Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

DOI: 10.37943/22YNTU3695

Dilyara Nazyrova
Doctoral researcher, Department of Information Systems
nazyrovadilyara@gmail.com; orcid.org/0000-0002-1148-4480
L.N. Gumilyov Eurasian National University, Kazakhstan
ECOSERVICE-S LLP, Kazakhstan

Zhangeldi Aitkozha
Doctor of Physical and Mathematical Sciences, Associate Professor, Department of Information Systems
aitkozha_zh@mail.ru; orcid.org/0000-0002-1213-5186
L.N. Gumilyov Eurasian National University, Kazakhstan

Seyit Kerimkhulle
Doctor of Science (Economics), Professor, Department of Information Systems
kerimkul_sye@enu.kz; orcid.org/0000-0002-5886-6064
L.N. Gumilyov Eurasian National University, Kazakhstan

Gulmira Omarova
PhD, Senior lecturer, Department of Information Systems
ogs12@mail.ru; orcid.org/0000-0003-2053-0255
L.N. Gumilyov Eurasian National University, Kazakhstan

COMBINED APPROACH BASED ON HARALICK AND GABOR FEATURES TO CLASSIFY BUILDINGS PARTIALLY HIDDEN BY VEGETATION

Abstract: Classification of urban area is important for urban planning, infrastructure management and detection of illegal constructions. However, automatic object recognition in urban environments is difficult due to textural similarity of materials, varying lighting conditions and partial overlap of buildings with vegetation. The identification of buildings partially hidden by green spaces is particularly challenging because their boundaries merge with the surrounding environment, which reduces the accuracy of traditional classification methods. In this study, a stepwise approach to object classification in aerial images is proposed to improve the recognition of buildings partially hidden by vegetation. The analysis was performed in two stages using three-channel high-resolution aerial images acquired from an unmanned aerial vehicle. In the first stage, classification was performed based on Haralick features computed from a co-occurrence matrix of gradations, which allowed the extraction of statistical texture features. However, this was insufficient for accuracy, so in the second stage, a Gabor filter was additionally applied to provide analysis of local texture features, taking into account the frequency and orientation of image elements. The final classification was performed using Random Forest algorithm, which allowed to divide objects into three categories: "buildings", "vegetation" and "buildings partially hidden by vegetation". The classes "buildings" and "vegetation" were considered as auxiliary, providing quality control of the classification and allowing us to focus on improving the recognition of objects partially occluded by vegetation. Experimental results confirmed that the proposed method is effective for recognizing buildings partially hidden by vegetation. The inclusion of the Gabor filter improved the classification accuracy of this class from 0.84 to 0.90, the completeness from 0.74 to 0.86, and the F1-estimation from 0.79

Received: 28.12.2024 Accepted: 26.06.2025 Published: 30.06.2025

to 0.88. The 11% improvement in completeness is particularly important because it indicates a reduction in the number of missed buildings. In comparison, the classification accuracy of fully visible buildings increased from 0.84 to 0.91 and that of vegetation from 0.88 to 0.95. Thus, the proposed method, which combines global and local texture features, demonstrated high performance to improve the identification accuracy of complex objects whose boundaries merge with the surrounding vegetation.

Keywords: texture analysis; Haralick features; Gabor filters; image classification; Random Forest; urban environment.

Introduction

Modern image analysis methods are widely used in urban environment monitoring tasks, including identifying hidden buildings and studying the influence of vegetation on urbanized areas. One of the urgent problems in this area is the classification of objects partially hidden by vegetation, as standard methods often encounter difficulties in processing complex texture patterns. Texture analysis has proven to be an effective approach to solving such problems. Texture-based features, such as Haralick descriptors [1], [2] and Gabor filters [3], have been successfully applied in a wide range of image classification tasks, including applications in urban monitoring. Machine learning approaches based on the use of diverse data and adaptive methods have proven to be an effective tool for classifying complex objects, as demonstrated in [4], where modern methods were used to analyze multidimensional features in agricultural tasks.

Features based on the common occurrence matrix of gray levels allow us to take into account statistical properties of texture such as homogeneity, contrast, entropy and other parameters that characterize the spatial distribution of pixel intensities in an image [5]. These features are effectively used to extract objects such as buildings, roads, and vegetation because each object has a unique texture characteristic that can be reflected through these parameters [6]. For example, [7] used a combined approach involving texture analysis and object-oriented feature extraction, which improved the classification results. A study [8] showed that integrating features with deep learning methods can also significantly improve the accuracy of object recognition in complex scenarios. However, standard feature-based methods have limitations due to the scale of analysis and image resolution, and they are less effective for classifying large objects [9].

In response to these limitations, methods that combine texture analysis with Gabor filters and multiscale methods are actively used to improve classification accuracy. Gabor filters, due to their ability to extract local features with orientation and frequency selectivity, overcome object resolution and scale problems [10]. These filters have been widely used in texture analysis and image classification, including object recognition tasks and satellite and aerial image analysis. For example, in [11], Gabor filters combined with local binary pattern operators were used for automatic building extraction from high-resolution remote sensing images, achieving high accuracy. Similarly, studies [12] and [13] also applied Gabor filters for the automatic extraction of buildings, confirming the effectiveness of texture-based methods in urban object detection. A study in [14] discusses the use of Gabor filters for texture analysis in multispectral images, which showed high accuracy in segmenting complex objects. These studies have demonstrated high accuracy in building detection and improved visualization for urban planning purposes. In addition, current studies [15], [16] show that combining texture methods with LiDAR data allows for more efficient classification of objects in urban environments.

Another promising area is the use of deep learning techniques such as convolutional neural networks (CNNs) to process texture features. The work in [17] shows how combining CNNs with texture-based features improves the classification accuracy of complex objects. Also, [18]

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

presented a study in which Gabor filters were integrated with CNNs to improve the identification of fine details in urban environments.

The aim of this study is to try to improve the classification of buildings partially hidden by vegetation using a combined approach based on Haralick texture features and Gabor filter. To achieve this goal, the following objectives are set:

1. Propose a method to improve the accuracy of urban object classification using Haralick features and Gabor filter to process texture features of objects partially hidden by vegetation.
2. valuate the accuracy of object classification using the proposed method and compare its performance with methods based solely on Haralick's features.
3. Apply the proposed method to classify objects in aerial images of urban area including buildings, buildings partially hidden by vegetation and vegetation.

Methods and Materials

This study uses a stepwise approach to classify objects in aerial images. We hypothesize that adding the Gabor filter to the Haralick features will improve classification accuracy by more fully accounting for the textural characteristics of objects.

At the first stage, a classification based on Haralick's features was carried out, which allowed us to assess their informativeness in identifying buildings partially hidden by vegetation. However, the analysis of the results showed that the classification accuracy for this category of objects was insufficient. Therefore, at the second stage, a combined method including Gabor filter was applied, which allowed taking into account additional textural characteristics and improving the recognition accuracy.

The study includes the following key steps:

1. Preparation of Input Data – Acquisition of high-resolution UAV imagery.
2. Initial Classification – Calculation of Haralick Features, Random Forest Model Training, and Evaluation of Classification Accuracy.
3. Method Refinement – Application of the Gabor Filter for Extraction of Additional Texture Features and Reclassification.
4. Comparative Analysis – Evaluation of Methodological Differences and Assessment of the Advantages and Limitations of the Combined Method.

Preparation of Input Data

The object of the study is optical images with 3 RGB channels acquired by a high-resolution unmanned aerial vehicle (UAV) covering an area of urban territory with dense vegetation. The imagery was taken during the summer period, when the vegetation is in peak state, which creates additional difficulties for object classification. The dense vegetation partially hides buildings, which requires more accurate methods to distinguish them. It is assumed that the images were taken under standard lighting and weather conditions, minimizing the influence of external factors on textural features of objects. It is also assumed that all objects in the images have clear contours, despite possible distortions due to vegetation, and that the images are of sufficient quality to extract Haralick features and apply the Gabor filter. Fig. 1 shows a fragment of the study area.

Figure 1. High-resolution aerial image with three RGB channels acquired in summer period

Initial Classification

To classify buildings partially hidden by vegetation, texture feature extraction is an important step. To analyze the texture features of objects, we used the Gray Level Coincidence Matrix (GLCM), which describes the probability distribution of pairs of pixels with certain brightness values located at a fixed distance and at a given angle.

This method allows extracting information about local texture patterns, which is especially important when analyzing complex and heterogeneous areas of the urban environment. The optimal analysis parameters were determined empirically in order to achieve a balance between accuracy and computational costs: the radius of neighboring pixels was set equal to 1, which allows capturing fine texture details; directions (angles) of 0°, 45°, 90° and 135° ensure the detection of texture features regardless of the orientation of structures; gray level quantization was performed at 16 levels, which provides sufficient detail of texture properties while minimizing computational costs. The main statistical characteristics of Haralick, namely energy (texture homogeneity), entropy (a measure of randomness of image intensity), correlation (how correlated a pixel is with its neighborhood), inverse difference moment (a measure of texture homogeneity), inertia (intensity contrast between a pixel and its neighborhood), asymmetry, texture convexity, and Haralick correlation, were computed based on GLCM. Table 1 summarizes the descriptions and mathematical formulas for each feature computed using the joint likelihood matrix (GLCM).

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

Table 1. Characteristics of Haralick features

Title	Description	Formula
Energy	Texture uniformity, a measure of how uniform the texture of an image is.	$$Energy = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P\,(i,j)^2 \quad (1)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix
Entropy	A measure of the randomness of the intensity of an image, reflecting the level of chaos.	$$Entropy = -\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P\,(i,j) log_2 P(i,j) \quad (2)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix
Correlation	How correlated a pixel is with its neighborhood.	$$Correlation = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P\,(i,j)ij - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (3)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix • μ_x and μ_y – mathematical expectations (mean values) for rows and columns of the joint probability matrix • σ_x and σ_y are standard deviations for rows and columns of the joint probability matrix
Inverse Difference Moment (IDM)	A measure of texture uniformity, reflecting the smoothness or intensity difference between pixels.	$$IDM = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{P(i,j)}{1+(i-j)^2} \quad (4)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix
Inertia	Intensity contrast between a pixel and its neighborhood.	$$Inertia = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i-j)^2 P(i,j) \quad (5)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix
Asymmetry	A property of intensity distribution related to texture asymmetry.	$$ClusterShade = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left(i+j-\mu_x-\mu_y\right)^3 P(i,j) \quad (6)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix • μ_x and μ_y – mathematical expectations (mean values) for rows and columns of the joint probability matrix
Textural prominence	A measure of texture contrast that takes into account the amplitude of texture elements.	$$Text.prom. = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \left(i+j-\mu_x-\mu_y\right)^4 P(i,j)\,(7) \quad (7)$$
		• P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix • μ_x and μ_y – mathematical expectations (mean values) for rows and columns of the joint probability matrix

Title	Description	Formula
Haralick Correlation	A measure of the intensity relationship between neighboring pixels.	$$Haralick\ Corr. = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P\,(i,j)ij - \mu_x\mu_y}{\sigma_x\sigma_y} \quad (8)$$ • P(i,j) – element of the GLCM matrix for values i and j • N – number of possible gray levels • i and j – pixel intensities in the GLCM matrix • μ_x and μ_y – mathematical expectations (mean values) for rows and columns of the joint probability matrix • σ_x and σ_y are standard deviations for rows and columns of the joint probability matrix

For further analysis and visualization, the computed Haralick features were assembled into a multi-channel image, where each channel corresponded to a separate texture feature. Thus, an image consisting of 8 channels was obtained, which made it possible to visualize the distribution of texture features in the image and use them for object classification. Fig. 2 shows a fragment of the study area with calculated Haralick features.

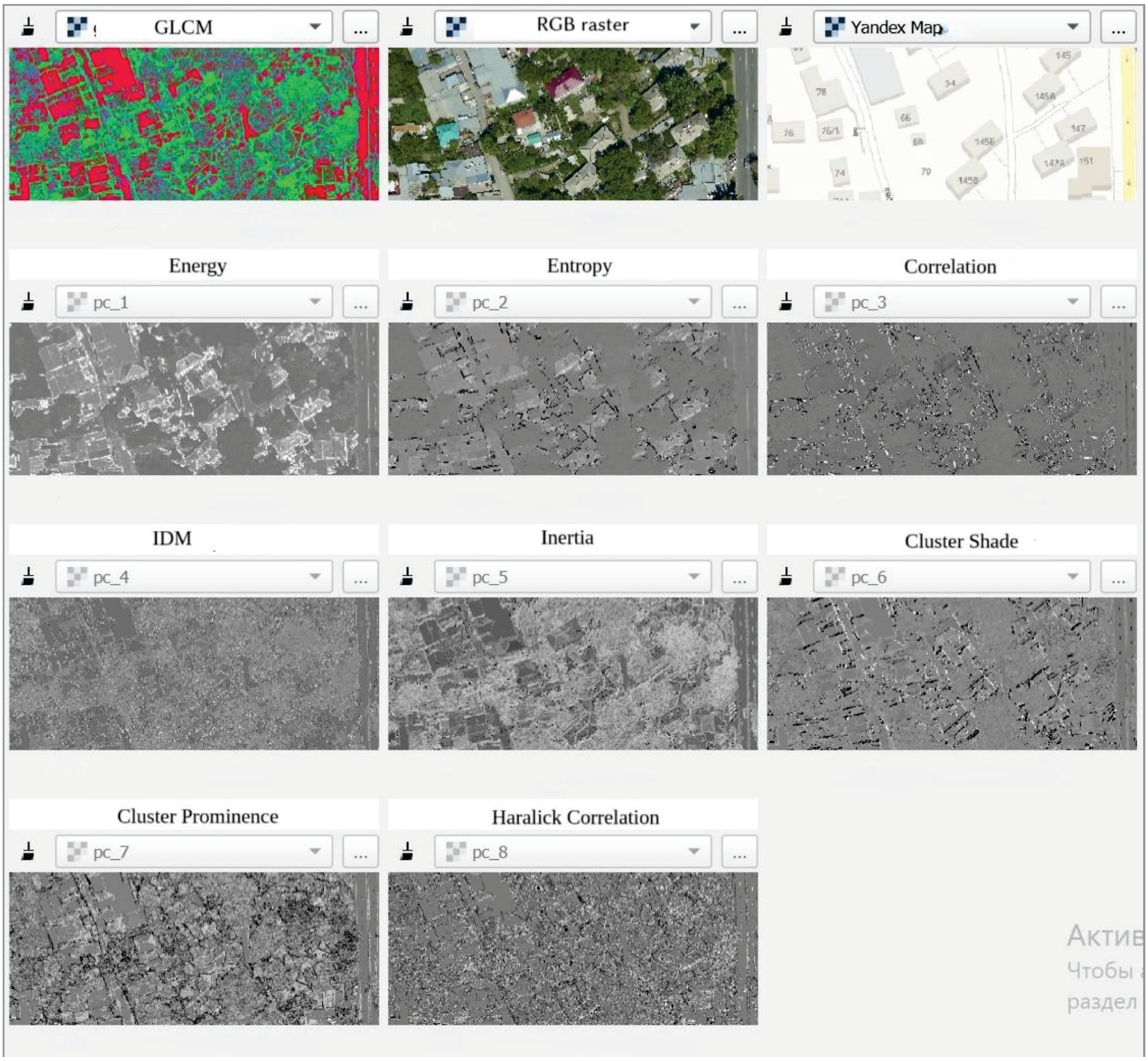

Figure 2. Visualization of 8 channels with Haralick texture features

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

The analysis shows that the roofs of the buildings exhibit a high degree of uniformity, which is reflected in the increased energy values. This reflects the regularity of textures characteristic of man-made surfaces. In contrast, vegetation patches are characterized by significantly higher entropy, indicating chaotic and varied textural elements, as well as increased contrast values, which is associated with abrupt changes in brightness.

To use the computed texture features in the task of classifying objects in images, two shape-files with labeled data were created: a training file and a test file. In each shapefile, objects were labeled based on their texture features and classes defined in the image.

The following classes are included in the breakdown:

- Buildings: objects that are fully visible in the image and not hidden by vegetation;
- Vegetation: areas occupied by vegetation, including trees and shrubs;
- Vegetated buildings: buildings partially hidden by vegetation, where vegetation overlaps part of the site;

Each object was measured as a polygon and a centroid was calculated for each polygon, for which the mean values of Haralick's texture features were then extracted. This data was used to create feature vectors that served as input to the classification algorithm.

A Random Forest (RF) model was used for classification, which was chosen because of its high performance on multidimensional features and its ability to handle object diversity and complex textures [19]. The RF model is able to consider the importance of each feature and successfully classify objects even if they are partially hidden by vegetation. 500 objects for each class in the training set and 100 objects for each class in the test set were used as training data. This provided sufficient statistical sampling for model training and validation. Fig. 3 presents a general flowchart of the classification process using Haralick features and Gabor filters, illustrating the main steps of the combined method. This figure serves as a guideline for further presentation, and a detailed description is presented in the Method Refinement section.

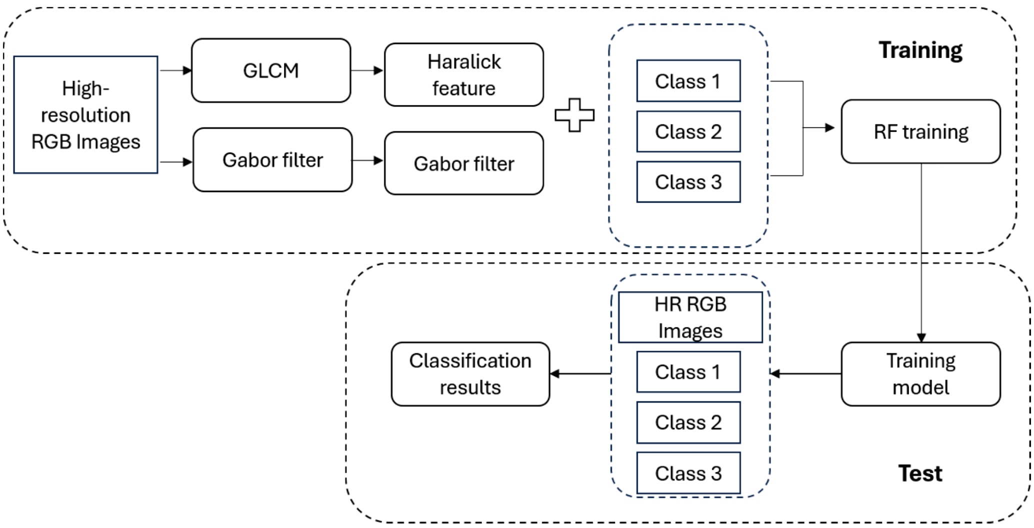

Figure 3. The process of object classification based on Haralick and Gabor features using random forest method

It is worth noting that the calculation of Haralick features for the whole image, not just for marked objects, proved useful as it allowed to take into account the environmental context of the objects, which is important for the correct interpretation of complex cases, such as partially hidden by vegetation buildings.

Training the RF model allowed to identify important textural features most informative for classification and automatically adapt to different types of objects, including partially hidden buildings. The results of object classification based on Haralick's texture features using Random Forest method are shown in Fig.4.

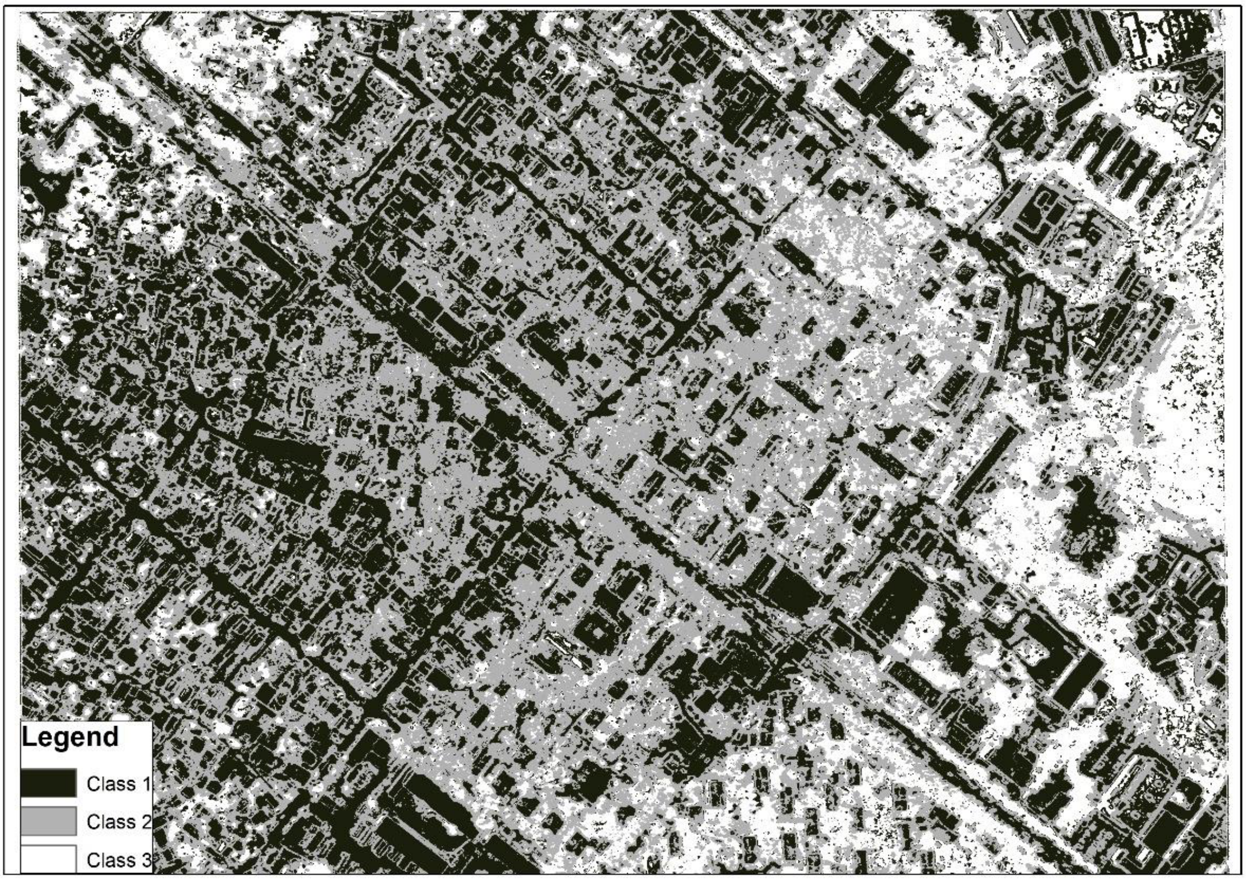

Figure 4. Result of object classification based on Haralick's texture features using random forest method

The classification result calculated the main accuracy metrics such as Precision, Recall and F1-score for each of the classes. The classification results are summarized in Table 2.

Table 2. Haralick's feature-based classification metrics

Class (Objects)	Precision	Recall	F1-Score
Class 1. Buildings	0.84	0.84	0.84
Class 2. Buildings partially hidden by vegetation	0.84	0.74	0.79
Class 3. Vegetation	0.88	0.98	0.92

The results shown in Fig. 5 and Fig. 6 demonstrate high classification accuracy for most classes, with the class “buildings partially hidden by vegetation” proving more difficult to accurately.

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

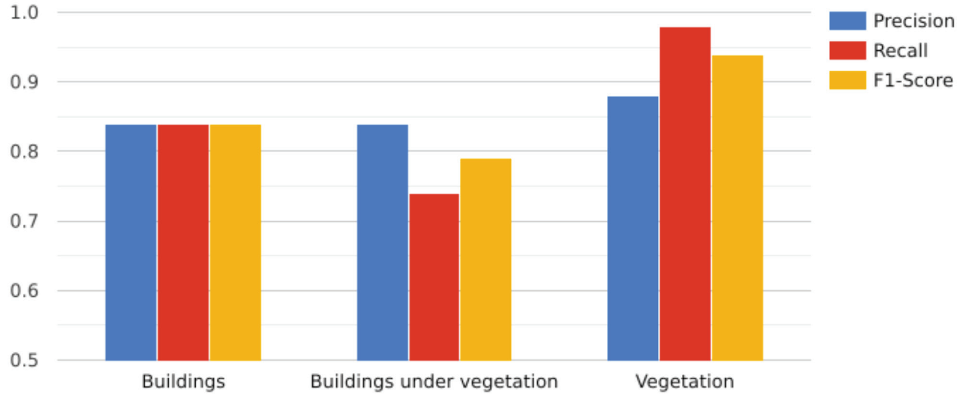

Figure 5. Haralick's feature based classification metrics

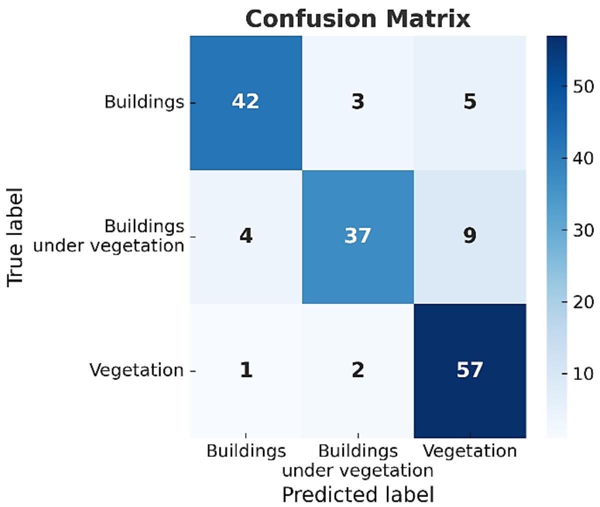

Figure 6. Haralick's feature based classification error matrix

Buildings (Class 1): The model showed good accuracy and completeness for this class, achieving a value of 0.84 for accuracy, completeness and F1-score, indicating the model's good ability to correctly classify building objects.

Buildings partially hidden by vegetation (Class 2): For this class, accuracy was 0.84, but completeness was slightly lower (0.74), indicating some difficulty in identifying objects partially hidden by vegetation. F1-score was 0.79, which is an average result for this class.

Vegetation (Class 3): The model showed excellent results for vegetation, with an accuracy of 0.88 and a very high completeness of 0.98, indicating the model's high ability to correctly classify vegetation objects. The F1-score was 0.92, which confirms the high performance of vegetation classification.

These results confirm the effectiveness of the model in the task of classifying urban objects based on texture features, while further improvement of the method is required for more accurate classification of objects partially hidden by vegetation, which was achieved in the next step with the application of the Gabor filter.

Method Refinement

Based on the assumption that adding additional texture features can improve classification accuracy, we apply a Gabor filter to extract additional features that help overcome the limitations of the Haralick feature-only approach. This refinement aims to improve classification by better accounting for texture variations and fine details that are not covered by Haralick features.

The Gabor filter was chosen for this study due to its ability to analyze the spatial-frequency characteristics of an image. This filter is a linear filter that extracts texture and contour features based on orientation and scale. For object classification tasks under conditions of partial vegetation overlap, such filter properties are key [20].

The mathematical description of the Gabor filter is given by the following equation:

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp\left(\frac{-x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) * cos\left(2\pi \frac{x'}{\lambda} + \psi\right) \tag{9}$$

where:

- x' and y' are coordinates in the direction rotated by an angle θ,
- λ is the wavelength,
- θ is the orientation angle of the filter,
- ψ is the phase shift,
- σ is the standard deviation of the Gaussian kernel,
- γ – aspect ratio (the ratio between the x-axis and the y-axis).

The main advantages of using it in research:

1. Selection of oriented textures.

Thanks to the θ parameter, the Gabor filter allows you to select textures at preset angles. This is especially useful for classifying buildings where roofs, walls, or shadows may have a well-defined orientation, even if partially covered by vegetation.

2. Analysis of spatial-frequency characteristics.

The parameter λ adjusts the wavelength, allowing the filter to be sensitive to textures of different scales. This helps to highlight large and small elements, such as roof lines or vegetation texture.

3. Stability to noise.

The Gaussian function suppresses noise and fine details, which improves image processing with a heterogeneous structure.

4. Local filtering.

Due to the σ parameter, which controls the filter area, it is possible to analyze local textural features, ignoring insignificant textures on the background.

During the experiments, various combinations of values were tested, which allowed optimizing the filter responses for each class of objects. Thus, the following parameters were determined for image analysis:

- Orientations (θ): 0, 45, 90, 135 – to highlight textures oriented at different angles;
- Wavelength (λ): 10 pixels – to emphasize the characteristic structures of objects;
- Phase shift (ψ): 0 – to highlight the main textural features;
- Gaussian width (σ): 4 pixels – to suppress small noises and highlight large elements;
- Aspect ratio (γ): 0.5 – to take into account the elongation of textures characteristic of vegetation;

The selection of these parameters was performed empirically through iterative testing on a held-out validation subset. For each candidate configuration of the Gabor filter, the classification performance – particularly the F1-score for the "buildings partially hidden by vegetation" class – was evaluated. The chosen setup ($\theta = [0°, 45°, 90°, 135°]$, $\lambda = 10$ pixels, $\psi = 0$, $\sigma = 4$, $\gamma = 0.5$) provided the most stable and accurate results. This process allowed fine-tuning the filter responses to maximize discrimination between building textures and overlapping vegetation, thereby improving both accuracy and generalization of the model. For example,

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

the wavelength (λ) was set to 10 pixels to accentuate the characteristic structures of objects such as buildings and vegetation. The width of the Gaussian (σ) was 4 pixels, which effectively suppressed small noises while preserving important textural elements. The aspect ratio (γ) 0.5 turned out to be the most suitable for taking into account the elongation of textures typical of vegetation.

This approach to setting the filter parameters allowed not only to improve the classification quality, but also to improve the generalizing ability of the model, which is confirmed by an increase in quality metrics such as Precision and Recall compared to the initial use of only Characteristic features.

Thus, a fixed-parameter Gabor filter was applied to each image channel, where a filter response with a specific frequency was calculated for each image channel. These filter responses were processed to extract additional textural features such as the mean of the responses. This allows the main textural features of the image to be extracted. The final data included additional features for each channel representing the image textural features extracted by the Gabor filter.

A Random Forest model trained on features obtained using a combination of texture analysis computing Haralick features and texture analysis, computing Gabor filter responses, was used to classify objects in the images. These features were used as input vectors. The results of object classification based on texture features of Haralick and Gabor filter are shown in Fig.7.

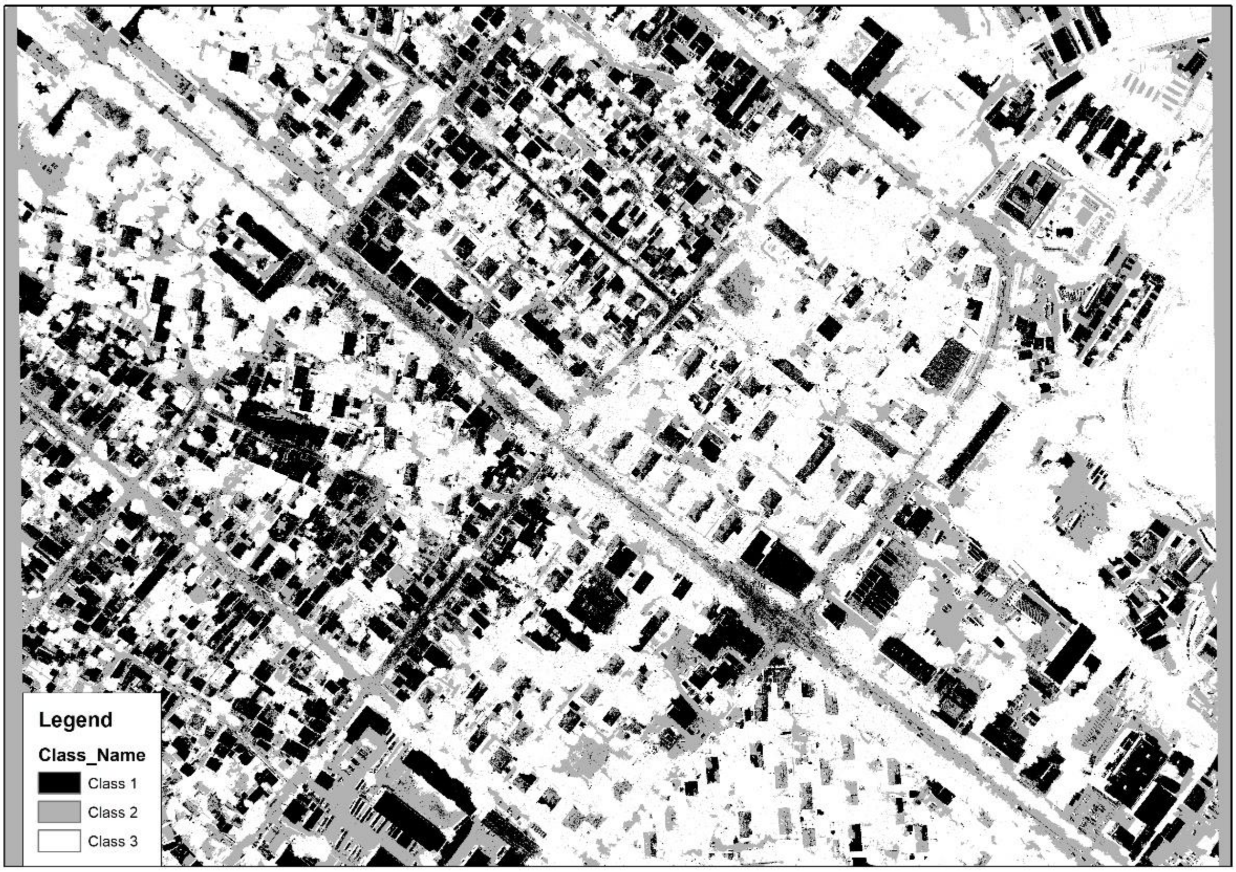

Figure 7. Classification of objects based on textural features of the Haralick and the Gabor filter using the random forest method

The use of the Gabor filter has significantly improved the classification accuracy compared to the results obtained using only Haralick features. Table 3 shows the improved metrics obtained using the Random Forest model in the test sample.

DOI: 10.37943/22YNTU3695

Table 3. Classification metrics based on Haralick features and the Gabor filter

Class (Objects)	Precision	Recall	F1-Score
Class 1. Buildings	0.91	0.90	0.91
Class 2. Buildings partially hidden by vegetation	0.90	0.86	0.88
Class 3. Vegetation	0.95	0.98	0.96

Fig. 8 and Fig. 9 show the classification metrics and classification error matrix obtained based on the Haralick features and the Gabor filter.

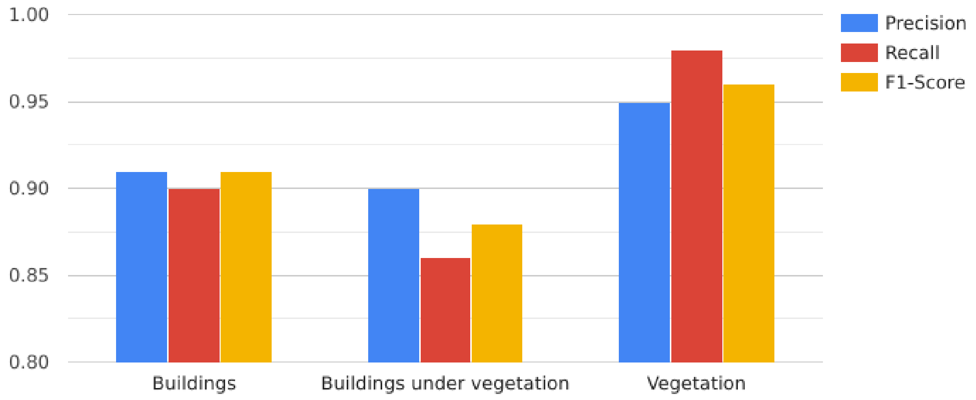

Figure 8. Classification metrics based on Haralick features and Gabor filter

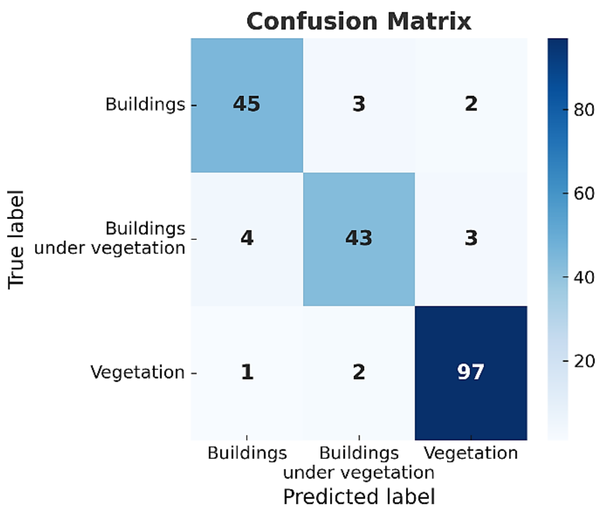

Figure 9. Classification error matrix based on Haralick features and Gabor filter

Thus, to improve the classification of objects partially hidden by vegetation, the study applied a Gabor filter to extract additional textural features. This filter effectively analyzes the spatial-frequency characteristics of the image to extract important textural features of objects such as roof lines and vegetation elements. As a result of using the Gabor filter with optimized parameters such as orientation, wavelength, phase shift and Gaussian width, the classification accuracy was significantly improved. The Random Forest model trained on Haralick features and Gabor filter responses showed a marked improvement in accuracy and completeness metrics for all classes, particularly for the "Buildings partially hidden by vegetation" class, where accuracy improved from 0.84 to 0.90. For the "Buildings" and "Vegetation" classes, high results

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

were also achieved, with accuracies of 0.91 and 0.95, respectively. These results confirm the effectiveness of the method refinement and show that the use of the Gabor filter helps to significantly improve the accuracy of classification of complex objects in urban environments.

Comparative Analysis

To analyze the effectiveness of the approach, Table 4 below provides a comparison of metrics for classification using only Haralick features and the combined approach (Haralick features and Gabor filter):

Table 4. Comparison of classification metrics for methods based only on Haralick features and the combined method (Haralick features and Gabor filter).

Class (Objects)	Classification based on Haralick features			Classification based on Haralick features and Gabor filter		
	Precision	Recall	F1-score	Precision	Recall	F1-score
Class 1. Buildings	0.84	0.84	0.84	0.91	0.90	0.91
Class 2. Buildings partially hidden by vegetation	0.84	0.74	0.79	0.90	0.86	0.88
Class 3. Vegetation	0.88	0.98	0.92	0.95	0.98	0.96

The results of the comparative analysis are also shown in Fig.10, Fig.11 and Fig.12.

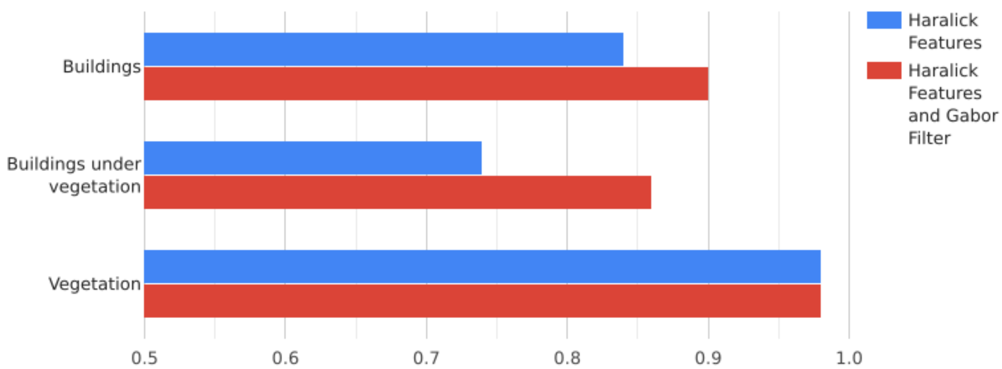

Figure 10. Comparison of classification accuracy: using Haralick features and combination of Haralick features and Gabor filter

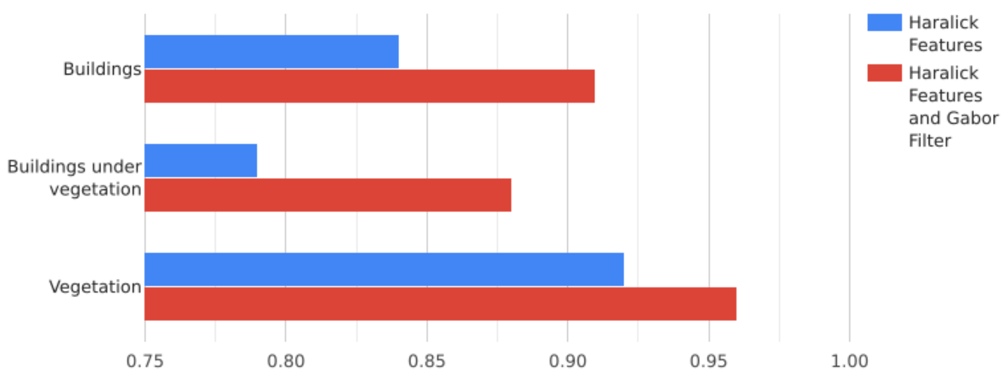

Figure 11. Comparison of classification completeness: using Haralick features and combination of Haralick features and Gabor filter

DOI: 10.37943/22YNTU3695

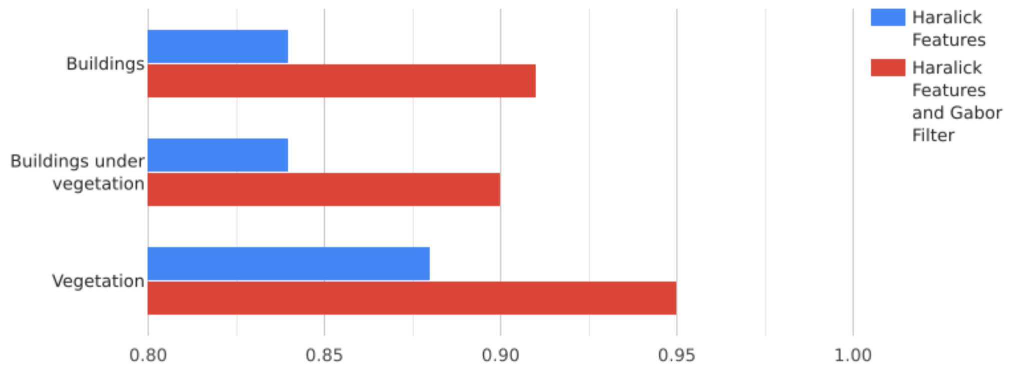

Figure 12. Comparison of F1 classification measures: using Haralick features and combination of Haralick features and Gabor filter

A comparative analysis of the classification methods showed that adding the Gabor filter significantly improves the results for all object classes. For the Buildings class, the accuracy increases from 0.84 to 0.91, which corresponds to an improvement of 8.33%. Also, F1-estimation increases from 0.84 to 0.91 (8.33% improvement) and recall increases from 0.84 to 0.90 (7.14% increase). In the "Buildings partially hidden by vegetation" class, accuracy increases from 0.84 to 0.90, giving an increase of 7.14%, F1-estimation increases from 0.79 to 0.88 (an increase of 11.39%), and recall increases from 0.74 to 0.86, corresponding to an increase of 16.22%. In the Vegetation class, the precision increases from 0.88 to 0.95 (7.95% increase), the F1-estimation increases from 0.92 to 0.96 (4.35% increase), and the recall remains unchanged at 0.98. Thus, applying the Gabor filter in combination with Haralick features leads to improvements in all key classification metrics, with the largest gains in the "Buildings partially hidden by vegetation" class.

Results and Discussion

The key objective of the study was to improve the classification accuracy of buildings partially hidden by vegetation through the combined use of Haralick texture features and Gabor filter. The results showed a significant improvement in classification accuracy for this category of objects. Thus, the classification accuracy of buildings partially hidden by vegetation increased from 0.84 to 0.90, indicating a significant improvement in recognizing such objects. The classification completeness increased from 0.74 to 0.86, which reduces the probability of missing objects of this category. In particular, F1 measures also showed improvement: for classification using only Haralick features it was 0.79, while for the combined approach with the Gabor filter it increased to 0.88, confirming an improved balance between classification accuracy and completeness.

These results are consistent with previous studies that used textural features to analyze urban environments. However, most of the works focused on classical texture classification without considering local spatial features such as frequency and orientation of features. The inclusion of the Gabor filter allowed these features to be taken into account, yielding a significant improvement in the results. This supports the hypothesis that the combined approach provides more accurate class separation, especially in complex cases of overlapping objects.

In comparison to modern deep learning approaches such as Convolutional Neural Networks (CNNs), our method offers interpretability and requires significantly fewer computational resources and training data. While CNNs demonstrate strong performance in object classification, their application often demands large annotated datasets and high computational capacity. Similarly, LiDAR-based methods provide rich spatial detail but require specialized hardware

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

and are not always available for every region. In contrast, the proposed method using texture-based features (Haralick and Gabor) remains lightweight, interpretable, and practical for scenarios where access to complex data or infrastructure is limited.

Despite the positive results achieved, the method has a number of limitations. First of all, its performance depends on the quality of the original data: reduced image resolution, illumination variations and weather conditions can negatively affect the classification accuracy. In addition, the method is sensitive to Gabor filter parameters such as scale and orientation, which requires additional calibration for different types of data. Another limitation is the limited testing – the method was tested on a single dataset during the study, so further validation on images taken under different conditions, including seasonal changes and illumination variations, is needed.

To overcome the identified limitations and to further develop the method, the following directions are possible:

To overcome the identified limitations and to further develop the method, several directions can be considered. First, it is possible to expand the feature set, which includes the inclusion of additional textural and spectral characteristics. This will increase the robustness of the method to changes in survey conditions. Second, hybrid methods that combine traditional classification methods with deep neural network models can be used. This will combine the advantages of interpreted features and the high efficiency of neural networks. Third, it is necessary to adapt the method to different types of imagery. In particular, a technique can be developed to adjust the parameters of the Gabor filter to different conditions such as seasonal changes in vegetation, which will increase the versatility of the approach. In addition, this method can be useful not only for classifying urban environment objects, but also for monitoring landscape changes, detecting unauthorized construction, and analyzing natural areas.

Conclusion

This study proposes a method to improve the accuracy of urban object classification aimed at improving the recognition of buildings partially hidden by vegetation. To achieve this goal, a combined approach combining Haralick texture features and Gabor filter was used.

The analysis of the results showed that the proposed method significantly improved the classification accuracy of objects partially hidden by vegetation. When using the combined approach (Haralick features and Gabor filter), the classification accuracy increased by 7.14% compared to using only Haralick features. This indicates that the addition of the Gabor filter improved the recognition of objects partially hidden by vegetation by better extracting texture features that may have previously been under-expressed in data based on Haralick features alone.

F1-value, which is the harmonic mean of accuracy and completeness, increased by 11.39%. This change indicates that the proposed method not only improved the accuracy but also im-proved the balance between accuracy and completeness. The 11.39% improvement in F1 score indicates that the model has become more robust to errors towards both false positive and false negative classifications, which is important for tasks where it is important to minimize both types of errors.

A particularly significant improvement is observed in the Recall metric, which increased by 16.22%. This increase confirms that the combined approach has significantly improved the completeness of the classification, i.e., reduced the number of missed objects. In the context of classifying buildings partially hidden by vegetation, this means that the model has become more sensitive and successful in detecting objects in this category that may have previously been missed. The increase in Recall indicates that the Gabor filter contributes to a more accurate extraction of textural features, such as edges and contours of objects that are difficult to distinguish using only Haralick features.

Thus, the proposed method using both Haralick features and the Gabor filter showed a marked improvement in all key classification metrics, which confirms its effectiveness in solving the problem of classifying objects partially hidden by vegetation, and allows us to reduce the error rate towards both false positive and false negative classifications.

References

[1] Kupidura, P. (2019). The comparison of different methods of texture analysis for their efficacy for land use classification in satellite imagery. *Remote Sensing*, *11*(10), 1233. https://doi.org/10.3390/rs11101233

[2] Jennifer, J. J., Vanmathy, S., Jobi Sahana, C. M., & Devi, G. (2016). Evaluation of image texture parameters for urban land cover classification. *Int J Res Sci Technol*, *6*(III), 183-190. https://www.researchgate.net/publication/319204736

[3] He, L., Liu, C., Li, J., Li, Y., Li, S., & Yu, Z. (2020). Hyperspectral Image Spectral–Spatial-Range Gabor Filtering. *IEEE Transactions on Geoscience and Remote Sensing*, *58*(7), 4818–4836. https://doi.org/10.1109/tgrs.2020.2967778

[4] Tussupov, J., Yessenova, M., Abdikerimova, G., Aimbetov, A., Baktybekov, K., Murzabekova, G., & Aitimova, U. (2024). Analysis of formal concepts for verification of pests and diseases of crops using machine learning methods. *IEEE Access*, *12*, 19902–19910. https://doi.org/10.1109/access.2024.3361046

[5] Kuffer, M., Pfeffer, K., Sliuzas, R., & Baud, I. (2016). Extraction of slum areas from VHR imagery using GLCM variance. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(5), 1830–1840. https://doi.org/10.1109/jstars.2016.2538563

[6] Girija, G., & Nikhila, R. I. (2018). Slum extraction approaches from high resolution satellite data – a case study of Madurai City. *Int. J. Pure. Appl. Math*, *119*, 14509-14514. https://acadpubl.eu/hub/2018-119-12/articles/6/1355.pdf

[7] Kohli, D., Sliuzas, R., & Stein, A. (2016). Urban slum detection using texture and spatial metrics derived from satellite imagery. *Journal of Spatial Science*, *61*(2), 405–426. https://doi.org/10.1080/14498596.2016.1138247

[8] Canayaz, E., Altikardes, Z. A., & Unsal, A. (2024). Haralick Feature-Based Deep Learning model for ankylosing spondylitis classification using magnetic resonance images. *2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA)*, 1–6. https://doi.org/10.1109/inista62901.2024.10683853

[9] Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from Space—15 Years of Slum Mapping Using Remote Sensing. *Remote Sensing*, *8*(6), 455. https://doi.org/10.3390/rs8060455

[10] Ansari, R. A., & Buddhiraju, K. M. (2019). Textural segmentation of remotely sensed images using multiresolution analysis for slum area identification. *European Journal of Remote Sensing*, *52*(sup2), 74–88. https://doi.org/10.1080/22797254.2019.1565419

[11] Shen, X., Wang, M., Peng, K., & Xiong, S. (2021, January). A building extraction method via Gabor filter and multi-orientation π local binary pattern operator. In *Twelfth International Conference on Graphics and Image Processing (ICGIP 2020)* (Vol. 11720, pp. 561-566). SPIE. https://doi.org/10.1117/12.2589349

[12] Munawar, H. S., Aggarwal, R., Qadir, Z., Khan, S. I., Kouzani, A. Z., & Mahmud, M. a. P. (2021). A GABOR Filter-Based protocol for Automated Image-Based building Detection. *Buildings*, *11*(7), 302. https://doi.org/10.3390/buildings11070302

[13] Zhang, D., Dai, G., & Xiang, S. (2023, February). Segmentation of urban high resolution remote sensing images based on mean shift with texture feature extraction by Gabor filtering. In *Fourth International Conference on Geoscience and Remote Sensing Mapping (GRSM 2022)* (Vol. 12551, pp. 620-627). SPIE. https://doi.org/10.1117/12.2668137

Scientific Journal of Astana IT University
ISSN (P): 2707-9031 ISSN (E): 2707-904X
VOLUME 22, JUNE 2025

[14] Cruz-Ramos, C., Garcia-Salgado, B. P., Reyes-Reyes, R., Ponomaryov, V., & Sadovnychiy, S. (2021). GaBor features extraction and Land-Cover classification of urban hyperspectral images for remote sensing applications. *Remote Sensing*, *13*(15), 2914. https://doi.org/10.3390/rs13152914

[15] Man, Q., Dong, P., & Guo, H. (2015). Pixel- and feature-level fusion of hyperspectral and lidar data for urban land-use classification. *International Journal of Remote Sensing*, *36*(6), 1618–1644. https://doi.org/10.1080/01431161.2015.1015657

[16] Lai, X., Yang, J., Li, Y., & Wang, M. (2019). A building extraction approach based on the fusion of LIDAR point cloud and elevation map texture features. *Remote Sensing*, *11*(14), 1636. https://doi.org/10.3390/rs11141636

[17] Yogeshwari, M., & Thailambal, G. (2021). Automatic feature extraction and detection of plant leaf disease using GLCM features and convolutional neural networks. *Materials Today Proceedings*, *81*, 530–536. https://doi.org/10.1016/j.matpr.2021.03.700

[18] P, P. D., & Sumathi, P. (2022). Deep Learning Techniques to Classify the Aerial Images with Gabor Filter. *International Journal for Research in Applied Science and Engineering Technology*, *10*(5), 1484–1489. https://doi.org/10.22214/ijraset.2022.42572

[19] Biau, G., & Scornet, E. (2016). A random forest guided tour. *Test*, *25*(2), 197–227. https://doi.org/10.1007/s11749-016-0481-7

[20] Malbhage, P., & Khoje, S. (2017, December). Building and Tree Detection by Fusing LiDar and Aerial Images for Urban Development Planning. In *2017 Ninth International Conference on Advanced Computing (ICoAC)* (pp. 1-8). IEEE. https://doi.org/10.1109/icoac.2017.8441323