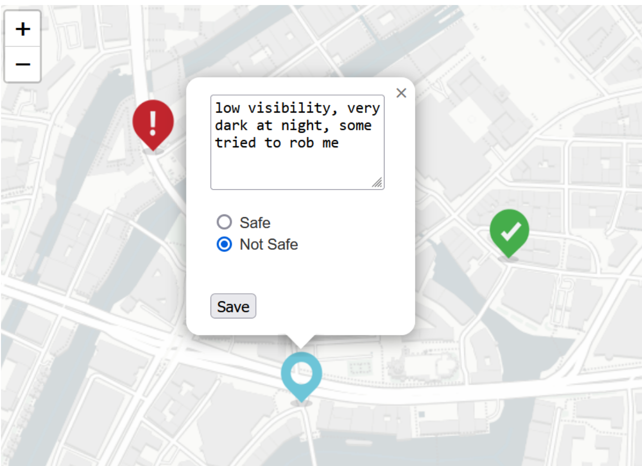

Fig. 7: Interface for Spot Review service.

5.4.3 Danger Map

The Danger Map is a tool that allows urban designers to determine the perceived level of risk in a particular area. By placing a location on the map, an even is triggered which generates an image using our data generation pipeline, does the inference using another function, and returns the retried perception of risk in that region. This tool can be used to identify areas that, according to our intelligent system, are perceived as not safe. By looking at the elements in that region, urban designers will be able to redesign that spot taking safety into account.

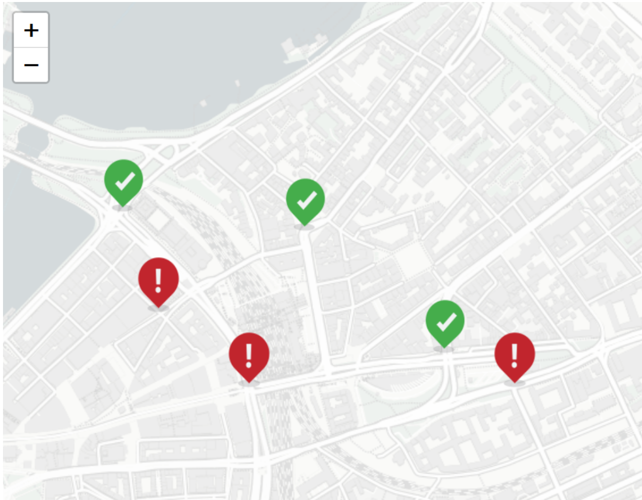

Fig. 8: Interface for Danger Map service.

5.4.4 Plan Evaluation

The Plan Evaluation tool is designed to provide urban planners and designers with a comprehensive analysis of their street network design. By submitting their plan, users receive an evaluation that includes a table with a score and a classification that highlights the strengths and weaknesses of their plan. This tool uses our algorithm to evaluate the design of the plan and provide feedback on how to optimize the design for success.

Grad-CAM (Gradient-weighted Class Activation Mapping) is a technique used in computer vision and deep learning to visualize and understand the regions of an input image that are important for a neural network's prediction. It provides a way to interpret the decisions made by a convolutional neural network (CNN) by highlighting the regions that contribute the most to its output.

Since our intelligent system so far has only knowledge of Google Maps satellite view, users will have to upload the designs with that same view in order for our platform to work. By applying GradCam to a new image, we are able of detecting which regions where more relevant when making the decision of classifying the spot. These visual feedback will allow users to study which elements might be present that can be correlated to the model decision, and try to iterate over the design in order to minimize the sensation of danger.

5.4.5 Public Transport Graph

The Public Transport Graph is a mapping service that displays the bus stops in a given area and assigns a safety score to each region.

Delaunay triangulation is a geometric algorithm that divides a set of points in a plane into a network of non-overlapping triangles, known as the Delaunay triangulation.

Fig. 9: Heatmaps generated by GradCAM highlight relevant sections of the image.

It is widely used in computer graphics, computational geometry, and mesh generation.

By mapping bus station coordinates and color grading based of the safety score, this tool enables users to evaluate how the safety score changes with moving between stops. This tool is useful for urban designers who want to evaluate the safety and efficiency of public transportation in their area. By identifying areas with low safety scores, designers can work to improve the safety of the public transportation system.

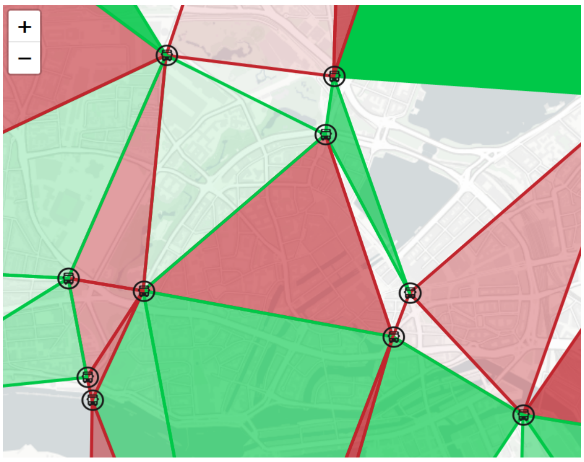

Fig. 10: Interface for Public Transport graph service.

6 Results

The results of the project indicate successful completion of the intelligent platform based on microservices. While the AI model did not achieve the optimal results, it provided a sufficient foundation to build the platform upon. The defined and implemented microservices architecture allowed for the creation of a robust and scalable platform that can effectively handle various tasks and functionalities.

The results obtained from the Google Maps images against the Open Street Map ones are below 60%, which is not significant enough to use results to answer hypothesis. Despite this, we saw a slight improvement when further improving the experiments, achieving a best score of 67.02% accuracy when using a finetunning approach.

Despite the AI model not reaching the desired performance levels, it still served as a viable starting point for developing the platform. By using a loosely coupled design, further iterations can improve the model and allow to easily change the input domain to other topics such as crime, mobility or visibility. The model's capabilities, although not the best, provided valuable insights and formed the basis for further enhancements and refinements.

By leveraging the intelligent platform, users can benefit from a wide range of features and services that facilitate the evaluation of street network designs. The platform empowers urban designers by offering comprehensive tools to assess safety and efficiency, enabling informed decision-making in urban planning processes. These tools offer close to real-time answer in inference, with responses under 1s when making single petitions to any endpoint, and the possibility of scaling in case of higher demand.

Overall, the project's results demonstrate successful implementation of the intelligent platform, highlighting the potential for future improvements and advancements in AI models to further enhance its capabilities and deliver even more accurate and impactful insights for urban design evaluation.

7 Conclusions

The project has successfully developed an AI-powered platform to identify safety risks in urban design. This platform will provide urban designers and developers with the necessary tools to evaluate safety in their designs, benefiting residents and visitors alike.

Although the current AI model may not have achieved optimal results, its development lays a strong foundation for future improvements. The initial capabilities demonstrate its potential to effectively identify safety risks, and further refinement and training can enhance its performance. The use of more robust algorithms can yield better results than traditional deep learning approaches.

The simplicity of the platform's design allows for adaptability and evolution. Prioritizing a user-friendly interface and intuitive features ensures that the platform can meet the changing needs of stakeholders and users. This flexibility enables iterative feedback and continuous improvement, leading to a more effective platform over time.

The adoption of a microservices approach in the platform's architecture enhances scalability. This ensures that the system can handle a growing user base and increasing data volumes. As more urban designers and developers join the platform, its responsiveness and ability to deliver timely safety evaluations are maintained.

In conclusion, the AI-powered platform for identifying safety risks in urban design has laid a strong foundation for future advancements.

7.1 Future work

While this project built a strong core for the intelligent platform, many improvements need to be done, specially in the AI algorithm section which was not the main scope during the development.

One of the main reasons behind the results of the AI models was the lack of data and the selection of the architecture. While this project implemented a simple binary classification task, other approaches more promising could replace the model in a future.

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