DATA-DRIVEN FRAMEWORK FOR ANALYZE THE VISUAL QUALITY OF STREETS: A SYSTEMATIC MEASUREMENT OF STREET QUALITY THROUGH STREET VIEW IMAGES UTILIZING DEEP LEARNING ALGORITHMS

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Abstract: The study developed a framework that utilizes deep learning algorithms to analyse the visual quality of streets (VQOS) through street view images (SVIs), while overcoming the constraints observed in existing practices. The study consisted of four main stages, including literature reviews and expert discussions, development of deep learning algorithms, testing of developed algorithms, and validation. The study developed both convolutional neural network (CNN) and feed forward neural network (FFNN) algorithms, using 2684 street view images extracted from Google Street View images and Cityscape datasets, rated by an expert panel and the general public. The proposed framework comprises stages such as the collection and rating of street view images, image processing, developing and training the CNN, and testing and validating stages. The proposed framework achieved 90.51% internal validation accuracy using the accuracy metric in Keras and 86.7% external validation accuracy, with an accepted level of kappa accuracy of 80%. Urban planners, designers, architects, and landscape architects can use this framework as a tool for quantitatively measuring and mapping the visual quality of streets and assessing the impact of proposed developments and guidelines on the visual quality of streets. This proposed framework will enhance the effectiveness of their new proposals and designs.

Keywords: *Visual Quality, Semantic Image Segmentation, Deep Learning, Street Design, Transport & Urban Planning*

1. Introduction

The streets give the city its identity and serve as its backbone. Streets are more than just a mode of transportation or movement; they are also a large urban gathering place. Streets are divided into two categories: movement and place. Streets are not simply linear places but also three-dimensional areas, including the built mass along the roadway and streetscapes. The street serves several purposes, including eating, sleeping, strolling, gathering, shopping, celebrating, and worshiping (Kost & Nohn, 2011). High-quality street space promotes not just urban vitality but also pleasant social interactions, outdoor activities, and public health (Handy et al., 2002; Ye et al., 2018). Effective street quality evaluation can improve cities' architectural and spatial environment quality, as well as the living environment and the creation of a distinct urban image, making it an important research area in urban spatial form research and landscape design. It is also a significant topic in landscape and urban planning (Zhao & Guo, 2022).

The present evaluation of street quality relies on two aspects: the composition of objective indicators based on the street environment (physical parameters) and people's subjective perceptions (Lange & Legwaila, 2012). The measurement technologies of the physical environment are based on spatial data that include traditional three-dimension spatial data, location-based services data (LBS), point of interest (POI) data, and transportation data. Traditional questionnaire surveys, emotional analysis of social media data, and physiologic perceptron analysis are the three types of pedestrian perception assessment methods currently used (Wan, Lu, & Sun, 2022).

The emergence of new techniques and methods provides a rare opportunity for the accurate, automated, and scientific assessment of the quality of streets. New methods, such as a collection of deep convolutional networks for reliably extracting spatial properties from SVIs, have evolved with the growth of machine learning techniques. Meanwhile, alternative machine learning approaches, such as artificial neural networks (ANNs), may be useful in tackling the complex relationships between multiple design components and quality in order to achieve an appropriate evaluation of this intangible value. In summary, new research opportunities for measuring the "unmeasurable" are rising with the emergence of new technologies (Ye, Zeng, Shen, Zhang, & Lu, 2019).

But very few studies have been done to measure quality of streets incorporating objective indicators and people's

subjective perceptions using automated new technologies: (1) Constructing the Quality Measurement Model of Street Space and Its Application in the Old Town in Wuhan (Tianyue Wan, Wei Lu and Peijin Sun, 2022) and (2) Intelligent Assessment for the VQOS: Exploration Based on Machine Learning and Large-Scale Street View Data (Jing Zhao and Qi Guo, 2022). Further, it is still difficult to assess the quality of a street using an objective physical environment and a non-objective subjective pedestrian experience and current research on the measuring of streets' quality focuses on the index system's development, data collection, and processing, with no verification of the measurement findings' reliability or the measurement model's validity (Wan, Lu, & Sun, 2022). Since individuals have their own unique opinions when measuring the quality of street space, the question for determining street quality on a broad scale is whether the assessments from expert panels are credible and consistent for quality estimate conclusions (LI, et al., 2021). As a consequence, there is a need to develop a new quantitative framework for measuring the visual quality of streets. This study proposed a new quantitative framework for measuring the visual quality of streets while validating and assessing the accuracy of the proposed framework and demonstrating the possible applications of proposed method in urban planning and design purpose.

2. The Conceptual Framework

2.1 VISUAL QUALITY OF STREETS
The human impression of the environmental factors connected with street space is referred to as streets' quality (LI, et al., 2022). The key word in this terminology is quality, which can be perceived differently in different contexts and may have different meanings depending on its application (Doğan, 2021). Slater (1985) developed the idea of comfort and categorized street comfort into three areas, namely physical, psychological, and physiological. Fruin (1971) highlights the synergy of safety, security, convenience, continuity, comfort, and beauty of streets in general. Physiological comfort is perceived through a variety of senses, including color, light, scent, sound, and thermal comfort, all of which are affected by the physical composition of street space.

2.2 METHODS OF VISUAL QUALITY ASSESSMENT OF STREETS
In terms of quality evaluation of streets, two methodologies are used: expert/design approaches and public perception-based approaches (zhao & guo, 2022). Further, many evaluation tools, such as walk score and stated of space index, have been presented to aid in accurate quality assessment and intervention planning (ye, zeng, shen, zhang, & lu, 2019). Ai and large data processing and analysis present a unique potential for automated street quality evaluation (zhao & guo, 2022). Several studies have been conducted in terms of assessing the quality of streets using street view images and machine learning algorithms.

2.3 INFLUENTIAL ATTRIBUTES FOR THE VISUAL QUALITY OF STREETS
There are multiple attributes that influence the street's quality. But considering the availability of semantic image segmentation models, classifiable categories of available image segmentation models and computation power, five main attributes were identified such as: greenery, sky view, building frontage, motorization and pedestrian space to assess visual quality of streets using developed FFNN model.

3. Methodology

This study contains four main phases as given in Figure 1. The first step consists of two major components: a literature review and an expert opinion survey. The second step is model development. Two main models have been developed in this study: the CNN model and the FFNN model. As the third stage, a python-based program developed to load the trained the model with weights and get the outputs for testing. The final stage is validation of the developed models. Both internal and external validation were conducted to identify the most suitable model for measuring the visual quality of streets.
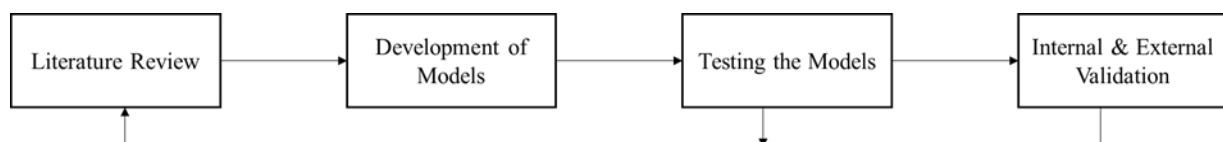

Figure 1, Summary of research design

3.1 DEVELOPMENT OF MODELS
In this study, two separate models were developed in analysing the visual quality of streets quantitatively. Therefore, this stage can be divided into two main parts such as,

Option 01 – Development the custom CNN models
Option 02 – Development custom FFNN model

3.2 DEVELOPMENT THE CUSTOM CNN MODELS
Here, proposed a methodology for developing custom CNN models in five stages. The models were trained with varying data amounts, and after the third stage, transfer learning was implemented using the MobileNet V2

architecture. To further improve performance, image augmentation techniques were applied in the final stage. The results demonstrate the effectiveness of this approach in enhancing the models' accuracy and generalization capabilities.

3.3 DEVELOPMENT CUSTOM FFNN MODEL
Influential attributes were identified through a literature review. With the aid of available computation power, an image segmentation model called SegFormer was chosen. Based on the identifiable categories from SegFormer, five attributes were determined: Greenery, Sky view, Building Frontage, Motorization, and Pedestrian Space. Subsequently, a FFNN model was developed to assess the visual quality of streets based on the outputs obtained from the SegFormer model.

3.4 EXTRACTION OF THE STEET VIEW IMAGES
Google Street View images are the main data source of this study. During the study 2684 street view images were extracted to train the models utilizing three methods have been utilized to extract GSV images, such as,
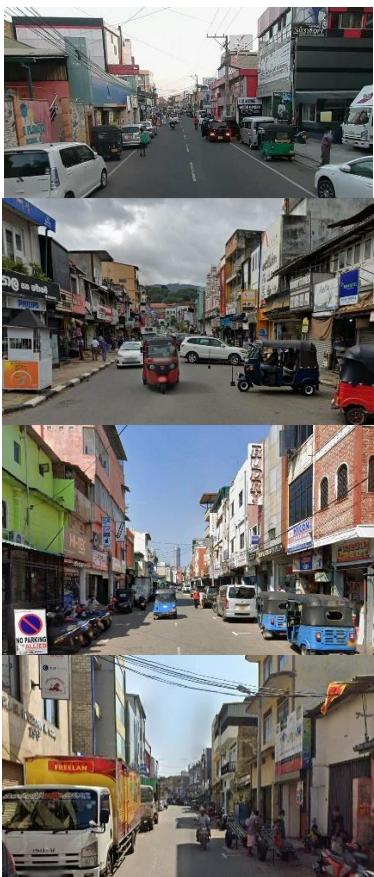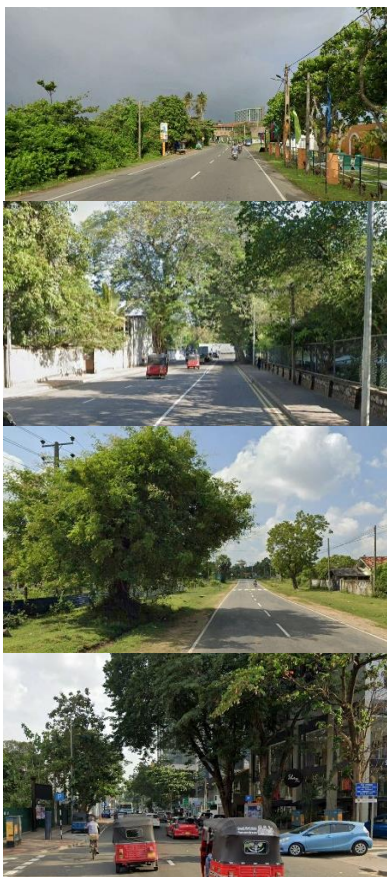
1. Manually collected using Google Street View and Snipping Tool
2. Using GSV static API
3. Already available Cityscapes data sets

Required number of images were identified through literature review and assessing the internal accuracy of developed models.

3.5 RATING THE STEET VIEW IMAGES
The extracted 2684 GSV images were divided into 54 sets where each set was consisted by 50 images and distributed among experts and general public for rating. 500 images were rated by general public and rest of the images were rated by the experts. The expert panel is consisting with professionals such as Town Planners and Architects, students who are following masters in urban designing and undergraduate students from the Department of Town and Country Planning, Department of Architecture and Department of Landscape Architecture of University of Moratuwa.

Table 1, Sample of rated images by the participants

Low Visual Quality	Moderate Visual Quality	High Visual Quality

3.6 ACCURACY ASSESSMENT
Both internal and external validation were used for the accuracy assessments of developed models.

3.6.1 Internal accuracy assessment

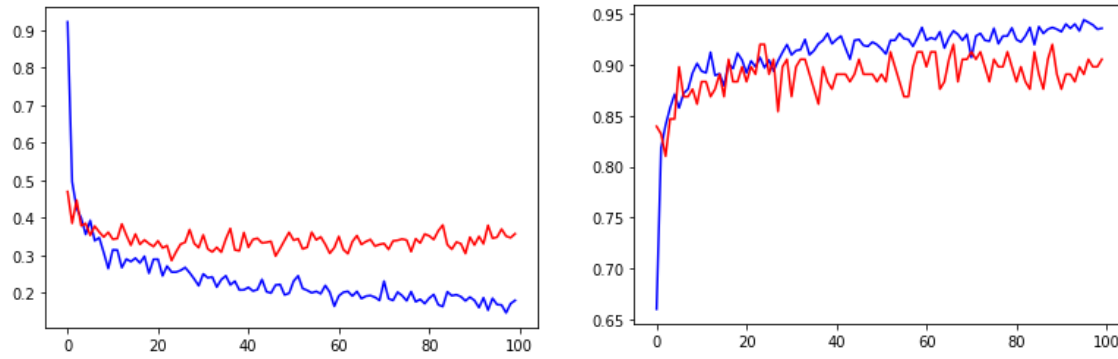Tenfold cross validation technique and accuracy metric in Keras was used for internal accuracy assessment.

Figure 2, The loss curve and the accuracy curve of the CNN model stage 05

3.6.2 External Accuracy Assessment

Kappa accuracy was calculated developing confusion metrices considering the actual and predicted ratings for the SVIs as the external validation.
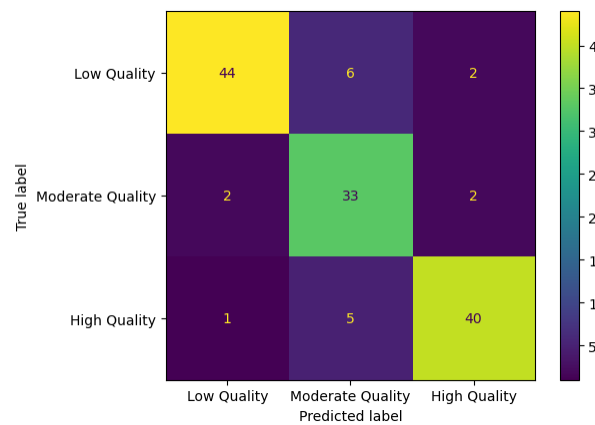

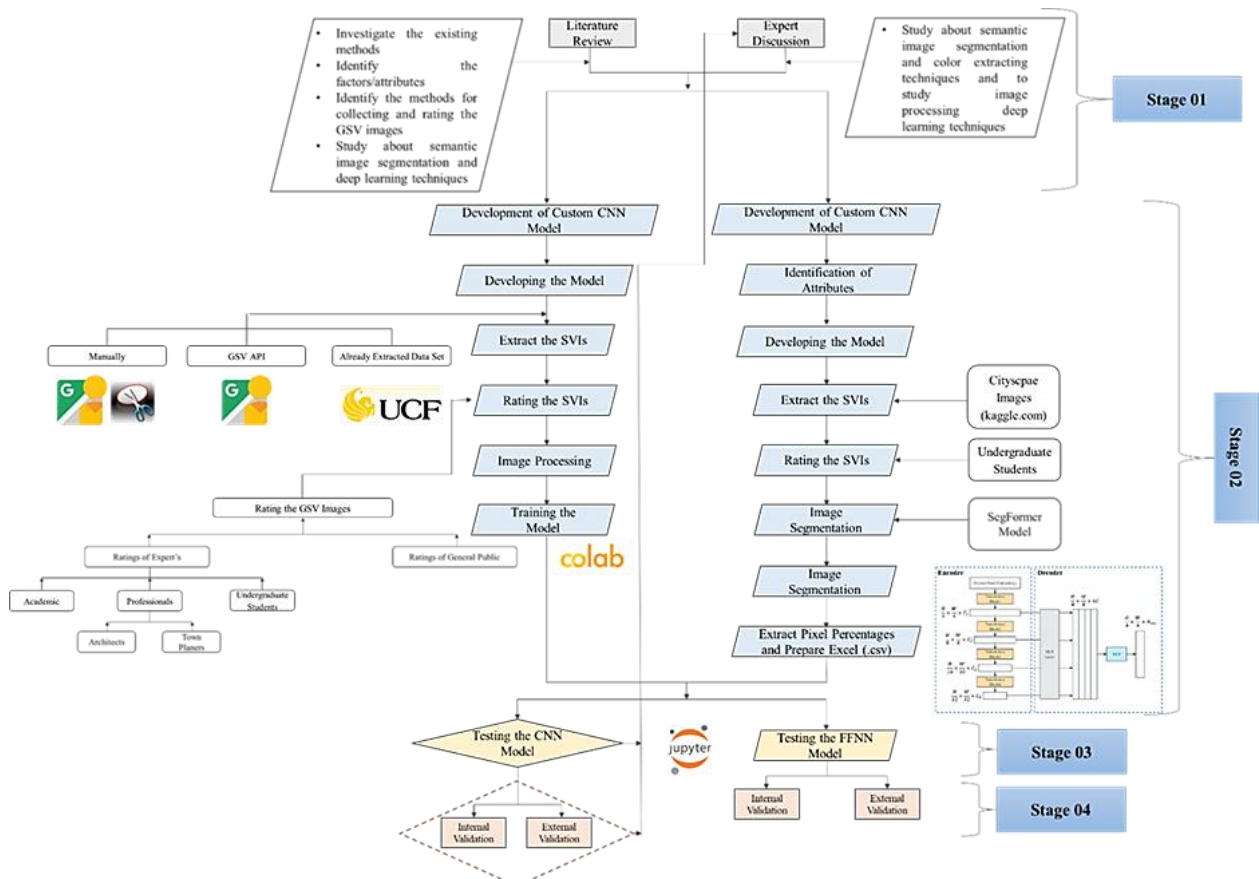Figure 3, Confusion matrix for experts' and general publics' rating vs CNN model stage 05 ratings

Figure 4, Detailed research design

4. Results

Both internal and external accuracy assessment of each stage of the developed custom CNN models and custom FFNN model were compared. By comparing the accuracy level of different stages of custom CNN models and custom FFNN model as well as the advantages of each model, the most suitable framework to measure the visual quality of streets was selected. Therefore, the fifth stage of custom CNN model is more suitable for measuring the visual quality of streets according to the analysis and results.

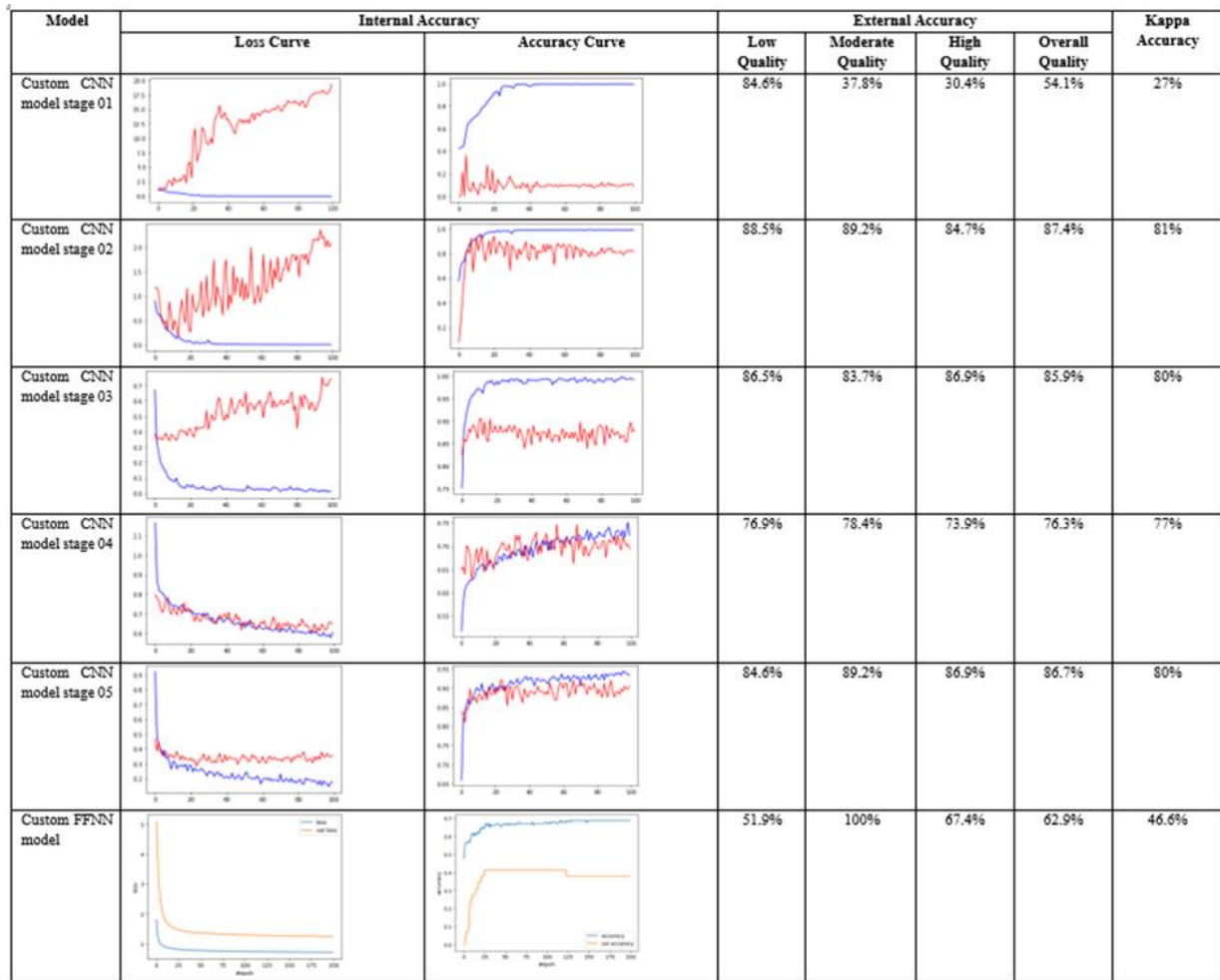| Model	Internal Accuracy		External Accuracy				Kappa Accuracy
	Loss Curve	Accuracy Curve	Low Quality	Moderate Quality	High Quality	Overall Quality	
Custom CNN model stage 01			84.6%	37.8%	30.4%	54.1%	27%
Custom CNN model stage 02			88.5%	89.2%	84.7%	87.4%	81%
Custom CNN model stage 03			86.5%	83.7%	86.9%	85.9%	80%
Custom CNN model stage 04			76.9%	78.4%	73.9%	76.3%	77%
Custom CNN model stage 05			84.6%	89.2%	86.9%	86.7%	80%
Custom FFNN model			51.9%	100%	67.4%	62.9%	46.6%

Figure 5, Comparison of developed models

The proposed framework for measuring the VQOS can be divided into three main parts: input, process and output.
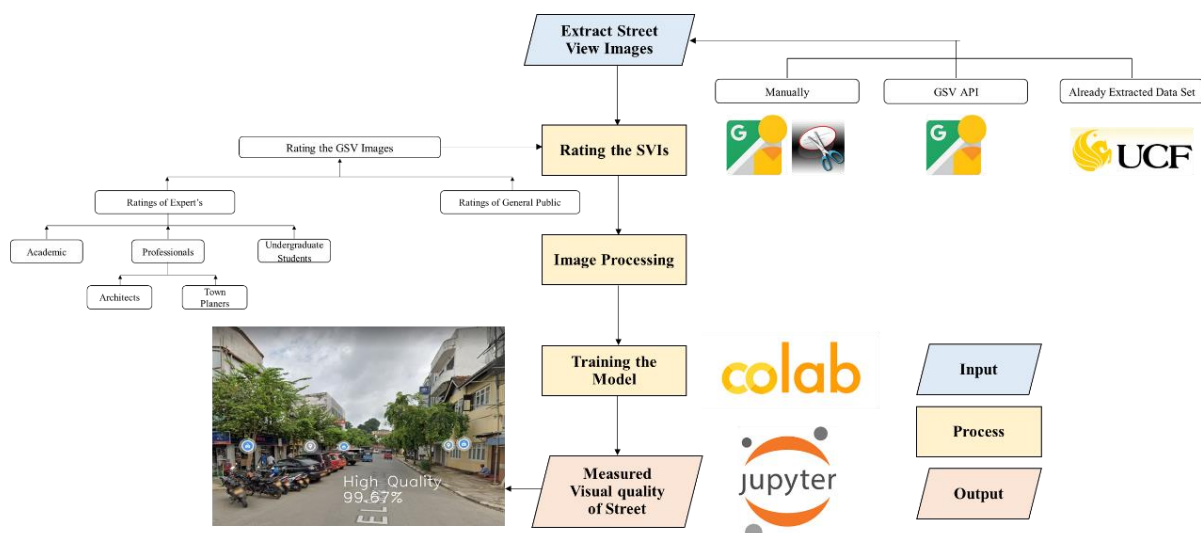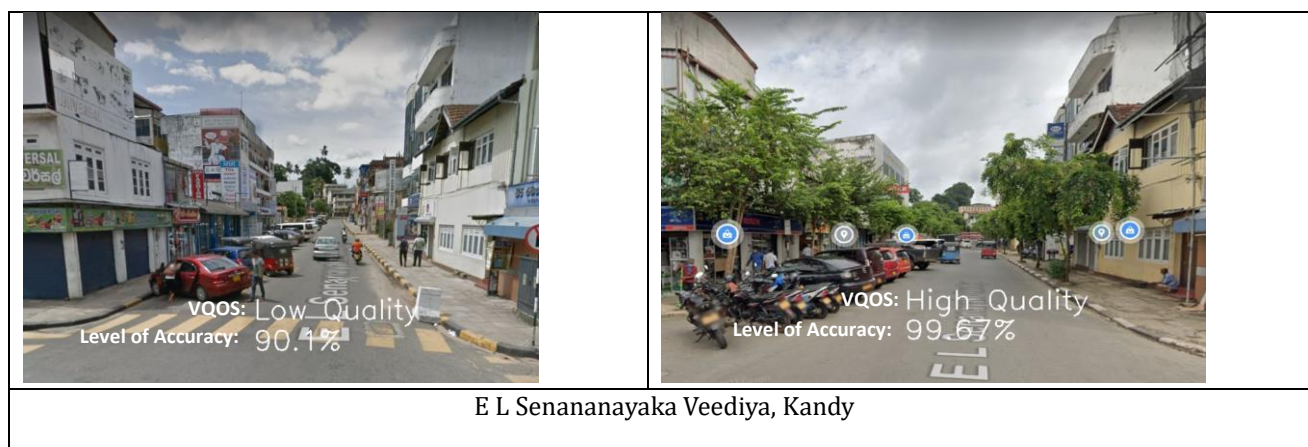
Figure 6, Proposed framework

5. Applicability of the Findings in the Context of Urban Planning and Designing

This research paper introduces a framework that can serve as a versatile tool in multiple applications related to the visual quality of streets. Firstly, it can be utilized as a tool for measuring the visual quality of streets, providing objective assessments based on identified attributes. Secondly, it can be employed as a tool for mapping the visual quality of streets, enabling the visualization and analysis of street aesthetics at a larger scale. Lastly, it can be utilized as a tool for assessing the impact of proposed developments and guidelines on the visual quality of streets, aiding decision-making processes. The proposed method offers valuable insights and practical applications for urban planners, designers, and policymakers in enhancing the visual aesthetics of urban streetscapes.

Table 2, Assess the impact of proposed developments towards the visual quality of streets

Before	After
VQOS: Moderate Quality Level of Accuracy: 91.71%	VQOS: Low Quality Level of Accuracy: 99.91%
Colombo-Kandy Road	
VQOS: Moderate Quality Level of Accuracy: 96.68%	VQOS: Moderate Quality Level of Accuracy: 97.45%
Colombo-Kandy Road	
VQOS: Moderate Quality Level of Accuracy: 99.97%	VQOS: Low Quality Level of Accuracy: 74.56%
Colombo-Kandy Road	
VQOS: Moderate Quality Level of Accuracy: 58.35%	VQOS: Low Quality Level of Accuracy: 98.54%
Piliyandala Road	

E L Senananayaka Veediya, Kandy

6. Conclusion and Recommendations

The research used deep learning algorithms to examine street view photos for visual quality, surpassing current limits. Existing studies are often based on manually gathered, small-scale datasets and use time-consuming methodologies to measure street quality utilizing an objective physical environment and a subjective pedestrian experience. Existing research concentrate on index system creation, data collection, and processing without verifying measurement results. The research offered a quantitative methodology for gauging street visual quality.

The research has four stages. In the first stage, literature reviews examined the existing methods and models used to quantify street visual quality, the factors/attributes that affect it, the areas to collect GSV images, the methods for collecting and rating them, semantic image segmentation and col-our extracting techniques, and image processing deep learning techniques. Additional expert conversations were held to identify factors/attributes that impact street visual quality, strategies for collecting and assessing GSV photos, semantic image segmentation, color extraction, image processing, and deep learning. The research created two major street quality models in the second stage. Model testing is the third step. At the fourth step, this research validated internally and externally. This research offered a quantitative approach for determining street visual quality after validation. The research also revealed ways to gather and grade SVIs and the number needed to train the algorithm. The framework includes SVI collecting, rating, image processing, CNN development, model training, testing, and vali-dation.

Lastly, the research examined how the suggested framework may be used in urban planning and design to measure, map, and evaluate VQOS-related changes and recommendations. The study has contributed with a simple and quantitative framework for measuring the visual quality of streets. Urban planners, urban designers, architects and landscape architects can employ this framework to quantitatively measure the visual quality of streets.

There are some limitations of practicing this prosed framework such as,
1. Only 2684 GSV images were able to extracted and rated for training the different stages of CNN models
2. Only 150 GSV images with segmentation were able to extracted and rated for training the FFNN model
3. Unable to utilize highly accurate image segmentation model
4. Manually captured GSV images can be subjective to the capturer
5.

These limitations can overcome by using the following approaches,
1. Using GSV API for extracting street view images
2. Using pair wise comparison and crowdsourcing approach to rate the images
3. Using GPUs, for training the developed models as well as image segmentation models

In this study, accuracy assessment of the proposed framework was conducted. Moreover, an assessment on effectiveness and efficiency of the proposed framework is required.

Further, this research and the developed concept can investigate a few future case study areas, but not limited to the following.

1. Identification of physical elements which create significant impact of visual quality of streets
2. Develop a model to measure the sense of place using Deep Learning Algorithms and SVIs
3. Develop a model to measure the safety of different places using Deep Learning Algorithms and SVIs

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