Iraqi Journal of Physics, 2025 *Vol.23, No.4, PP.119-132*
https://doi.org/10.30723/ijp.v23i4.1415 *P-ISSN: 2070-4003*
E-ISSN: 2664-5548

House Detection from High-Resolution Satellite Images Using Artificial Neural Network Classifier

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Abstract
This research aims to develop an automated system for detecting built-up areas in rural regions, addressing challenges in accurately identifying residential buildings. One of the main difficulties lies in distinguishing between building surfaces, streets, and unpaved roads, as they exhibit similar brightness levels. In this study, high-resolution RGB satellite images from World View-2 satellite with a spatial resolution of 0.46 m were utilized, and an automated system for detecting built-up areas was developed. The system extracts 13 discriminative features categorized into pixel-based and area-based metrics to enhance the differentiation between buildings and non-built-up areas. These features include color-based metrics, such as the average gray value, greyness1, and greyness 2, which capture variations between color channels, as well as hue calculations derived from advanced equations to improve surface distinction. Additionally, local statistical metrics, contributed to refining detection accuracy by reducing noise. These features were selected based on their effectiveness in handling the variability in building materials and textures commonly found in rural environments. Furthermore, an Artificial Neural Network (ANN) classifier was trained to distinguish between built-up and non-built-up areas. To further enhance detection accuracy, post-processing techniques, including median filtering, gap removal, and eliminating irrelevant narrow slices were incorporated. The system's performance was evaluated using accuracy, precision, recall, and F1-score metrics to ensure the robustness and reliability of the building detection process. The results demonstrated that the ANN classifier effectively detects buildings while overcoming challenges posed by irregular shapes and varied surface characteristics.

Article Info.

Keywords:
House Detection, ANN, Rural areas, Feature Extraction, Post Processing.

Article history:
Received: Dec. 30, 2024
Revised: Mar. 21, 2025
Accepted:Apr. 06, 2025
Published:Dec.01,2025

1. Introduction

In the field of remote sensing, the availability of high-resolution satellite images provides detailed information about the land cover, which is facilitated by the extraction of distinctive features of buildings [1-3], making it possible to accurately detect buildings for applications, such as urban mapping, change monitoring, damage detection, population estimation and land use analysis [4, 5]. This is needed due to rapid urbanization, urban expansion, and rural development [6, 7].

The difficulties and challenges facing the accurate detection of residential buildings in rural areas are many, including the significant differences in size and design of the houses, which leads to irregular shapes that are difficult to distinguish from other features [8,9]; houses containing extensions or structures attached to the main building [10]; scattered spatial distribution of houses instead clustered, the differences in building materials, such as clay or stone tiles and the differences in roof types [11,12], which causes a problem in the mismatch of texture and reflection. One of the main challenges identified is the difficulty of distinguishing between the roofs of buildings, streets and unpaved dirt roads due to their similar brightness levels [13,14]. Artificial neural networks are computational models inspired by the neural structure of the human brain and are designed to recognize patterns and solve complex problems [15]. They consist of several interconnected layers of nodes (neurons) that process input data, enabling them to learn from the original data [16]. Artificial neural networks excel at many tasks, such as classification, segmentation, and pattern recognition, which makes them suitable for many tasks, such as building detection, as they can automatically recognize structures from images [17,18]. Their main characteristics include their ability to approximate nonlinear functions and adapt to new data through training, in addition to their ability to handle extensive data efficiently [19,20]. It has been widely used in various fields due to its superiority in processing complex visual data. Artificial neural networks have proven effective in automating the identification of structures from satellite and aerial images [21]; features can be learned from raw data automatically, improving efficiency and accuracy in work, unlike using traditional methods, such as thresholding, edge detection, region growing, and rule-based classification, where features are manually extracted and processed. These methods are time-consuming and prone to errors, unlike machine learning approaches that automate feature learning and improve accuracy [22]. Cui et al. [23] used a method that combined artificial neural networks and object-oriented classification. This method involved dividing the image into small regions, such as individual buildings and then classifying these objects using artificial neural networks. This approach improved the computational efficiency and accuracy of building detection.

Wang et al. [24] presented a method that used morphological feature profiles with artificial neural networks to detect buildings with minimal human intervention. These studies demonstrated the potential of these hybrid methods to address the difficulties of detecting buildings in complex environments. Hoeser and Kuenzer [25] explored the use of lidar data with artificial neural networks to improve the geometric accuracy of building detection. This indicated the importance of combining artificial neural networks with complementary methods to achieve accurate and reliable results.

The aim of this study is to develop a system that considers small buildings in rural areas, characterized as small building areas separated by vast regions of groves of trees or crops; usually, the buildings are located next to unpaved breeze roads.

2. Methodology of the Proposed System

Fig. 1 presents the layout of the proposed developed system for building area detection in rural areas where the density of buildings is low (i.e., they are separated distinctly). The system consists of several stages designed to process high-resolution images and classify them as building or non-building areas.

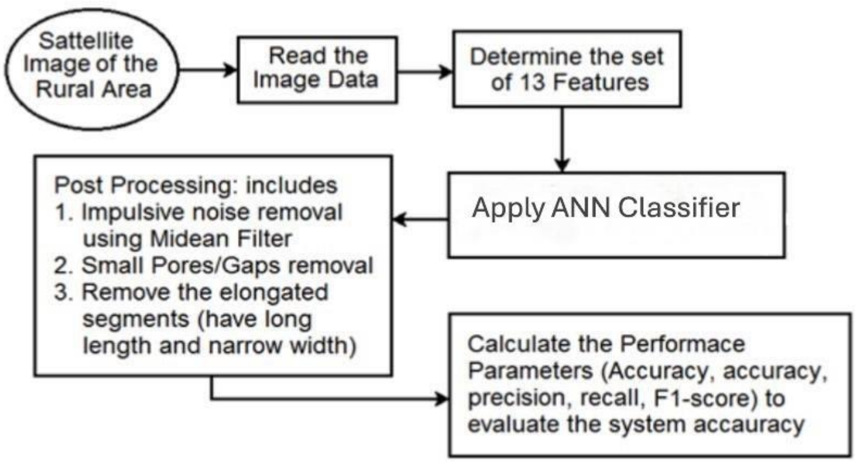

Figure 1: The Layout of the Proposed System.

The first stage involves loading the satellite images (of high resolution < 0.5 meter/pixel); the next step is extracting the discriminating features (in this study, about

13 most discriminating features were used, as listed in Table 1) designed to distinguish between buildings and other land cover types(non-building), which is particularly difficult in rural. These features were specifically chosen to address the large variability in building materials and textures typically found in rural environments. They were categorized into pixel-based and area-based metrics to enhance differentiation between built-up and non-built-up areas.

Pixel-based features include color-based metrics, such as average gray value, greyness1, and greyness2, which capture variations between color channels and help distinguish buildings from their surroundings and hue calculations, to improve the ability to differentiate between various surfaces based on their spectral properties. Area-based features incorporate local statistical metrics, including mean and standard deviation computed within a 3×3 pixel window, which help refine detection accuracy by reducing noise and improving classification reliability. After extracting the features, The Artificial Neural Network (ANN) classifier was trained on labeled features to perform binary classification on imbalanced data, employing techniques to address the class imbalance The ANN was designed with two hidden layers—10 nodes in the first layer and 4 in the second. The learning rate ranged from 0.005 to 0.2, and momentum was set to 0.95. The network was trained using the backpropagation method, with Tanh used in the hidden layers and Logistic (sigmoid) in the output layer for binary classification.

The architecture was adjusted for imbalance to handle data variations, although specific techniques like oversampling, under-sampling, or loss function modifications were not detailed. The model's performance was evaluated using the Mean Squared Error (MSE), with normalized MSE values of approximately 0.000237 for training and 0.000275 for testing, indicating high accuracy. After that, post-processing was applied to enhance the classification processes by removing the unwanted regions using image processing methodology. The applied post-processing techniques were chosen to refine the classification results by addressing common noise and structural inconsistencies in the detected built-up areas. This was done through the following operations:

A- Median Filtering (Applied 3 Times), which was used to eliminate isolated noise (both black and white pixels) while preserving edges. It was applied several times to enhance its effectiveness in smoothing small, misclassified regions without overly blurring significant structures.
B- Gap and pore removal were used to help fill small gaps within detected buildings, ensuring more continuous and realistic representations of built-up areas.
C- Narrow slice remover was applied to eliminate elongated, thin structures that may result from classification errors, particularly those with long traces in one direction and narrow widths in the perpendicular direction. This step prevents false positives from being classified as buildings.

These operations collectively enhance classification accuracy by reducing misclassifications, improving object continuity, and ensuring that the detected buildings have realistic shapes. Performance was done to calculate accuracy and measure overall correctness. Still, it may be less effective for imbalanced data, precision was applied to ensure that non-building areas were not misclassified as buildings, and finally recall was assessed to ensure that most buildings were detected, to minimize false negatives. The F1 score was considered to balance precision and recall, making it ideal for handling imbalanced data.

These metrics provide a comprehensive evaluation of detection accuracy and reliability.

2. 1. Determination of Discriminating Features

For classification purposes between building areas and other places, a list of 13 features was proposed to handle variability due to an unbalance between the number of samples belonging to the two types, building and non-building regions, where the number of pixels in building areas is much smaller than the number of pixels in non-building areas, which makes it difficult to achieve accurate classification. The features include two main categories: features extracted from individual pixels and features extracted from the region (3×3) surrounding a certain pixel. The first category is features extracted for single pixels, which have the numbers 1 to 6, listed in Table 1; the second category is based on the group of pixels surrounding each pixel; these features have numbers 7 to 13 in Table 1.

Table 1: The list of the applied discriminating features.

#	The applied Feature Name	
1	**Mean** = (Red+ Green+ Blue)/3	
2	**Greyness1** = **StdDev**(Red, Green, Blue) / Mean	
3	**Greyness2** = (Mx-Mn) /Mean	Mx=Max(Red, Green, Blue) Mn=Min(Red, Green, Blue)
4	**Greyness3**=(Mx-Mn)/ Mx	
5	**Greyness4=SdDev**(Red, Green, Blue) / Mx	

6	**Hue of the pixel**	Dif=Mx-Mn
		If Mx=0 then Hue=0
		if Mx=Red then
		Hue=60*(Green-Blue)/Dif
		If Hue<0 then Hue=Hue+360
		if Mx=Green then
		Hue=120+60*(Blu-Red)/Dif
		if Mx=Blue then
		Hue=240+60*(Red-Green)/Dif

7	Local mean of Grey(3x3)= $\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=1}^{1} Mean(x+i,y+j)$; i & j $= -1$ to 1	
8	Local mean of StdDev(3x3)= $\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=1}^{1} Std(x+i,y+j)$; i & j $= -1$ to 1	
9	Local mean Hue(3x3)=$\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=-1}^{1} Hue(x+i,y+j)$; ; i & j $= -1$ to 1	
10	AvgDifMean(3x3)= $\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=1}^{1} abs(Mean(x,y) - Mean(x+i,y+j)$; i & j $= -1$ to 1	
11	StdDifMean(3x3)=S$td\big(abs\big(Mean(x,y) - Mean(x+i,y+j)\big)\big)$; i & j $= -1$ to 1	
12	AvgDifHue(3x3)=$\frac{1}{9}\sum_{i=-1}^{1}\sum_{j=1}^{1} abs(Hue(x,y) - Hue(x+i,y+j)$; i & j $= -1$ to 1	
13	StdDifHue(3x3)=$Std\big(abs\big(Mean(x,y) - Mean(x+i,y+j)\big)\big)$; i & j $= -1$ to 1	

2. 2. Using Artificial Neural Network Classifier

ANN classifiers seek to classify a set of features belonging to a specific class as a function of the inputs. The input features as independent variables are categorized into certain indices. The fully connected neural network was adopted; see Fig. 2. Model training was performed using MATLAB.

The neural network was designed with 2 hidden layers to handle the imbalance problem. The first hidden layer contained 10 nodes, while the second one had 4. The number of nodes was chosen to balance model complexity and computational efficiency, ensuring the network could capture the necessary patterns without overfitting. The learning rate was set within the range of 0.005 to 0.2 to allow flexibility in adjusting the training speed. Additionally, a momentum of 0.95 was used to accelerate convergence and reduce oscillations during training. These settings were chosen to optimize the network's performance while addressing the imbalance in the data. The backpropagation network was applied to train the nodes of the networks; for input and hidden layers, the hyperbolic tangent (tanh) sigmoid was used (see Fig. 3), while for the output nodes, the logistic function was adopted (see Fig. 4).

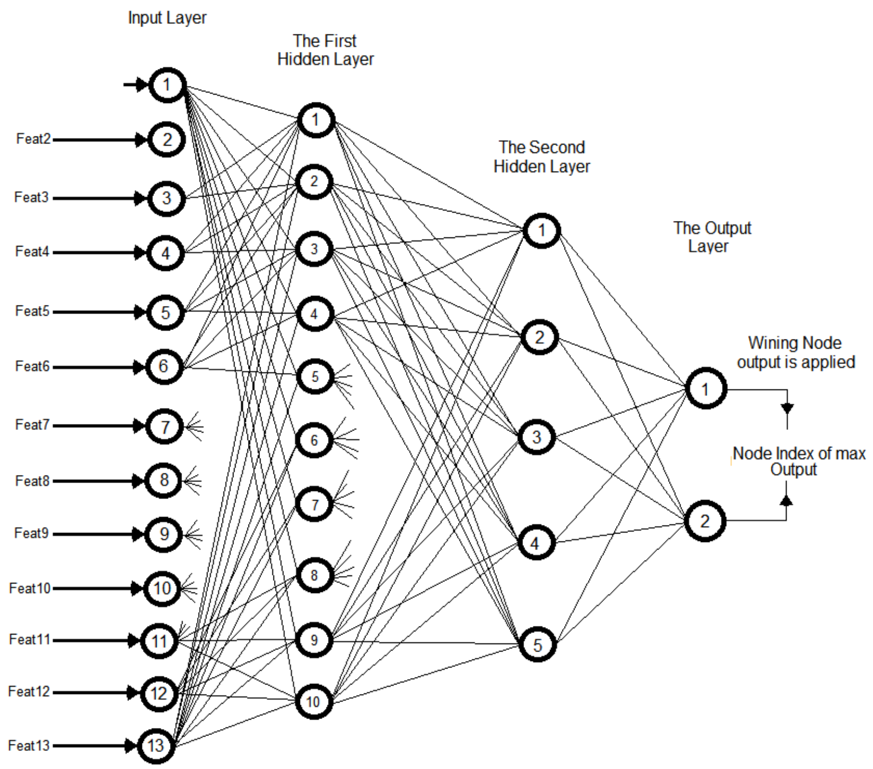

Figure 2: The adopted fully connected ANN as the classifier.

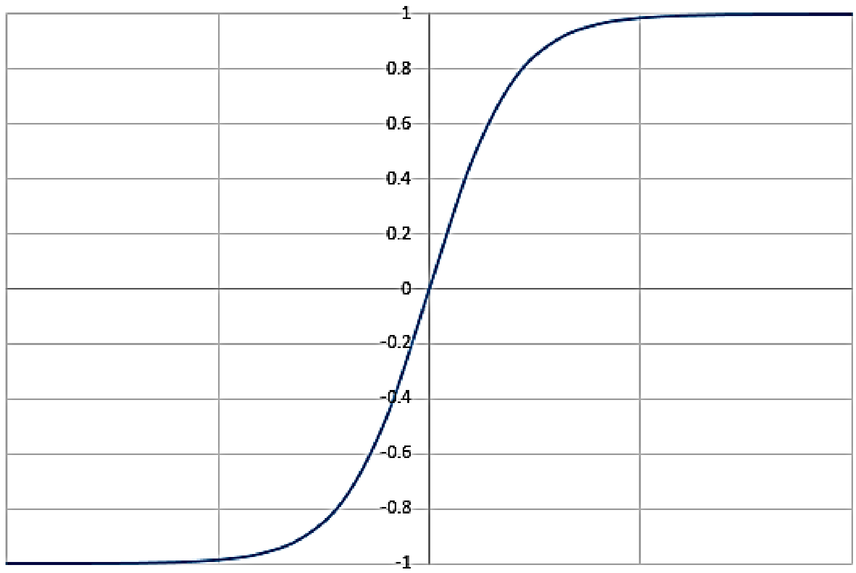

Figure 3: The S-shape of tanh(x) of the sigmoid function.

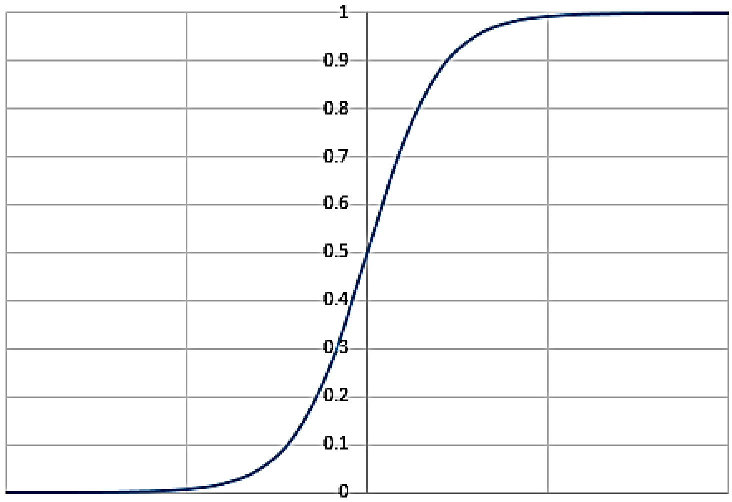

Figure 4: The S-shape of a logistic function of the sigmoid function.

2. 3 Activation Functions Used in Neural Networks

1. Tanh (Hyperbolic Tangent) Function

The tanh function maps input values were in the range [-1, 1], effectively handling both positive and negative values. Centering data around zero is useful for improving learning speed, which enhances gradient flow during training, as shown in Fig. 3. It is commonly used in hidden layers of neural networks to improve training efficiency.

2. Logistic (Sigmoid) Function

The logistic function maps inputs are to the range [0, 1], making it ideal for binary classification. It transforms input values into probabilities, ensuring smooth gradient updates, as shown in Fig. 4. It is widely used in the output layer of classification networks for probability-based predictions.

2. 4. Post Processing Stage

After the classification process, a set of post-processing techniques, see Fig. 5 was applied as follows:

1. Median filter: to remove impulsive noise as an isolated pixel with its neighbors and is applied 3 times.
2. Gap and pore removal: to detect and remove small gaps and pores in the classified building areas.
3. Elongated segments that have long directions and narrow width, which are due to unpaved roads that resemble buildings in terms of brightness were removed.
4. Some sets of morphological criteria were used to filter out irregular shapes.
5. Removing abnormal sizes of assigned patches that are either too small to provide useful information or too large containing irrelevant data. Removing them improves the accuracy and efficiency of the detection process.

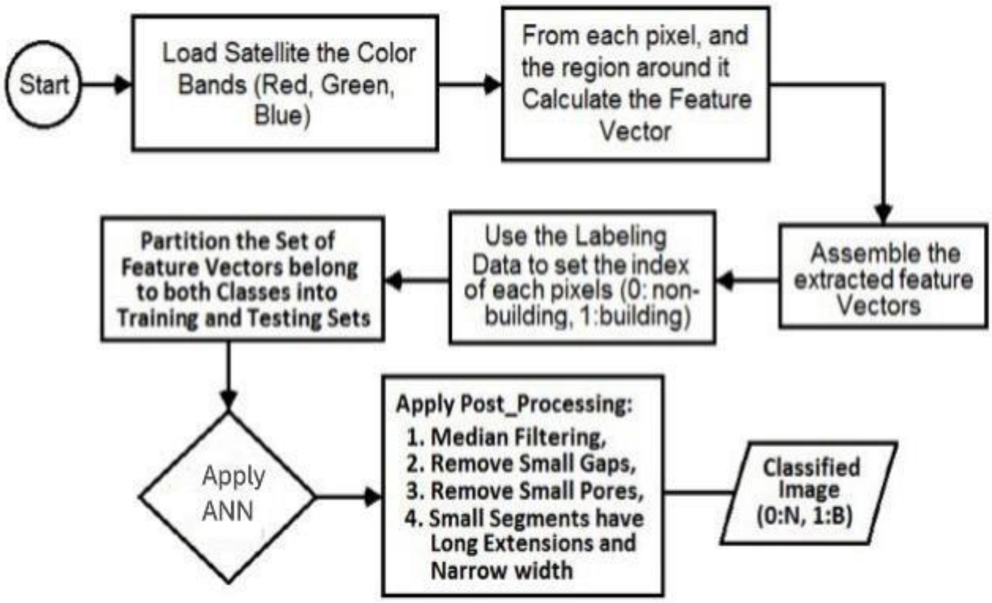

Figure 5: Block diagram of the applied classification method.

2. 5. The Determination of Performance Measures

The following key performance metrics are essential for evaluating the accuracy and reliability of building detection of a machine learning model in classification:

1. Accuracy is a measure of the ratio of correct predictions to the total number of samples and is computed as (TP+TN)/(TP+TN+FP+FN). It measures the overall correctness but may be misleading with imbalanced data
2. Precision: it measures the proportion of true positive predictions among all positive predictions and is computed as TP/(TP+FP), ensuring buildings are correctly identified, reducing false positives.
3. Recall: it measures the proportion of true positive predictions among all actual positive cases and is computed as: TP/(TP+FN). It captures the majority of buildings, minimizing false negatives.
4. F1 score: measure the harmonic mean of precision and recall and is computed as: 2*(Precision * Recall)/ (Precision + Recall)). It balances precision and recall, making it ideal for handling class imbalance.

In this study, manually labelled ground truth data was created by outlining buildings using high-resolution satellite images. The system's output was then compared pixel-by-pixel with this reference to ensure accurate performance evaluation.

where TP is the number of instances where the model correctly predicted the positive (building) class.

TN is the number of instances where the model correctly predicted the negative (non-building) class.

FP is the number of instances where the model incorrectly predicted the positive (building) class.

FN is the number of instances where the model incorrectly predicted the negative (non-building) class.

3. Results

The two images used for testing were captured from the WorldView-2 satellite, which has a spatial resolution of 0.46 meters. They provided clear and detailed views of rural land areas.

The WorldView-2 satellite was launched on October 8, 2009, by MAXar. It was designed to meet the growing commercial demand for high-resolution satellite imagery. Its main characteristics include:

- Orbit Altitude: 770 km
- Orbit Type: Sun-synchronous
- Orbit Period: 100 minutes
- Equator Crossing Time10:30 AM
-Resolution: Panchromatic imagery with 0.46-meter resolution and 8-band multispectral imagery with 1.84-meter resolution
-Spectral Bands: It has 8 spectral bands, including blue, green, and red, and additional bands, such as coastal blue and yellow, for enhanced environmental analysis. In the research, images containing three bands were used: red, green, and blue.

WorldView-2 provides one of the highest resolutions available for spaceborne imagery, ideal for environmental monitoring and land use analysis. These images capture various land features, such as buildings, roads, and vegetation, which are essential for analyzing and detecting specific objects in rural environments, as shown in Figs. 6 and 7. They display good examples of rural lands of the study area: Baghdad Governorate, Iraq, with coordinates (33.3152°N, 44.3661°E).

Figs. 6 - 9 show the corresponding figures after fixing marks for the building areas.

Figure 6: Image (A) of the first rural area.

Figure 7: Image (B) of the second rural area.

Figure 8: Image (A) of the first rural area after fixing marks for the building areas.

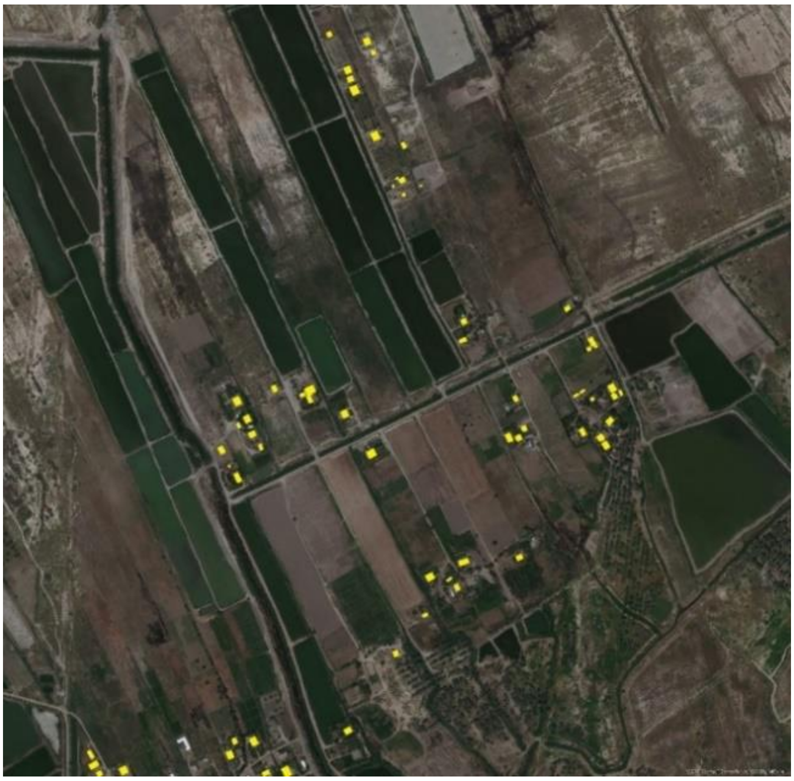

Figure 9: Image (B) of the second rural area after fixing marks for the building areas.

Figs. 10 and 11 show the results of applying the ANN classifiers on the Figs. 8 and 9. Also, Figs. 12 and 13 are the results of applying post-processing on Figs. 6 and 7.

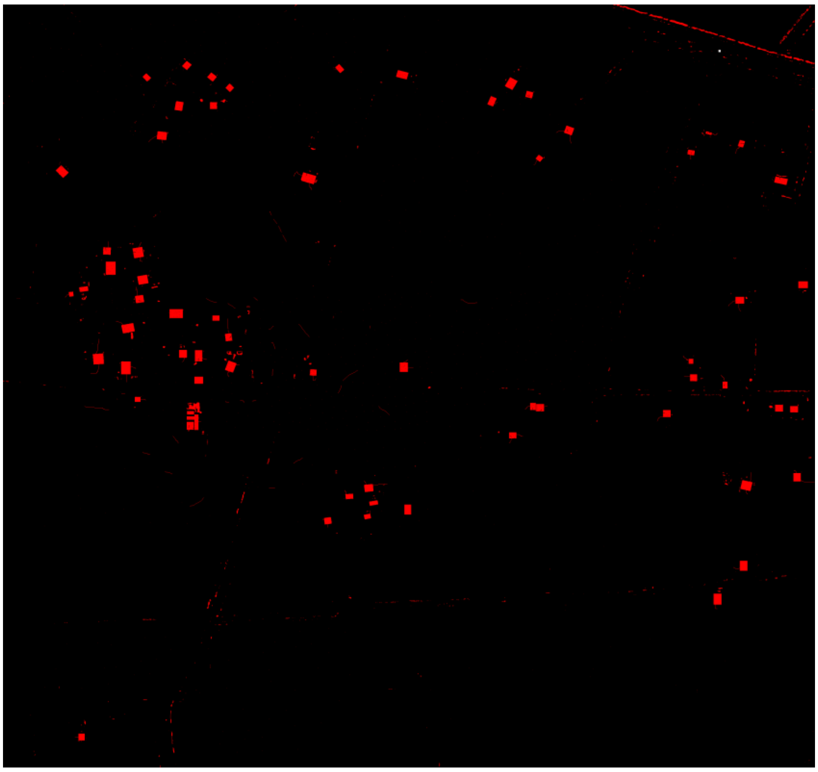

Figure 10: The results of applying ANN-Classifier on image (A) of the first rural area.

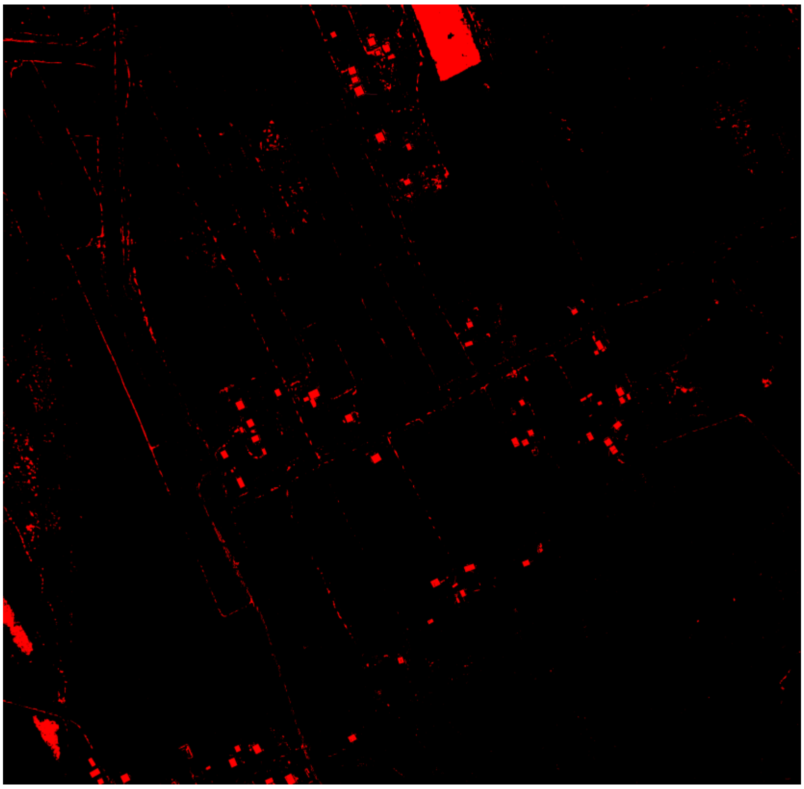

Figure 11: The results of applying ANN-Classifier on image (B) of the second rural area.

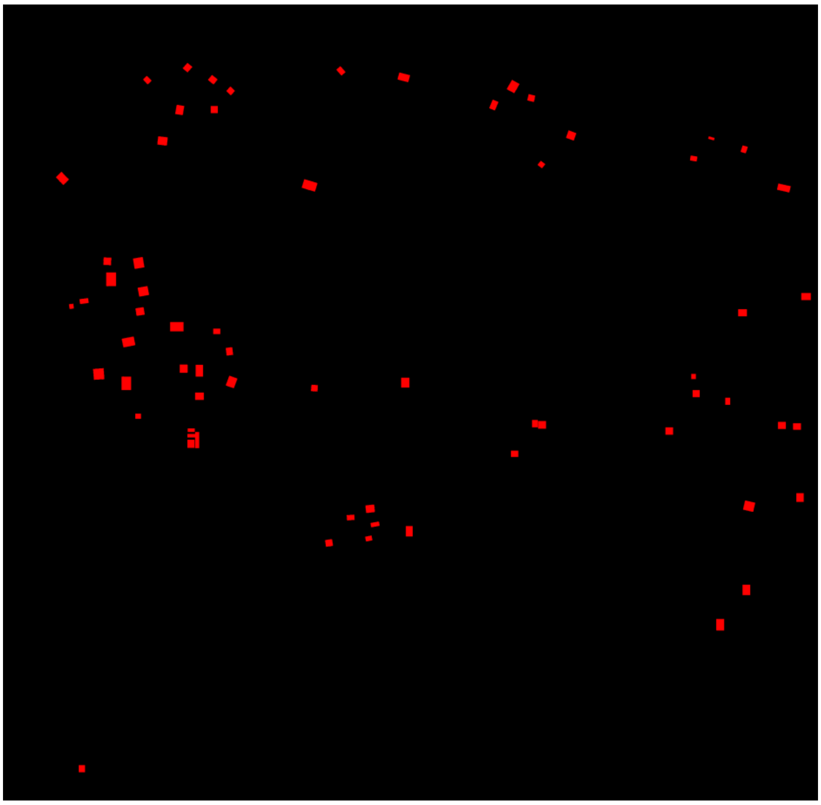

Figure 12: The results of applying post-processing on image (A) produced using ANN on a rural area.

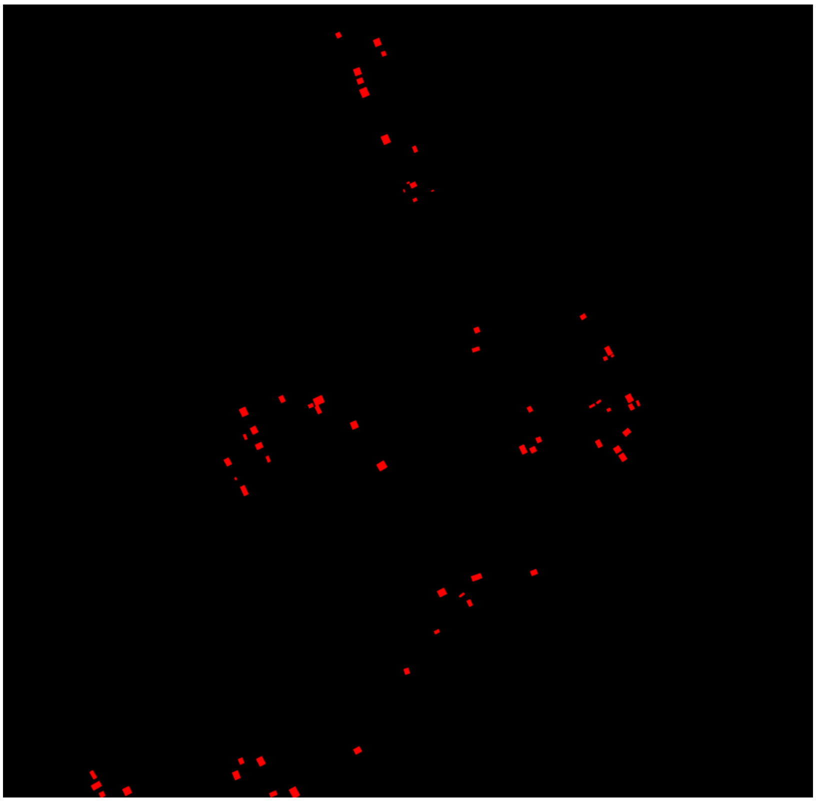

Figure 13: The results of applying post-processing on image (B) produced using ANN on a rural area.

These results demonstrated the accuracy of classification, clearly distinguishing between buildings and non-built-up areas, and improved detection accuracy after post-processing.

4. Performance Metrics

The performance metrics (Accuracy, Precision, F1 score) were used to evaluate the effectiveness of the ANN classifiers in detecting buildings and distinguishing them from non-built areas. Post-processing significantly improved performance by reducing errors like false positives, enhancing overall detection accuracy. Table 2 shows the performance results.

Table 2: The performance results.

Image	Operation	TP	TN	FP	FN	Accur.	Precis.	F1-score
First Image	Classifier Only	53452	8565030	1653	7715	0.9989	0.970	0.919
	Classifier+ Post Processing	54609	8565030	496	7715	0.9990	0.991	0.930
2^{nd} Image	Classifier Only	30965	8600097	859	7747	0.999	0.973	0.878
	Classifier+ Post Processing	31569	8600097	255	7747	0.999	0.992	0.887
	Classifier Only	30965	8600097	859	7747	0.999	0.973	0.878
	Classifier+ Post Processing	31665	8600097	159	7747	0.999	0.995	0.889

5. Conclusions

The results showed that the use of an artificial neural network classifier has an effective performance in detecting buildings from high-resolution satellite images due to the efficiency of the classifier and its ability to deal with complex patterns. Post-processing techniques also improved classification accuracy.

This research relies on three main categories of features: (1) the set of features extracted from individual pixels; (2) the set of features extracted from groups of neighboring pixels; (3) brightness, gray, and hue are the main features that distinguish building surfaces. The brightness and similarity of unpaved streets to building surfaces was the most difficult discrimination problem, and to reduce its negative impact, a post-processing stage was applied; this stage consists of the following operations: median filtering, removing small pores, gaps, and removing sections classified as building areas with abnormally long extensions and narrow widths, as these techniques effectively addressed the problems. Some suggestions to improve the results achieved from this work are: using the set of features extracted using Convolutional Neural Network, as it uses convolutional layers to extract features from the input effectively, or they can be used as supplements to those applied in this work. Future studies could explore ensemble methods like Random Forest or Support Vector Machines, especially in scenarios with complex feature interactions. Also, deep learning-based feature extraction and hybrid classification models should be explored.

Conflict of Interest

The authors declare that they have no conflict of interest.

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الكشف عن المنازل من صور الأقمار الصناعية عالية الدقة باستخدام مصنف الشبكة العصبية الاصطناعية

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[2] جامعة تكنولوجيا المعلومات والاتصالات، بغداد، العراق

الخلاصة

يهدف هذا البحث إلى تطوير نظام آلي للكشف عن المناطق المبنية في المناطق الريفية، ومعالجة تحديات تحديد المباني السكنية بدقة. تكمن إحدى الصعوبات الرئيسية في التمييز بين أسطح المباني والشوارع والطرق غير المعبدة، نظرًا لتشابه مستويات السطوع فيها. في هذه الدراسة، استُخدمت صور أقمار صناعية RGB عالية الدقة من القمر الصناعي WorldView-2 بدقة مكانية تبلغ 0.46 متر، وطُوِّر نظام آلي للكشف عن المناطق المبنية. يستخرج النظام 13 خاصية تمييزية مُصنّفة إلى مقياس قائم على البكسل ومقياس قائم على المساحة، وذلك لتحسين التمييز بين المباني والمناطق غير المبنية. تشمل هذه الخصائص مقاييس قائمة على اللون، مثل متوسط قيمة اللون الرمادي، و ودرجة الرمادية 1 ودرجة الرمادية 2، التي تلتقط الاختلافات بين قنوات الألوان، بالإضافة إلى حسابات التدرج اللوني المستمدة من معادلات متقدمة لتحسين تمييز الأسطح. بالإضافة إلى ذلك، تُسهم المقاييس الإحصائية المحلية، مثل المتوسط والانحراف المعياري المحسوبين ضمن نافذة 3×3 بكسل، في تحسين دقة الكشف عن طريق تقليل تأثيرات الضوضاء. تم اختيار هذه الميزات بناءً على فعاليتها في التعامل مع التباين الكبير في مواد البناء والقوام الشائع في البيئات الريفية. علاوةً على ذلك، تم تدريب مُصنِّف شبكة عصبية اصطناعية (ANN) على التمييز بين المناطق المبنية وغير المبنية. وتم دمج تقنيات المعالجة اللاحقة، بما في ذلك تصفية المتوسط، وإزالة الفجوات، واستبعاد الشرائح الضيقة غير ذات الصلة، لتعزيز دقة الكشف بشكل أكبر. تم تقييم أداء النظام باستخدام مقاييس الدقة، والدقة، والتذكير، ودرجة F1 لضمان متانة وموثوقية عملية الكشف عن المباني. أظهرت النتائج أن مُصنِّف الشبكة العصبية الاصطناعية (ANN) يكتشف المباني بفعالية مع التغلب على التحديات التي تفرضها الأشكال غير المنتظمة وخصائص الأسطح المتنوعة.

الكلمات المفتاحيه: كشف المنازل، الشبكات العصبية الاصطناعية، المناطق الريفية، استخراج الميزات، المعالجة اللاحقة .