QUBAHAN ACADEMIC JOURNAL
VOL. 4, NO. 2, June 2024
https://doi.org/10.48161/qaj.v4n2a557

# The Analyze Comparative of Physics Computational Thinking Skill (CTs) in Experiment Laboratory

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**ABSTRACT:** The development of 3D scanning technologies has made it possible to obtain an increasing amount of data about the external world, which leads to the need for efficient methods of processing acquired data to recognize objects. Traditional approaches face accuracy, speed, and reliability problems due to the complexity and diversity of object shapes, sizes, degrees of detail, and the presence of noise and artifacts in the data. Therefore, our goal was to improve the object recognition efficiency. It is necessary to determine the method of obtaining geometric and topological parameters. In the paper it is proposed to use the method of Laplace-Beltrami, which allows to calculate distances and angles between points within a given area. Next, it is necessary to determine which parameters will be used to analyze the obtained geometric data. We propose the use of three spectral descriptors – Heat Kernel Signature (HKS), Weave Kernel Signature (WKS) and the wavelet descriptor (SGWT). Then, we develop a high-accuracy recognition method based on spectral and topological invariants processed using a convolutional neural network. Subsequently, the parameters of the descriptors are calculated, and then they are calculated through the neural network, resulting in the classification of the object. In summary, the structure of the proposed method comprises the computation of the Laplace-Beltrami spectrum, the construction of spectral distribution maps, and the subsequent processing of this information using a neural network. After analyzing the results, we found that the proposed method has a recognition rate of 0.9 s and recognition accuracy of 97%. It was shown how much more effective the use of the three descriptors was compared to the use of each one individually. An example of object recognition using the proposed method was also given. The methodology outlined in this paper utilizes machine learning to achieve high levels of accuracy in the classification of different objects. Effectiveness of the proposed method in this study enhance existing recognition systems and open new opportunities for their application in various fields, including robotics, agriculture, and navigation. This research demonstrates considerable potential for further development and application in the field of agriculture, underscoring the continued necessity for research in this area.

**Keywords:** 3D scanning; invariants; descriptors; machine learning; convolutional neural network

## I. INTRODUCTION

Artificial intelligence (AI) and computer vision technologies are increasingly being applied in medicine, agriculture, and security systems [1, 2]. One of the functions of AI is the recognition and classification of 3D objects. The ability to process the 3D images used in this function is becoming essential because it makes it possible to work efficiently with 3D data, increasing the accuracy and informativeness of analysis compared to the processing of 2D data [3, 4].

Recognition of 3D objects is challenging due to the variety of shapes and sizes, noise, and artifacts in the data [5]. In addition, differences in 3D data representations, such as point clouds and polygonal models, introduce additional complexity in the recognition process [6]. Besides, it is necessary to comply with accuracy and speed requirements when recognizing 3D objects of different details [7-9]. As most recognition methods are based on the comparison of two images, namely the acquired image and reference image, there is a problem with the systematization of the results. These problems motivate the development of new methods and algorithms that provide stable performance with various input data [10,11].

This study aims to investigate a method for recognizing 3D objects that can effectively work with agricultural objects of varying details. The importance of such system operation is due to the need for regular monitoring of plants to provide timely protection from pests and diseases, watering and feeding, and soil tillage. In the context of developing automated systems for agricultural production, it is essential that the means of object recognition can identify different objects at a specified speed. The improvement of existing systems is due to the performance and reliability requirements under diverse plant forms and structures [12].

This study investigates and adapts modern recognition approaches, such as spectral methods, to implement a universal system that can effectively handle the tasks at hand. Developing such a method involves analyzing 3D data, identifying key characteristics of objects, and applying adaptive algorithms to their classification and identification [13, 14].

The findings presented in this paper contribute to the existing body of knowledge in this field.

The object recognition method has a wide range of applications in various industrial fields. The construction of methods and algorithms for the segmentation and recognition of three-dimensional objects allows for the acceleration of the processing of three-dimensional data and the enhancement of the quality of searches for relevant objects. The developed algorithm allows to increase the recognition accuracy of various objects by 16% on average and significantly increase its speed. The developed method has the following parameters:

- recognition accuracy of 97%;
- average recognition speed of 0.9 s.

## II. LITERATURE REVIEW

Accurate recognition of 3D objects of different details makes it possible to actively develop agriculture by implementing automated processes. Object recognition methods are based on the use of a point cloud–a group of points that have certain coordinates and form a 3D surface. Significant problems in the issue of obtaining information for monitoring and calculating coordinates arise due to negative factors related to natural impact, for example, changes in atmospheric transparency and atmospheric factors. Thus, traditional point cloud-based methods face accuracy and noise susceptibility problems.

Shah et al. [15] developed a method for modeling and recognizing 3D objects through keypoints called Keypoints-based Surface Representation (KSR) [15]. This method differs from traditional approaches by using geometric relationships between 3D key points to describe a surface, thereby improving the recognition speed and accuracy. KSR shows high efficiency for noisy data with different grid resolutions, thus reducing the computational complexity. Validation on the UWA and Stanford 3D Models datasets confirmed high object recognition accuracy of 94%. A significant disadvantage of the method is the speed of 3D object recognition, which was 28.3 s.

Madi et al. [16] proposed a technique for comparing deformable 3D objects represented by graphs or triangulation meshes [16]. The method uses a unique graph-matching technique through triangle-star decomposition of meshes, and simplifies the comparison by reducing the number of analyzed components, thereby increasing computational efficiency. This approach reduces computational complexity and expands the analyzed space, improving the criteria for the differences between objects; it also includes methods for classifying deformable objects and defining the metric space through graph-based embedding. As discussed, the developed triangle-star-based distance measure fulfills the base metric conditions except identity. The method efficiency was demonstrated on the TOSCA and SHREC11 databases, showing high accuracy (84.45%) and noise immunity when comparing deformable 3D objects, making it suitable for analyzing objects subject to shape changes. However, as the authors stated in the paper, the proposed algorithm does not have high productivity and consumes a significant time for data processing.

Liu et al. [17] considered the problem of recognizing 3D objects and estimating their spatial position, which is essential for robotics and manufacturing [17]. The key challenge is extracting stable features from point clouds. The proposed network architecture for unsupervised learning extracts important features from point clouds while preserving object geometry and optimizing resources. The network includes an encoder to integrate discriminative features, and training is performed on synthetic data. In testing, feature comparison with a database and subsequent verification ensures accurate recognition and position estimation of objects. The method is effective under various conditions and prevents information loss. The disadvantage of this method is its dependence on data quality and inability to adapt to different scenes.

Zhao et al. [18] introduced a novel descriptor named Histograms of Point Pair Features (HoPPF) to describe the local surfaces of 3D objects, providing high descriptiveness and robustness at low computational costs [18]. The study described by Zhao aimed to improve the extraction of correspondence points between point clouds for 3D perception. The descriptor uses normal reorientation and Poisson-disk sampling strategy to minimize data redundancy and splits local point pairs into regions to create sub-descriptors combined into a HoPPF vector. This enables efficient representation of geometric information proven on various datasets with 94% accuracy. The proposed HoPPF outperforms state-of-the-art methods in terms of robustness and descriptiveness. The point-pair separation technique offers the versatility to modify other pairwise descriptors. However, this method has no adaptation for robotics and is not workable with colors.

Zhou et al. [19] proposed a method for recognizing 3D objects in complex scenes based on generating and testing hypotheses using Hough space [19]. The innovation consists of a self-tuning measure to reduce the number of false matches while considering the geometric consistency between the models and scenes. Testing on four datasets showed the method's superiority in terms of high recognition accuracy (95%) even with overlapping objects and high levels of false positives. The advantages of the proposed method include accuracy in complex scenes and efficient use of geometric information. The disadvantage of this method is the need for careful selection of parameters and potentially high computational costs when processing big data.

Li et al. [20] presented an algorithm to recognize and estimate the position of 3D objects in industrial scenarios using an extended histogram representation of viewpoint features (PVFH) [20]. This algorithm provides high accuracy and can process images with uniform colors and similar geometry. Tests of industrial-part recognition confirmed the superiority of the algorithm over similar algorithms, demonstrating improved location estimation and computational efficiency. The accuracy of this method (43.2%) depends on the segmentation accuracy, which proves the method's unsuitability for noisy scenes.

Donghyun Lee created a new neural network architecture that integrates tensor decomposition and quantization to optimize a convolutional neural network [21]. This method significantly reduces the model size, lowering memory and computation requirements, and is suitable for resource-constrained devices. Their designed quantized tensor train convolutional neural network (QTTNet) demonstrated high compression ratio with minimal loss of accuracy on the ModelNet40 and UCF11/50 datasets. Despite having 87.2% accuracy, the method requires an accurate selection of input parameters and does not have a high overall efficiency.

Li et al. [22] developed a 3D object detection system for autonomous vehicles that uses Lidar data and RGB images [22]. This system focuses on cars, cyclists, and pedestrians by combining feature extraction from RGB and converting point clouds into Bird's Eye View using sparse convolution. The Region Proposal Network (RPN) optimizes the classification and bounding box regression. Tests on KITTI data and the CARLA simulator demonstrated sufficient system performance under real-world conditions, emphasizing the importance of integrating Lidar and RGB data for accurate object detection (equal to 76%). However, this method cannot process continuous data flow and images with high noise pollution.

Garcia-Garcia et al. [23] analyzed the effects of noise and occlusion on convolutional neural networks (CNNs) for 3D object recognition [23]. They investigated the influence of different 3D data representation methods on CNN training using Caffe on the 3D CAD model data of Princeton ModelNet models modified by noise and occlusion simulations. The results emphasize the significance of selecting the data representation to improve the robustness of the CNN to external noise. The recognition accuracy of the method was 90%. Its disadvantage is low efficiency.

Santos et al. [24] proposed an object detection method using a camera based on a CNN [24]. The model is error-tolerant and provides 90% accuracy. The disadvantages of this method are the limited number of recognizable objects and the ability to recognize only simple, noise-free images.

The literature reveals a key challenge in the balance between accuracy, speed, and reliability of recognition systems. Methods such as PVFH, which are robust for object recognition, encounter problems with accurate segmentation and occlusions. CNN approaches that use labeled 2D images for 3D recognition are inefficient in complex environments and require significant computational power. Automated systems that can process detailed 3D objects quickly and accurately are required. Studies should focus on developing robust algorithms in complex environments by combining geometric processing and machine learning. This paper proposes a new framework to improve speed and accuracy, which will contribute to automation systems.

## III. MATERIALS AND RESULTS OF THE STUDY

The study was conducted over several phases as indicated in the flowchart (Figure 1). In the first part of the research, a review of existing systems was presented. This research built on the strengths of existing work; however, the authors' aim was to create their own object recognition system. A method was selected that partitions the outer surface of the image objects using a triangular mesh. The triangles partitioning the surface were then processed using the Laplace-Beltrami operator to obtain information about the shape and size of the object, and the spectral invariants of the object were calculated to concretize the shape. The obtained data were processed using a convolutional neural network. Thus, the objects in the image are recognized.

### *1. OBJECT PARTITIONING USING A TRIANGULAR MESH*

When an image of an object is received from the camera, its surface is partitioned into a triangular mesh (Figure 2). Within the objective analysis using data obtained through laser scanning, the considered mesh consisting of surface points is formed. To accurately determine the discrete analog of the operator, it is necessary to consider the discrete representation of the surfaces of the analyzed objects. Let us introduce the following assumptions: a given mesh approximates the surface of the studied object in 3D space with Cartesian coordinates. This mesh consists of vertices V, edges E, and triangles T. Let us define the number of vertices as n. Each of the points that make up such a grid has its own area, as shown in Figure 3. Edges eij connecting pairs of vertices pi and pj are linear segments defining the proximity between vertices. For each pair of points pi and pj, an interconnection eij is established. The triangles T formed at vertices pi, pj, and pk create the surface structure. The angles αij and βij opposite the edge Pij are described in the context of their geometric relationship.

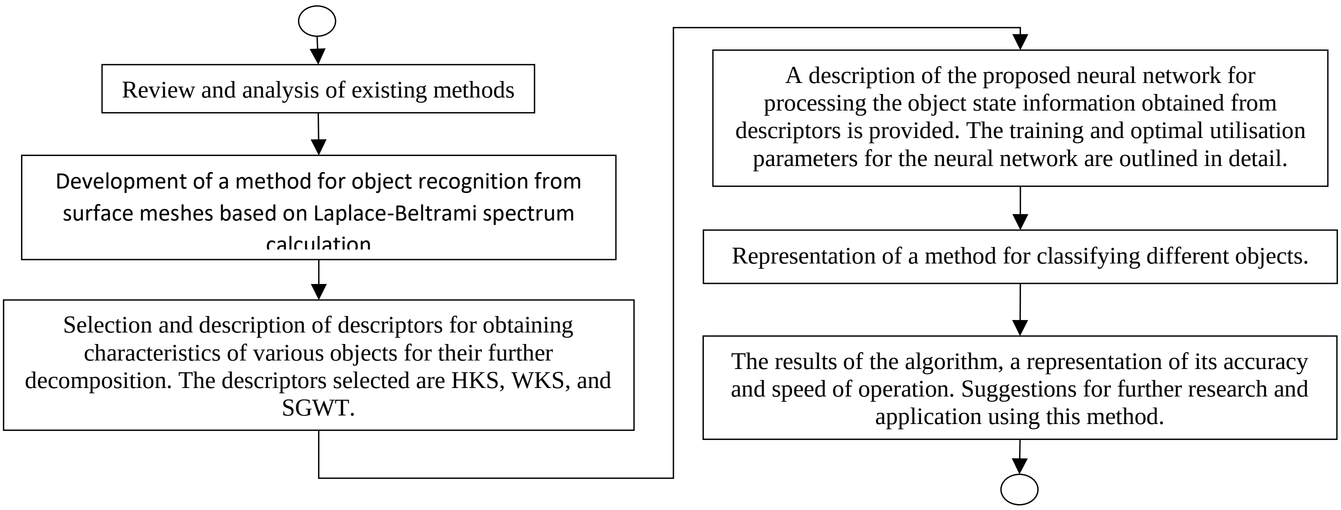
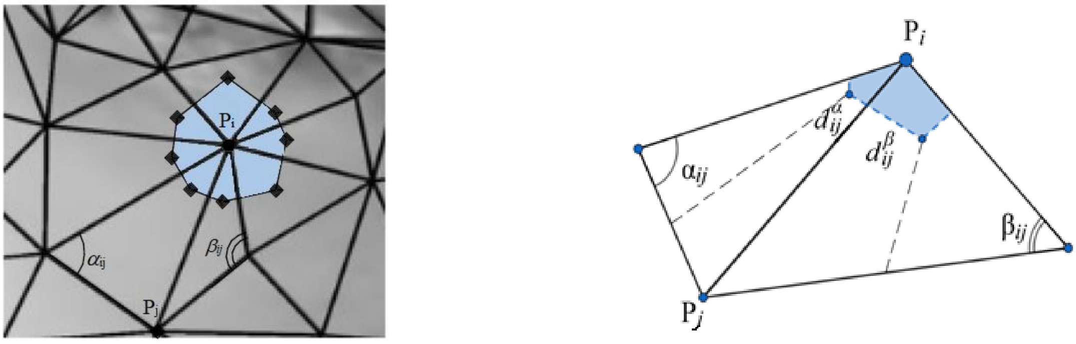



FIGURE 1. Flowchart of the study. Source: Author's own compilation.

(a) (b)

FIGURE 2. Partitioning of the object surface using a triangular mesh: (a) Initial tomato model; (b) tomato surface partitioned by a triangular mesh. Source: Author's own compilation.




(a) (b)

FIGURE 3. Point pi associated with neighboring points: (a) Voronoi area (shown in blue); (b) cotangent weights. Source: Author's own compilation.

Figure 3 shows that the Voronoi region is given by lengths $\boldsymbol{d_{ij}^{\alpha}}$ and $\boldsymbol{d_{ij}^{\beta}}$ calculated as follows (1):

$$\boldsymbol{d_{ij}^{\alpha} = |ctg\ \alpha_{ij}| \cdot \|P_i - P_j\|} \qquad (1)$$
$$\boldsymbol{d_{ij}^{\beta} = |ctg\ \beta_{ij}| \cdot \|P_i - P_j\|}$$

where $\boldsymbol{\alpha_{ij}}$ and $\boldsymbol{\beta_{ij}}$ – angles marked in Figure 2 (a and b); Pi and Pj are points connecting neighboring areas.

## 2. CALCULATION OF LAPLACE-BELTRAMI SPECTRUM

Modern 3D graphics widely use methods that rely on the spectral properties of graphs, among which the Laplace-Beltrami operator Δ_LB (2) stands out. The Laplace-Beltrami spectrum operator is a mathematical tool that describes the distances and angles between points in a given area.

Δ_LB f=div(grad(f)) (2)

where f is a twice-differentiable function set with no exception to all vertices denoted by p_i∈P.

This operator is essential in differential geometry because its spectral characteristics reflect the geometric and topological aspects of 3D objects. This operator is used to model diffusion processes on the surface of an object and analyze its internal properties in detail. The operator provides a complex description of the object in 3D space. The operator properties, such as the invariance of the spectrum to scaling and isometric transformations, make it an indispensable tool for shape analysis. The use of this operator simplifies the calculation of the object area.

Let us write the Laplace-Beltrami operator as follows:

Δ_LB (f(p_i ))=1/a_i ∑_(p_j∈N(p_i ))▒〖ω_ij (f(p_i )-f(p_j )) 〗 (3)

where ai and ◎ij are weighting coefficients of all vertices and edges e_ij=(e_i,e_j )∈E. For practical use, using the Laplace-Beltrami operator in matrix form is rational.

## 3. MATRIX OPERATOR DISTRIBUTION

The Laplace-Beltrami matrix is the difference between diagonal matrix D consisting of dij elements and the W matrix, and diagonal matrix D consisting of wij elements. The proposed model provides an accurate description of an object's shape. In this way, we obtain a matrix that, after spectral decomposition, consists of vectors that provide information about the object's shape. The key properties of the Laplace-Beltrami matrix operator are symmetry, robustness to noise, and integrity, making it an essential tool for analyzing volumetric shapes. The operator's efficiency is further enhanced by using the geometric features of the mesh, such as the area of the Voronoi region, to provide an accurate description of objects.

## 4. DESCRIPTORS BASED ON SPECTRAL DECOMPOSITION

Wavelet, wave, and thermal conductivity descriptors are helpful tools for analyzing volumetric data because of their robustness to change and accuracy in conveying object contour data.

### 4.1 Heat Kernel Signature

Heat Kernel Signature (HKS) thermal conductivity descriptor analyzes the heat distribution over the object's surface, thus determining its shape. The heat transfer process is described using the so-called heat kernel function, which is closely related to the spectral decomposition of the discrete Laplace-Beltrami operator. This descriptor represents a set of h(p, t) values for the discrete case, which is defined by the triangular grid. Consequently, the distribution of descriptor values with respect to time provides insight into the shape of the object. As the time interval progresses, the entropy of the distribution of HKS values over the surface increases, and the HKS values begin to describe increasingly global geometric characteristics of the object shape.

### 4.2 Weave Kernel Signature

Weave Kernel Signature (WKS) represents surface points as quanta and describes the object shape through the probability of the existence of these quanta at different energy levels and time moments. The probability of finding a quantum can be estimated from the vectors of the Laplace-Beltrami operator and the energy density function. WKS provides robustness to scale and isometric changes. The obtained values are transformable on a logarithmic scale, providing more accurate information about the object's shape. WKS is stable to little variations of the object in the initial images and demonstrates how surface characteristics change with energy.

### 4.3 Wavelet descriptor

The wavelet descriptor (SGWT) is used to obtain information about the object's shape by analyzing the transformations in the vertices of the mesh that form the object's surface. Unlike HKS and WKS, a wavelet descriptor uses fluctuations to analyze the shape of an object. There are two wavelet descriptors: high-frequency, which focuses on details, and low-frequency, which covers the overall shape. As a result, SGWT provides a complete picture of the fine details and the overall structure of an object. Thus, the wavelet descriptor combines local and global approaches to create a detailed surface description.

## 5. COMPRESSED DESCRIPTORS

Spectral descriptors provide information about all points of an object given different levels of heat and energy. However, when the numbers of points that form objects differ, these descriptors have different amounts of input data, which makes training neural networks much more difficult. In order to simplify the CNN inputs, they should first be placed into a general format. Data compression by bringing it to a standardized size does not lead to the loss of meaningful information. For this purpose, descriptors are allocated to points at which specific parameters change, and select the same number of these parameters. In this way, using HKS, WKS, and SGWT, the information for each point is obtained and integrated into matrices of the same size. Subsequently, we divided the values into the same number of intervals, which enabled us to create compact maps of the spectral distributions. Finally, we obtain compressed data that includes information about the distribution of the descriptors, which makes the data more convenient to analyze and use in various applications, including machine learning. Spectral distribution maps allow us to consider two similar objects based on their shapes and class memberships. These maps demonstrate robustness against changes in the shape of objects, such as isometric transformations or minimal changes in shape and number of elements, while providing a clear distinction depending on the object's class.

Distribution maps are productive for object classification. The selection of such maps is difficult because the geometric characteristics and surface features of an object are unknown in advance. The following presents a variant of combining available maps into a single system, which is necessary for the initial correct selection of these maps. To realize this process, we use machine learning to create a convolutional neural network with further training on the available map samples.

## 6. NEURAL NETWORK STRUCTURE

The input data for system building were spectral maps of DH, DW, DS, and DN distributions. Figure 4 shows the network structure: input data, convolutional blocks, and a fully connected layer.

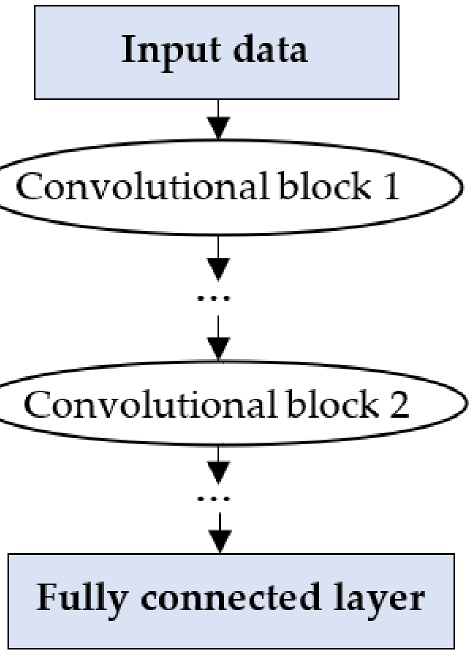



FIGURE 3. Structure of the convolutional neural network used for object classification. Source: Author's own compilation.

The convolutional blocks perform dimensionality reduction and filtration of the input data. These data pass through an appropriate set of convolutional blocks to gather into a single vector, along with the input information, for transfer to a fully connected layer. The process consists of calculating the convolution of vectors for the considered object with dimension 5x5. Then the result of this calculation is reduced using pooling and filtered using the activation function. On the next block the same reduction procedure takes place, producing a 3x3 matrix. This process results in establishing an appropriate class for the given subject.

In the fully connected layer, learning takes place using forward and backward traversal. In the forward pass, the output matrix is calculated as follows:

$$\hat{y}^{(d)} = \sigma_{fl}\left(h^{(d)}\right), d = 1, 2 \tag{4}$$

where $h^{(d)} = W^{(d)} y^{d-1} + b^{(d)}, y^{(0)} = f$, and activation function looks like $\sigma_{fl}\left(h^{(d)}(i)\right) = e^{h^{(d)}(i)} / \sum_i e^{h^{(d)}(i)}, i = 1, \dots, \left|h^{(d)}\right|$. The displacement correction vector and the weight correction matrix will be employed as a backward step:

$$\Delta b^{(d)} = \left(\partial Y / \partial \hat{y}^{(d)}\right) * \left(\partial \sigma_{fl} / \partial \hat{y}^{(d)}\right) \tag{5}$$
$$\Delta W^{(d)} = \Delta b^{(d)} \left(\hat{y}^{(d-1)}\right)^T, d = 2, 1$$

In the fully connected layer, training is based on the error back propagation method takes place and the calculated weights are assigned to the object, which depend on the parameter setting the learning rate.

## 7. *OPTIMIZATION METHODS FOR MACHINE LEARNING*

The next step in acquiring information about an object in an image is machine learning. Traditional methods require retraining and the low speed of the iterative process. When a neural network has too many parameters, it can start to "learn by heart," leading to overtraining. A dropout regularization method helps prevent this. The method's essence is to "turn off" randomly some neurons during training to make the network more stable and to exclude the dependence on specific neurons. When testing the system, the results from these neurons were multiplied by a coefficient related to the probability of turning off during training. This method is useful for neural networks with many links. However, for convolutional neural networks, this method is ineffective for several reasons, including the risk of vanishing gradients, which would cause the termination of the learning process, and overtraining probability.

https://doi.org/10.48161/qaj.v4n2a557

In this paper, optimization to improve the learning rate of the neural network employs batch normalization and adaptive learning techniques to improve the stability of the network. Batch normalization modifies the input data by dividing them into small groups, speeds up training, and improves efficiency by reducing the number of required iterations. However, using normalization too often can lead to overtraining. The batch normalization first calculates the mean and variance of each batch, followed by data normalization to improve the stability of the learning process. These steps help the network learn more efficiently by making each layer independent of the input data scale of the previous layer.

### 8. *OBJECT CLASSIFICATION ALGORITHM*

The above method, which attempts to classify items, is described by a special algorithm. The proposed method relies on a three-stage algorithmic calculation (Figure 5):

- Laplace-Beltrami spectral calculation;
- Building spectral distribution maps;
- Recognition of the considered objects using a convolutional neural network.

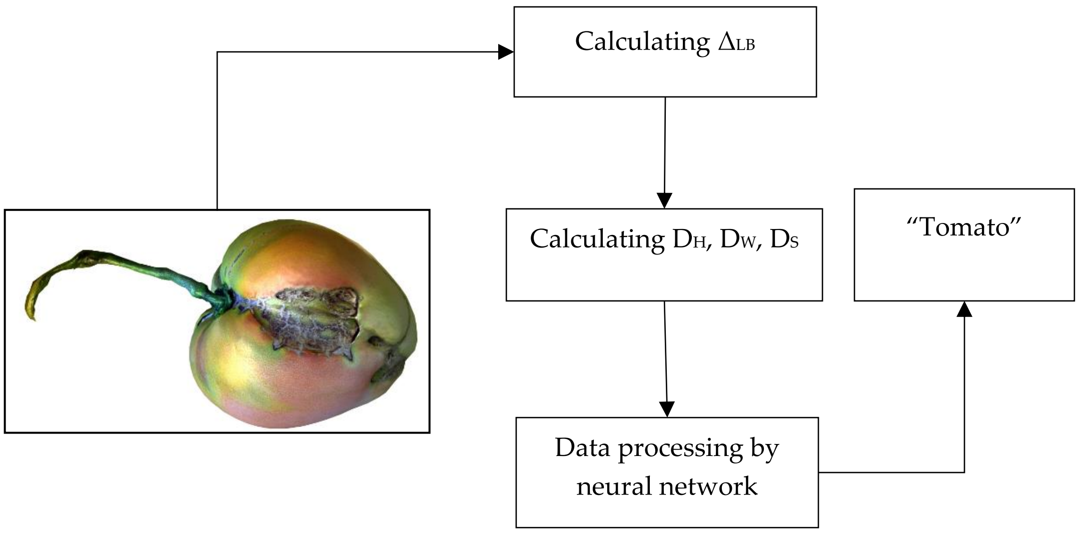



FIGURE 4. Stages of object classification methodology. Source: Author's own compilation.

The analysis process uses the Laplace-Beltrami system for the studied object with its surface S and a set of vertices of triangles P and T. It is necessary to calculate the coefficients ◎i and ◎i to create the Laplace-Beltrami operator (Δ_LB). Then, the spectral decomposition of this matrix occurs to obtain the eigenvalues ◎ and eigenvectors ◎. The next step is to build spectral maps based on the found ◎ and ◎ for the WKS, SGWT, and HKS descriptor parameters, after which DH, DW, and DS calculations compress the information. In object identification using a convolutional neural network, DH, DW, and DS spectral maps are processed through specific network channels, and classification is performed through a data forward pass. The neural network training involves a structured analysis of objects based on the available training samples. The DH, DW, and DS spectral maps are integrated into the network, and the weights are updated iteratively through forward and backward passes applying techniques to prevent overtraining and accelerate the learning process.

## IV. ANALYSIS AND DISCUSSION OF THE RESULTS

The primary scientific contribution of this study is to create and analyze innovative and improved techniques for 3D object identification in agriculture. The results have both theoretical and practical relevance in the context of the main challenges of agricultural automation. This paper presents a detailed machine learning-based method for accurate object identification, focusing on the following aspects:

- Developing a methodology for performing spectral analysis of the discrete Laplace-Beltrami operator applicable to 3D objects;
- Determining and describing descriptors such as thermal conductivity, wave and wavelet descriptors based on the spectral decompositions of the discrete Laplace-Beltrami operator and adapted for the identification of 3D objects represented as triangular meshes were determined and described;
- A method for compressing the above descriptors using spectral distribution maps;
- Representing the structure of a neural network for the recognition task, including techniques for improving the quality and increasing the learning rate;
- Formulating an identification algorithm, including spectral distribution maps and machine learning technology.

Table 1 presents the recognition accuracy of the developed algorithm on the test sample. The 400 experimental models for recognition were taken from McGill Database. They were divided into test and training models in a ratio of 1:3. In the training process, objects with isometric (not changing the shape and size of the object) and non-isometric transformations were used.

**Table 1**. Evaluation of recognition accuracy. Precision – percentage of correctly classified objects; Recall – percentage of classified objects belonging to a particular class; Fscore – harmonic mean of Precision and Recall; Accuracy – percentage of general correct classification of the results obtained by different algorithms.

| *Spectral maps* | *Precision* | *Recall* | *Fscore* | *Accuracy* |
|---|---|---|---|---|
| $D_H$ | 94,5 % | 93,5 % | 93.3 % | 93.5 % |
| $D_W$ | 89,5 % | 86.9 % | 86.7 % | 86.9 % |
| $D_S$ | 91,8 % | 89.8 % | 89.7 % | 89.8 % |
| $D_H \oplus D_W \oplus D_S$ | 97,4 % | 97.1 % | 97.1 % | 97.1 % |

**Table 2.** shows that the obtained values demonstrate the effectiveness of the simultaneous application of the three spectral maps. The overall recognition accuracy of the method proposed by the authors is 97%, which exceeds the accuracy of the methods described in the literature review of this paper.

| *Authors of the algorithm* | *Recognition accuracy* | *Recognition speed* |
|---|---|---|
| Shah et al. [15] | 94% | 28.3 s |
| Madi et al. [16] | 84.45% | – |
| Zhao et al. [18] | 94% | – |
| Zhou et al. [19] | 95% | – |
| Li et al. [20] | 17% | – |
| Donghyun Lee [21] | 87.2% | – |
| Li et al. [22] | 76% | – |
| Garcia-Garcia et al. [23] | 90% | – |
| Santos et al. [24] | 90% | – |
| Current investigation | 97% | 0.9 s |

This study achieved the following scientific results:

- A method of object identification based on the use of algebraic invariants; this method integrates universal statistical parameters, ensuring its applicability to the initial selection of objects from a set;
- A novel object recognition approach based on topological and spectral invariants, where topological parameters filter objects and identification matches spectral profiles with data from an existing database;
- Study of the applicability of machine learning methods to object recognition tasks, which resulted in the selection of the optimal type of deep learning algorithm–convolutional neural networks (CNN) for spatial data analysis;
- A method for invariant 3D object recognition based on point cloud input data using high-accuracy machine verification that relies on Laplace-Beltrami spectrum analysis and the creation of spectral distribution maps for subsequent recognition using CNNs.

The developed invariant approach to 3D object recognition integrates a module for spectrally and topologically invariant object segmentation and identification in software, which can be particularly helpful for terrain analysis.

The presented method, which is based on multiple descriptors, is trained on a dataset with 20 iterations. This number allows for the achievement of acceptable accuracy. As an illustration of the object detection process, Figure 6 presents the outcomes of visualizing the spectral distribution maps for an object.

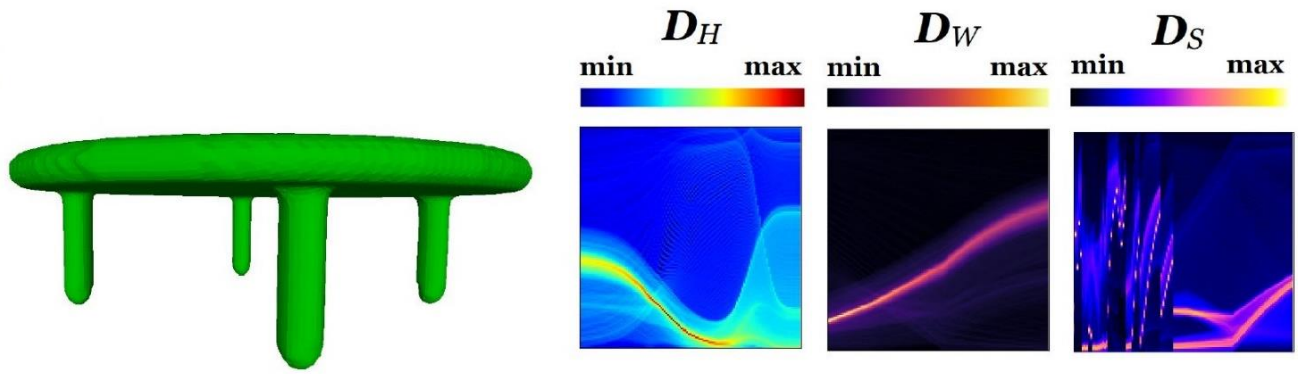



FIGURE 5. Example of object detection using DH, DW, DS descriptors. Source: Author's own compilation.

## V. CONCLUSION

The use of 3D models in numerous agricultural applications, such as assessing ripeness, distinguishing crops from weeds at harvest time, and assessing vegetation biological conditions, makes the task of accurate recognition across fields urgent. The use of spectral methods and machine learning for 3D data processing, as demonstrated in this paper, opens new horizons for developing versatile and high-performance recognition systems for precision agriculture.

The main advantage of the proposed method is its ability to efficiently process objects of different details using invariant descriptors that are adaptable to various conditions and apply convolutional neural networks for object classification and identification. This approach provides robustness against noise and data artifacts, which is essential for practical applications in the field.

However, this study has several limitations, including the dependence on the quality and amount of training data required to train the neural network. In addition, questions remain regarding big data processing, which may require further optimization of algorithms and system architectures.

Future research may focus on further optimizing recognition algorithms to reduce computational costs and increase processing speed without reducing accuracy. Integration with other technologies, such as unmanned aerial vehicles and ground-moving platforms equipped with scanning devices and manipulators, is also essential. This study highlights the vast possibilities for agricultural development and applications, emphasizing the importance of continuing work in this direction.

### Funding statement

Some results of this research were obtained as part of the work under the Subsidy Agreement dated July 14, 2023 No. 075-15-2023-599 on the topic: "Development of intelligent, high-precision tools for analyzing terrain and managing transport systems intended for highly productive agriculture" with the Ministry of Science and Higher Education of the Russian Federation.

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