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Deep Convolutional Neural Networks For Classification of Satellite Images

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Abstract— Deep learning algorithms that can learn from image, video, audio, and text data are becoming more successful as hardware power increases. Given the effectiveness and benefits of deep learning in many domains with more data, architecture should see similar implications. This study examined textures using particular rather than overall images. The deep convolutional neural network model classified 4500 satellite photos of clouds, deserts, greenery, and water. The constructed model classified previously unused test data (675 images) with 0.97 accuracies for cloud images, 0.98 for desert images, 0.96 for green areas, and 0.98 for water bodies. Although cloud and desert photos and green and water body images are comparable, this textural success shows that it can detect, analyze, and classify architectural elements. Deep convolutional neural networks can recognize, analyze, and classify architectural materials and elements, enabling shape recognition among many data to help architects collect helpful information. Thus, it will provide more extensive data than manual data analysis, enabling more accurate decisions. Understanding deep convolutional neural network data categorization characteristics explains architectural design differences and similarities. This condition reveals the hidden relationship in designs, allowing architects to create unique designs..

Keywords- Convolutional neural networks, Deep learning, Analyzing images, Identifying surface textures

I. Introduction

The architectural design process uses facts and expertise to solve design challenges and make judgments. As computer technologies and hardware advance, architectural design tools and procedures change. Thus, architect and designer tools and procedures affect architectural design. Data is increasing as technology advances. Machine learning algorithms, a subset of computer science using artificial intelligence, recognize, evaluate, learn from, and make judgments based on these expanding data. Machine learning allows computers to make conclusions and learn algorithms using mathematical and statistical operations without programming. In many disciplines, machine learning analyzes more data than humans and makes more accurate predictions. It automates routine chores and aids decision-making.

Hinton and Salakhutdinov [1] introduced deep learning by introducing hierarchical neural network techniques to learn data attributes. Deep learning is a subset of machine learning that uses multi-layer artificial neural networks. Deep learning is gaining popularity due to increased GPU capacity and processing capability for extensive data. Unlike typical machine learning methods, it can learn from photos, movies, sounds, and texts. Deep learning can extract attributes without computer involvement, unlike typical machine learning. Deep learning, a subset of machine learning, simplifies data definition, classification, and processing. Given the success and benefits of machine learning in other domains, architecture is likely to follow suit.

Architectural designs and features are visually classified using machine learning and computer vision. Understanding classification features helps explain design variances and similarities. Yoshimura et al. [2] classified 34 architects' works using a deep convolutional neural network (DCNN) model that classified photos by visual similarity. Llamas et al. [3] classified architectural heritage photos using convolutional neural networks (CNN) and said these techniques can help digitally document architectural heritage. Obeso et al. [4] used convolutional neural networks to classify building architectural styles in digital photographs of Mexican cultural heritage. This technique can improve video description tasks, especially automatic cultural heritage documentation.

The classification procedure automates architectural design activities. As technology advances, 3D models of buildings have more architectural elements, so architects separate each geometry into semantically correct layers after the draft model is finished to model faster in the first stage of schematic drawings. Dividing geometries into layers is simple and requires no particular skills. Yetis et al. [5] wanted to automate architects' and designers' work to minimize workload and increase performance. To label architectural elements in parametric design environments (Rhinoceros, Grasshopper, Grasshopper Python, and Grasshopper Python Remote), they used and compared five machine learning models: logistic, KNN, SVM, naive Bayes, and decision tree.

In architectural design, classification can correct situations that are impossible or difficult to change after design. Fuzzy logic, an artificial intelligence technology, was used by Diker and Erkan [6] to split classroom window design efficiency into seven classes. They said employing the model in the early design stage can help create classroom window designs that provide enough visual comfort. Some structural system decisions made during architectural design may necessitate modifications, causing time and expense losses. Bingöl et al. [7] developed an Irregularity Control Assistant using deep learning and image processing to help architects assess structural system decisions for earthquake compliance early in architectural design. They said their Irregularity Control Assistant will help architects make proper judgments early in the design process and reduce implementation project corrections.

Hardware power that can process more data allows visual data processing. This development will be crucial for architectural data processing. Unlike earlier studies, this study uses photos based on texture rather than function, design style, or building type. This study investigated the effectiveness of deep neural networks in categorizing satellite photos with various natural textures. Visualizing architectural structures with image processing will provide a new perspective on material detection and classification, thanks to deep convolutional neural network classification of satellite images with different properties. Thus, deep learning approaches can visually classify architectural designs, features, and materials using computer vision. A balanced data collection comprising 4500 satellite photos of cloudy (1125), desert (1125), green area (1125), and water (1125) was employed to increase model accuracy.

II. LITERATURE REVIEW

Machine learning is a subfield of AI that allows computers to learn and improve autonomously based on past performance without human intervention. Mitchell [8] provides a definition of machine learning that is consistent with the idea of learning by doing: Some task classes learn from experience concerning T, and the performance measure P if the performance of the computer program on tasks at T (task) improves with experience of E (experience). This is why researchers in machine learning seek to create intelligent computers that can access and learn from data. Traditional programming logic focuses on obtaining output data from the input data, and therefore, the output data to establish the appropriate program for the type of problem while using the software or by training machine learning machine with logic input and output data for the type of problem is obtained from the appropriate program or software [9]. To this end, machine learning's primary goal is to enable machines to acquire knowledge and automatically adjust without human guidance. Machine learning allows them to draw more accurate inferences based on past experiences, now or in the future, so robots can help make the right decisions.

Deep learning is a subfield of machine learning that uses algorithms known as artificial neural networks modeled after the human brain's structure and function. In deep learning, we employ multilayer deep neural networks. Inspired by the structure of the human brain, scientists have created deep neural network algorithms, a multi-layered variant of artificial neural networks. Deep neural networks are represented by networks with more than one hidden layer in addition to an input layer and an output layer. In deep neural networks, features are learned from the first to the last layer, with the output data from each layer serving as the input data for the following layer. Weights, bias, and an activation function are all components of a neuron in a deep neural network. The bias value is then multiplied by the output value produced by the neurons using the input value and the weights. This obtained output value (used to determine if the neuron can be active) is regulated by several activation functions (tanh, sigmoid, relu).

III. DATA SET

The model utilized "Satellite Image Classification Dataset-RSI-CB256" from "Kaggle." This dataset contains 5631 satellite photos of cloudy (1500), desert (1131), green (1500), and water (1500) from sensors and Google Maps snapshots. To balance the data set, 1125 photos from each class were employed (Figure 1).

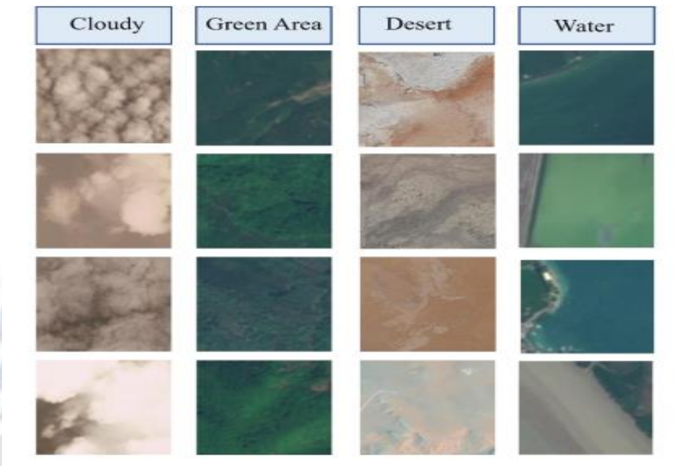

Figure 1. Satellite picture data sets used as examples.

Figure 1 displays examples of the classes in the data set.

IV. METHODOLOGY

A. Deep Convolutional Neural Network (DCNN)

Convolution, pooling, and fully connected layers comprise deep convolutional neural networks with hyperparameters like stride, pixel padding, filter (core), and activation functions.

B. Convolution layer

This layer extracts picture properties initially. This layer processes input images as matrices. Filters determine image attributes in the layer [10]. Images are filtered, and the matrix is multiplied. Add the multiplication values to reveal the result.

C. Pooling layer

The pooling layer receives the image after convolution. The pooling layer creates a smaller, more understandable output vector from incoming data. A pooling layer-specified sizing

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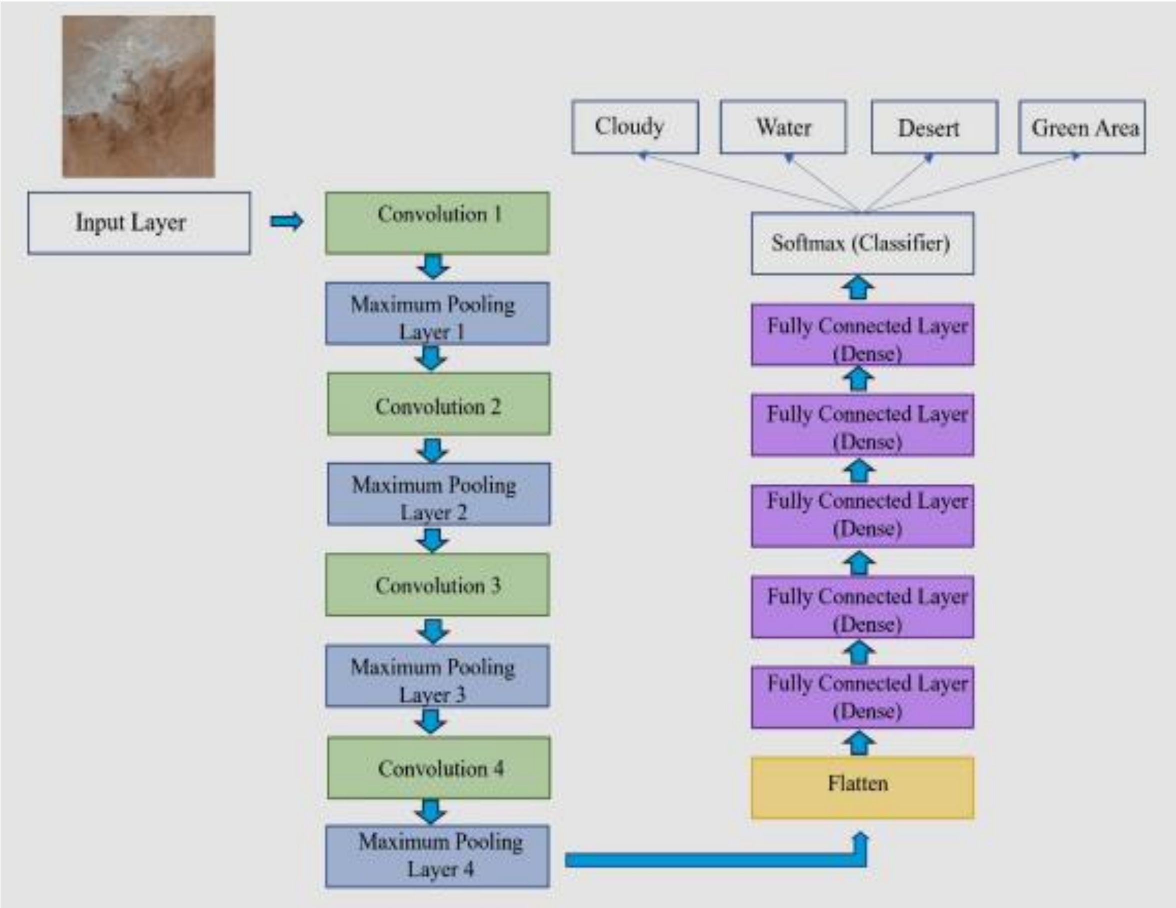

Figure 2. This new architecture for Deep Convolutional Neural Networks

matrix is used. This scaling matrix matches the image step shift. Different pooling methods exist. Usually, maximum and average pooling are utilized. The maximum or average pooling method is used if the matrix's maximum values or average are taken. The primary goal of this layer is to minimize network parameters [11]. This layer reduces size and loses information. Losing information helps the neural network by reducing computational effort on subsequent layers and preventing memorization [12, 13]. Reducing parameters controls network incompatibility.

D. Fully connected layer

Convolutional neural network topologies flatten before this layer to employ the matrices from the convolution and pooling layers sequentially in the fully connected layer. The flattening procedure prepares the fully linked layer's input data. Hidden layer coefficients are operated on. Data are associated with the density function and output after coefficient operations [14]. Labeling result values is done in the network output layer. The fully linked layer has one-to-one connections between neurons.

The fully connected layer classifies the input image into training dataset classes using these high-level features.

E. Classification layer

It is the final layer of the classification-focused deep convolutional neural network model. This layer classifies data so the output values equal the number of classes in the model. Deep convolutional neural networks use the SoftMax classifier in this layer [15]. The classifier predicts probability values between 0 and 1 for each class in this layer, and the model predicts the class with the highest probability [16].

The constructed deep convolutional neural networks have four double convolution layers, a maximum pooling layer repeated four times, a flattening layer, and four densely linked layers. Convolutional layers have a 3x3 core size, while maximum pooling layers have a 2x2 core size. Hidden layers use ReLU activation functions. With four classes in the output layer, SoftMax is the activation function. The free Google Colaboratory application and Python programming language were utilized to create the deep convolutional neural network model. The general architecture of the deep convolutional neural network model is presented in Figure 2.

V. PERFORMANCE EVALUATION CRITERIA

Performance evaluations can determine model success or quality. In supervised learning, categorization performance is measured in many ways. Confusion matrix, accuracy, precision, recall (sensitivity), and F1-score ratios assessed performance.

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A. Confusion matrix

This analytical tool indicates how well a classifier classifies class labels. Thus, it is a n*n matrix that represents the number of correct and incorrect predictions made by comparing classification model results to actual results. The matrix size is n*n if the data set has n class labels. Four evaluations are employed for categorization estimates [17]:

True Positive (TP): Model-predicted positive class labels.

True Negative (TN): Model-predicted negative class labels.

False Positive (FP): Incorrectly predicted positive class labels by the model.

False Negative (FN): This model predicted negative class labels wrongly.

B. Accuracy

Equation 1 gives the ratio of correct model predictions to all forecast

$$\frac{T_p + T_f}{T_p + T_f + F_p + F_n} \quad (1)$$

C. Precision(pre)

Success is determined by how many of all model-predicted positive samples are identified correctly (Equation 2).

$$\frac{T_p}{T_p + F_p} \quad (2)$$

D. Recall (Sensitivity/Re)

It measures positive situation prediction (Equation 3).

$$\frac{T_p}{T_p + F_n} \quad (3)$$

E. F1 score (F score)

Equation 4 calculates precision and recall (sensitivity) as the harmonic mean of the criteria.

$$\frac{Pre \times R_e}{Pre + R_e} \quad (4)$$

Where T_p, T_f, F_p *and* F_n denote true positive, true negative, false positive, and false negative.

VI. RESULTS OF THE MODEL

75% of the dataset was trained, 15% tested, and 15% validated. The model was trained using 100 epochs, a 0.0001 learning rate, and an Adam optimization algorithm. Figure 3-4 shows training and validation epoch accuracy and loss rates.

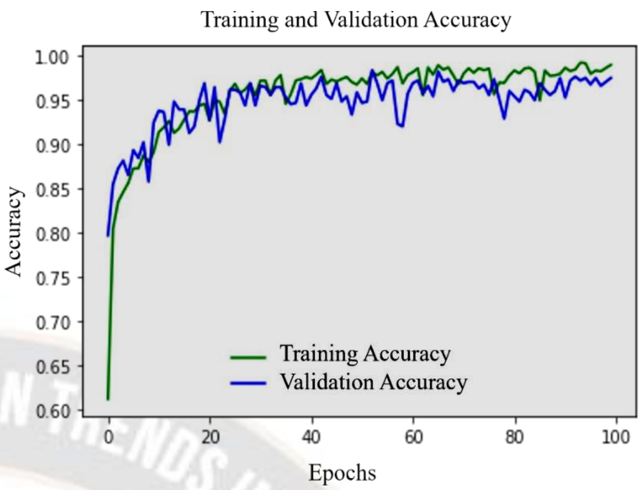

Figure 3. Graph showing training and validation accuracy using the created model

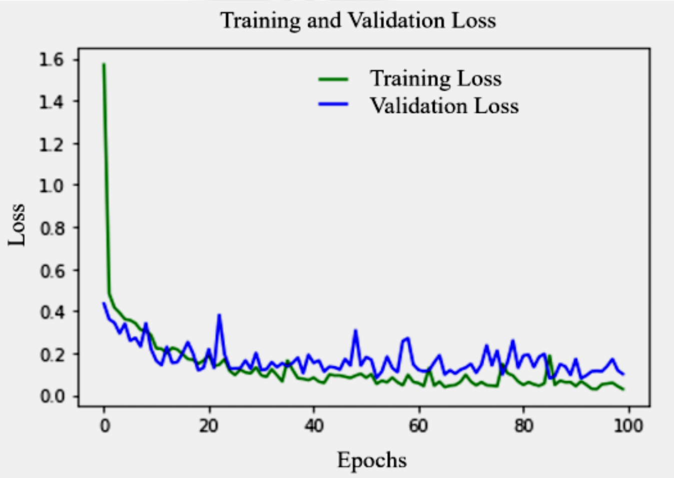

Figure 4. The generated model's training and validation loss curves

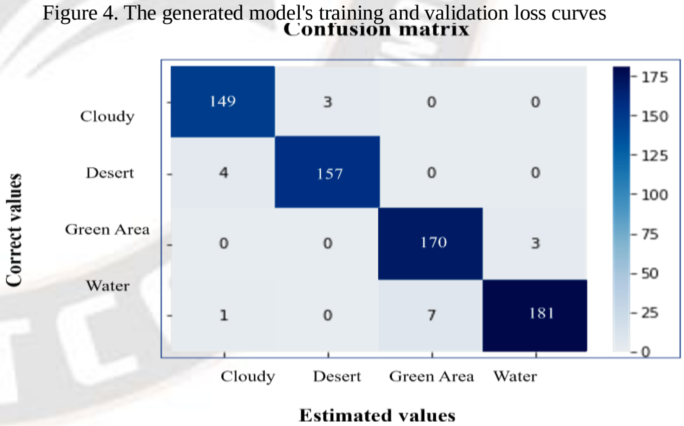

Figure 5. The resulting confusion matrix from the model development process

The constructed deep convolutional neural network model was evaluated using several criteria. Accuracy, precision, recall (sensitivity), and F1-score assessed model estimating effectiveness. These values are based on class confusion matrices. The confusion matrix from the created model is presented in Figure 5, and the performance criteria tested using it are shown in Table 1.

TABLE 1. The developed model's performance results

	Cloudy	Desert	Green area	Water
Accuracy	0.97	0.98	0.96	0.98
Precision(Pre)	0.97	0.98	0.96	0.98
Recall (Sensitivity/Re)	0.98	0.98	0.98	0.96
F1 score	0.97	0.98	0.97	0.97

VII. CONCLUSIONS AND FUTURE SCOPE

Machine learning algorithms, an artificial intelligence application in the computer science subfield, recognize, evaluate, learn from, and make judgments from these data as technology advances. Processing visual data with deep learning can help acquire appropriate and valuable data with shape recognition among many data, especially in the information collection stage of the architectural design process, especially with increased hardware power. Obtaining more thorough information (which manual searches may miss) can assist in making more accurate selections. Traditional methods yield inconsistent and erroneous findings, but machine learning reduces error.

The deep convolutional neural network model identified satellite pictures. Even if desert and hazy photographs are similar, all but 8 of 675 test images were correctly categorized. Only one of these eight photographs is water. Although the green area and water photos are similar, all but ten were categorized correctly. This shows that visual processing of architectural structures can succeed. Unlike other studies, this success in texturing has demonstrated that it can detect, analyze, and classify building materials in architectural structure views. Learning data characteristics for machine learning classification discusses design variances and similarities, revealing hidden design linkages. This lets architects and designers create more unique designs. In addition, the ability to process visual data can help acquire appropriate and valuable data with shape recognition among many data, especially during the information collection stage in the architectural design process, enabling more accurate decisions.

The classification method can automate architectural design work. As technology advances and 3D modeling becomes more complex, architects divide each geometry into semantically correct layers after the draft model is finished to model faster in the first stage of schematic drawings. Architecture and design professionals can save time and enhance performance by automating tedious tasks with classification. It can also archive growing data (architectural artifacts, building styles, etc.) with classification. This decreases the digital documentation workload and automates it. This study's model allows architectural elements to be classified, separated, and distinguished. As architectural features, construction systems, and technology advance, classification methods become more important. According to the study's paradigm, façade applications, material classification, and data archiving can be inspired by correctly classified satellite photos. Additionally, data capture may reveal new design aspects that manual data cannot, giving designers new views.

REFERENCES

[1] Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks, Science 2006; 313(5786): 504-507.

[2] Müller, M. U., N. Ekhtiari, R. M. Almeida, and C. Rieke. 2020. “Super-Resolution of Multispectral Satellite Images Using Convolutional Neural Networks.” ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS, 2020) 33–40. doi:10.5194/isprs-annals-V-1-2020-33-2020..

[3] Park, H., N. Kim, S. Park, and J. Choi. 2020. “Sharpening of Worldview-3 Satellite Images by Generating Optimal High-Spatial-Resolution Images.” Applied Sciences 10 (20): 7313. doi:10.3390/app10207313.

[4] Obeso AM, Vázquez MSG, Acosta AAR, Benois-Pineau, J. Connoisseur: classification of styles of Mexican architectural heritage with deep learning and visual attention prediction. In Proceedings of the 15th international workshop on content-based multimedia indexing, 2017; 1-7.

[5] Yetiş G, Yetkin O, Moon K, Kılıç Ö. A novel approach for classification of structural elements in a 3d model by supervised learning. In Proceedings of the 36th eCAADe Conference, 2018; 129-136.

[6] Shendryk, Y., N. A. Rossiter-Rachor, S. A. Setterfield, and S. R. Levick. 2020. “Leveraging High-Resolution Satellite Imagery and Gradient Boosting for Invasive Weed Mapping.” IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 13: 4443 4450. doi:10.1109/JSTARS.2020.3013663.

[7] Bingöl K, Aslı ER, Örmecioğlu HT, Arzu ER. Depreme dayanıklı mimari tasarımda yapay zeka uygulamaları: Derin öğrenme ve görüntü işleme yöntemi ile düzensiz taşıyıcı sistem tespiti, Gazi Üniversitesi Mühendislik Mimarlık Fakültesi Dergisi, 2022; 35(4): 2197-2210.

[8] Wang, Y., S. M. A. Bashir, M. Khan, Q. Ullah, R. Wang, and Y. Song, … Y. Niu. 2022. “Remote Sensing Image Super-Resolution and Object Detection: Benchmark and State of the Art.” Expert Systems with Applications 197: 116793. doi:10.1016/j.eswa.2022.116793. .

[9] Kavuncu SK. Makine öğrenmesi ve derin öğrenme: Nesne tanıma uygulaması. Kırıkkale Üniversitesi, Fen Bilimleri Enstitüsü, Master's Thesis, 2018; 157p.

[10] Narın D, Onur TÖ. Investigation of the effect of edge detection algorithms in the detection of covid-19 patients with convolutional neural network-based features on chest x-ray images. In 2021 29th Signal Processing and Communications Applications Conference (SIU), 2021; 1-4.

[11] Önal MK, Avci E, Özyurt F, Orhan A. Classification of minerals using machine learning methods. In 2020 28th Signal Processing and Communications Applications Conference (SIU), 2020; 1-4.

[12] İnik Ö, Ülker E. Derin öğrenme ve görüntü analizinde kullanılan derin öğrenme modelleri, Gaziosmanpaşa Bilimsel Araştırma Dergisi, 2017; 6(3): 85-104.

[13] Ergün GB, Güney S, Ergün TG. Köpeklerdeki uzun kemiklerin evrişimsel sinir ağları kullanılarak sınıflandırılması, Fırat

Üniversitesi Mühendislik Bilimleri Dergisi, 2021; 33(1): 125-132.

[14] Yamashita R, Nishio M, Do RKG, Togashi K. Convolutional neural networks: an overview and application in radiology, Insights into imaging, 2018; 9(4): 611-629.

[15] Bozkurt F, Yağanoğlu M. Derin evrişimli sinir ağları kullanarak akciğer x-ray görüntülerinden covid-19 tespiti, Veri Bilimi, 2021; 4(2): 1-8.

[16] Zhou, Y., R. Zhang, S. Wang, and F. Wang. 2018. "Feature Selection Method Based on High-Resolution Remote Sensing Images and the Effect of Sensitive Features on Classification Accuracy." Sensors 18 (7): 2013. doi:10.3390/s18072013.

[17] Rizaludin Mahmud, M., S. Numata, and T. Hosaka. 2020. "Mapping an Invasive Goldenrod of Solidago Altissima in Urban Landscape of Japan Using Multi-Scale Remote Sensing and Knowledge-Based Classification." Ecological Indicators 111: 105975. doi:10.1016/j.ecolind.2019.105975.