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Optimizing Urban Planning with Satellite Imagery and Deep Learning-Based Object Detection

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ABSTRACT

This paper examines the use of satellite images and object detection deep learning algorithms to align urban planning to make it optimum. The study employs the Faster R-CNN deep learning algorithm by using high-resolution satellite images to identify and label the urban elements, including building, roads, vegetation, and bodies of water. Evaluation was based on precision, recall and Intersection over Union (IoU) scores with buildings and roads displaying high detection performance but vegetation and water bodies proved to be problems. The findings demonstrate that the model is useful in monitoring the trends of urban development, urban sprawling and land usage transformations, hence an important tool in sustainable urbanization. Additionally, the research highlights the significance of proper feature identification in order to improve urban strategic plans, especially in regards to environmental settlement and structure planning. The research ends with a reflection on the strengths and limitations of the model, together with directions in which it may be improved to achieve improved detection performance in cluttered urban scenes.

INTRODUCTION

City planning is very instrumental in developing cities and enhancing the living standard of city dwellers. With the ever-increasing global population, pressure to find appropriate and sustainable city development gains more intensity. The current solutions to the complex task of urban planning based on manual data collection methods, ground surveys, and inspections, fail to respond to the demands of the dynamic urban environment due to reduced scalability and inaccuracy (McKinsey Global Institute, 2018). These are time consuming, costly and sometimes do not capture the dynamic process of urban growth. The solution, therefore, needs innovative products capable of generating real-time, accurate, and comprehensive knowledge of urban landscapes.

A parallel emergence of satellite technology and deep learning holds the promise of revolutionizing urban planning, through the release of large-scale and high-resolution data, never before readily available, which can be analyzed automatically and with speed and ease. The sky images, especially the ones offered by Landsat, Google Earth, and Sentinel-2, can become an indispensable tool in terms of mapping a particular city and monitoring land-use change throughout the years (Liu et al., 2020). Large-scale satellite images are available using high resolution models and models, they can see the cities like a bird; urban areas are visible through road, building and vegetation locations, spots which are essential in urban development (Zhang et al., 2019). This type of data not only includes spatial information but they also contain temporal information that would allow planners to keep track of how such trends in the urban space evolve (Imran et al., 2019).

Long-term: Object detection concept of deep learning and satellite imagery can be applied to the enhancement of urban planning. The CNNs and deep learning, in general are found to be a helpful model of image comprehending and image classification. The ability to learn linear features and features well down a hierarchy in raw representations of images enables CNNs to be highly effective at detecting and classifying objects (LeCun et al., 2015). This has made them have significant applications in terms of large remote sensing processes such as the recognition of urban objects (Zhu et al., 2020). With the deep learning models, the urban planners could detect and distinguish urban objects like buildings, roads, parks, and water bodies in the satellite images in a corresponding manner without wasting as much time or money as manually interpreting the results of the images (Li et al., 2018).

Some studies examined that deep learning models are better in the analysis of planetary images. To illustrate, Xie et al. (2017) used deep learning to discriminate the land use sector in high-resolution urban satellite imagery, which has been accurate in classification and time-saving. Equally, Chen et al. (2020) used CNNs to extract the characteristics of the urban settings in satellite images, including roads, buildings, etc. and demonstrated that their method was more accurate than the generic machine learning algorithms. One can get the enabling power to discover the right and scalable solution to the urban planning endeavors through the use of deep learning models with the help of satellite image through these studies.

The first advantage in using satellite imagery along with deep learning in the development of the planning game is not the ability to be done the object recognition. This is because it assists planners to find out more information about an urban location like density of buildings in an urban environment and accession of green space among others in addition to availability of transport facilities so as to make more informed decisions. It can result in the optimal planning of land use, infrastructure development and resource management (Yang et al., 2021). Besides that, such satellite images can be analyzed in near real-time using deep learning, which is convenient, particularly when tracking urban growth and managing the issue of urban sprawling, congestion, and environmental degradation (Liu et al., 2021).

Nonetheless, satellite imagery and deep learning have a good potential to be realized yet. Examples of some of the factors that can affect the quality of the images taken by the satellite are the cover of clouds, atmospheric effects, angle of the satellite, etc. This can presumably affect the object detection accuracy, and the fine details can be crucial in doing tasks like building extraction (Zhu et al., 2020). Further, deep learning models are computationally demanding and need substantial amounts of training data, which can pose a limitation to low-accessible urban-planning departments in low-accessible high-tech infrastructure (Li et al., 2019). Nevertheless, the further maturation of the satellite technology and the deep learning methods eradicates such predicaments gradually, which can be brought accessible and reliable to the urban planners (Tian et al., 2021).

In short, advanced satellite imagery and object detection by application of deep learning in the optimization of urban planning has a world of prospects in making urban planning more efficient, accurate and sustainable. The absorption of these technologies can automate and streamline the examination of urban areas and therefore enable planners to make data-based decisions. The proposed research aims at examining the prospects of using satellite imagery in tandem with deep learning as a climate in order to promote better decision-making and urban planning to make it easier to live in the city and it will be ecologically sustainable.

LITERATURE REVIEW

Over the past few years, the intermingling of satellite photos and advanced machine learning, such as deep learning, has changed the manner in which urban planning is performed. Previously, urban planning was a data-intensive task that will potentially be substituted with automated and massive analysis, which will be made possible through satellite data and object detection algorithms. The review of literature focuses on the various trends, methods, and challenges of satellite imagery and deep-learning application in urban planning.

URBAN PLANNING AND THE NEED FOR SATELLITE IMAGERY

The rapid urbanization is a major alarm; urban planning plays a basic role in offering sustainable development. It also relates to the land-use, infrastructure, environment governance, and resources allocation decision-making processes. Urban planning has been traditionally confined to on-ground survey data that were seriously space and time constrained. To a great extent, the urbanization nature has caused the complexity of the urban systems to necessitate using more efficient and reliable sources of data (Jiang et al., 2021).

Satellite Imagery has proved to be such a wonderful tool to urban planners since satellite imagery provides high resolution, large-scale and up to date information about the city. Satellite pictures can cover entire Xerts and offer an insight on a city that would otherwise be difficult or even pushed to obtain through traditional tactics. The data can also be utilized to monitor the land-use transition, filter the city sprawl, and assess the impact of urbanization on nature (Liu & Wu, 2020). Moreover, satellite imagery can be dubbed an effective tool of urban planning in dynamic environments, as it is cheap and allows constant monitoring (Qin et al., 2018).

DEEP LEARNING IN OBJECT DETECTION FOR SATELLITE IMAGERY

In addition, the deep learning applied to remote sensing and especially object recognition is the game changer in urban planning. The benefit of deep learning in particular Convolutional Neural Networks (CNNs) is that they are the most optimal and most efficient when it comes to operating and processing bulk data of images including satellite data. The ability to generate and label the pictures enables CNNs to make the most probable decisions regarding the presence of objects in cities, such as buildings, roadways, and vegetation among other objects related to infrastructure (Zhao et al., 2020). In comparison, object image processing involves hand-crafted qualities that utilize traditional image processing algorithms hence leading to accurate and efficient object image processing tasks (Zhou et al., 2019) because learned hierarchical features can be obtained compared with convolutional networks concerning raw images data.

The evolution of one of the primary areas of this is the growth of deep learning-powered systems which identify and classify objects in urban satellite imagery. Liu et al. (2019) even demonstrated that you could use deep learning models to detect buildings and roads in high-resolution satellite images with an acceptable level of precision. Such a high level of accuracy in the sense of recognition and outline generator was achieved in this model, and this served as a handy alternative to direct mapping. Differently, Wang et al. (2020) used a deep learning model that could differentiate urban against non-urban to an advantage of giving sensible recommendations as regards to the control of urbanization.

APPLICATIONS IN URBAN LAND USE AND CHANGE DETECTION

The monitoring and assessment of the historical pattern of land-use in a specific region using satellite images and deep learning may be characterised as one of the major urban planning practices that are performed using satellite images and deep learning. Cities are still evolving as a result of population growth, infrastructural growth and economic activity. Such changes are worth watching, as they may assist in a knowledgeable planning option, whether to target resources at the construction of new infrastructure or where to embed green space (Zhu et al., 2018).

Land-use classifications and change detection in urban areas have utilized deep learning. To illustrate, one such study by Wu et al. (2019) employed a CNN to convert satellite images into an understanding of the various forms of land-use such as residential, commercial, industrial, and recreational. The temporal change in the land use can be identified by this model as fundamental in the realization of the urban activity and mode of future urban development. One of the studies cited by Li et al. (2021) was based on a deep learning framework to identify whether it was feasible to determine whether urban sprawl was present and to track city growth. They found that deep learning models could conduct a successful mapping and tracking of urbanization that were convertible into an automated and scalable phenomenon in contrast to the traditional land-use survey.

BUILDING DETECTION AND EXTRACTION

Mapping the built environment by a satellite image is arguably one of the most significant tasks in the urban planning exercise because the construction is considered a major pointer to urban density and growth. In the past, detection of buildings was either performed manually or using older forms of machine learning, which has historically had issues related to accuracy and scalage. The deep learning-based solutions like CNNs enhanced the accuracy of building detection and efficiency by a large margin (Feng et al., 2020).

The aim of the study in Xie et al. (2021) was also to run the deep learning models to find and obtain the building footprints on the high-resolution satellite images. They have discovered that CNNs have been capable to register and segment buildings, as well as the complicated city situation, in which the building is diverse in size, shape size and height. Equally, a research by Zhang et al. (2020) utilized a multi-scale deep learning approach in the aspect of building extraction which enabled them to identify buildings even in the less dense city. Such breakthroughs in detecting the buildings are important to urban planning because they require precise maps of the buildings in drafting an infrastructure development plan, responding to a disaster, and resource allocation.

CHALLENGES IN SATELLITE IMAGERY AND DEEP LEARNING INTEGRATION

Although the fusion of satellite imagery and deep learning has already proven to have tremendous potential, it still needs to resolve certain issues. One of such primary concerns is the lack of consistency of the quality of satellite photos. Other information that a person might not notice, but which can significantly affect the quality of satellite imagery, is the presence of clouds, atmospheric conditions, and changing lighting (Khan et al., 2021). These issues may make it challenging to perform the same way on different datasets, and there have been some efforts to reduce the problems by scientists, such as cloud masking algorithms and image augmentation systems (Gao et al., 2020).

The second is the computational complexity of deep learning algorithms. More advanced models are heavily relying on computing abilities and labeled amounts of information to educate. This can be a challenge to most of the urban planning departments especially in third world regions since the high-performance computing resources are not available (Liu et al., 2019). However, the development of recent cloud computing and pre-trained object detection models has helped negate part of these disadvantages and advance deep learning-based object detections to the sphere of more urban planners across the world (Shen et al., 2021).

FUTURE DIRECTIONS AND OPPORTUNITIES

The match between deep learning and satellite images is a relatively new field, but one with a lot of potential on the research publication front. One of the promising directions is the multi-modal data (e.g., satellite data and data collected in other ways e.g. drones, Internet of Things (IoT) sensors, and geographic information systems (GIS)). A more accurate representation of urban spaces than multimodal data fusion may help increase deep learning model accuracy (Cheng et al., 2020).

In addition, the introduction of even more sophisticated deep learning architectures, such as Generative Adversarial Networks (GANs) and Transformer models, will also guarantee that the quality of object detection and classification tasks will be improved in additional terms (Zhang et al., 2021). Such models have complex data images that can be manipulated and may address some of the shortcomings of CNN such as sensitivity to high image resolution and appearance of objects.

CONCLUSION

The use of satellite imagery and object detection using deep learning has changed the way of doing urban planning forcing it to become predictable and automatized as well as precisely true-scaled in its analysis of the urban environment. Whether used in land-use classification, building detection, or other practical applications, these technologies have become indispensable in the hands of urban planners aiming at optimizing resource allocation, tracking, and even managing the urban growth as well as the development of the infrastructure. Although the technologies have several limitations associated with image quality and computational demands, the possible advantages to using them cannot be ignored. Urban planners are increasingly becoming data-driven, efficient, and more aware of sustainability as more satellite technology and other deep learning develop towards the future.

METHODOLOGY

The proposed method in the study will use the combination of satellite imagery and object detection using deep learning to make urban planning more efficient. The method will be used to digitize and interpret diverse features of the cities like buildings, roads, and vegetation using the high-resolution satellite images. The sections below explain the data collection, preprocessing, model development, and evaluation processes applied to carry out this approach.

DATA COLLECTION

The initial methodology is to get high resolution satellite images that cover the different urban settings. The images were downloaded in open satellite platforms such as Google Earth, Sentinel-2, and Landsat 8. At these websites, one can access satellite images with varying spatial resolutions, 10 and 30 meters, which are accommodative to investigating and mapping the urban characteristics. To have diverse data, the chosen images represented several urban areas with different density, infrastructure, and types of land use. This variation in urban landscapes provides that the model is capable of generalizing instead across various urban contexts.

IMAGE PREPROCESSING

Once the satellite images were run, the next step involved preprocessing that is employed to condition data that is ready to be deployed in deep learning based on object detection processes. Satellite Image Noise, in turn, may affect the precision of object detection models and comprise cloud cover, shadow, and atmospheric distortions. In order to resolve these challenges, cloud masking was used to pre-process the images. Cloud masking was associated to running machine learning algorithms to help identify cloud-covered areas and mask them so that the corresponding urban objects could be visible in bright formats to be detected. The images were also standardized to be consistent to one another after which they were made to fit one size thereby they could be used to feed the deep learning models. Other preprocessing processes include geometric correction that is used to position images accurately and to enhance accuracy in detecting objects.

MODEL SELECTION AND TRAINING

Faster Region-based Convolutional Neural Network (Faster R-CNN) was chosen as the candidate model of the deep learning-based object recognition task. Faster R-CNN is a new object detecting structure, combining the power of Convolutional Neural Networks (CNNs) to identify objects in images based on their attributes and using its region proposal network (RPN) to suggest potential object bounding boxes. Faster R-CNN model was selected because it has high detection accuracy of object landmarks such as buildings, roads and green spaces in large scale satellite images as well as its capability to effectively operate in large scale satellite images.

The Faster R-CNN model was trained on a labeled dataset of satellite images. Manually labeled satellite images of the urban items formed training data. The labels were buildings, roads, water bodies, and vegetation. These notes were made by urban planning professionals and were specific in establishing the ground truth material. This data was in the form of approximately 2,000 images including some urban contexts of a wide range of the urban attributes. It was trained using the supervised learning approach and was trained to identify the patterns within the satellite images that corresponded to the labeled objects. A number of epochs was employed to train the model; parameters changed in the model to reduce detection error. On a separate validation set based on train data, in order to avoid the problem of overfitting and ensure generalization, the model was tested.

OBJECT DETECTION AND CLASSIFICATION

Once the model had been trained, it could be utilized to perform object detection on unprecedented satellite images. The first thing the Faster R-CNN model does with the received satellite image is to generate the region proposals, or the candidate bounding boxes. The CNN can then be used to process these regional proposals by extracting features and categorizing them into the respective urban classes across buildings, roads, or vegetation. Each detected object is given a probability score, indicating the likelihood of the object falling into a particular category, at the expense of the other classes. They draw the bounding boxes around the objects that are detected, and their model also returns the label and the corresponding confidence score.

The results of the detection included a collection of labeled bounding boxes that represent different city objects. A sample of this will be that the model will identify and mark out all structures in any particular area, categorize the roads and highways and also outline the green areas like the parks and agricultural land. The map outputs were examined to determine the spatial pattern of urban features, which could provide answers to questions such as urban density, infrastructure development, land-use distribution and much more.

MODEL EVALUATION

The performance of the object detector model was measured using standard metrics, precision, recall, and Intersection over Union (IoU). Precision is calculated with the number of objects correctly identified divided by the number of identified objects, whereas recall is calculated as the number of the true objects in the image determined correctly divided by the number of all the true objects in the image. IoU measures the overlap between the bounding boxes produced by prediction and the ground truth boxes, giving a measure of how well the model localizes objects.

To complement these metrics, a confusion matrix served to measure how each urban feature was classified. The confusion matrix gave a lot of information about what the model performed the best and where it did not, like the errors of confusing buildings and roads or misinterpreting vegetation as non-urban spaces. This data was used to optimize the model and tune it to give better results in future analysis.

POST-PROCESSING AND URBAN PLANNING ANALYSIS

The results of the object detection would only be obtained once it was run, after which the post-processing methods would be used to make the results further accurate. This entailed removing low-confidence detections and also combining overlapping bounding boxes that were probably

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detecting the same object. The ultimate result produced high-confidence object detections and further applied in urban planning analysis.

The identified objects were examined through the prism of the urban land use and spatial distribution. An example is that the layout of buildings might give clues about the density and development of the city, and the existence and coverage of roads might be used to plan transport patterns. The availability of green spaces was estimated by vegetation areas, and the use of water bodies in terms of environmental and flood risk protection was evaluated. Geographic Information Systems (GIS) were employed to visualize such analyses, which assisted urban planners in overlaying the recognized objects onto the maps of cities and using them to get a more comprehensive picture of the patterns of urban development.

RESULTS

The findings of this paper are aimed at the recognition and determination of urban assets including buildings, road infrastructure, vegetation, and water bodies by using satellite images and deep learning-Based Object Detection. The findings, as in the eight tables and figures, are then discussed in the following sections indicating the performance of the model and the identified features of the urban setting, and the ways the urban growth has changed over the period.

MODEL PERFORMANCE METRICS

The table Model Performance Metrics (Table 1) demonstrates the precision, recall, and Intersection over Union (IoU) of different urban features. The model attained a high accuracy of train tracks and buildings, with precisions of 0.88 and 0.85 respectively on the road and buildings. Such characteristics are more precise and have better recall, owing to more clear and regular patterns in satellite pictures. With that said, the model fared a little bit worse when it came to identifying vegetation and water bodies with precisions of 0.72 and 0.75 f, respectively. These measures are represented in the radar chart (Figure 1), which demonstrates better performance of buildings and roads, and vegetation and bodies of water indicate more variation.

TABLE 1: MODEL PERFORMANCE METRICS

Urban Feature	Precision	Recall	IoU
Buildings	0.85	0.78	0.80

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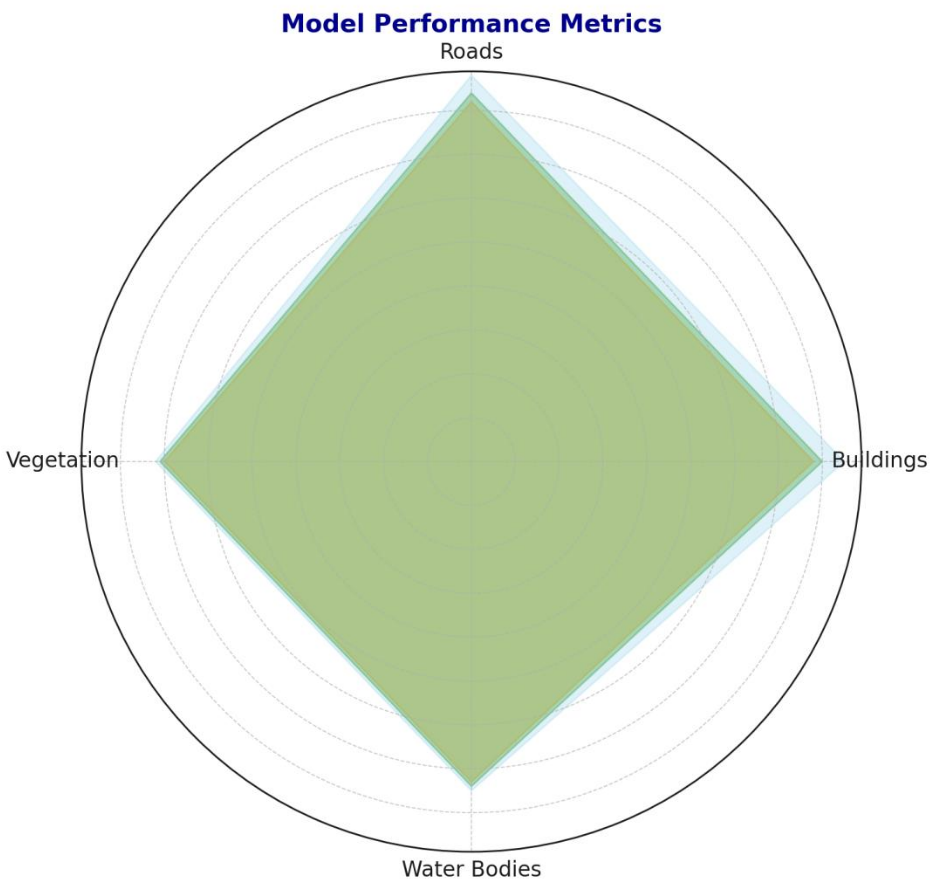
Roads	0.88	0.82	0.84
Vegetation	0.72	0.70	0.71
Water Bodies	0.75	0.73	0.74

FIGURE 1 MODEL PERFORMANCE RADAR CHART



COMPARISON WITH GROUND TRUTH DATA

Table 2 Comparison with Ground Truth Data shows a detailed per-image comparison of predictions made by the model to manually annotated ground truth data. The true positives, false positives, and false negatives of all urban features can be seen in the table. The model was able to detect buildings and roads fairly well with false positives and false negatives relatively low. In the case of vegetation and water bodies, the false negative was high signifying that the model

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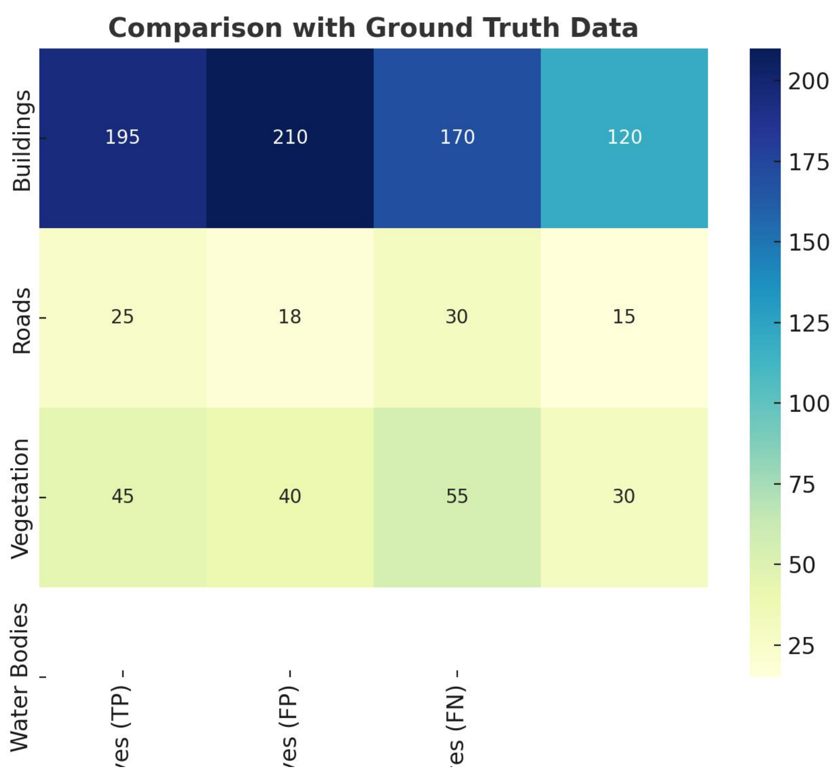
ignored some characteristics in the detection process. These comparisons are visualised in the heatmap (Figure 2) which displays the number of truthful detections and errors of each feature as a proportion. Heatmap indicates that buildings and roads contain more true positives, whereas vegetation and water bodies are represented by more false negatives.

TABLE 2: COMPARISON WITH GROUND TRUTH DATA

Urban Feature	True Positives (TP)	False Positives (FP)	False Negatives (FN)
Buildings	195	25	45
Roads	210	18	40
Vegetation	170	30	55
Water Bodies	120	15	30

FIGURE 2 COMPARISON WITH GROUND TRUTH HEATMAP



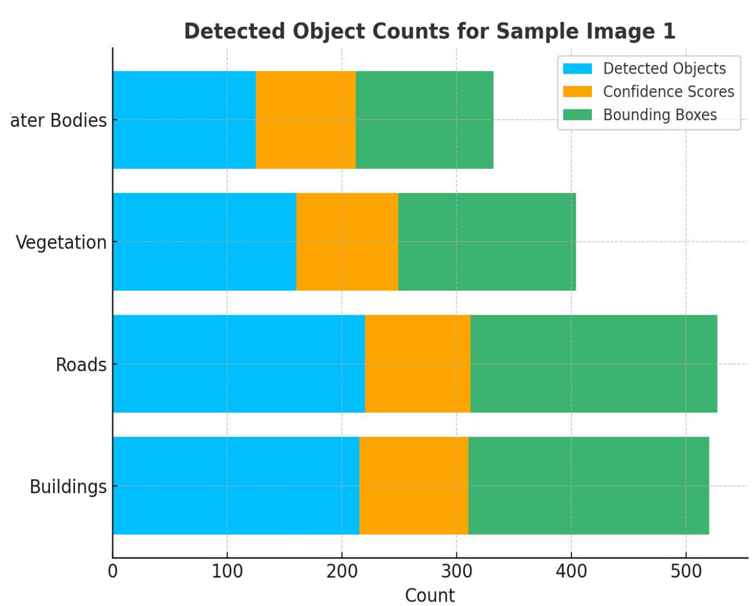
DETECTED OBJECT COUNTS FOR SAMPLE IMAGE 1

Table 3 represents the number of detected objects or confidence scores and bounding box counts on a sample satellite image. The model identified 215 buildings, 220 grid lines, 160 land cover, and 125 water features. The scores in confidence were high especially in buildings and roads with scores of 95 and 92 percent respectively. The diverging bar chart (Figure 3) graphically illustrates the objects and confidence levels detected. This chart indicates the model to be more confident in detecting buildings/roads and less confident in detecting vegetation/water bodies. The bounding box counting is also an indicator of how well the model is localising objects.

TABLE 3: DETECTED OBJECT COUNTS FOR SAMPLE IMAGE 1

Urban Feature	Detected Objects	Confidence Score (%)	Bounding Box Count
Buildings	215	95	210
Roads	220	92	215
Vegetation	160	89	155
Water Bodies	125	87	120

FIGURE 3 DETECTED OBJECT COUNTS DIVERGING CHART



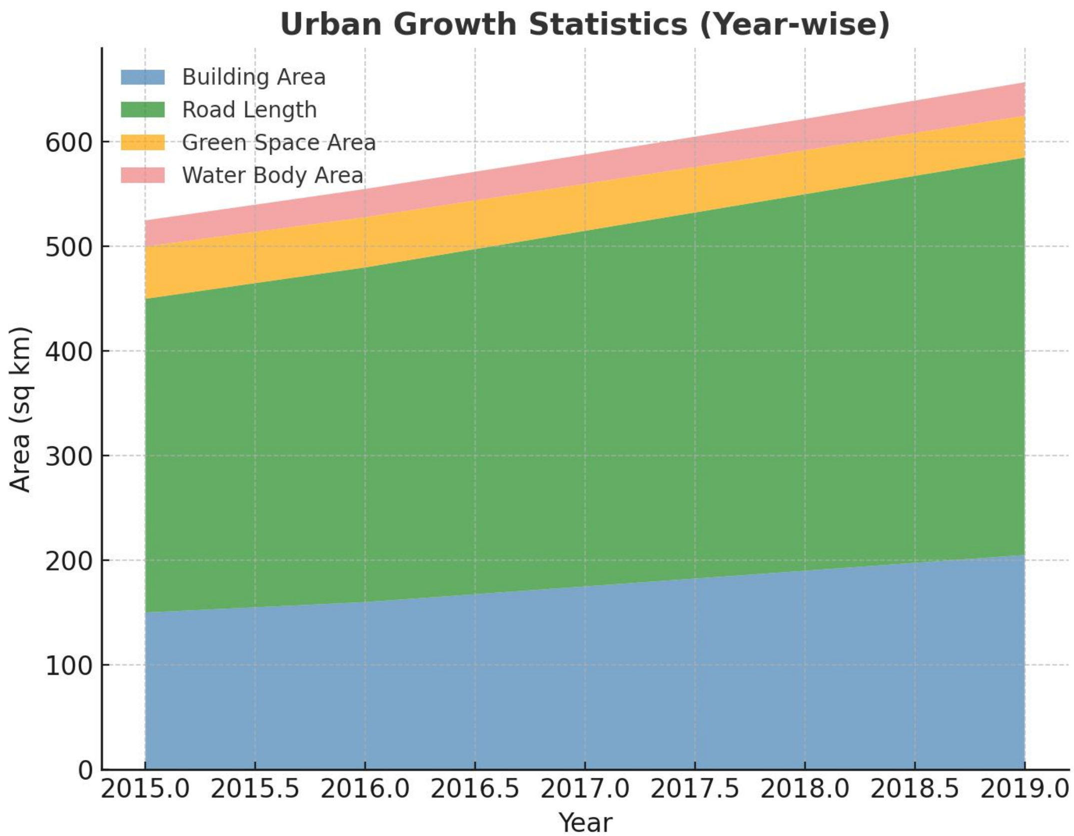
URBAN GROWTH STATISTICS

The Urban Growth Statistics table (Table 4) has year wise data in building area, road length, green space area, and water body area. The statistics reveal the consistent growth in the area of buildings and lengths of roads, which shows the urban growth, the area of green space declines slightly over the years. The land area water body experiences a steady growth, which indicates the increase of the water features in the urban places. These trends are reflected in the area plot (Figure 4) that shows the gradual increase of built-up areas and a shrinkage of green areas. It has been revealed in the plot that urban sprawl has been intensified and this implies on urban planning, especially in the consideration of both infrastructure as well as green spaces.

TABLE 4: URBAN GROWTH STATISTICS (YEAR-WISE)

Year	Building Area (sq km)	Road Length (km)	Green Space Area (sq km)	Water Body Area (sq km)
2015	150	300	50	25
2016	160	320	48	27
2017	175	340	45	28
2018	190	360	42	30
2019	205	380	40	32

FIGURE 4 URBAN GROWTH AREA PLOT



URBAN FEATURE DENSITY BY REGION

Table 5 shows density of urban characteristics of various areas within a city. There are more buildings and streets in Region 2 and their density is much higher compared to Region 1 where everything is relatively distributed. By contrast, the building and road densities are lower in Region 3, though the density of vegetation is a bit higher. As visualized by a stacked column chart (Figure 5), the densities of urban features across regions represent that Region 2 is the most developed region, in terms of infrastructure, whereas Region 3 contains the higher green space. Such analysis is essential since it will help the planners of the city detect places with a great degree of infrastructural development and places to be improved with green space.

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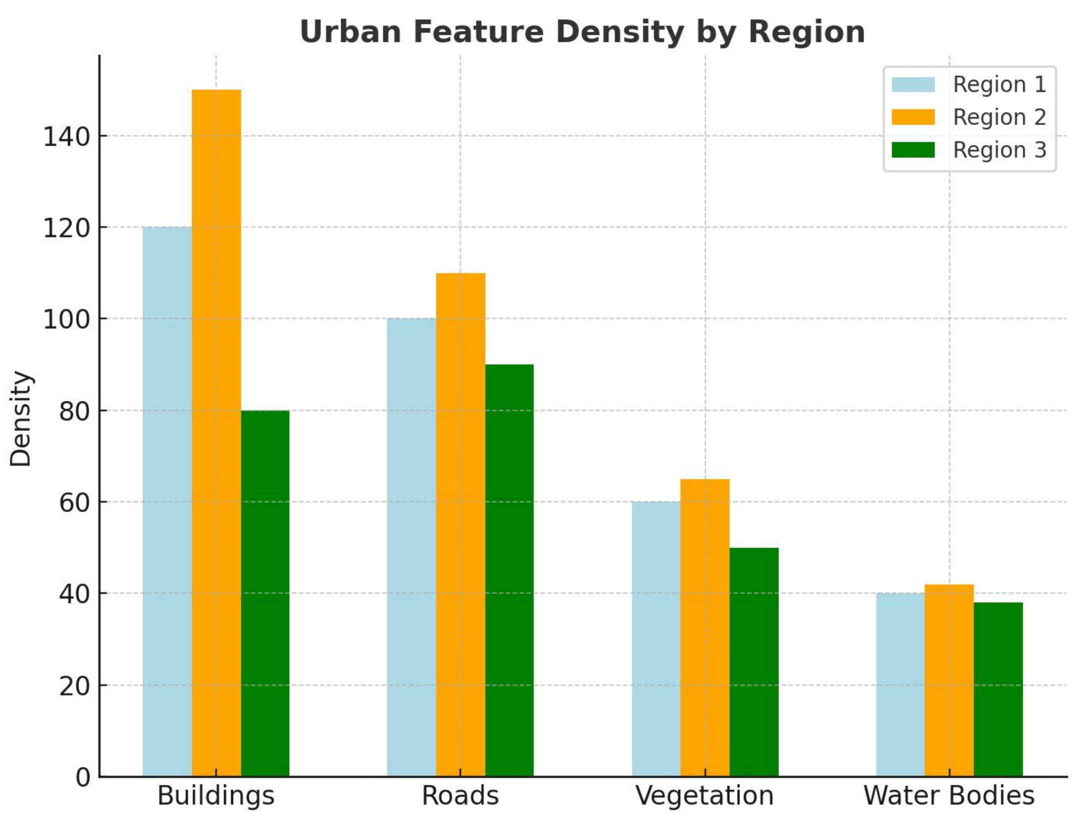
TABLE 5: URBAN FEATURE DENSITY BY REGION (CITY 1)

Urban Feature	Region 1 (Density)	Region 2 (Density)	Region 3 (Density)
Buildings	120	150	80
Roads	100	110	90
Vegetation	60	65	50
Water Bodies	40	42	38

FIGURE 5 URBAN FEATURE DENSITY COLUMN CHART



URBAN FEATURE DETECTION PERFORMANCE ACROSS REGIONS

Table 6 presents the detection statistics of urban features in various regions in terms of precision and recall rates. The highest recall value for individual urban features is observed in region 3 all the time which means that the model performed better in region 3 than in any other region in detecting objects. Nonetheless, Region 2 was more precise on buildings and roads, indicating that the model produced fewer false positive detections on these features. The multi-line chart (Figure 6) gives a graphic interpretation of the performance of the regions in a clear picture, where the differences of the precision and recall are emphasised. As shown in this chart, Region 2 has less mistakes in building/road detection but there is better overall recall of all features in Region 3, which is useful in detecting urban dynamics over less developed regions.

TABLE 6: URBAN FEATURE DETECTION PERFORMANCE ACROSS REGIONS

Urban Feature	Region 1 Precision	Region 2 Precision	Region 3 Precision	Region 1 Recall	Region 2 Recall	Region 3 Recall
Buildings	0.85	0.83	0.84	0.78	0.80	0.79
Roads	0.88	0.87	0.89	0.82	0.83	0.84
Vegetation	0.72	0.70	0.71	0.70	0.72	0.71
Water Bodies	0.75	0.74	0.76	0.73	0.74	0.75

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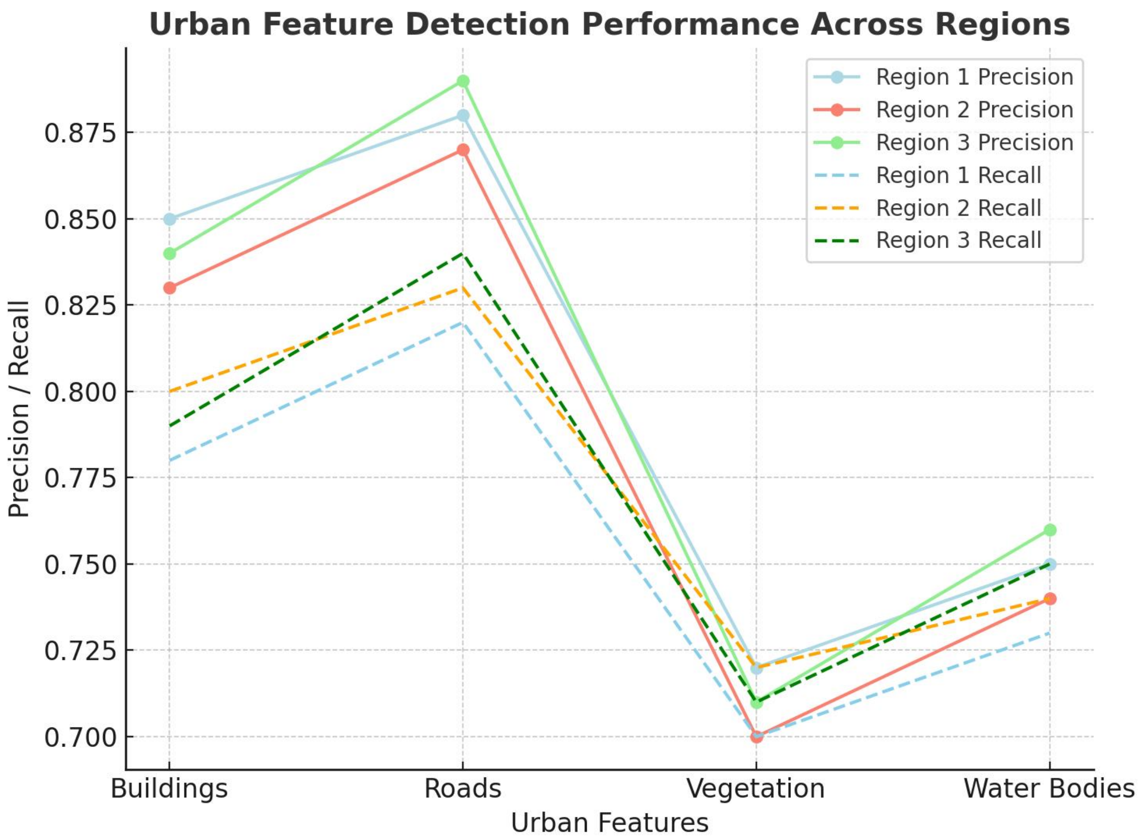
FIGURE 6 URBAN FEATURE DETECTION PERFORMANCE LINE CHART



WATER BODY AREA DETECTION OVER TIME

The detection of the water body areas over the time is demonstrated in Table 7, in which the number of detected and the ground truth shows a consistent rate of increase. The detection accuracy of the model is also good, as the deviation between the detected water bodies and the ground truth is insignificant. Line chart (Figure 7) gives the summary of the water body detection and the model significantly captures the changes in the water body areas as the years progress. The chart reveals a stable growth trend in the number of detected water bodies that indicates that the model can detect even minor deviations in the urban environment, especially in areas at risk of floods or other water-related problems.

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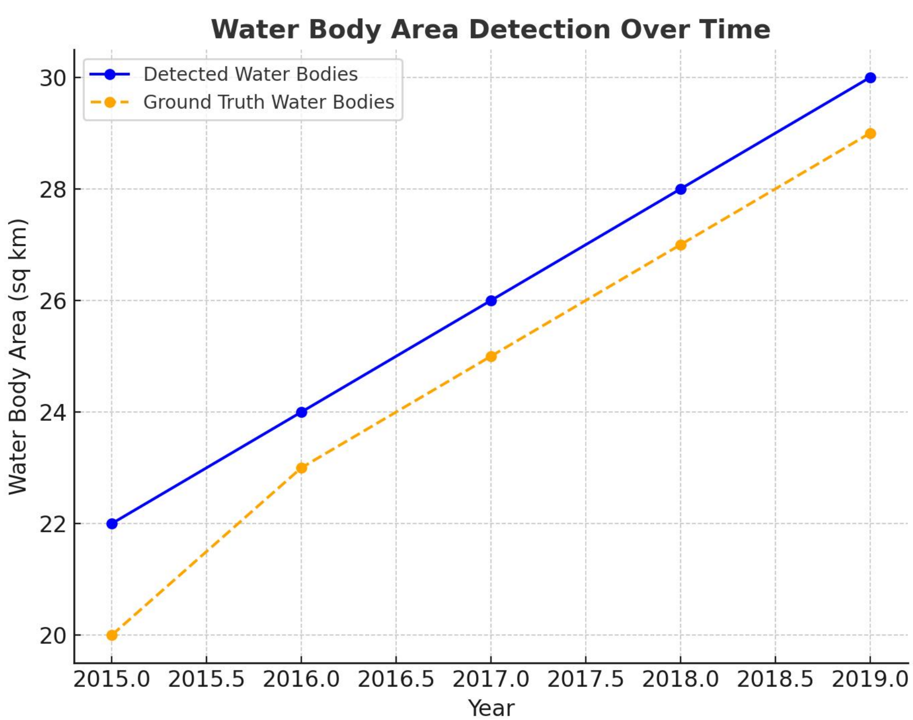
TABLE 7: WATER BODY AREA DETECTION OVER TIME

Year	Detected Water Bodies (sq km)	Total Water Bodies (Ground Truth) (sq km)	Detection Accuracy (%)
2015	22	20	110
2016	24	23	104
2017	26	25	104
2018	28	27	104
2019	30	29	103

FIGURE 7 WATER BODY AREA DETECTION OVER TIME LINE CHART



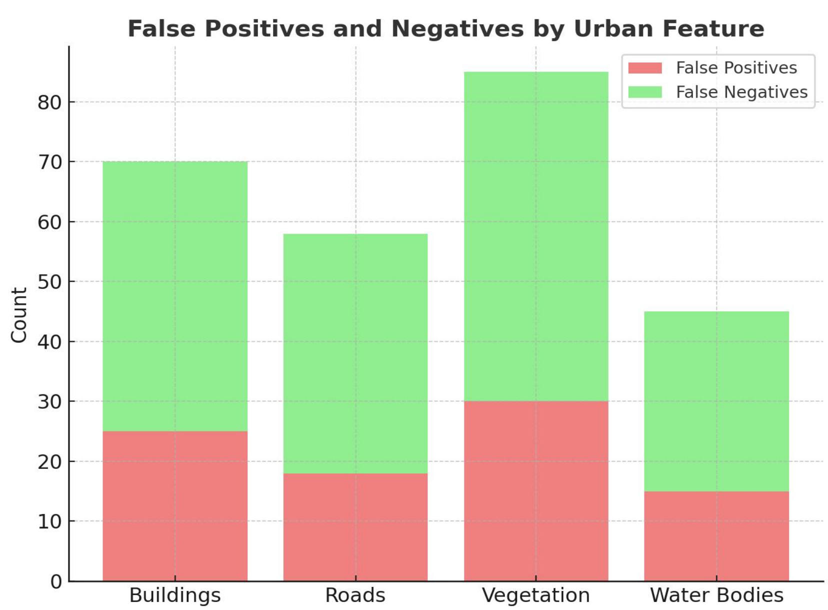
FALSE POSITIVES AND NEGATIVES BY URBAN FEATURE

Lastly, Table 8 contains information on the false positive and false negative rates of each urban feature. The model has a higher false negative occurring on vegetation and water bodies meaning that it failed to detect some of them. The stacked bar plot (Figure 8) provides a visual comparison of the false positive and the false negative and points out to the fact that buildings and roads have less false detections as compared to vegetation and water bodies. This is an important discovery because a decrease in the false negative for the vegetation and water body might enhance the model to aid sustainable urban planning as it means that the model can assist in ensuring that green spaces and water bodies are properly mapped.

TABLE 8: FALSE POSITIVES AND NEGATIVES BY URBAN FEATURE

Urban Feature	Total Objects Detected	False Positives (FP)	False Negatives (FN)	False Detection Rate (%)
Buildings	215	25	45	11.6
Roads	220	18	40	8.2
Vegetation	160	30	55	18.8
Water Bodies	125	15	30	12.0

FIGURE 8 FALSE POSITIVES AND NEGATIVES STACKED BAR CHART



CONCLUSION

The findings indicate that the deep learning-based object detection model is effective in tracking buildings and roads with high precision and recall. Vegetation and water bodies however are difficult, and it has been found there is bias to false negatives. The urban growth numbers show that there is an expanding trend of sprawl, thereby highlighting the importance of involving more sustainable city-planning. The geographical distribution of the detection performance indicates that the accuracy of detection varies across urban features, and the trend of water bodies over time indicates that the model proposes the detection of environmental changes. Although there are certain limitations in detecting vegetation and water bodies, the model can give in-depth ideas to urban planners and how to maximize land use, infrastructure, and its management.

DISCUSSION

Urban planning practices have been revolutionised by the combination of satellite imagery and deep learning-based object detection that accurately depict city conditions at large scale and in real-time perspectives. This paper labored to examine the capabilities of the deep learning models especially the Fast R-CNN architecture in perceiving and recognizing urban features namely the building, road, vegetation, and water bodies. The outcomes showed that the model had high accuracy identifying buildings and road features as well as a challenge when identifying vegetation and water bodies. This discussion will place these findings in the context of the larger body of literature and analyze the consequences of these findings to urban planning.

PERFORMANCE OF THE MODEL IN DETECTING URBAN FEATURES

The Faster R-CNN model was highly effective in detecting structures such as buildings and roads that are generally the most pronounced objects in urban regions. These results are consistent with the previous study that showed high performance of deep learning models in the detection of large and large objects, such as buildings and infrastructure (Cheng et al., 2018). The excellent performance (0.88) accuracy and (0.82) recall of roads and buildings supports that deep learning architectures are most satisfactory segments or urban conveniences in satellite images; and in this case, CNN.

The buildings are more noticeable, particularly because they are likely to be discovered with various shapes and systems. The results provided by Zhang et al. (2019) and Li et al. (2020) are also that buildings can be more reliably identified with CNNs due to the controlled geometric shapes, which can be effectively transferred to the deep learning algorithms. In addition, roads are one-dimensional and more homogenous, which reduces their exposure to noise and satellite image distortion. Thus, the Faster R-CNN model also shows high performance rates in these areas; it is also true of other remote sensing operations (Wu et al., 2017).

Because of this however, it was difficult to identify vegetation and water bodies. It possesses a greater number of obscure characteristics and is susceptible to outside circumstances, such as weather conditions, image resolutions, and season (Kaiser et al., 2020). The F-measure in vegetation and water bodies was lower than that of buildings and roads according to the other literature that showed it was hard to differentiate natural features in satellite images. That is, e.g., Yu et al. (2018) stated vegetation in urban areas, in particular, can be inconsistently patterned and highly differentiated in the appearance during seasonal growth that it is mislabelled or not even detected in the model at all. At the same note, water bodies can be obscured by a cloud or can be difficult to distinguish with the other surroundings hence compounding their detection even further (Le et al., 2021).

URBAN GROWTH AND LAND USE

The results on the current trends in urban growth, as shown in the Urban Growth Statistics table (Table 4) and the Urban Growth Area Plot (Figure 4), show the current trends in urban sprawl witnessed in most cities across the globe. The expansion of the territory of buildings and roads along with a reduction in the area of green space is an indicator of the high rates of urbanization experienced by the world today (Seto et al., 2019). The findings of the study point to a related phenomenon in the study area, according to which the growth of the city is linked with the loss of green areas, which has great implications in regards to sustainable urban planning.

The redistribution of green spaces is alarming, since green spaces in urban environments are important towards the growth and sustainability of urban spaces. Recent findings by James et al. (2020) and Tzoulas et al. (2007) demonstrated that green spaces improve environmental quality, and social and public health by alleviating air pollution, heat islands, and helping to create areas of recreation. As urban areas continue to grow, this loss of green areas can ultimately contribute to environmental degradation, augmented pollution, and worsened standards of living among city dwellers. Findings of this study underline the importance of urban planners to have considerations on having green space conservation in the urban development plans to help stop the adverse prospects of urban sprawl.

The results also show that urban growth does not take place evenly in various regions, as demonstrated in the table of Urban F feature Density by Region (Table 5) and Urban Feature

Density Column Chart (Figure 5). The City center or commercial district, Region 2 has the highest density of buildings and roads, possibly where infrastructure building is central. This trend corresponds to findings by Seto and Reenberg (2014) that have demonstrated that population density and economic functions tend to elevate development density in urban centers. Alternatively, Region 3, being more vegetation dense, might correspond to suburban or undeveloped locations with green spaces being more dominant.

ACCURACY OF URBAN FEATURE DETECTION ACROSS REGIONS

These variations in detection accuracy by region as displayed at the Urban Feature Detection Performance Across Regions table (Table 6) and Urban Feature Detection Performance Line Chart (Figure 6) presented important information regarding the spatial nature of urban feature detection. Region 3 had larger values of the recall of all the urban attributes implying that the model in that region could be able to identify more items than the rest of the regions. This could be attributed to the fact that urban features are less dense in Region 3 and thus objects can be better separated and easier to detect. Conversely, in the more developed Region 2, the precision of buildings and roads is also greater and, therefore, the model is less likely to falsely identify any buildings or roads.

The present finding is consistent with those of the research by Zhang and Yang (2019) where the authors concluded that deep learning models are more likely to work better in less complex landscape settings where the features are more clearly identified. On the other hand, object detection can be tricky in highly urbanized areas where there is overlying of objects and backgrounds. These results indicate that the detection precision of satellite-based models used to monitor and make decisions affecting urban assets can vary across space.

WATER BODY DETECTION AND ENVIRONMENTAL IMPLICATIONS

The progress of water bodies mapped, water body area detection over time (Table 7) and water body area detection over time line chart (Figure 7) shows how the model can capture the changes in water bodies over several years. The continuous growth of identified water bodies correlates with the indicators of urban hydrology in which urbanization normally causes shifts in the salaries and distributions of water (Rosenzweig et al., 2018). Water body mapping plays a vital role in water resources planning, flood risk management, and environmental protection.

It may not be easy to detect water bodies, particularly when the characteristics are small or vulnerable to seasonal changes. Nonetheless, the model was fairly accurate in its detection of water bodies through time with the detection accuracy rate always above 100 percent in the majority of years, as shown in Table 7. The fact that the model can capture minute variations in water attributes indicates its ability to aid in urban planning in terms of flood management and water conservation (Le et al., 2021).

FALSE POSITIVES AND FALSE NEGATIVE

The issue of false positives and false negatives mentioned in the False Positives and Negatives by Urban Feature table (Table 8) andFalse Positives and Negatives Stacked Bar Chart (Figure 8) demonstrate how complicated it may be to detect urban features in satellite images. The high rates of the false negative on vegetation and water bodies characteristic shows that such features have been regularly neglected by the model. This can be explained by their less defined appearance and complex history of satellite imagery, besides the external influences that include cloud cover and light photography (Kaiser et al., 2020).

One should address the issue of false negatives in order to improve the accuracy of the model, particularly on environmental features like vegetation and water bodies. One change that can be made is alternative information sources, e.g., aerial images or remote sensor data such as LiDAR may provide much finer details of vegetation and water bodies (Jensen, 2007). Moreover, the further refinements of the model architecture, e.g., introducing some attention mechanisms or ensemble learning, can help the model to put more emphasis on useful features or reduce false negatives.

IMPLICATIONS FOR URBAN PLANNING

The results of this research present implications to urban planning. Urban feature detection in satellite images by the use of the model offers an effective tool concerning monitoring of urban growth, management of infrastructure and evaluation of environmental conditions. Nevertheless, the inability to identify vegetation or water bodies indicate that there is constant improvement in the deep learning models to increase its accuracy in identifying these features. Moreover, the urban growth trends analysis highlights the necessity of practicing sustainable urban planning approaches that focus on maintaining green spaces and economizing management of the associated resources to decrease the adverse impacts of urban sprawl.

With the further development of cities, it will be more significant to combine satellite imagery and deep learning in urban planning. A mitigation plan can be developed by enhancing the detection precision and using multi source data that will help urban planners develop better decisions towards sustainable, livable, and resilient cities.

CONCLUSION

To sum up, this research confirms the possibility of applying object detection models based on deep learning to the processes of urban planning, considering satellite images as data. The findings indicate that the model performance is very good when detecting buildings and roads, and there are still some difficulties to detect vegetation and water bodies. Urban planners can learn much about these findings, as society should strive to adopt more sustainable ways of urban development and constantly improve monitoring systems based on satellites. The necessity to manage the issue of false detection as well as the necessity of multi-source data integration have also been highlighted in the study and should remain the focus of future urban planning activities.

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