OBJECT BASED APPROACH FOR IMAGE FEATURE EXTRACTION FROM UAV DATA

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ABSTRACT:

This present study explores the potential of utilizing Unmanned Aerial Vehicle (UAV) data for mapping urban areas, emphasizing the effectiveness of combining UAV technology with Object-Based Image Analysis (OBIA) in updating maps. In dynamic urban environments where changes occur frequently, this combination provides a rapid and efficient method for map updates. The study's primary objective was to extract valuable information from UAV data using OBIA. The research methodology involved capturing UAV images, followed by photogrammetric processing to generate orthophoto, Digital Surface Model (DSM), and Digital Terrain Model (DTM). Subsequently, OBIA was employed to classify the image, utilizing a range of machine learning-based algorithms for image classification. A comparative analysis was conducted to evaluate the performance of different classification algorithms. It was observed that the K-Nearest Neighbour (KNN) algorithm demonstrated superior performance, outperforming all other algorithms in accurately classifying the image.

1. INTRODUCTION

Urban areas are seeing the faster development, so it is necessary to employ a system that can update this profile right away. The Unmanned Aerial System (UAS) is one of the current technologies being used for mapping in recent years. "UAV Remote Sensing" is a more customizable, easy to use, and more affordable solution when UAS technology is combined with the distinctive data collecting strategies, preprocessing techniques, and analytical capabilities of an established domain of remote sensing [1]. Additionally, UAVs may operate quite nearer to the target and take data with resolutions of a few centimeters, which is sufficient for earth observation. Unique capabilities in earth observation are offered by UAV platforms, imaging, and sensor systems for both academic and commercial purposes. [2]. Due to their cheaper costs, ability of acquiring very high resolution (VHR) data, and weather independence operation to a higher degree as compared to other remote sensing platforms, UASs are being utilised in a variety of areas such as image classification and mapping[3][4], water resource management [5], crop monitoring [6], Urban environment and management [7][8], disaster and rescue [9][10], construction and infrastructure inspection [11][12], and many more. UAV-Remote sensing plays a crucial role in the classification and mapping of land use and land cover (LULC) thanks to the availability of VHR data taken by UAVs and the quick advancement of sensor technologies and data processing techniques [13]. Typically, there are still just a few data extraction techniques for UAVs, and conventional methods are typically applied. Orthophoto elements are frequently manually identified and digitally captured for mapping applications utilizing visual interpretation abilities. These methods, however, are time-consuming, expensive, and repetitious.

Spectral characteristics form the basis of pixel-based classification method which is traditionally utilized to assist extraction of low-level features. The bottleneck of this type of classification is that the pixels present in the overlapping region are misclassified owing to the class confusion. Additionally, high resolution images have relatively low performance for pixel-based classification. Pixel-based techniques produce "salt and pepper" effects because they are unable to fully utilize the texture and contextual information included in Very High Resolution (VHR) imagery [14]. These shortcomings of the pixel-based classification approach can be overcome by Object Based Image Analysis (OBIA). In order to automatically extract data from VHR photos, the OBIA classification technique offers significant promise [15][16][17][18]. OBIA has the advantages of effectively employing textural, geometrical, spatial, vector representation; elevation profile; spatial understanding of geographic scenes; and contextual properties of image features [19]. For many remote sensing applications, OBIA is a powerful substitute for the conventional pixel-wise classification methods since it offers multiscale and hierarchical picture object representation.

OBIA approaches begin with picture segmentation and move on to feature extraction and classification using contextual data. In this study, an effort is made to evaluate OBIA's capacity for precise classification of metropolitan areas that have been mapped by UAV using VHR data. In this study, an urban area located within Nagpur city in Maharashtra, India was chosen as the study site. To collect data, a UAV was employed, which captured visible RGB images. The collected imagery underwent preprocessing to generate photogrammetric products such as orthophoto, Digital Surface Model, and Digital Terrain Model. Subsequently, OBIA was applied to further classify the image. Multiple classification algorithms such as Naïve Bayes, Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) were used to classify the image. Finally, a comparative analysis was conducted, revealing that KNN outperformed all other classifiers in terms of overall accuracies.

2. STUDY AREA AND DATASET

2.1 Title and Author Information

This study was performed in an urban area situated in the Indian city of Nagpur, Maharashtra. The geographical extent of the study area spans from 79° 02' 50.28" E longitude to 79° 03' 01.83" E longitude and from 21° 08' 51.43" N latitude to 21° 08' 35.75" N latitude. It is located in the campus of Laxminarayan Institute of Technology (LIT), Nagpur, Maharashtra. LIT is a state-owned higher-education institute of Chemical Engineering in Nagpur. It is directly managed by Nagpur University. The study area (Figure 1) is having man-made infrastructures such as building, road, shed. Natural features, include bare soil, grass, shrubs. The UAV data was obtained using the NINJA UAV that contains visible RGB image data. The campus occupies approximately an area of 87 acres. For this study a set of 569 imagery was acquired having a ground sampling distance of 4.58 cm.

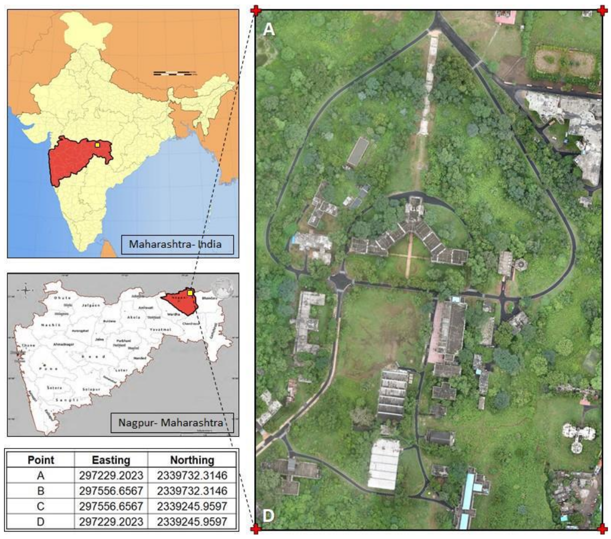

Figure 1. Study area

3. METHODOLOGY

The methodology of this study consists of three components. (i) Data Acquisition and Preprocessing of UAV Data. (ii) Segmentation and Feature Extraction. (iii) Classification and comparative analysis. The complete flow chart of methodology is illustrated in Figure 2.

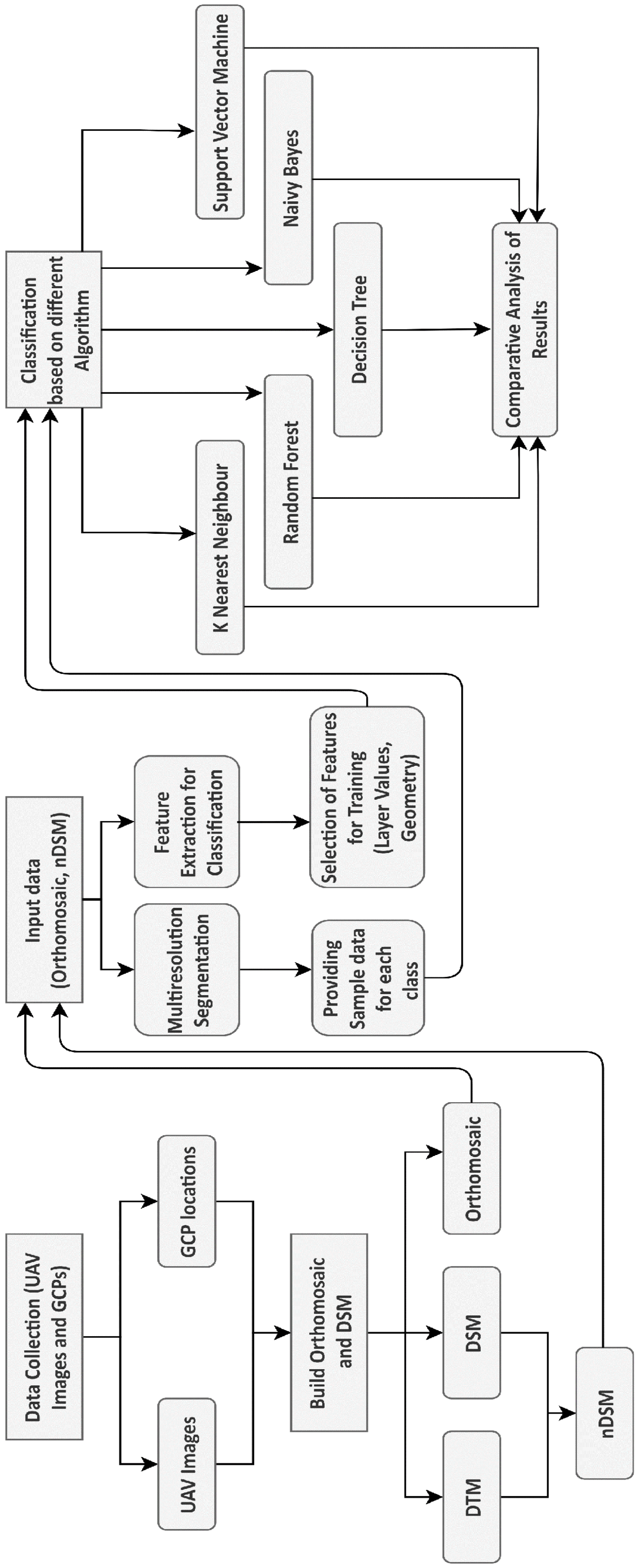

Figure 2. Methodology Flow chart

3.1 Data Acquisition and Preprocessing of UAV Data

The images were acquired using the **NINJA UAV** according to the image acquisition plan shown in Figure 3. To collect high-resolution airborne data, this well-known apparatus functioned as a completely autonomous drone. During the flight, this model had an optical sensor (having colour bands corresponding to red, green and blue) fitted that was a non-metric camera with a 16.1 MP resolution. The area covered during the flight was around 87 Acres. 569 images were captured with frontal overlap of 85% and side overlap of 65%. A total of 6 GCPs were collected in the area. Pix4Dmapper software was utilised for processing the raw UAV data for the study. The orthorectified image with the DSM and DTM were produced for the study area. The WGS84 datum coordinate system and the 44 N zone in UTM projection were used to establish all of the data geometrically. Through this orthorectified image, the average ground sampling distance (GSD) was 4.58 cm. Figure 4 and Figure 5 shows orthomosaic and DSM of the study area.

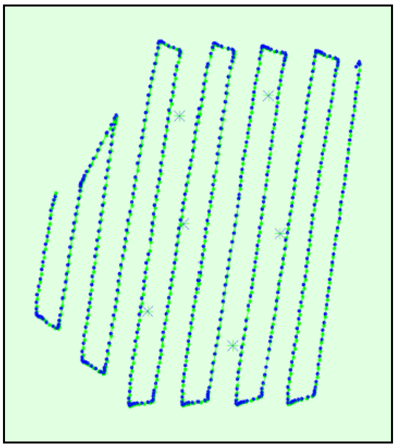

Figure 3. Image acquisition plan

Figure 4. Orthomosaic of the study area

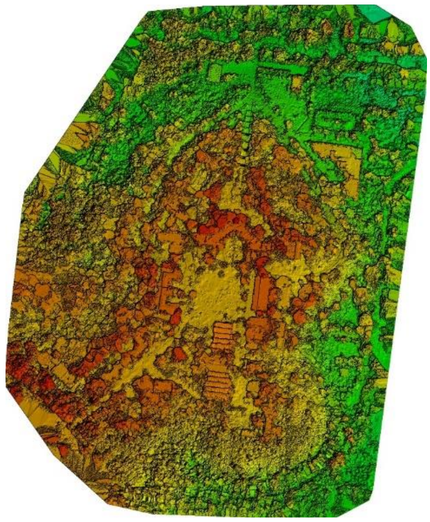

Figure 5. DSM of the study area

3.2 Segmentation and Feature Extraction

The segmentation process, which splits an image into useful pieces that are related to things in the actual world, is the first and most crucial step in the application of the OBIA technique. Applications of remote sensing data include a variety of image segmentation techniques, including quadtree, checkerboard, contrast split, multiresolution, spectral difference, contrast filter, and multi-threshold [20]. Multiresolution segmentation (MRS) is one of the most frequently utilized image segmentation techniques among them. The multiresolution model was selected for the investigation because it enhances item homogeneity and decreases average heterogeneity. In order to extract the segments needed for the categorization of urban features, the multiresolution segmentation method has demonstrated to be quite effective [21]. According to the comparative analysis done by [22], MRS gives greater differentiation among various LULC classes than other approaches.

In MRS, image segmentation aims to achieve similarity among image objects within the analyzed image. To accomplish this, several parameters, including size, shape, texture, and more, are employed for the segmentation process. It is implemented using the e-Cognition version 9.0 software and is a form of bottom-up, region-based segmentation method. Shape and colour are regarded as primary object features by MRS in eCognition. Scale factor is the characteristic that has the greatest impact on the average object size in the image [23][24][25]. This element is influenced by the image's spatial resolution and characteristics [26][27]. Colour density and smoothness are correlated with shape and compactness variables. The quantity of spectral data that has to be combined to create the segments is then determined [28]. Initially, a trial-and-error procedure was used in this study to determine the appropriate scale parameter range for the segmentation of the image. The Taguchi technique was used to further refine the segmentation scale.

The analysis was performed with different scale factors at 8, 25, and 70. The validity of the segmented image was determined by visual interpretation. The primary criteria involved determining whether the image object was under-segmented, and any over-segmented image objects were eliminated from consideration. To generate meaningful segmented objects, the compactness parameter was set to 0.8 and the shape parameter to 0.2. Table 1 shows different values tried for the parameters in order to get the optimum parameters for best segmentation results. Finally, trial-3 was considered for further processing, in which considered scale parameter was 70. Shape Ratio is taken 0.8 as data is more differentiable with pixel color value instead of shape. Compact ratio is taken 0.8 as more compact segments are tending to be homogeneous. In the feature extraction step various features are selected which will be used during the classification of the image. Table 2 shows various features selected for further classification of the image.

Table 1. Segmentation Parameters

	Scale	Colour	Shape	Compactness
Trial-1	8	0.1	0.9	0.9
Trial-2	25	0.5	0.5	0.5
Trial-3	70	0.8	0.2	0.8

Table 2. Selected Features

Feature	Value
Layer Values	**Mean:** • Blue • Green • Red • nDSM
	Standard Deviation: • Blue • Green • Red • nDSM
Geometry	**Extent:** • Length/Width • Area • Border Length
	Shape: • Compactness • Roundness • Rectangular fit

3.3 Classification and Comparative Analysis

Following the segmentation of the image with MRS, OBIA is used to classify the generated image objects. Once feature selection is done, next step is the collection of training samples and classification of the image based on the selected features and collected training samples. Image is classified using five classification algorithms: Naïve Bayes, Support Vector Machine (SVM), Decision Tree, Random Forest, and k-Nearest Neighbour. Finally, classified results obtained using various algorithms are analysed for comparative evaluation.

4. RESULTS AND DISCUSSIONS

The MRS image segmentation technique is used to perform object-based image analysis on the selected region. The orthomosaic image's red, green, and blue layers, together with DSM derivatives, were utilised as input for image segmentation. The segmented images obtained using different segmentation parameters (Table 1) are shown in Figure 6.

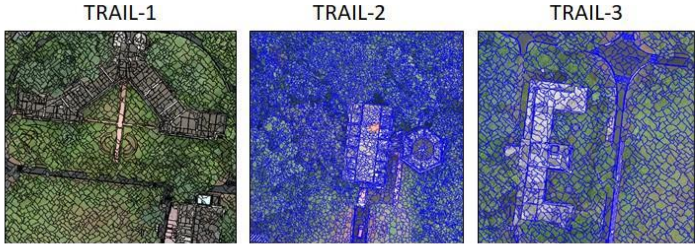

Figure 6. MRS Segmentation using different parameters

After segmentation, training samples were selected and image was classified using different image classification algorithms by considering various features as mentioned in Table 2. Classification results obtained using different image classification algorithms are presented in Figure 7-Figure 11. Figure 7 shows the classified output obtained using Naïve Bayes classifier. There are many regions where misclassification was observed. In Figure 7, subset 1, here a part of tree was misclassified as 2-storey and 3-storey building. Similarly, in subset 2, a portion of the road near zebra crossing was misclassified as water body. In subset 3, a portion of water in water tank was misclassified as 2-storey building.

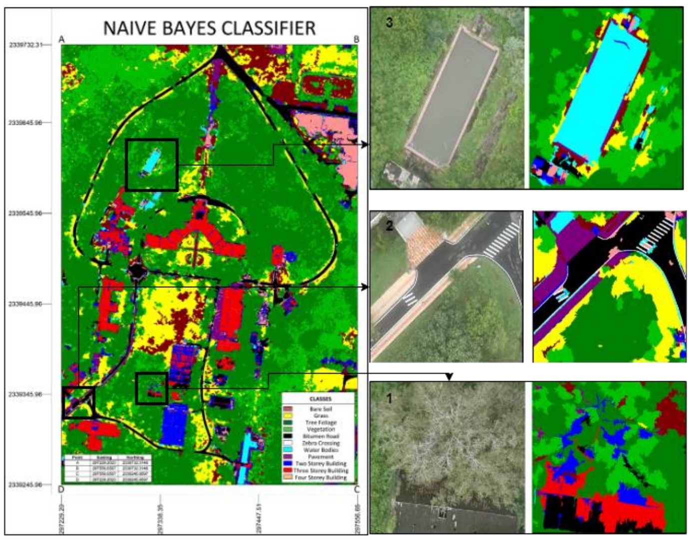

Figure 7. Classified output using Naive Bayes classifier

Classified output obtained using SVM is presented in Figure 8. Some of the misclassified regions are: subset 1, here a part of tree was misclassified as 3-storey building. Similarly, in subset 2, a portion of road near zebra crossing was misclassified as water body and 2-storey building. In subset 3, a portion of water in water tank was misclassified as 2-storey building.

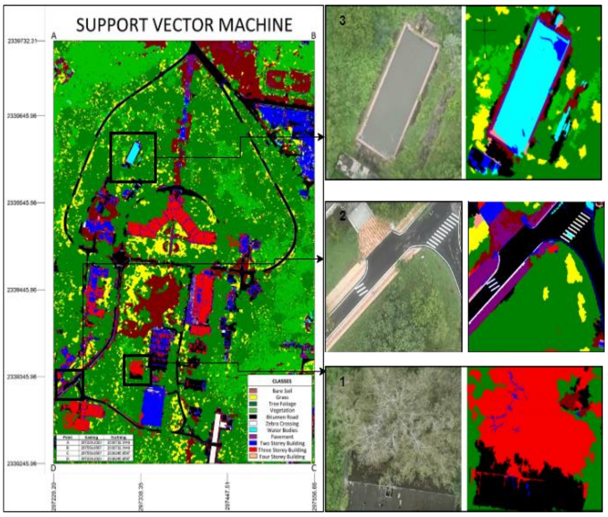

Figure 8. Classified output using SVM classifier

Figure 9 shows the classified output obtained using decision tree classifier. Some of the misclassified regions are: subset 1, here a part of tree was misclassified as 2-storey and 3-storey building. In subset 2, a portion of road around zebra crossing was misclassified as 4-storey building and a portion of road near zebra crossing was classified as vegetation. In subset 3, a portion of water in water tank was misclassified as bare soil.

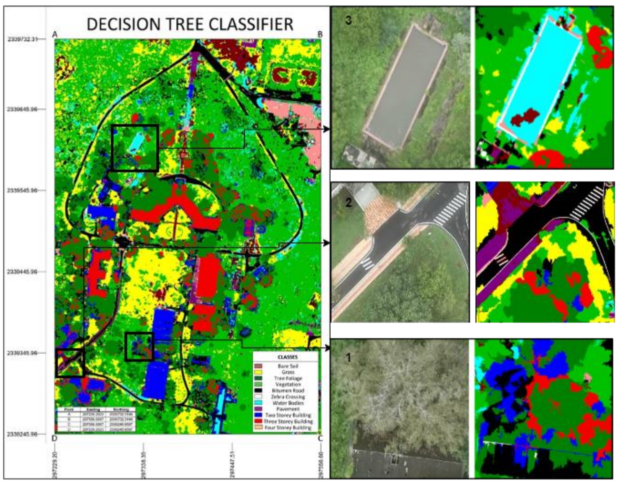

Figure 9. Classified output using Decision Tree classifier

Figure 10 presents the classified output obtained using random forest algorithm. Some of the misclassified regions are: subset 1, here a part of tree was misclassified as 2-storey and 3-storey building. In subset 2, a portion of road around zebra crossing was misclassified as water body. In subset 3, water in water tank was correctly classified.

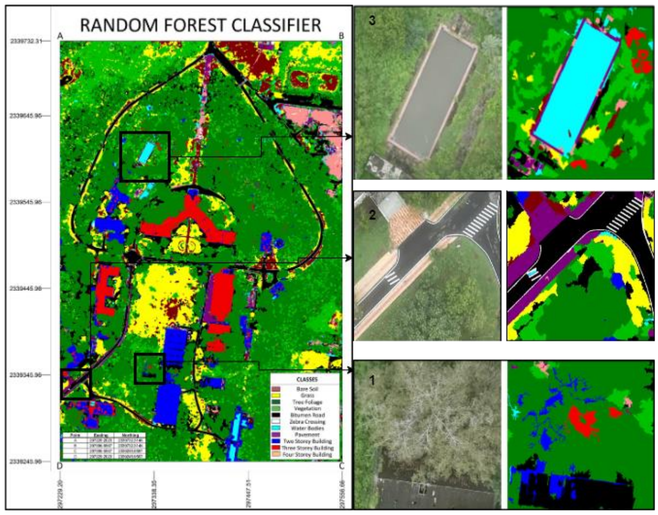

Figure 10. Classified output using Random Forest classifier

Figure 11 presents the classified output obtained using KNN classifier. Almost all portions of the image were correctly classified. KNN classifier outperforms all the other algorithms in terms of accuracy.

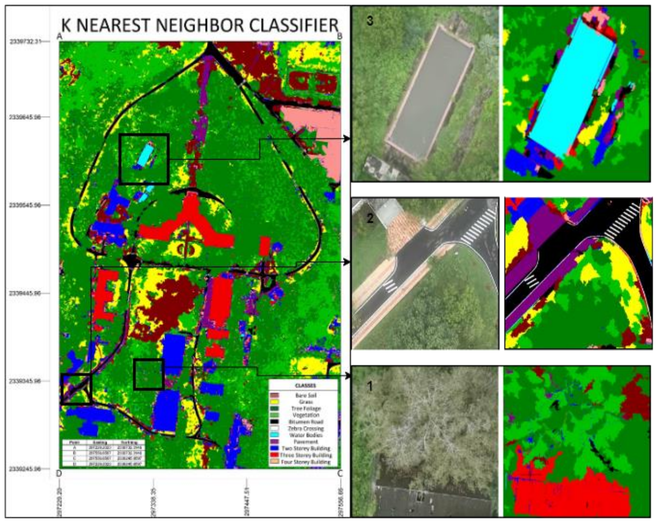

Figure 11. Classified output using KNN classifier

The accuracy assessment involved overlaying the classified image onto the manually classified image. Table 3 displays the overall accuracy achieved by using different classifiers for various classes. Among the classifiers, KNN exhibited superior performance for the bitumen road class, while RF and SVM performed poorly. Almost classifiers performed well for the zebra crossing class. KNN yielded the highest accuracy for water bodies, whereas DT had the lowest accuracy. For pavement class, KNN produced the best results, while SVM had the lowest accuracy. KNN outperformed all other classifiers for both 2-storey and 3-storey buildings, whereas SVM performed the worst. In summary, KNN produced the highest overall accuracy compared to the other classifiers.

Table 3. Overall accuracy of different classifiers

Classifier	Accuracy (%)					
	Bitumen Road	**Zebra Crossing**	**Water Bodies**	**Pavement**	**2 Storey Building**	**3 Storey Building**
Naive Bayes	71	83	86	84	80	88
Support Vector Machine	69	89	67	74	71	73
Decision Tree	73	93	58	92	87	83
Random Forest	67	95	78	86	83	93
K Nearest Neighbour	**89**	**93**	**87**	**94**	**89**	**93**

5. CONCLUSIONS

This study has explored the potential of utilizing UAV data in mapping urban areas. The combination of UAV technology with Object-Based Image Analysis (OBIA) has proven to be a rapid and effective method for updating maps, particularly in dynamic urban environments. The research findings have shed new light on the application of OBIA in extracting valuable information from UAV data. In this study, UAV images were captured and underwent photogrammetric processing, resulting in the generation of orthophoto, DSM, and DTM products. The obtained orthophoto in combination with nDSM was then classified using various machine learning-based algorithms for image classification. Among the algorithms tested, it was observed that KNN exhibited superior performance. However, it should be noted that the use of deep learning techniques for analysing UAV imagery remains an unexplored area in this study. Deep learning models require a large amount of training data to achieve accurate results, and due to limited training data availability, these techniques were not considered in this research. Future studies will focus on collecting a larger training dataset and investigating the potential of deep learning-based methods for processing UAV data in urban applications.

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