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A NOVEL FRAMEWORK FOR ROAD DATA SURVEYING BASED ON DEEP-LEARNING AND GIS

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ABSTRACT

This paper proposes a novel framework for road data surveying and 3D urban visualisation based on deep-learning technologies, open data, and GIS techniques. Existing road inventory preparation methods are time-consuming, labour-intensive, inefficient, and lack an acceptable method for 3D urban visualisation in Sri Lanka. Thus, modern approaches are not applicable due to a lack of resources, technology, and financial capacity; the proposed framework will enable us to overcome these weaknesses.

The study comprised of three main stages: a literature review, development of the framework, and its validation in Ranna area. The framework was applied to two consecutive model validation events: the first related to the road data surveying model and the second to the 3D urban visualisation model. Its proposed returned KAPPA Accuracy Scores were 92% and 90% respectively.

The findings of this study further the use of cutting-edge deep learning and mapping techniques in transport and urban planning, making the preparation of road inventory surveys and 3D urban visualisations more cost-effective and efficient. Transport engineers, urban and regional planners, geographers, and GIS experts can employ the proposed framework for road data collection and 3D urban visualisation.

Keywords: *Road and Land Use Data, Deep Learning, Open Data, Transport Planning, GIS*

1. INTRODUCTION

The transportation system is considered one of the essential components of modern urban development [1]. It helps to increase mass passenger and resource distribution and to enhance the accessibility. In such a context, road inventory surveys provide essential information for decision-makers and engineers to evaluate diverse characteristics of the transportation system (i.e., road safety, level of service, passenger and vehicular demand, quality of the transportation network, etc.) [2], [3]. Therefore, maintaining road inventory information in a fresh and up-to-date manner contributes to efficient and sustainable transportation management [4], [5]. There are many techniques to collect road inventory information. A number of research have been conducted using diverse techniques [6], [7], [8]. However, many of these techniques are costly, labour-intensive, and unable to capture rapid changes in transportation networks [3].

Therefore, in this study we introduce a novel framework to collect road inventory information including road material, road type, and surrounding land use character of a road network. This framework is useful for sustainable transportation management and development because it provides many types of information on current road networks [9].

Road material information is very important to identify the road segments that require maintenance during road construction projects. At the same time, road type information provides essential information to estimate passenger car units (PCU), level of service (LOS), and traffic flow patterns of the transportation network [10], [11], [12]. Information of the land-uses alongside the road network is important to understand urban development patterns in a given area and the quality of the transportation systems that serves the area [13], [14], and [15]. The framework extracts each of these types of information using cutting-edge, deep learning and mapping techniques.

At present, diverse technologies are used to extract road inventory information, such as field inventory, photo/video logs, integrated GPS/GIS mapping systems, aerial photography, satellite imagery, virtual photo tourism, terrestrial laser scanners, and mobile mapping systems (i.e., vehicle-based LiDAR and airborne LiDAR) [2], [8], [16], [17], [18]. The field inventory data collection method delivers rich road inventory data as it follows the in-situ data collection method [7]. This method has several limitations such as the crew being exposed to traffic, lengthy field data collection time, and lower accuracy due to human biases of the surveyors and the technical faults of equipment, etc. Therefore, many studies tend to use ex-situ, (i.e., remote) road inventory information extraction methods by using the image classification techniques with terrestrial laser scanners, aerial photography, satellite imagery, and LiDAR data. However, this approach also has significant limitations and failures due to the nature of data used. For example, although LiDAR, a relatively new type of mobile mapping system, can collect large amounts of detailed 3D road data, it requires expensive equipment and significant data reduction to extract the desired inventory data [6]. Hence, the use of these techniques is not feasible in developing countries. On the other hand, satellite imagery and aerial photography have limitations due to low spatial accuracy of sensors and the non-availability of diversified imaging indexes that capture feature objects [11]. Therefore, it is difficult to design a general-purpose algorithm to effectively extract road material, type, and land use feature information based on imagining indexes and classification techniques [10].

This paper proposes an innovative framework to collect road inventory information related to road material, road type, and land use features using state-of-the-art computer visioning technologies and Google Street View Imagery (GSVI). Unlike satellite imagery, GSVI is free and widely available in many countries, and it is free of cloud distortions [13], [19], and [20]. The most important benefit of the GSVI is that, since the images are taken from the road with a 360° view, they detect surrounding land use features and roads without disturbance [20]. Therefore, it is relatively more convenient to extract road information from the GSVI and to classify corresponding road network materials, types, and land use features. Therefore, the proposed method is well-suited for developing countries to prepare their road inventory systems in a cost-effective, efficient, and accurate manner.

This study tries to overcome four major limitations noted in previous research in this area.

- existing road data collection methods are expensive, labor-intensive, and unable to capture rapid changes in transportation systems.
- multi-spectral imaging indices are incapable of capturing ground objects due to the similar spectra and textures of feature objects in imageries.
- satellite images have several limitations due to their aerial nature and spatial accuracy.
- most state-of-the-art road data collection systems use expensive and labour-intensive methods of primary and secondary data collection. Hence, those approaches are not feasible for developing countries.

Considering the above limitations, the primary objective of this study was to propose a sophisticated modelling framework to collect road inventory information in countries like Sri Lanka. It used the Southern Province of Sri Lanka as its demonstration area. Figure 1 depicts the process adopted in the study.

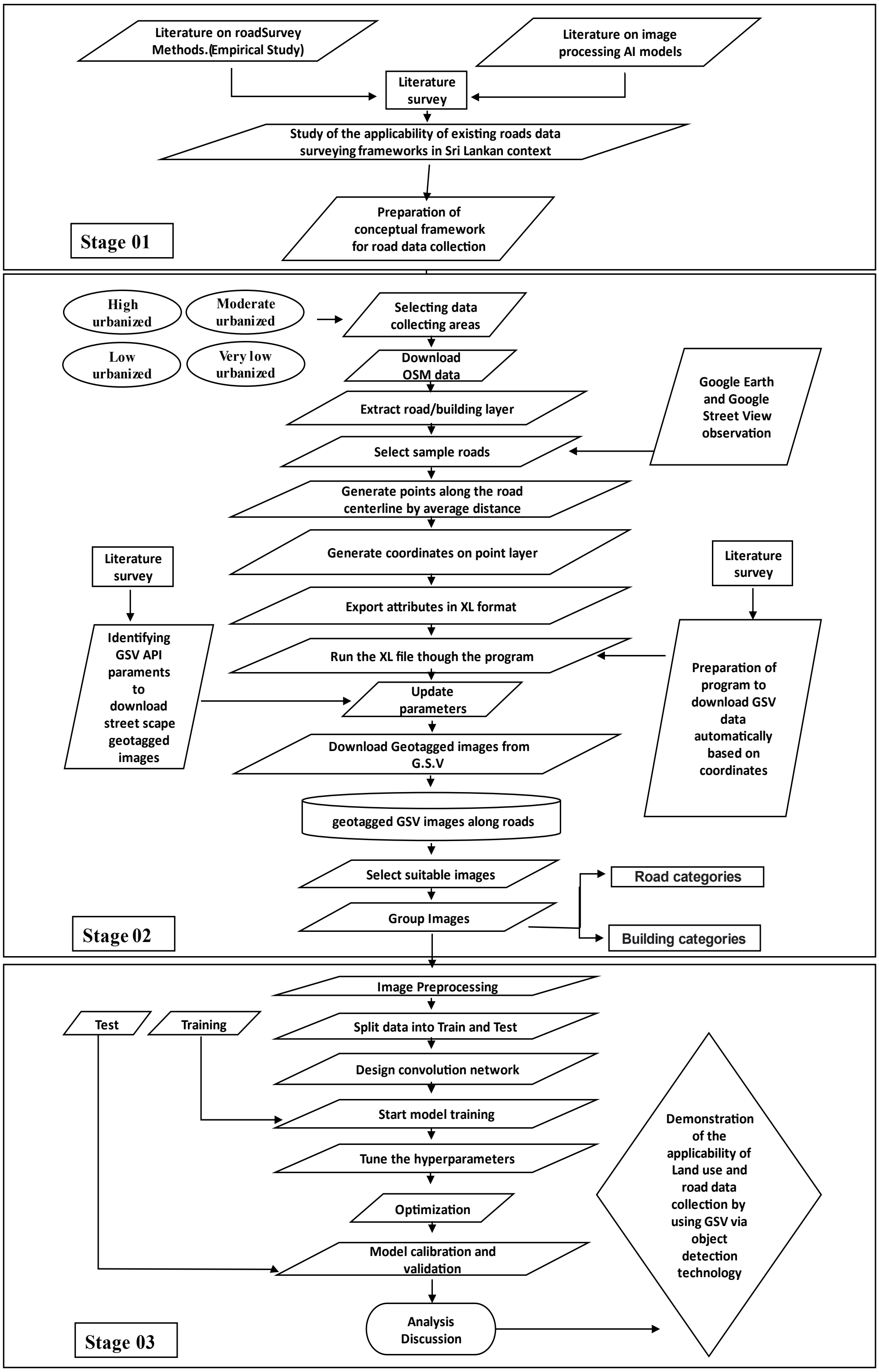

Figure 1: Research Design

The findings of this study may contribute to a more accurate approach to capturing the road information that may be essential for future transportation management and development, land use visualisation, and land value capture models.

The rest of this paper is organised as follows: the model formulation section discusses the proposed analytical framework; it is followed by the accuracy assessment; analysis and results; and the conclusion of the study.

2. MODEL FORMULATION

Literature review, model development, application, and validation were the main steps of model formulation. This literature review has two main components. The first component examines existing road and building classification systems. Different road categorisation and building use mapping methodologies were studied at this point. In the second component, the efficacy of several models in identifying urban features, the limitations of existing classification methods, and the limitations of using global approaches in Sri Lanka were reviewed.

Following this, a semi-automated framework was formulated to circumvent the aforementioned limits. Therefore, the Road Category Model (RCM) and the 3D Urban Visualisation Model (3D UVM) were developed as core elements of this study. The main technical approach employed to develop this framework is deep learning (DL). Finally, a demonstration was carried out to test the validity of the suggested framework, and an expert interview survey was conducted to determine its efficacy in Sri Lanka. This section delves into the framework's development in depth.

2.1. Proposed Framework

The Road Classification Model (RCM) and 3D Urban Visualisation Model (3D UVM) are included in the proposed framework. Both models employ GSV pictures and OSM data as their primary inputs. Apart from these, Digital Elevation Model (DEM) was the secondary input for 3D UVM. OSM data was extracted using QGIS software, while GSV photographs were retrieved using custom Python software.

The primary processing phases for each model are explained in the sections that follow.

2.1.1. Road Classification Model (RCM)

As part of the RCM model's initial process, polyline properties needed to be retrieved from the extracted OSM data. This data consisted of five categories. Significant road layers were then necessary to choose amongst the transportation routes. Following the selection of road layers, sample points and road segments were identified.

Using QGIS geometry tools, the GPS information for the attribute table of the point layers were updated. The GSV image processing model was employed in the second stage of data processing, which was the most important phase. Using updated GPS coordinates and proper parameters, the Python script collected GSV pictures of the roadways. The georeferenced GSV images for the defined locations were then directly downloaded. The image processing model was then assigned to work with these GSV images. Each image categorised as two-lane demarcated asphalt, two-lane not demarcated asphalt, one-lane asphalt, one-lane concreates, two-lane concrete, and four-lane asphalt roads.

2.1.2. 3D Urban Visualisation Model (3D UVM)

Building footprints were extracted from the OSM polygon layers. The same method as in RCM was employed to produce a GPS point layer for specified road layers. As a result, based on context, the distance between points needed to be maintained. The 3D UVM then functioned similarly to the RCM. This model can predict GSV images in four different categories since it has been trained to distinguish commercial and residential buildings into two height categories (one storey and two or more floors). In the building footprint layer, the height and building use information were modified. Finally, the new building footprint was merged with the DEM layer using the Agis threeJS plugin.

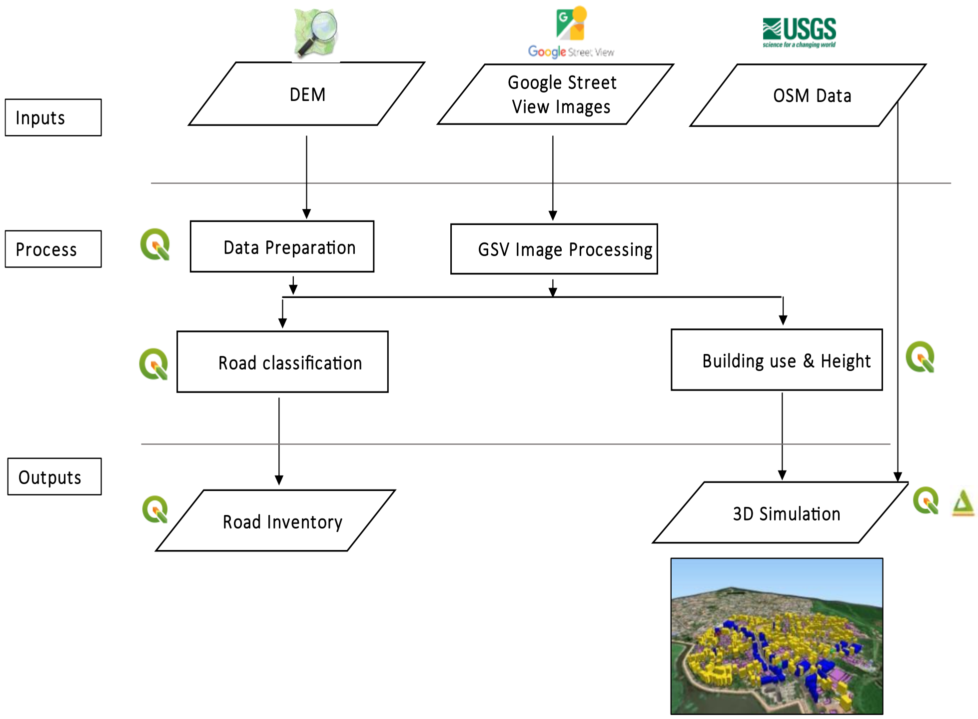

Figure 2: Structure of the Proposed Framework

Figure 2 depicts the combined processes of both models. The major outputs of the framework are 3D urban visualisation and information on road categorisation by location. Once both models are operational, users can construct a 3D urban environment by merging DEM with road layers, which specify road material and the number of lanes.

2.2. Testing of the Proposed Framework

Ranna, a locality in Sri Lanka's Hambantota district, was the study area selected for the testing/demonstration of the novel method. It was chosen as the most appropriate study area within walking distance of the research team because of COVID-19 and transportation restrictions that prevailed during the research period. Several types of roads exist within Ranna's borders. The location of the case study area is depicted in Figure 3.

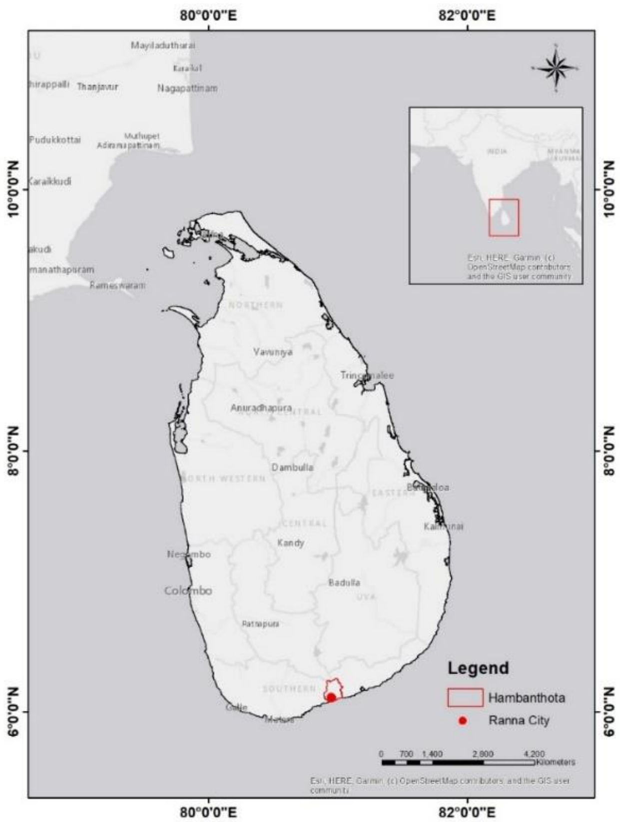

Figure 3: Location of Ranna in Sri Lanka

In a large urban centre, only commercial land uses may be seen along the roads. In small towns like Ranna, however, a single road might include a mix of land uses such as residential, commercial, and other uses. Table 1 summarises the basic profile of the location.

Table 1: General Information on Ranna

	Area (sq.m)	Population Density	Urbanisation Level
Ranna	4,276,409*	1656*	Relatively lower

Source: * Department of Census and Statistics, Sri Lanka (2012) Compiled by the authors

2.3. Data

The RCM was formulated using two key public data sources, as indicated in Table 2.

Table 2: Main Data Sources Used for RCM

Data	Source
OSM data	Open Street Map
Google Street View Images (GSV)	Google street view static API

Source: Compiled by the authors

The 3D UVM was created using data from four different sources (Table 3).

Table 3: Main Data Sources Used for 3D UVM.

Data	Source
OSM data	Open Street Map
Google Street View Images (GSV)	Google street view static API
Google Earth Image	Google Earth Pro
DEM	USGS Earth Explorer

Source: Compiled by the authors

OSM data is part of the VGA (Voluntary Geographic Information) collection, which is a widely available free and open-source resource. Table 4 shows the data extracted from the OSM for this study.

Table 4: Data Extracted from OSM

OSM Source	Extracted Data
Polyline	Road
Multi Polygon	Building footprint
Points	Industry, Education, Institute

Source: Compiled by the authors

GSV images were the other major data source in this study. GSV is the world's most widely employed streetscape data source. GSV images provide you with a 360-degree perspective of an area. GSV images were used to create road section views and streetscape view images in this research.

2.4. Data Preparation

OSM data acquired via QGIS open layers plugin under the data preparation. QGIS and Open Layers Plugins are freely available resources that can be used without financial outlay. The process of data acquisition is shown in Figure 4. According to this, transportation layers, POI data, and building footprint data were gathered from OSM.

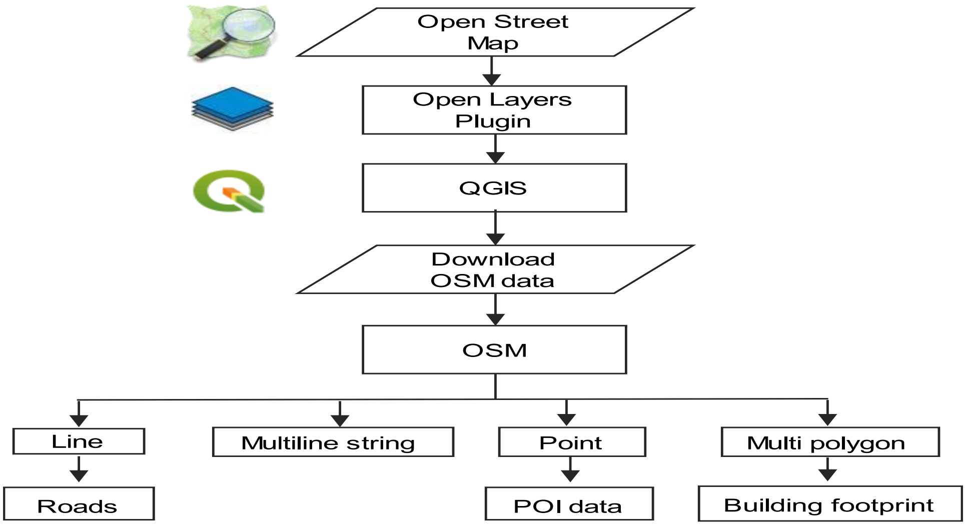

Figure 4: OSM Data Acquiring Process

GSV Statistic API was applied to acquire GSV images via an HTTP URL request. A python-based automated program was developed, as depicted in Figure 5, to capture GSV images based on the coordinates and the API parameters.

```
location = '6.02999718865,80.7931057252'
apiargs = {
'size': '600x300', # max 640x640 pixels
'location': location,
'heading': '210',
'pitch': '0',
'fov':'100',
'key': 'key'}
```

Figure 5: GSV API Image Extraction Parameters

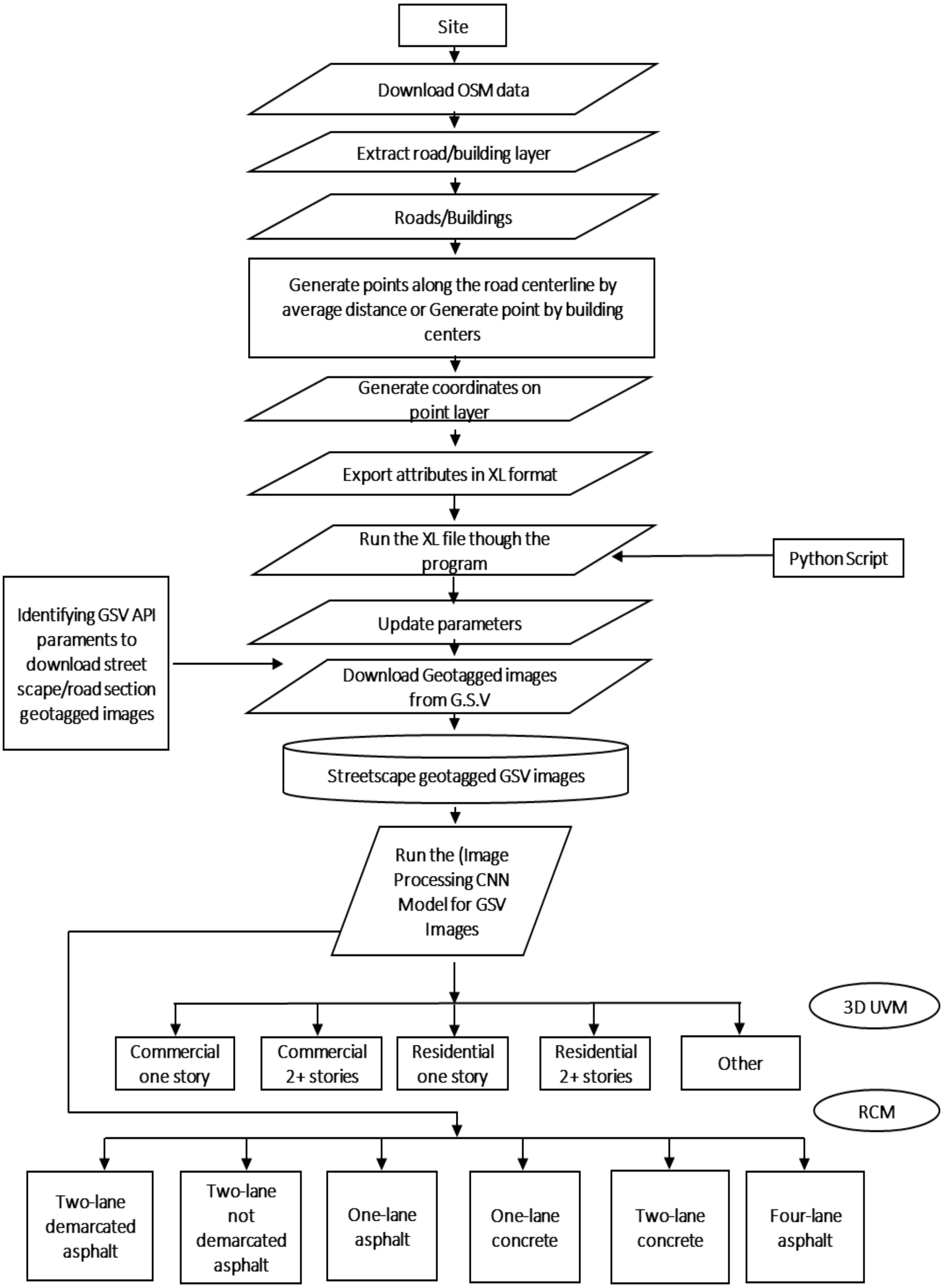

Figure 6: GSV Image Preparation

Figure 6 presents the GSV image preparation process. GSV images were also captured to their respective coordinates. The GPS positions of the selected roadways were prepared as part of that procedure. Highly urbanised, moderately urbanised, and low urbanised were the three urban classifications applied to pick routes for sample data collecting. As a result, 45 cities were chosen. Figure 7 exhibits some sample images from seven different cities.

Figure 7: A Collection of Sample Images from Different Cities in Sri Lanka

Subsequently, a point layer was created for each route that spanned a large distance. Later, a built python script was employed to retrieve GSV images from the road point locations with GPS information. For RCM training, images were categorised into two-lane demarcated asphalt, two-lane not demarcated asphalt, one-lane asphalt, one-lane concrete, two-lane concrete, and four-lane asphalt categories; for 3D UVM training, images were categorised into commercial single-storey, commercial two or more floors, residential single-storey, residential two or more floors, and other categories.

Figures 8 and 9 exhibit examples of the above-mentioned categories. In the RCM, 2500 images were gathered for each category, and 5000 for the 3D UVM. To extract road features, the dataset was optimised with multiple locations. Roads in developed areas, rural areas, and areas with vegetation cover are examples of location types. However, 3,046 images from the GSV collection have been altered by vehicles, humans, and vegetation. These images were deleted from the total of 50,000.

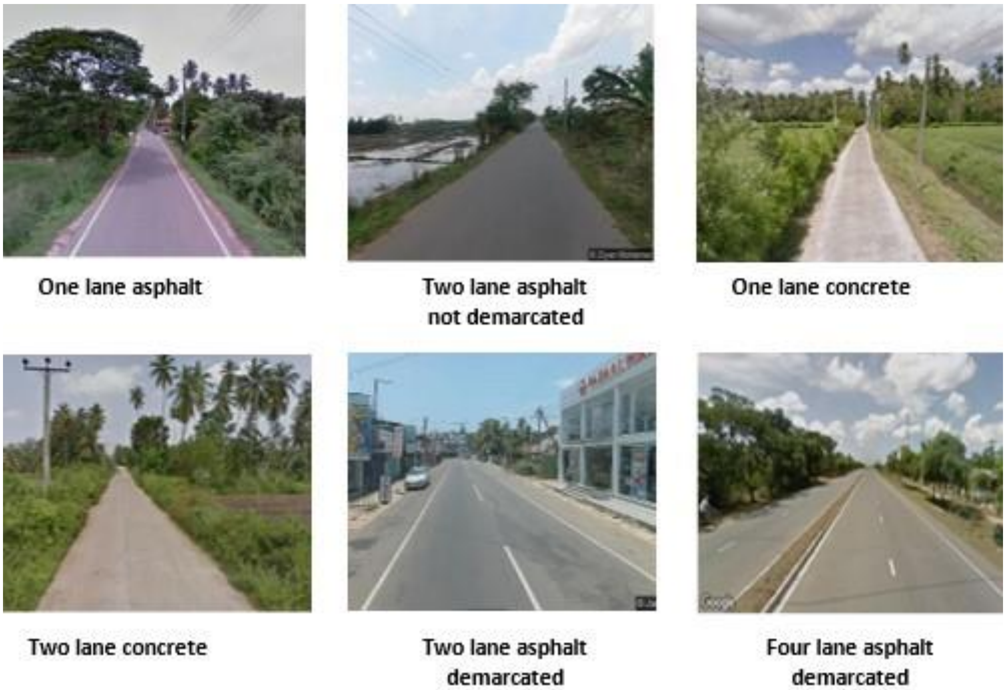

Figure 8: RCM Training Categories

Figure 9: 3D UVM Training Categories

2.5. Model Calibration

The image processing (IP) model is the centrepiece of this proposed framework. It was built with the "Keras" and "TensorFlow" libraries and Python was exploited as the programming language. The model was developed using the "transfer learning" technique in this study. As a result, it does not need a large number of training samples. Using classified GSV images, IP models were trained. 80% of the images were exploited to train the models, and 20% of the total images were utilised to test each model in the process. For binary classification, the sigmoid activation function was utilised. Therefore, the last layer was activated using SoftMax, whereas the middle levels were activated with "Relu" and model's optimiser was "adam." In addition, both models were built using the same CNN architecture. The mini batch selecting method was chosen at random in that process, and it was repeated to obtain a significant value while increasing accuracy.

SoftMax,

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad \text{……………………………………………………..} \quad (1)$$

σ = SoftMax

$\vec{z}$ = input vector

e^{zi} = standard exponential function for input vector

k = number of classes in the multi-class classifier

e^{zj} = standard exponential function for output vector

Sigmoid,

$$S\,(x) = \frac{1}{1+e^{-x}} \quad \text{……………………………………………………} \quad (2)$$

$S\,(x)$ = Sigmoid function

e = Euler's number

2.6. Model Validation

The validation and use of the framework in the study are discussed in this part. Six roads and structures along the designated roads were chosen considering the following factors.

(i) The GSV image quality of the roads.

(ii) Hierarchy of the roads.

(iii) 5 KM buffer from the town canter.

The study executed accuracy assessment in the RCM model, 3DUVM model separately. In addition, the effectiveness of the proposed framework was investigated based on an expert survey.

Under RCM validation, accuracy was first discussed with the testing dataset, followed by a comparison of model predictions and manual road category classification. Finally, the RCM model accuracy was determined using the kappa accuracy and confusion matrix.

$$k = (\,p_o - \,p_e)/(1 - \,p_e) \quad \text{………………………………….……} \quad (3)$$

p_o = Probability of observed agreement.

p_e = Probability of agreement by chance.

Similar to RCM model validation, 3DUVM accuracy was discussed with the testing dataset first. After that, the 3DUVM model forecast was compared with the manual categorisation of the buildings. Kappa accuracy was employed to demonstrate the model correctness in the 3DUVM model as well.

To measure the effectiveness of the proposed framework and to identify limitations of the proposed framework in the real on-the-ground application, eight criteria were selected based on literature reviews. The rationale of conducting an expert survey was to evaluate the above-mentioned criteria. Thus, participants needed to know the existing LU mapping techniques, road inventory methods in Sri Lanka, and the proposed framework techniques.

A snowball sample method was employed to conduct the expert survey. Therefore, ten professionals were selected from different professions based on the expert recommendations. The professions and the institutional affiliations of survey participants are listed in Table 5.

Table 5: Participants in the Experts' Survey

Profession	Institution
Academic	University of Ruhuna
Town Planner	Urban Development Authority
Postgraduate Researcher	University of Huddersfield, UK
Surveyor	Survey Department Sri Lanka
Town Planner	Urban Development Authority
Surveyor	Survey Department Sri Lanka
Planner/ Scientist	National Building Research Organisation
Postgraduate Researcher	Osaka University Japan
Planner	General Sir John Kotelawala Defence University
Surveyor	Survey Department Sri Lanka

Source: Compiled by the authors

3. RESULTS AND DISCUSSION

This section delves into the evaluation of the proposed framework. First, trained models were tested using a testing image set. Both models were fine-tuned using test data. Therefore, both models were found more than 90% accurate with the training dataset (Figures 10).

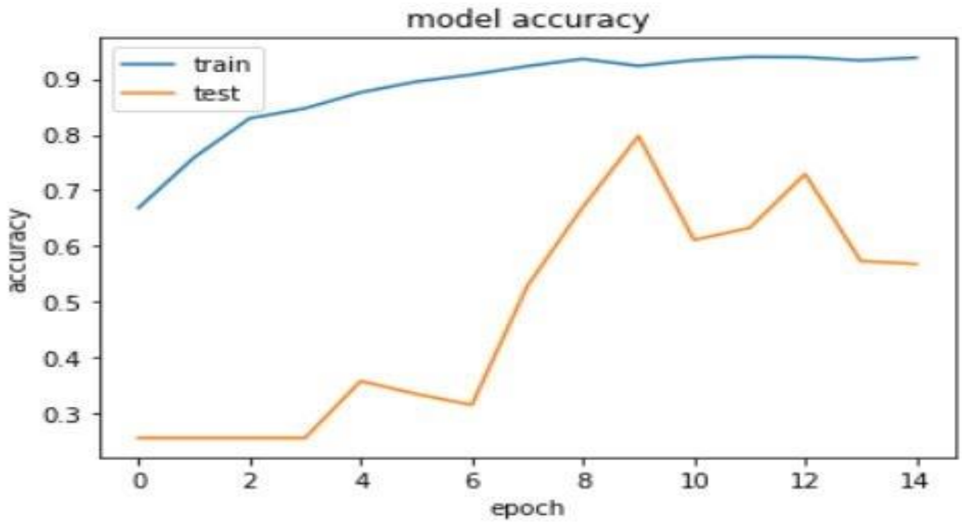

Figure 10: Testing of the Accuracy of the Model with Sample Data

3.1. RCM Results

As explained in the method, five different types of roads were chosen based on the road selection criteria. Figure 11 indicates the accuracy level for each road type. One-lane asphalt, for example, exhibited 100 % accuracy, which is significant in the RCM model. One lane concrete category had the lowest accuracy of 80%. Because Ranna is a small town, samples for the four-lane asphalt road category were not available. Most importantly, all road classifications had an accuracy rate of greater than 80%. The RCM accuracy of Kappa is 92%. Therefore, the RCM model was found to be useful in classifying road types in Sri Lanka.

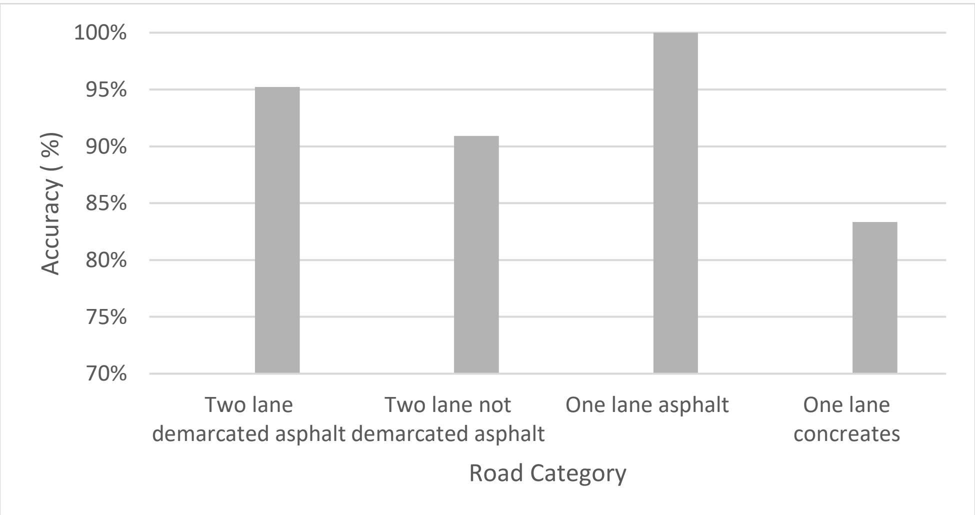

Figure 11: Level of Accuracy of the RCM by Road Types

Table 6: Level of Accuracy of the RCM Tested with Confusion Matrix

	Two lanes demarcated asphalt	Two-lane not demarcated asphalt	One lane asphalt	One lane concreates	Grand Total
Two lanes demarcated asphalt	95%	5%	0%	0%	100%
Two lanes not demarcated asphalt	9%	91%	0%	0%	100%
One lane asphalt	0%	0%	94%	6%	100%
One lane concreates	0%	0%	0%	100%	100%

Source: Compiled by the authors

According to the confusion matrix presented in Table 6, 5% of the images in the two-lane demarcated asphalt category were mislabelled as two-lane not demarcated asphalt. The road material in both groups is similar in this scenario. It demonstrates that the model correctly identified asphalt as road material. Furthermore, 6% of one-lane asphalt road images have been classified as one-lane concrete: this meant that although the model has identified the lane type, it had not identified the material. Therefore, the study was carried further to reveal the model's flaws. The failed images were then evaluated to determine the causes. The images that were incorrectly classified revealed other irrelevant features but not road components, according to the results. The reason for misclassification is the use of GSV images in this study. This can be avoided simply by visiting the location and capturing geotagged photographs instead of GSV images.

3.2. 3D UVM Results

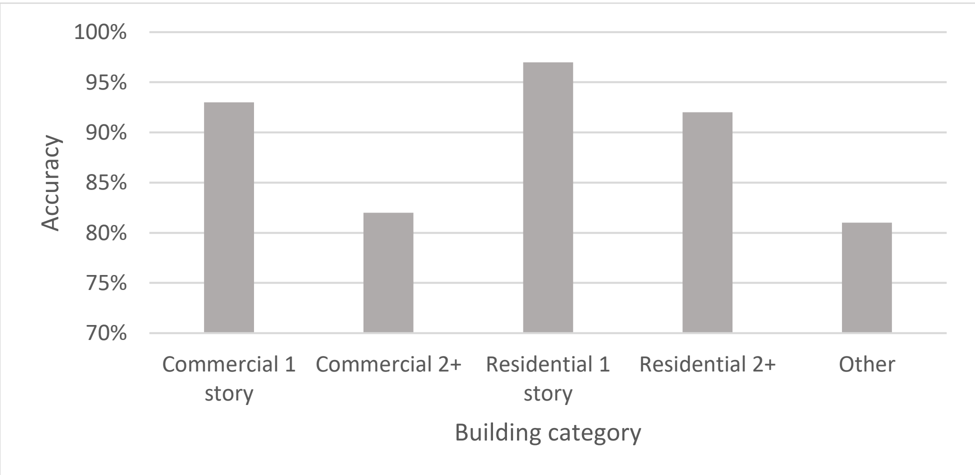

Figure 12: Level of Accuracy of the UVM by Building Category

According to the accuracy level of the 3D UVM model which presents by Figure 12, the highest accuracy shows in the residential one-story category that is 97%. The commercial one-story category shows the second-highest accuracy that is 93%. Also, the residential two or stories category shows a 92% level of accuracy, and the commercial two or more stories category shows 82%. Significantly, all the categories of the 3D UVM show an accuracy of more than 80%. At the same time, 3D UVM models' kappa accuracy is 90%. Therefore, the 3D UVM is significant on building category and height identification in the SL context (Figure 13)

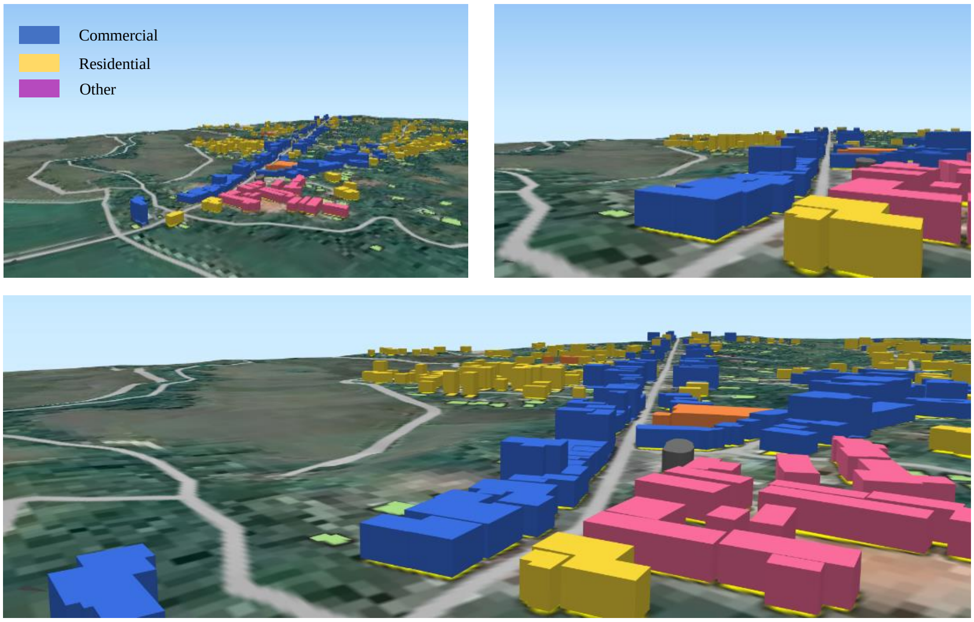

Figure 13: 3D Urban Visualisation - Ranna

3.3. Effectiveness of the proposed framework

According to the expert survey results in Figure 14, the proposed framework scored highest in terms of cost-effectiveness, time effectiveness, efficiency, labour effectiveness, and the level of importance in planning: these demonstrated the higher effectiveness of the proposed framework. And usability, learnability, and applicability in the Sri Lankan context indicate moderate effectiveness. However, the expert survey proved that the efficiency of the proposed framework is significant under the selected criteria. In concluding the effectiveness analysis, none of the parameters scored less than 3 and most of the parameters have scored more than 3 value range. Therefore, it proves that, in terms of all parameters, the proposed framework is effective in the Sri Lankan context. Therefore, the study has successfully achieved its objectives by developing an effective framework to classify roads and built-up land use.

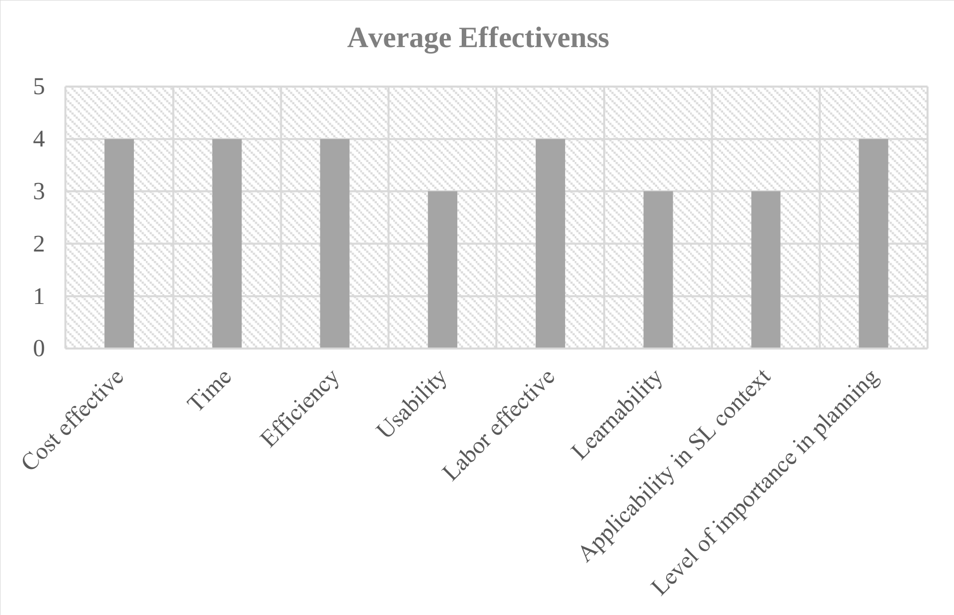

Figure 14: Effectiveness of the Proposed Framework

4. CONCLUSION

The key contribution of this work is the development of a methodology to collect road inventory information and map buildings with their uses and heights in urban areas. The study uses state-of-the-art of deep learning technologies and GIS mapping techniques. Field surveys are currently conducted to acquire road inventory data. This method is inefficient, time-consuming, and, most critically, cannot be updated on a regular basis. At the same time, due to a lack of data sources and mapping methodologies, little emphasis has been paid to mapping 3D land uses. Therefore, the proposed framework has effectively fulfilled the study's goal of providing an efficient framework for collecting road inventory information with 3D land use. Furthermore, the use of deep learning and GIS, both of which have superior performance and methodologies, brought further value to the proposed framework.

The proposed framework yielded KAPPA accuracy of 92% for the road inventory information surveying model and 90% for the 3D urban visualisation model, according to the research. As a result of the model's accuracy, the proposed framework is ideal for collecting road inventory and 3D land use data. Furthermore, expert discussions through detailed interviews suggest that the framework can be applied to the Sri Lankan setting. Therefore, key findings demonstrate that the study has built an efficient, financially feasible, labour-effective, and accurate framework for collecting road inventory and urban visualisation. Despite the fact that the study achieved its aims, it is not free from limitations. These can be found in a critical review and that may be addressed in future research. The first such limitation is the framework's applicability, which is dependent on GSV image coverage. Because the GSV databases in developing nations do not cover the entire road network. Second, since GSV images are not updated on a regular basis, output information will not be updated. However, these limitations can be addressed by employing a variety of data sources. Therefore, more research utilising a variety of AI techniques and data sources is required. Also, the testing of the framework and the model was limited to one particular study area. However, it is essential to test it in more areas to generalize the validity of the proposed framework. Although the framework has several limitations, the paper presented an effective application for collecting road inventory and 3D land use data, that was tested in Sri Lankan urban area. Since this framework can use streetscape images to map building uses and collect road data, it can be given inputs with manually collected images for higher accuracy. Therefore, those involved in transportation planning and management, urban development, and the similar engagements can employ the proposed framework to collect road information and 3D land use data for the purpose of developing effective transportation management and urban planning strategies that will lead to sustainable development.

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