The Jahangirnagar Review: Part II: Social Science, Vol. 49, No.1. June-2025
ISSN 1682-7422 © Jahangirnagar University

Python-based Convolutional Neural Network Analysis of Satellite Imageries to Develop a Landscape Ecology Triangle

Abu Tanvir Mohammad Tazrian[1]
Samira Meherin[1]
Tania Islam Toma[1]
Khandakar Hasan Mahmud[2]

Abstract: *This research aims to understand the applicability of Python-based Convolutional Neural Networks (CNNs) in combination with satellite imageries to classify the landscape types and create the Landscape Ecology Triangle for Bangladesh. Prevailing as a field that involves the manual interpretation and empirical observation of landscapes, landscape ecology is becoming infused with deep learning, thus creating new approaches to the analysis of spatial data. Unlike previous research that has concentrated on the characterization of landscape, this research classifies seven types of landscape: City, District Town, Upazila Town, Paurasabha, Urban Fringe, Rural Fringe, and Rural. This study also used secondary data from the World Bank databases and other reliable sources, in addition to satellite imageries, to classify and describe the landscape types. Data about the proportions of the landscape elements especially the built-up areas were collected and compiled from a literature review that included the relevant research articles. These data were used to train a specific CNN model that was intended to identify landscapes according to their ecological and structural properties. The derived Landscape Ecology Triangle offers a conceptual model that not only categorizes different types of landscapes but also quantifies the proportion of various landscape components within each type, thereby offering a better understanding of the landscape processes. When applied to the classification of landscape types, the approach can give an understanding of the best places for living based on ecological conditions and the suitability of the environment, thus promoting further ecological studies and better practices of land use in Bangladesh.*

Keywords: Landscape Ecology Triangle, Landscape Types, Landscape Elements, CNN Model, Suitability of the Environment, Deep Learning in Ecology

[1] Postgraduate Research Student, Department of Geography and Environment, Jahangirnagar University
[2] Professor, Department of Geography and Environment, Jahangirnagar University. Email: khmmahmud@juniv.edu

Introduction

The increasing pace of urbanization in Bangladesh presents a growing challenge for sustainable land use and environmental conservation. As cities expand, natural landscapes are being transformed into built-up areas, significantly impacting biodiversity, air quality, and the overall ecological balance (Forman & Godron, 1986). *Land Use and Land Cover (LULC)* classification is crucial for understanding these changes, but traditional methods like *Anderson's Classification System* require manual interpretation of satellite imagery, which is both time-intensive and prone to errors (Anderson et al., 1976).

The introduction of *Convolutional Neural Networks (CNNs)* has revolutionized the analysis of satellite imagery, allowing for the automated classification of landscapes based on their spatial and spectral properties (LeCun, Bengio, & Hinton, 2015). CNNs, with their ability to recognize complex patterns, offer a scalable solution for analyzing large datasets, significantly improving both the accuracy and consistency of landscape classification tasks.

In this study, a CNN model is developed to classify satellite images into three main categories: *Water, Vegetation*, and *Built-Up Area* (including built-up and barren land). Additionally, this research introduces the *Landscape Ecology Triangle*, a conceptual tool that categorizes landscapes based on the proportion of built-up areas, vegetation, and water bodies. Drawing inspiration from the *Soil Texture Triangle*, which is used to classify soils based on their composition of sand, silt, and clay (Brady & Weil, 2008), the Landscape Ecology Triangle offers a visual framework for understanding how urbanization impacts natural ecosystems. The relationship between LULC types and the *Air Quality Index (AQI)* is also explored to highlight the role of natural features in improving air quality (Kampa & Castanas, 2008). The broad aim of this research is to categorize landscapes by developing a *Landscape Ecology Triangle* with the assistance of a *Convolutional Neural Network (CNN)* model.

Literature Review

Landscape ecology has shown remarkable strides because remote sensing technologies and machine learning techniques employ Convolutional Neural Networks (CNNs) for their work. The land use and land cover (LULC) analysis sector frequently makes use of traditional landscape classification techniques known as Anderson's Classification System (Anderson et al., 1976). The process of mapping satellite imagery through human interpretation demands substantial manual labor since it involves many errors in readings. The traditional classification techniques prove useful but fail to identify precise features in their analysis while also struggling to process extensive satellite image datasets of diverse areas including Bangladesh.

Landscape classification underwent a drastic transformation when CNNs became available because they powered automated processes that produce scalable accurate assessments of landscape features. The recognition achievement of the U-Net architecture (Ronneberger et al., 2015) led to its status as an essential component in CNN-based models that analyze satellite images. The application of deep learning models for landscape feature identification in high-resolution imagery was explored by Li et al. (2019) among other recent studies about CNN use in landscape classification. The *LoveDA* dataset serves as an advancement in domain-adaptive semantic segmentation for remote sensing according to Junjue-Wang (2021) while demonstrating the capabilities of CNNs for LULC classification.

Remote sensing analysis faces ongoing difficulties in separating two features which generate similar spectral reflections such as water bodies and built-up areas. The integration of water bodies and built-up environments creates difficulties for proper classification in urban areas. Research utilizing CNNs has established their value for element classification but few studies examine an overall landscape classification method which evaluates various elements together at once.

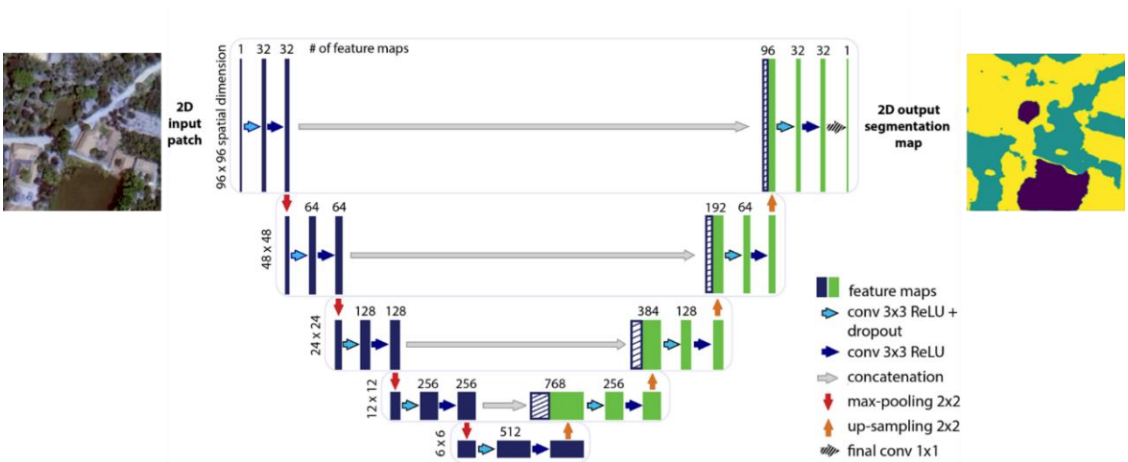
The literature covers extensive research about environmental effects of urbanization on air quality and landscape classification approaches. Based on Kampa & Castanas (2008) the main pollution problems in urban landscapes primarily affect built-up areas. Research about merging environmental factors including the Air Quality Index (AQI) measurement into landscape classification models remains poorly understood in existing studies. Research addresses a void in knowledge by incorporating AQI measurements into the Landscape Ecology Triangle thus enabling the development of an innovative system for assessing present environmental conditions with ecological factors.

Advanced landscape classification has experienced a revolutionary leap because of CNN methods yet current models fail to integrate areas with vegetation and water bodies and human settlements into unified categories. The innovative system presented in the study uses the Landscape Ecology Triangle to classify landscapes by showing ecological elements versus measures of urbanization for enhanced environmental variable interpretation.

Methodology

Data Collection and Preprocessing

Google Earth Pro provided satellite imagery to cover multiple physical regions encompassing urban zones together with rural districts and environmentally critical areas in Bangladesh including the Sundarbans. A preprocessing process using NumPy along with OpenCV and PIL libraries updated these images to meet uniform criteria. The CNN model gained accurate understanding of image features because preprocessing adjusted image brightness and contrast and removed noise while segmenting the images into smaller sections.



Source: Frontiers in Neuroscience, 2019

Figure 1: Schematic Diagram of CNN (U-Net)

CNN Model Development

The CNN model for landscape classification was developed using Python and deep learning libraries such as *TensorFlow, Keras, NumPy,* and *OpenCV*. The model architecture is based on the *U-Net* model, renowned for its effectiveness in semantic segmentation tasks (Ronneberger et al., 2015). This architecture features an *encoder-decoder* structure that allows for detailed feature extraction and pixel-level classification, which is essential for landscape classification.

The model architecture consists of the following:

- **Convolutional Layers**: Nine convolutional layers (c1 to c9), each with a 3×3 kernel size, ReLU activation, and 'same' padding. The number of filters increases progressively from 16 to 256.
- **Pooling Layers**: MaxPooling2D layers (p1 to p4) after every two convolutional layers, downsampling spatial dimensions by a factor of 2.
- **Output Layer**: A **Conv2D** layer with softmax activation and a kernel size of 1×1, which assigns each pixel to one of the predefined categories (4 classes by default).
- **Transposed Convolutional Layers**: Used for upsampling, with *Conv2DTranspose* layers (u6 to u9) restoring spatial resolution and preserving high-resolution information through concatenation with earlier feature maps.
- **Dropout Layers**: To prevent overfitting, dropout layers are added after each convolutional layer, with rates set between 0.2 and 0.3.

The dataset was split into training and validation sets with an *80/20 split*, and various data augmentation techniques, such as flipping, rotating, and scaling, were employed to enhance model robustness.

Pseudocode for CNN Model:

The model's performance was assessed using key metrics such as *accuracy, precision, recall, F1 score,* and *Intersection over Union (IoU).*

Import Libraries and Model: numpy, matplotlib, pyplot, tensorflow, keras, sklearn, torchgeo, segmentation_models, patchify, os, cv2, pillow

Loading Images and Labels: root_directory = 'dataset/'
item = cv2.imread**(**os.path.join**(**path, item_name**)**, 1**)**
patches = patchify**(**item, **(**patch_size, patch_size, 3**)**, step=patch_size**)**

Data Splitting: X_train, X_test, y_train, y_test = train_test_split(image_dataset,

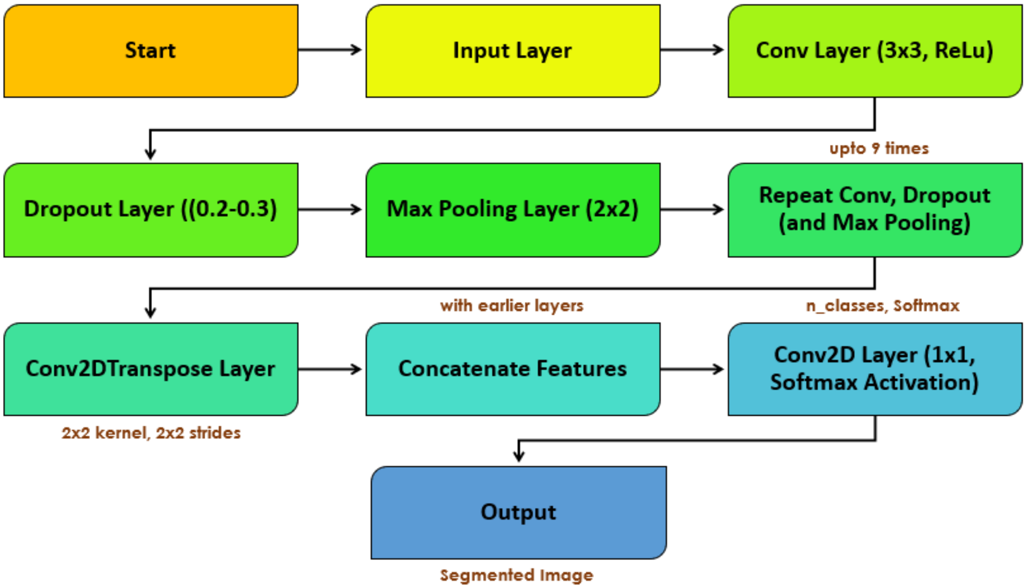


Figure 2: Flowchart for CNN Architecture

Source: Compiled by Authors, 2024

labels_cat, test_size = 0.20, random_state = 42)

Initialize Model

```
def multi_unet_model(n_classes=4, IMG_HEIGHT=256, IMG_WIDTH=256, IMG_CHANNELS=1):
    inputs = Input((IMG_HEIGHT, IMG_WIDTH, IMG_CHANNELS))
    c1, p1 = encoder_block(inputs, 16, 0.2)
    c2, p2 = encoder_block(p1, 32, 0.2)
    c3, p3 = encoder_block(p2, 64, 0.2)
    c4, p4 = encoder_block(p3, 128, 0.2)
    c5 = conv_block(p4, 256, 0.3)
    u6 = decoder_block(c5, c4, 128, 0.2)
    u7 = decoder_block(u6, c3, 64, 0.2)
    u8 = decoder_block(u7, c2, 32, 0.2)
    u9 = decoder_block(u8, c1, 16, 0.2)
    outputs = Conv2D(n_classes, (1, 1), activation='softmax')(u9)
```

Model Compilation: model.compile(optimizer='adam', loss=total_loss, metrics=metrics)

Model Compilation: model.compile(optimizer='adam', loss=total_loss, metrics=metrics)

Model Training: model.fit(X_train, y_train,

```
        batch_size = 20,
        verbose=1,
        epochs=150,
        validation_data=(X_test, y_test),
        shuffle=False)
```

Model Training

The model was trained using the *Adam optimizer*, which dynamically adjusts the learning rate during training. The *Dice Loss* function was combined with *Categorical Focal Loss* to handle class imbalance and focus on hard-to-classify areas.

To evaluate model performance, key metrics such as *accuracy, Jaccard Coefficient (IoU),* and *Mean Intersection over Union (mIoU)* were employed. These metrics assess the correctness of predictions and the overlap between predicted and actual segments. The model was trained over a specified number of epochs and batch sizes, ensuring reliable results through rigorous validation on the test set.

Expected Outcomes

The expected outcome of this process is a comprehensive list of identified landscape types, each associated with standardized parameter values, such as the proportions of built-up areas and other significant elements. These values will be integrated into the *Landscape Ecology Triangle,* offering a framework to visualize and quantify landscape structure, composition, and function.

By leveraging secondary data from reputable sources and employing systematic methodology, this research aims to provide a robust and scalable approach to landscape ecology analysis, contributing to ecological research, conservation efforts, and sustainable land management practices.

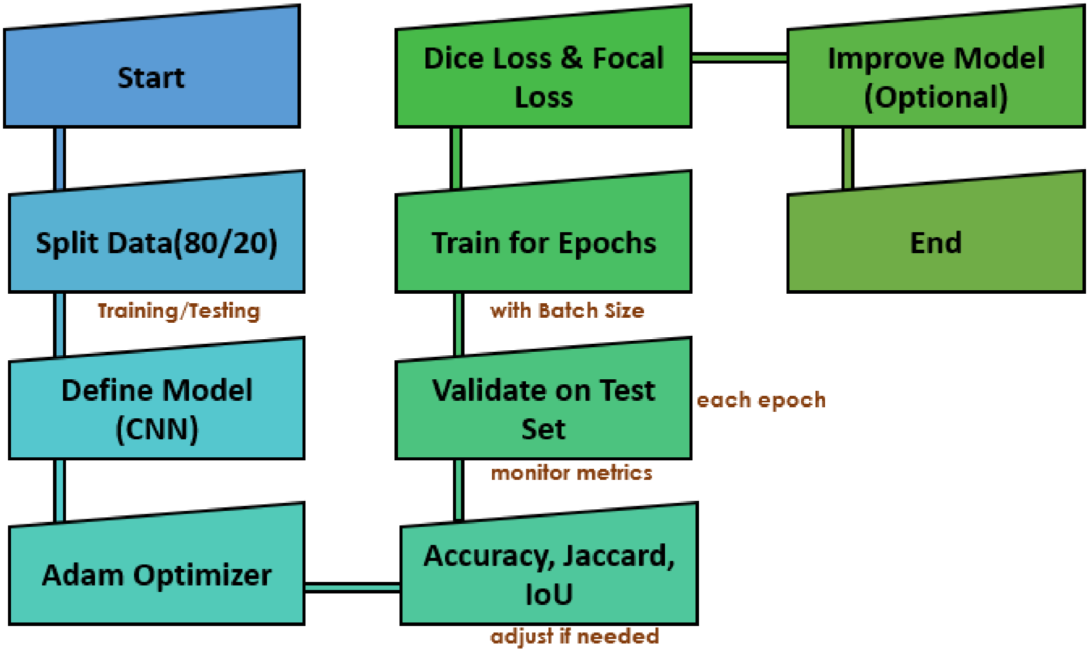


Figure 3: Flowchart for Training and Validation

Source: Compiled by Authors, 2024

Result and Discussion

Development of the Landscape Ecology Triangle

The *Landscape Ecology Triangle* is modeled after the *Soil Texture Triangle*, which classifies soils based on the proportions of sand, silt, and clay (Brady & Weil, 2008). Similarly, the Landscape Ecology Triangle categorizes landscapes based on the relative proportions of built-up areas, vegetation, and water bodies. This framework allows researchers and planners to visualize how urbanization alters the ecological balance in different regions.

The study classified landscapes into seven primary types based on the percentage of built-up areas, providing a gradient from urban to rural. Cities, with more than 75% built-up areas, represent the most urbanized category. Following this are District Towns, having 65-75% built-up areas, and Upazila Towns, which are moderately urbanized with 55-65% built-up areas. Paurasabha, with 45-55% built-up areas, represents a transition between urban and semi-urban regions. The Urban

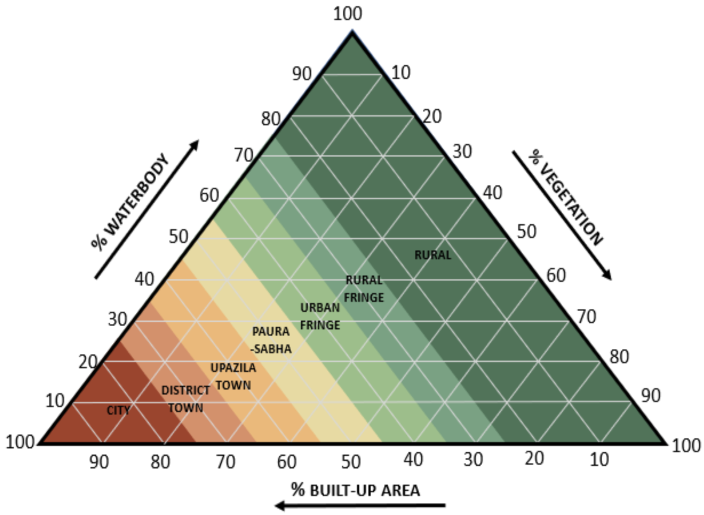
Fringe, marked by 35-45% built-up areas, bridges urban and rural areas, while the Rural Fringe, with 25-35% built-up areas, is closer to rural landscapes. Finally, Rural areas, comprising less than 25% built-up areas, are predominantly natural or agricultural. This classification provides a clear representation of the urban-to-rural continuum.

The seven primary landscape types identified were:

Table 1: Landscape Types with Standard Range of Values of Built-up Area

Sl. No.	Landscape Types	Standard Range of Built-Up Area (%)	Proximity
1	City	> 75	Urban
2	District Town	65-75	
3	Upazila Town	55-65	
4	Paurasabha	45-55	
5	Urban Fringe	35-45	
6	Rural Fringe	25-35	
7	Rural	< 25	Rural

Source: Compiled by Authors, 2024



Source: Compiled by Authors,

Figure 4: Landscape Ecology Triangle

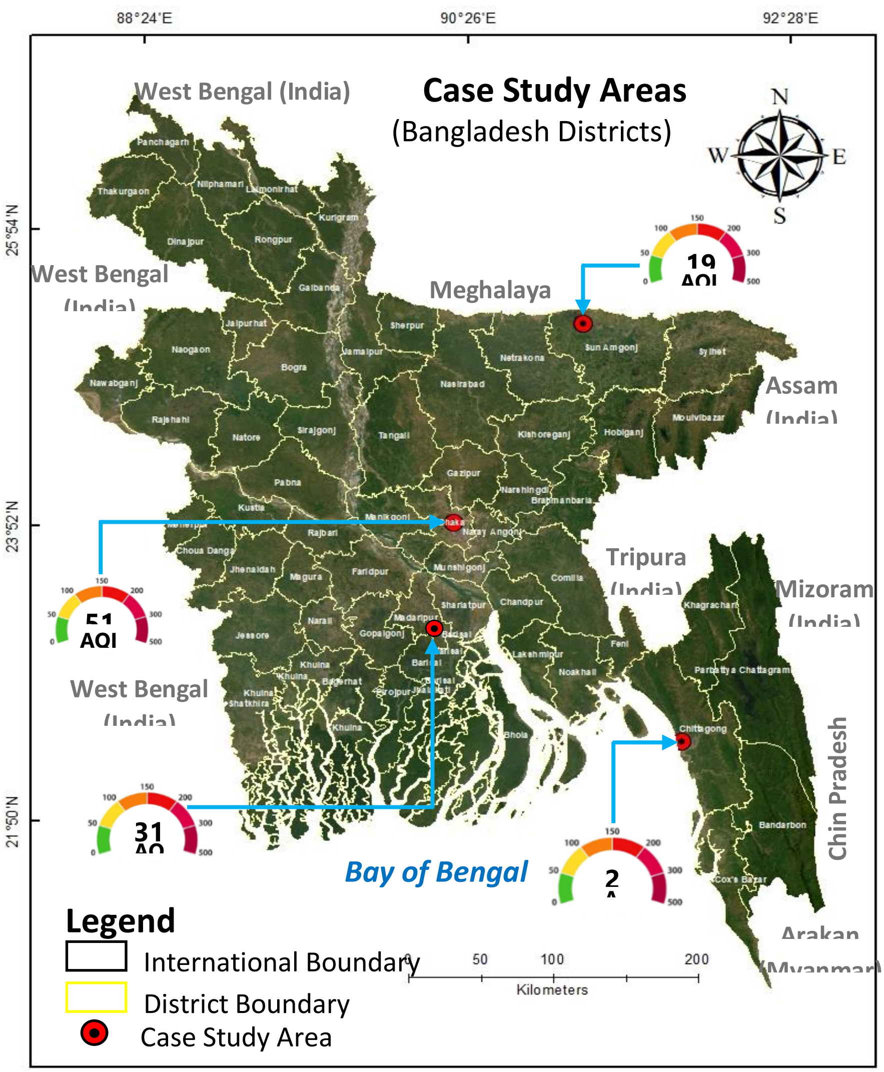
Relationship with Air Quality Index (AQI): Case Studies

Urban areas with high proportions of built-up land are often correlated with poor air quality, as measured by the *Air Quality Index (AQI)* (Kampa & Castanas, 2008). The results of this study demonstrate that landscapes with higher vegetation and water body coverage tend to have lower AQI levels, highlighting the role of natural features in absorbing pollutants and mitigating urban heat islands.

Table 2: Case Study Areas with AQI

Case Study Areas	**Air Quality Index**
Dhaka City, Dhaka	51
Tahirpur Village, Sunamganj	19
Madaripur Paurasabha, Madaripur	31
Pahartali Thana, Chattogram	25

Source: Compiled by Authors, 2024



Map 1: Map of Case Study Areas

Source: Compiled by Authors, 2024

Case Study-1: Dhaka City, Dhaka

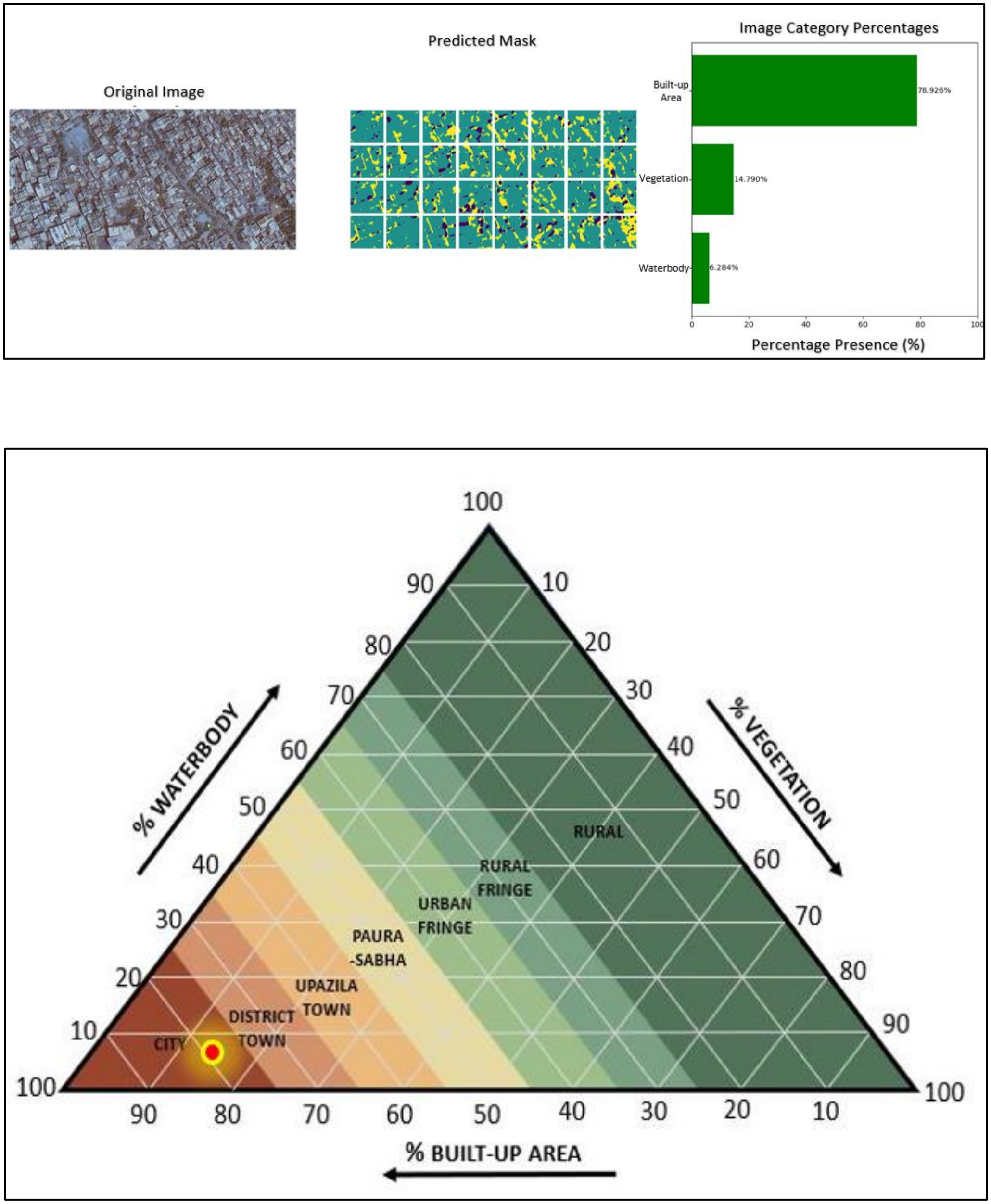
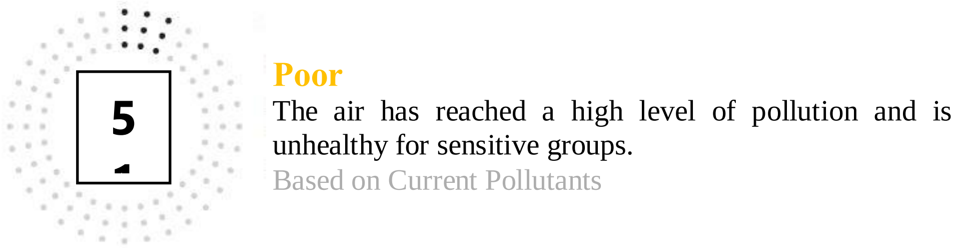


Figure 5: CNN Model Implementation on Dhaka City

Source: Compiled by Authors,



Source: AccuWeather, 2024

Figure 6: Air Quality Index of Dhaka City

Geographical Analysis

Dhaka is one of the most populous cities in the world being the capital city of Bangladesh with high population density. It is situated in the central geographic zone of Bangladesh and in the Dhaka division. It is mainly urbanized where built up area dominate the city’s structure and comprises of residential, commercial, industrial and infrastructural structures such as roads and bridges. The natural resources have been exploited to support the growing urbanization hence limited availability of natural resources such as green areas and water sources. The few and scattered pieces of vegetation are mostly located in parklands and roadside trees only which are not enough to reverse the impacts of the highly developed structures. While Dhaka has lost most of its water bodies due to encroachment and the rest have become polluted due to industrial wastes.

Suitability as an Ideal Habitat

Given its ecological profile, Dhaka City falls into the "City" category within the Landscape Ecology Triangle, which denotes landscapes dominated by built-up areas. The heavy concentration of infrastructure, coupled with limited vegetation and water bodies, significantly impacts the city’s livability. This imbalance contributes to various environmental issues, including air pollution, heat islands, and poor water quality. The Air Quality Index (AQI) of 51 indicates that the air in Dhaka has reached a level of pollution that is unhealthy for sensitive groups, such as children, the elderly, and individuals with pre-existing health conditions. The lack of sufficient green spaces exacerbates these problems, reducing the city's capacity to mitigate pollution and regulate its microclimate. Consequently, Dhaka's ecological characteristics render it far from an ideal habitat for healthy living. The city’s environmental conditions highlight the challenges of urban sustainability and underscore the need for increased green infrastructure to enhance livability.

Case Study-2: Tahirpur Village, Sunamganj

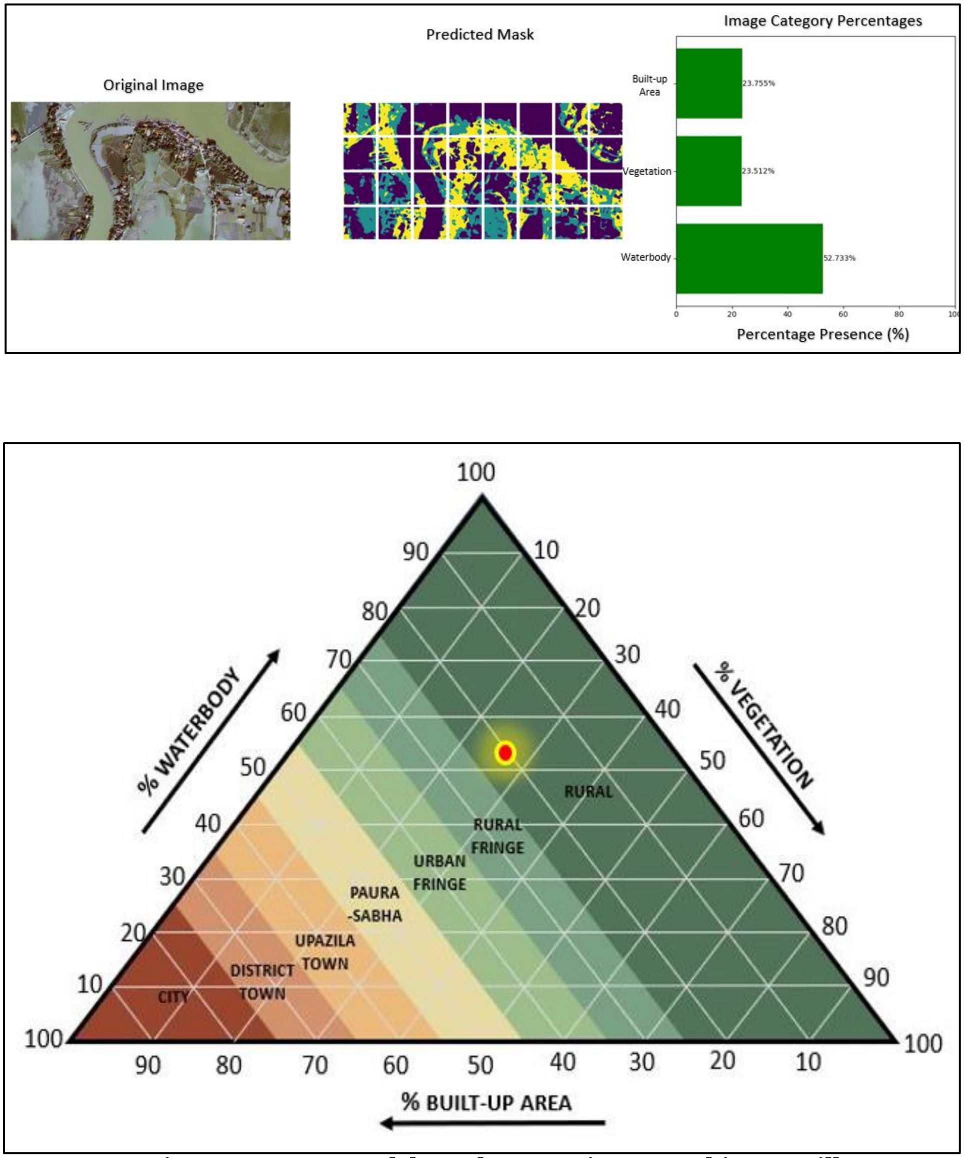


Figure 7: CNN Model Implementation on Tahirpur Village

Source: Compiled by Authors,

Figure 8: Air Quality Index of Tahirpur Village

Source: AccuWeather, 2024

Geographical Analysis

Tahirpur Village is situated in the Sunamganj district which is situated in the north-eastern part of Bangladesh. This area falls under the haor region where large areas of land is swamp, river and flood plains are common during the rainy season. The land use is mainly agricultural with large areas of water resources like rivers, beels, and floodplain wetlands that play very important roles in the regulation of floods, water purification, and support of biological diversity. The vegetation in the village is well developed with agricultural fields, homestead gardens, and small natural vegetation. These include; low population density of built-up areas, which is made up of isolated homesteads and small rural facilities, thus the natural character and ecological health of the landscape is preserved. The ideal habitat is the extent to which a given site is suitable to support a population of a given species.

Suitability as an Ideal Habitat

As shown in the Landscape Ecology Triangle, Tahirpur is located in the “Rural” part due to its landscape that comprises of water bodies and vegetation. These features make the environment to be healthy for living as well as being inclusive of other aspects of nature. The AQI of the village is 19 which shows that the air quality is very good and the village does not suffer from the pollution which is common in the urban centres. The existence of natural resources not only contributes to the existence of various animal species, but also improves the living standards of inhabitants by offering fresh air, beautiful landscapes and opportunities to earn a living through the production of natural products. These ecological features qualify Tahirpur to be the natural habitat for living, especially for those who want to lead a natural life. This is a clear contrast to the city’s setting and presents a picture of the ecological face of a village.

Case Study - 3: Pahartali Thana, Chattogram

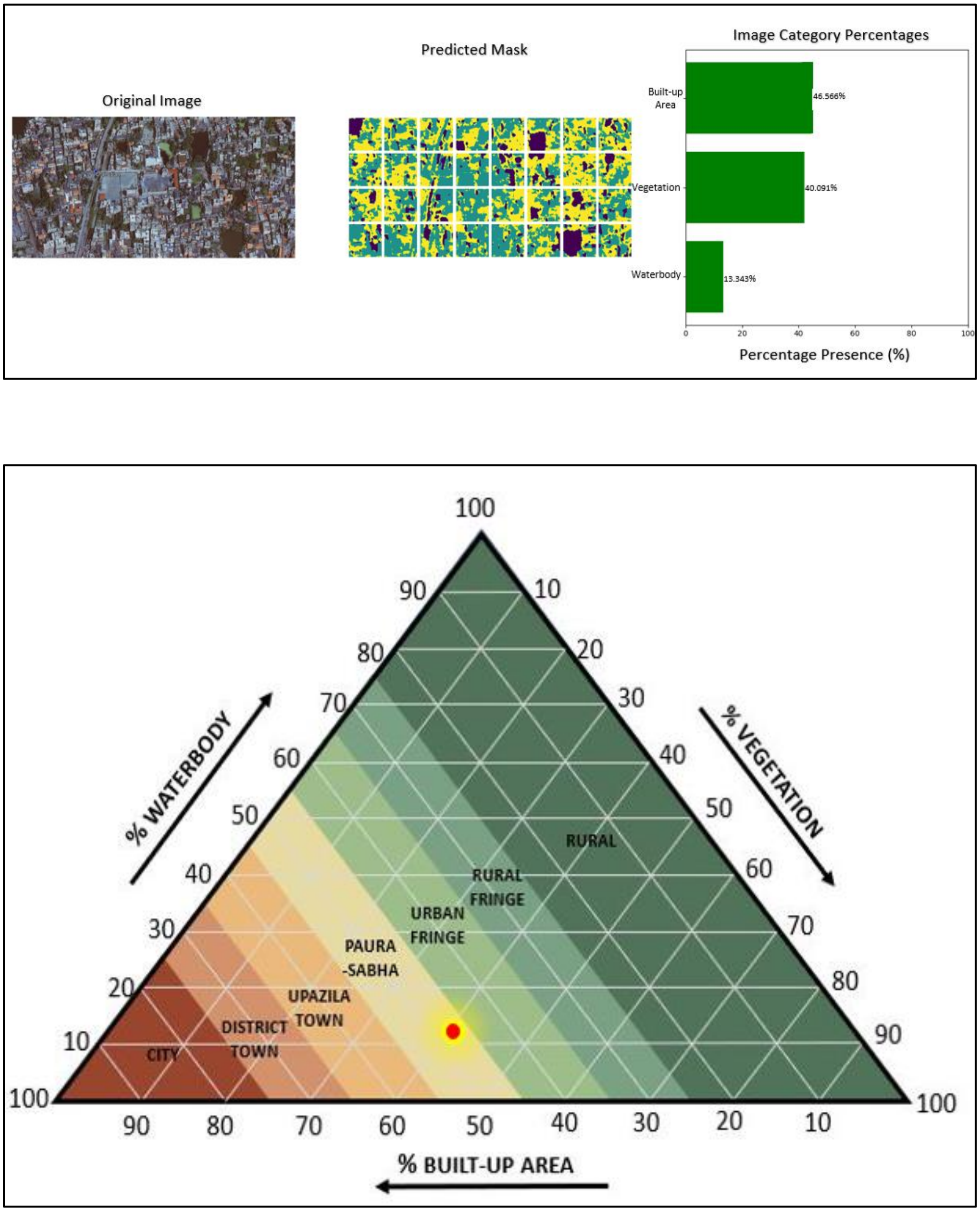
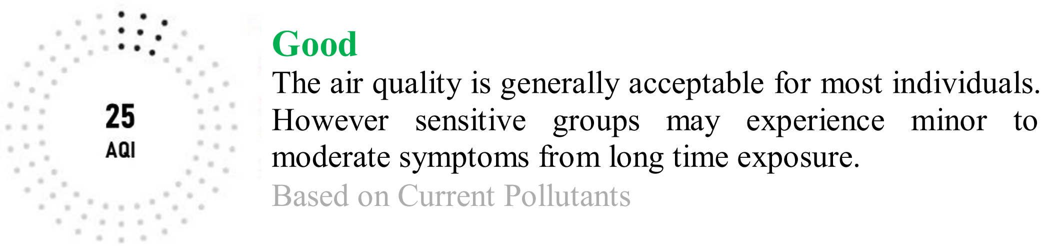


Figure 9: CNN Model Implementation on Pahartali Thana

Source: Compiled by Authors,



Source: AccuWeather, 2024

Figure 10: Air Quality Index of Pahartali

Geographical Analysis

Pahartali Thana is situated in the southern region of the Bangladesh, and it is under the Chattogram City Corporation. The geography of Pahartali is relatively unique in the context of other urban areas because of its relatively elevated land, sizeable forest cover, the presence of natural water sources. Unlike the central city area of Chattogram where buildings are tall and structures are congested, Pahartali is relatively suburban with houses surrounded by hills and trees. The vegetation is vast and consists of forested hills, gardens as well as parks. Also, lakes and streams are also natural resources that enhance the aesthetic and ecological value of the area as they act as natural wildlife habitat and water reservoirs.

Suitability as an Ideal Habitat

However, due to the vegetation and water bodies of Pahartali, it has been found that it falls in the “Paurasabha” category of the Landscape Ecology Triangle even though it is in a major urban region. These elements do not only act as aesthetic and environmental improvements of the area, but also provide healthier living conditions than developed urban areas of the city. The AQI of 25 means that the air quality is good which means that the environment is healthy for humans. The area is well developed and the natural environment is useful and appealing, it is suitable for dwelling and for that reason it is ideal for those who want to experience the city life and at the same time embrace the natural environment. The geographical characteristics of Pahartali also show that natural elements must be incorporated into urban design in order to build functional and comfortable cities.

CNN Model Performance

The CNN model achieved an overall accuracy of 92%, with particularly strong performance in identifying vegetated areas (IoU: 91.21%). However, some misclassification occurred between water bodies and built-up areas, which can be attributed to spectral similarities in certain regions. This result suggests that further refinement in distinguishing water from other landscape features would improve overall performance.

The model's robustness was tested across various landscapes, including urban, rural, and ecologically sensitive regions. It consistently performed well in classifying vegetated areas, demonstrating its potential for large-scale environmental monitoring.

Table 3: Per-class Metrics

Class	IoU	Dice Coefficient	Precision	Recall	F1 Score
Waterbody	0.6814	0.8105	0.7226	0.9229	0.8105
Built-up Area	0.7588	0.8629	0.9	0.8287	0.8629
Vegetation	0.9121	0.954	0.955	0.953	0.954

Source: Compiled by Authors,

Per-class metrics were used to assess how well the model performs for each specific class: Water, Other, and Vegetation are the major categories that need to be considered while evaluating the impacts. The Intersection over Union (IoU)

Table 4 : Overall Metrics

Metrics	Value
Accuracy	0.9201
Average IoU	0.7841
Average Precision	0.8592
Average Recall	0.9016
Average F1 Score	0.8758

Source: Compiled by Authors, 2024

calculated the overlap between the predicted and ground truth regions and the higher value of IoU means better segmentation. The Dice Coefficient like IoU measures the overlap of the predicted and actual regions which is helpful while dealing with imbalanced classes.

Overall metrics were calculated to provide a summary of the model's performance across all classes combined. These metrics offer a high-level view of the model's effectiveness and its generalization capabilities.

Accuracy, which represents the ratio of correctly predicted instances to the total number of instances, reflects the overall correctness of the model's predictions. The Average IoU is the mean IoU across all classes and indicates the general quality of

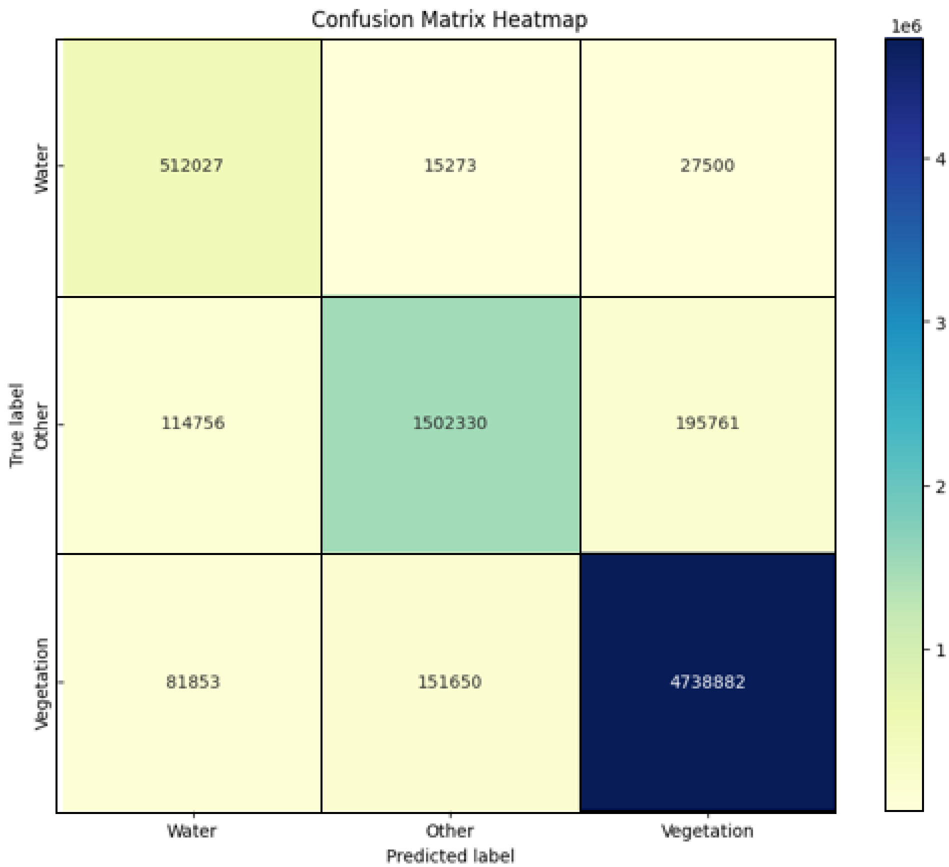


Figure 11 : Confusion Matrix Heatmap

Source: Compiled by Authors, 2024

the segmentation. Average Precision reflects the model's accuracy in positive predictions across all classes, while Average Recall shows the model's ability to capture all relevant instances. The Average F1 Score, balancing precision and recall, gives an overall measure of the model's classification performance.

The confusion heatmap displays the classes Water, Other, and Vegetation. The rows represent the true labels, while the columns represent the predicted labels. The values within the matrix indicate the number of instances for each true-predicted class pair. High values on the diagonal of the heatmap indicate correct predictions, while low values off the diagonal suggest minimal confusion between classes.

The confusion matrix heatmap provides a visual breakdown of correct and incorrect predictions.

- **True Labels (rows)** vs. **Predicted Labels (columns)**:
    - Diagonal values (e.g., 512,027 for Water, 1,502,330 for Other, and 4,738,882 for Vegetation) show correct classifications.
    - Off-diagonal values (e.g., 15,273 Water misclassified as Other) indicate misclassifications.
- **Color Scale**: Darker colors represent higher numbers, which helps quickly identify areas where the model performs well (darker on diagonal) and where it struggles (darker off-diagonal).

The model performs best in the identification of “Vegetation” class which incurs the highest number of correct classifications while incurring low misclassifications. A certain level of ambiguity is observed between “Water” and “Other” - category, however, the overall level of accuracy is rather high.

Confusion matrix also gives the graphical representation of how the model is performing in distinguishing between the different classes (Water, Other, Vegetation). The diagonal elements are the correct classification while off diagonal elements are the misclassifications. For instance, the model was able to accurately attribute 512,027 instances to Water, 1,502,330 instances to Other and 4,738,882 instances to Vegetation. The misclassifications are relatively lower hence the model performance is good especially for Vegetation class.

- **Strengths**: It can be observed from the model that a high level of IoU, Dice Coefficient, Precision, Recall, and F1 Score are achieved in segmenting “Vegetation”. The overall accuracy was 92 percent. It proved to be 01% effective in all classes which is an indication of its efficiency.
- **Areas for Improvement**: The model is quite effective, however, there is a scope of improving the “Water” class to decrease the misclassification as a result of slightly lower IoU and F1 Score than the “Vegetation”.

The *Landscape Ecology Triangle* thus serves as a predictive tool for assessing how landscape composition affects air quality, providing a basis for incorporating green spaces into urban planning to improve environmental health.

Knowledge Domain-based Contribution

In the 1950s, Benjamin Bloom participated as the coordinator of an organization of educationists whose mission was to devise an assessment model for gaining a greater understanding that would be useful in developing and evaluating educational programs. The organization determined that there are three distinct domains of education-

1. Cognitive Domain
2. Psychomotor Domain
3. Affective Domain

Domain	Contribution
Cognitive	• Advanced understanding of landscape ecology through the development of the Landscape Ecology Triangle and the classification of landscape types. • Provides new conceptual frameworks and tools (e.g., “Convolutional Neural Network model”) to recognize and recall complex patterns in satellite imagery, aiding research in landscape ecology and environmental management.
Psychomotor	• Practical application of Python-based Convolutional Neural Networks-CNNs involves complex technical skills, including data acquisition, preprocessing, model training, and analysis. • The research process requires and hones high levels of precision in programming and geospatial analysis, contributing to professional and educational development in geospatial analysis and machine learning.

Affective	• The research fosters appreciation for the environment by identifying ideal habitats for living based on ecological characteristics. • The Landscape Ecology Triangle highlights the importance of balanced ecological environments, potentially inspiring stronger commitments to environmental stewardship and sustainable living.

This research successfully applied a *Convolutional Neural Network (CNN)* to automate the classification of landscapes in Bangladesh, achieving high accuracy in detecting vegetation, water bodies, and built-up areas. The *Landscape Ecology Triangle* provides a novel conceptual framework for visualizing the spatial relationships between urban development and natural features. By automating LULC classification, this research offers a scalable, objective method for analyzing large datasets, addressing the limitations of manual approaches like *Anderson's Classification System.*

The study also explored the relationship between landscape types and *Air Quality Index (AQI)*, demonstrating the importance of natural features in improving air quality in urban areas. The findings of this study contribute significantly to *the Cognitive, Psychomotor*, and *Affective Domains*, reflecting its interdisciplinary impact on landscape ecology, urban planning, and environmental management. Furthermore, the integration of CNNs with satellite imagery not only enhances the precision and efficiency of landscape classification but also opens avenues for real-time monitoring of environmental changes. This approach can be instrumental in tracking urban sprawl, deforestation, and water body shrinkage, enabling proactive decision-making. The Landscape Ecology Triangle serves as a versatile tool for both academic research and practical applications, such as zoning regulations, sustainable land-use planning, and ecosystem service assessments. By linking landscape types with AQI, the study underscores the critical role of balanced ecological structures in mitigating urban environmental challenges, paving the way for more resilient and sustainable urban ecosystems.

Recommendations for Future Research

- **Short-Term**: Improve the CNN model's accuracy in detecting water bodies, particularly in areas with mixed land use patterns.
- **Mid-Term**: Expand the application of the Landscape Ecology Triangle to include additional variables such as soil quality, biodiversity, and climate data.
- **Long-Term**: Test the scalability of the CNN model and Landscape Ecology Triangle in different geographic and ecological regions worldwide.

Concluding Remark

This research has the potential to be regarded as a significant step forward in the science of landscape ecology, particularly when seen in the context of the diverse terrain that Bangladesh possesses. In addition to the fact that there has been a dearth of research on the application of satellite imagery for the purpose of landscape classification, this study has successfully applied CNNs that are based on Python to the satellite imagery for the purpose of landscape classification. This has resulted in a novel approach to classification, as opposed to the traditional method of interpretation. The conceptual understanding of landscape spatial dynamics, which focusses on the connection between urbanization, vegetation, and water bodies, has been significantly advanced by the formation of the Landscape Ecology Triangle, which is a significant addition to this understanding.

The findings of this research also indicate that machine learning has the potential to considerably enhance the landscape approach by providing knowledge that is more precise, efficient, and objective regarding the behaviors and interactions that contribute to the construction of our surrounds. Furthermore, by defining the research scope as the built-up area domain in the first instance, this study creates the basis for the subsequent investigation of other important components of the landscape, including vegetation and waterbodies, which are indispensable for the analysis of ecological processes.

In the proposal that was made, a clear path of future work was suggested. It was suggested that the CNN model should be further expanded and improved, and that additional ecological data should be incorporated into the model. Additionally, it was suggested that such research should be applied on a bigger scale. The findings of this research have significant implications for the future, including the design of cities and environments, the preservation of natural resources, and the promotion of sustainable development. In conclusion, the findings of this research not only contribute new information to the existing viewpoints in the field, but they also offer tools and recommendations that can be utilized to make more informed decisions about the preservation and enhancement of our landscapes.

References

AccuWeather. (2010). Local weather from AccuWeather.com - Superior accuracy. Retrieved from https://www.accuweather.com/

AirNow. (2021). Air quality index (AQI) basics. Retrieved from https://www.airnow.gov/aqi/aqi-basics/

Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). A land use and land cover classification system for use with remote sensor data (U.S. Geological Survey Professional Paper 964).

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A deep convolutional encoder-decoder architecture for image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(12), 2481-2495.

Bloom, B. S., Engelhart, M. D., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). Taxonomy of educational objectives: Handbook I: The cognitive domain. David McKay Co.

Forman, R. T., & Godron, M. (1986). Landscape ecology. John Wiley & Sons.

IQAir. (n.d.). Empowering the world to breathe cleaner air. Retrieved from https://www.iqair.com/

Jensen, J. R. (2005). Introductory digital image processing: A remote sensing perspective (3rd ed.). Prentice Hall.

GitHub. (2021). LoveDA: A remote sensing land-cover dataset for domain adaptive semantic segmentation. Retrieved from https://github.com/Junjue-Wang/LoveDA

Krathwohl, D. R., Bloom, B. S., & Masia, B. B. (1973). Taxonomy of educational objectives: Handbook II: Affective domain. David McKay Co.

Levin, S. A. (1992). The problem of pattern and scale in ecology: The Robert H. MacArthur award lecture. Ecology, 73(6), 1943-1967.

Li, J., Huang, C., Ding, Y., & Li, X. (2019). Mapping coral reefs using deep learning approaches and high-resolution remote sensing imagery. Remote Sensing, 11(15), 1750.

Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: A review. Frontiers in Public Health, 8, 14. https://doi.org/10.3389/fpubh.2020.00014

National Geographic. (2023, October 19). Air pollution. Retrieved from https://education.nationalgeographic.org/resource/air-pollution/

Pasher, J., King, D. J., & Friesen, W. O. (2006). Applying landscape ecology to the analysis of land use planning alternatives: An example from the Thompson-Okanagan, British Columbia, Canada. Landscape and Urban Planning, 78(1-2), 101-112.

Simpson, E. J. (1972). The classification of educational objectives in the psychomotor domain. Gryphon House.

Townshend, J. R., Hansen, M. C., Huang, C., Veverka, S., & Rogan, J. (2012). Detecting and monitoring vegetation changes using temporal variation analysis. Remote Sensing of Environment, 119, 88-106.

Turner, M. G. (2005). Landscape ecology: What is the state of the science? Annual Review of Ecology, Evolution, and Systematics, 36, 319-344.

Wang, F., Jia, K., Yan, S., & Liu, Y. (2018). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 9, 1420.

World Bank. (2020). How do we define cities, towns, and rural areas? World Bank Blogs. Retrieved from https://blogs.worldbank.org/en/sustainablecities/how-do-we-define-cities-towns-and-rural-areas#:~:text=To%20show%20this%2C%20we%20defined