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COMPARISON OF DEEP LEARNING-BASED MODELS FOR DETECTION OF DISEASED TREES USING AN IMAGE COMPRESSION ALGORITHM

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The object of the research is the application of deep learning algorithms using an improved mathematical lossless image compression method for recognizing and identifying dead trees in aerospace images.

The main problem that has been solved is the archiving of images due to their large volume on disk and the possibility of their further processing by deep learning methods such as convolutional and capsule neural networks, which have shown high efficiency and accuracy in image recognition and classification tasks using the proposed new image compression method.

The article presents a comparative analysis of the performance of three YOLO (You Only Look Once) models with different types of architectures, such as YOLOv5, YOLOv7 and YOLOv8, to assess the effectiveness of their work for the task of recognizing aerospace tree images obtained from satellites, drones, and aircrafts.

Comprehensive analysis of YOLO models presents that model YOLO v8 turned out to be most effective with a positive accuracy of 88.2 %, a recall of 77.4 %, and a mAP50 score of 87.2 %. Moreover, the average detection time was only 0.052 seconds for each image, even though the model size remains very small – 21.5 MB. These results suggest a much better usage of time and precise identification of dead trees, and classified targets with high efficiency.

From the research, there is significant prospects of global forest management especially on forest reduction and protection of ecosystems through accurate assessment on the health of forestry. The proposed approach is universal and can be used in real life conditions, providing a good compromise of the speed, accuracy and resources required for forest monitoring and management

Keywords: YOLO model, image compression, computer vision, forest management, deep learning

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1. Introduction

Over the past few decades, the scientific and the technology developing arena have tremendously advanced in case of artificial intelligence (AI) particularly in one of its branches known as Computer Vision. These are pioneering changes whose effects are revolutionizing large-scale environmental coverage especially through operational remote sensing. The exploration of data collected from satellite or aerial images, known as remote sensing, has been very useful in monitoring change processes on the surface of the earth. When integrated with elements of computer vision, it is a very effective way of analyzing the large data sets that are produced, of harnessing the processes and of identifying some very important aspects that generally cannot be seen manually.

Forest, that cover roughly one third of the Earth's land area, intervenes in support of global ecosystem stability and service provisions, including species conservation, climate moderation, and decreased greenhouse gas emissions. But it remains a concern that forests are threatened by human activities, climate change and other diseases that can cause destruction of forests and its inhabitants within short period of time. Early diagnosis of tree ailments is very important in inhibiting pathogen that causes large scale death in the valuable forests that is important in the survival of these ecosystem. Conventional approaches of assessing the status of the forests are usually cumbersome, manpower intensive and restricted in space. However, using satellite imagery utilizing AI technology provides for the large, fast, and consistent coverage of large geographical areas to be provided to the forest managers and the environmentalists in form of early warning systems.

Deep learning on natural resources monitoring process, which was applied by utilizing Convolutional Neural Networks CNNs has demonstrated a lot of benefits. These networks have proved more adaptable in learning from image data and are superior to conventional mathematical algorithms in detecting and identifying objects in an image as well as in segmenting the same. Recent innovations in more complex CNN structures have paved way to new techniques of detecting diseased trees in a highly accurate manner especially if tested in a highly dense forested area or difficult to reach location. It is quite useful when it comes to the remote sensing where the data processing is not only required at the high-resolution levels, but there are also minor differences in the overall health of trees that are to be identified using the common algorithms as well as naked eyes.

Another reason for active research in the field is the increasing number of international initiatives to fight deforestation, support sustainable forest use and stimulate protection of biodiversity. Goals set in the United Nations Agenda on sustainable development and the Paris Agreement separate the use of new approaches to observe the forest state and counteract unfavorable processes. Computer vision-based AI systems can support these goals by supplying effective information to conservationist adieux to support the strategy and policies. In this regard, the recognition of tree diseases by satellite imagery is an important area of research for now, forest health is closely related to the Earth's carbon cycle, water availability, and wildlife.

Nonetheless, several limitations are still seen with the use of AI in monitoring the environment Even today, there are certain difficulties observed in applying artificial intelligence for the preservation of environment. This is one of the challenges of using satellite imagery datasets where the data that users get are humongous and is composed of numerous files that are hard to separate. Such detailed or high-resolution imagery entails large sizes which bring about challenges in storage, transmission and real-time processing. This brings the need to come up with the most efficient preprocessing techniques which include the data compression algorithms that compress image data in order to make its size smaller. The rationale for enhancing these algorithms is made on the basis of their potential to make the analysis of satellite imagery at large scales and with high-resolution more realistic for researchers and practitioners.

Moreover, the above factors make the detection of forest diseases complex since they can be influenced by matters like different trees' species, climate, and presence of other similar signs resulting from various sources of stress. Sc interpreted by die a few changes in color or structure of the leaves or density of the foliage layer that may be like other factors not related to diseases such as water stress or presence of pests. There is, therefore, an increasing demand for more sophisticated nuance AI models which differentiate between such attributes. It is possible to look forward at the prospect of overcoming these challenges by continuing the development of deep learning AI and studying new architecture of choice models, choice data sets for training, and choice methods for deployment at an improved rate.

Also, the incorporation of AI in monitoring systems of the forests offers an opportunity to eliminate logistical challenges of monitoring through physical surveillance. Automated detection systems can work for a long time and possibly without getting tired hence can perform the task of monitoring remote and large forested regions. This relieves pressure off the human resource while at the same time increasing the efficiency of the assessments of forest health. However, to achieve such a great potential of these systems, further investigation is required to improve the accuracy and flexibility of the systems useful for adapting to the variations in the environment and different forests in the world.

From an operational point of view, still, the implementation of computer vision and deep learning in the field of forestry has definite advantages. Such knowledge leads to early and accurate diagnosis of tree diseases hence giving an opportunity to control the spread of the disease and reduce its impacts on the environment. Moreover, automation also helps the conservation of forests by providing constant, accurate data with which to monitor long-term environmental changes, intermittent climatic variations and even with reforestation activities. This study is needed given the growing number of environmental incidents that are threatening the sustainability of ecosystems including fires, pests, and invasive species.

Therefore, due to the progress in artificial intelligence as well as the need for the development of enhanced earth observation techniques for monitoring trees' health, the configuration of AI-based systems for tree diseases identification from satellite imagery is not only valid but necessary. The difficulties correlated to big data, differentiation of diseases, and algorithm practices serve as factors that explain the need for more future studies. Hence, researchers ought to extend the application and improvement of AI models for the environment, and thus make forestry practices more sustainable and effective for the welfare of the people and the forests.

Hence, studies on the use of computer vision and particularly deep learning algorithms in identification of diseased trees from satellite images can be considered as useful. It tackles various environmental issues while applying state of the art AI features for better forest condition assessment and protection.

2. Literature review and problem statement

Recent research [1] has made significant progress in the field of image compression, addressing numerous challenges but also highlighting areas for further exploration. The work [1] provides a thorough overview of modern compression techniques, focusing on the trade-offs between quality, processing speed, and computational complexity. However, it is shown that many compression algorithms [2], such as the K-means clustering-based adaptive algorithm for nested images, perform poorly when applied to high-resolution satellite imagery. This limitation stems from the sequential processing modes and excessive processing time, which are impractical for real-time applications. The CCSDS-MHC algorithm, as discussed in [3], demonstrates some promise by incorporating parallel processing techniques. Nevertheless, its application to specific platforms, like the Raspberry Pi, raises concerns about scalability and generalization to more demanding systems.

One of the major unresolved issues in this area is the reliance on singular data sources such as AVIRIS [4–6], which limits the generalizability of the findings to other satellite systems. The applicability of compression methods developed for AVIRIS to more complex multi-source imagery, such as hyperspectral or multispectral data, remains an open question. This concern is echoed by [7], which highlights the need for algorithms that consider the diverse characteristics of aerospace images, such as spectral range and spatial resolution. The objective difficulties associated with processing such vast datasets and the high computational cost of existing methods make this area ripe for further research.

The work [8] suggests that a possible way to overcome these limitations is through hybrid approaches that combine lossy and lossless compression techniques. However, even this solution may not fully address the specific needs of aerospace imagery, as pointed out by [9], where the quality loss during compression could hinder object detection tasks. Similarly, [10] used a lossy compression method to aid in classification tasks, but it is evident that data loss compromises accuracy, especially in high-stakes applications like environmental monitoring.

The study conducted by [11] employs deep learning methods like CNNs to enhance image compression for remote sensing. However, as noted by [12], while deep learning models such as CNNs offer promising solutions for high-dimensional data, the computational burden they impose, particularly in processing large-scale satellite data, is significant. Thus, their widespread adoption is currently constrained by hardware and cost limitations. The integration of CNNs with remote sensing, as explored by [13], shows potential for improving detection accuracy in diseased tree monitoring, but the associated computational complexity remains a fundamental issue.

A more comprehensive approach, as suggested by [14], involves combining advanced compression algorithms with machine learning models tailored to specific environmental applications, such as tree health monitoring and land cover classification. This approach has been employed in [15], which demonstrated that compression tailored to object detection and environmental monitoring could significantly reduce data storage requirements without sacrificing detection accuracy. However, as noted by [16], the scalability of these methods for real-time, large-scale monitoring remains a challenge, particularly in terms of maintaining a balance between accuracy and processing speed.

All this suggests that it is advisable to conduct further studies focused on developing more efficient image compression algorithms that address the specific needs of aerospace imagery, especially for environmental monitoring applications. By leveraging advancements in deep learning, such as the work by [17] on image classification in large datasets, future research could aim to develop models that optimize both compression and detection performance.

Thus, deep learning combined with remote sensing has shifted the focus of the computer vision in its current form. Although these contributions are significant, scholars have identified the need to come up with a more systems approach that can accord a systematic way of providing solution to global challenges in the field. The application of deep learning has enhanced what is known as remote sensing, a pioneering technique of computer vision that allows for the analysis of complex imagery. However, there is still a lot of potential for further improvement and growth in this discipline; specifically, it can be stated that further serious developmental effort is required to produce more complex and integrated models that could be used to better understand and manage a wider array of issues in this field. In this way, researchers can build on these specifics to improve the utilization of deep learning, remote sensing, and other advancements in the field of computer vision to augment applications across a range of industries.

3. The aim and objectives of the study

The aim of this study is to compare different YOLO models by using images processing method based on the improved mathematical algorithm of compression without lossless for diagnosing tree diseases in the framework of the phytosanitary control of forestry. This will allow:

– conduct earlier diagnostics of tree diseases and ensure high-quality phytosanitary control of forestry;

– expand the application of AI models (YOLO) for the environment to better assess forest health and protect it earlier;

– improve approaches to forest health monitoring and natural resource management.

To achieve this aim, the following objectives were established:

– improve of an algorithm for image compression without losses;

– implement different YOLO architecture models for already compressed without losses images dataset;

– determine the best model by comparing features and results to obtain high–resolution data.

4. Materials and methods

4. 1. Object and hypothesis of the study

The object of the study is the application of deep learning algorithms using an improved mathematical lossless image compression method for recognizing and identifying dead trees in aerospace images.

The main hypothesis is the finding of the efficient data pre-processing methods based on AI configuration and advanced image compression algorithms can make large-scale and high-resolution satellite imagery analysis more realistic for researchers and practitioners.

Assumptions made in the study are the research on the use of computer vision and deep learning algorithms for identifying diseased trees from satellite images can be considered necessary, in demand and timely.

Simplifications adopted in the study are the following:

– there are used three distinguished models: YOLOv5, YOLOv7, and YOLOv8 for the training. These models are known for their advancements in clear object detection and localization;

– the lossless algorithm for compressing aerospace images was adopted to ensure the preservation of image fidelity amidst the compression process. This algorithm employs regression techniques.

This research has used the improved research methodology based on the preprocessing image compression.

At the same time, it was used an approach of using an algorithm for detecting diseased trees based on the YOLO models and the different learning rates.

This approach leverages the strengths of YOLO to more accurately detect infected trees in aerial and satellite imagery.

It was used a method of combination of the deep learning algorithms with remote sensing data for detecting of the diseased and healthy trees with high accuracy.

The all steps of creating a learning model and implementing an algorithm based on the YOLO models are given and explained in the Fig. 1.

According to the Fig. 1 the entire study methodology is divided into two main stages: the description of an implemented algorithm for compressing images without loss of quality and comparation of different YOLO models to obtain an improved classification model.

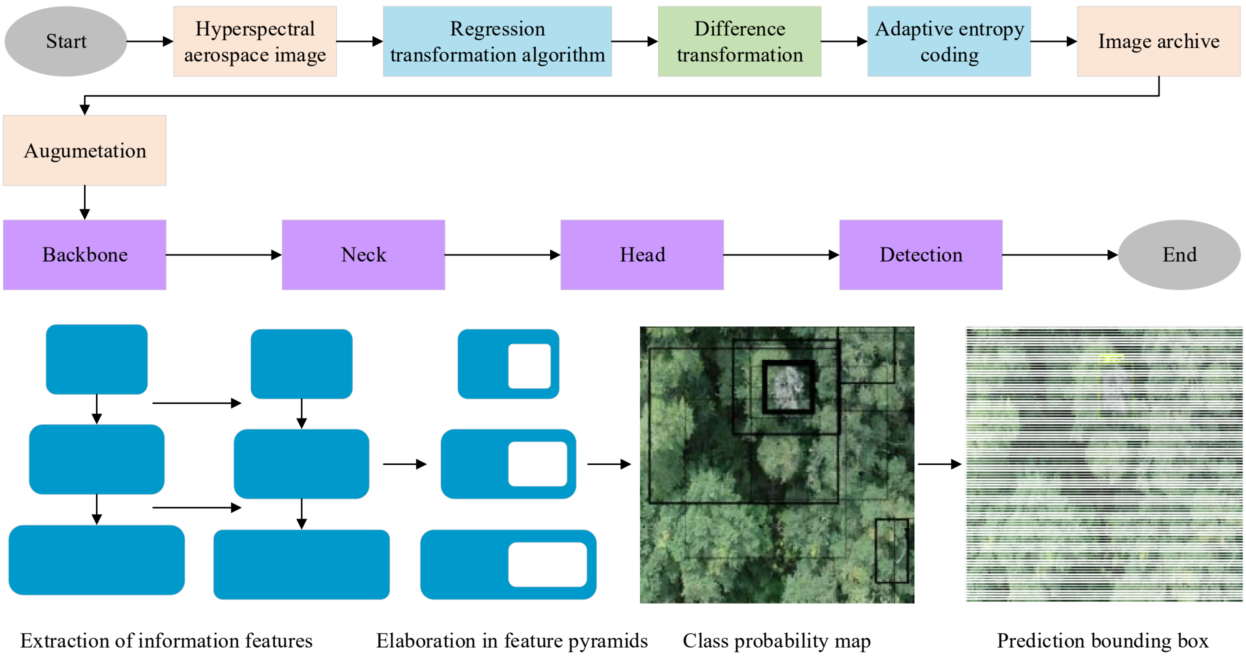

Fig. 1. The algorithm of compression and training process structure using YOLO architecture

The considering methodology based on the fast inference speed images in real time of YOLO, is known as a powerful and effective tool for object detection demonstrated an impressive accuracy and real-time performance.

4. 2. Methodic of an algorithm for image compression implementation

In this research introduces the improved methodology on comparation and adapting of the classification model of diseased trees and compression of images based on the mathematical apparatus of the difference-discrete transformation.

Description of the modeling methods and algorithms including the sequence of stages for design of the mathematical model is the following:

– calculation of the correlation value between all pairs of image channels and determination of the channel encoding and decoding sequence;

– regression transformation algorithm;

– obtaining channel differences and their block-by-block conversion;

– compression by statistical algorithm.

Description of the lossless compression algorithm are given below:

Step 1. It is calculating the values of the correlation matrix between all pairs of channels A and B, while identifying the most correlated groups of channel pairs. Based on the matrix, the sequence of transformation will be formed and determined(encoding) and reverse transformation by constructing a strongly branching tree.

Step 2. Regression analysis based on step 1. The linear regression coefficients between the values of the generative (main vertex of the tree, BI) and regressed (RI) channels of aerospace images are calculated by creating optimal values for forming arrays of differences between BI and RI.

Step 3. Block-by-block conversion. The idea of the transformation is to calculate the differences based on step 2 by the block-by-block separation of data. The effectiveness of this separation is that the differences obtained do not cover the entire range of the image, but only a certain block. Due to this, they are effectively compressed by an entropy algorithm.

Step 4. Compression by a well-known statistical algorithm.

The detail explanation of the methodology based on the proposed algorithm was presented below.

It is fact that aerospace images are obtained in the spectrum of a single wavelength, it is assumed that some degree of dependence can be determined between pairs of channels.

To determine the magnitude of this dependence, the Pearson correlation coefficient calculation formula (also known as the linear correlation coefficient) is used. The formula requires two sequences of data, so two sequences of samples are first extracted from a pair of files. This happens as follows: a two-dimensional data matrix of one channel is represented in the form of a linear array (passing the matrix line by line from left to right and rows from top to bottom), and then a certain number of samples are selected from it (denoted by the letter (m); dividing the array into approximately identical segments). From the second channel, a sequence of samples is extracted that are in the matrix at the same positions as the samples from the first channel. The resulting sequences are denoted by the letters (x) and (y), and the individual values are (x_i) and (y_i) (i) from 1 to (m) inclusive). Additionally, the arithmetic averages of both sample sequences (1) are needed for the formula (1):

$$x=\frac{1}{m}\sum_{i=1}^{m}x_i,\quad \bar{y}=\frac{1}{m}\sum_{i=1}^{m}y_i. \tag{1}$$

Next, it is necessary to apply the formula (2):

$$r=\frac{\sum_{i=1}^{m}\left(x_i-\bar{x}\right)\left(y_i-\bar{y}\right)}{\sqrt{\sum_{i=1}^{m}\left(x_i-\bar{x}\right)^2}\sqrt{\sum_{i=1}^{m}\left(y_i-\bar{y}\right)^2}}. \tag{2}$$

Samples are extracted for large channel matrices, because a calculating the formula for all values would take a huge amount of time. By setting the upper threshold for the number of samples, the dependence of the calculation time on the image size is removed.

By calculating the coefficients for all pairs of channels of the same image, a coding sequence is built naturally, starting from large values to smaller ones.

Regression (regressive) transformation. The method of the transformation is to bring into compliance with the encoded pair of channels some structure that:

– allowed to unambiguously restore one of the original channels according to the data of another channel;

– occupied as little disk space as possible.

To do this, the following algorithm was defined. In each encoded pair of channels, a generating channel (master) and a regressed channel (slave, compressible) are defined. It has been experimentally confirmed that the principle of definition has a rather insignificant effect on the compression index; therefore, without wasting time on sorting through both options, the channel with a smaller index is chosen as the generating channel (assuming that all channels were originally numbered).

On the next step is given an explanation how the difference matrix is considered. Before that, the linear correlation coefficient was calculated. The methodic of linear regression in this case is to find real values of k and b such that the matrix formed from the data of the encoded pair according to the following formula (3):

$$d_{ij} = \left(x_{ij} \cdot k + b\right) - y_{ij}. \quad (3)$$

Here and further x_{ij} and y_{ij} the values in the master and slave matrices, respectively) would have as small values as possible. Next, the matrix d with the values d_{ij} will be called B «the difference matrix B». A sufficiently good linear correlation indicator (close to one), calculated beforehand, leads to sufficiently low values d_{ij}. Knowing the values of k, b and the matrix d, can reconstruct the matrix y from the values of the matrix x (4):

$$y_{ij} = \left(x_{ij} \cdot k + b\right) - d_{ij}. \quad (4)$$

Standard formulas used to calculate linear regression parameters (5):

$$k = \frac{\overline{xy} - \overline{x} \cdot \overline{y}}{x^2 - \left(\overline{x}\right)^2},$$

$$b = \frac{\overline{x_2} \cdot \overline{y} - \overline{x} \cdot \overline{xy}}{\overline{x^2} - \left(\overline{x}\right)^2}. \quad (5)$$

when $\overline{x}$ will be calculated (6) and $\overline{xy}$ (7):

$$\overline{x} = \frac{1}{i \cdot j}\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}, \quad \overline{y} = \frac{1}{i \cdot j}\sum_{i=1}^{m}\sum_{j=1}^{n} y_{ij}. \quad (6)$$

$$\overline{xy} = \frac{1}{i \cdot j}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}, y_{ij}\right), \quad \overline{x^2} = \frac{1}{i \cdot j}\sum_{i=1}^{m}\sum_{j=1}^{n}\left(x_{ij}^2\right), \quad (7)$$

where $m$is a height, n is width.

In each compressed channel, it is needed to put the values k and b in Double format (8 bytes, 15 decimal places in decimal format). By encoding the only main generating channel for the image (the generating channel of the first pair) independently of the others, it is possible to restore it later in the first place, then gradually restore all the other compressed channels (as mentioned earlier, through the coefficients k and b).

The absence of losses is ensured during transformations. After receiving the matrix d and before writing it to the file, it is rounding the values to the nearest integer (in the case of a fractional part equal to 0.5 to a smaller integer). This does not prevent a lossless recovery. According to formula (3) the explanation of the above method is given below.

The matrices x and y are integers, so the value $w_{ij}=x_{ij}*k+b$ has the same fractional part (let's denote it q) as the number d_{ij} before rounding. The integer part of the numbers will be denoted by square brackets, and the fractional part by curly brackets. So, $q=\{d_{ij}\}=\{w_{ij}\}$.

To reverse decode AI, perform the following actions:

Step 1. Decoding arrays of differences by the Huffman algorithm.

Step 2. Formation of regression transformation arrays by finding the sums between the generating channel and its average value.

Step 3. Formation of the initial arrays based on the available OHR coefficients and obtaining the initial data of AI.

According to the indicated steps the comparison of three different processing methods is presented in Fig. 2, below.

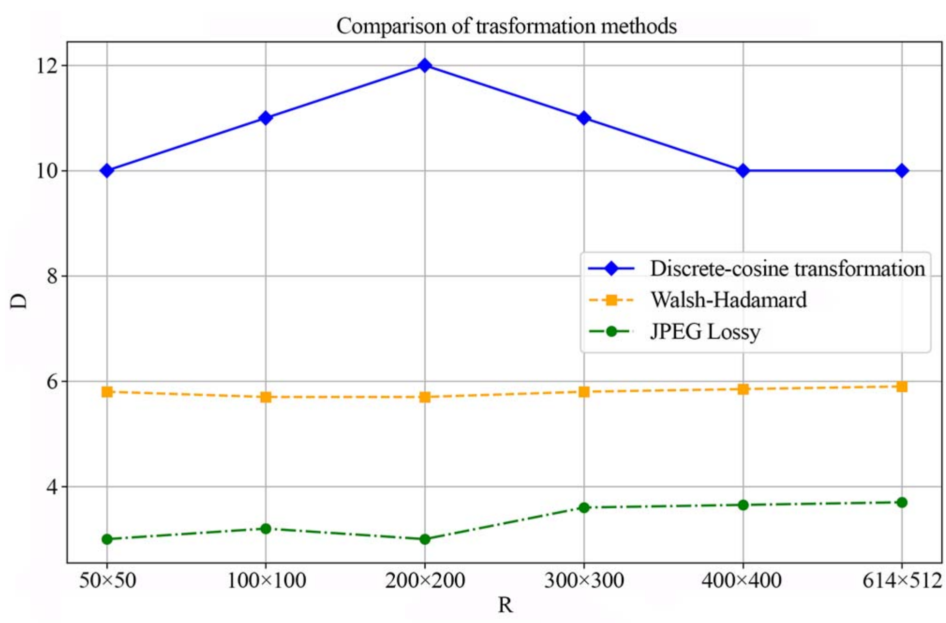

Fig. 2. Comparison of three different processing methods

5. Experimental research results on development of the compression algorithm and detection models

5. 1. The proposed lossless image compression algorithm based on the integration of deep learning in environmental monitoring system

Based on the integration of deep learning in environmental monitoring system it has achieved the following results:

1) It was developed the image compression algorithms without losses based on discrete-difference transformations allows to increase the compression ratio to (R=12).

2) This algorithm has been designed using the adaptive transformations based on the Walsh-Hadamard transformation, discrete-cosine transformation, and the generated quantization table and subsequent adaptive coding [17–25].

3) To improve the efficiency of the applied algorithm and to determine the optimal compression parameters, experiments were conducted on the following parameters: *Cor* – specified correlation value; N – AI channel group number; R – AI channel size; K – number of channels in group N.

4) Based on the results of the experiments on the dependence of the correlation on the selected channel groups and the best channel, it was found that the Cor value decreases proportionally to K. Experiments were performed on the number of channel occupancies, which show that with K=[5:50], the compression ratio is higher than with K=[50:100].

5) It was found that the dependences of the compression ratio of the algorithms taking into account the correlation and channel grouping are higher than if all 224 channels are fed to the input, which means that subtraction (difference transformations) using regression analysis are effective when selecting certain channel groups, then the difference values will be the smallest, which will allow storing the original channels in the smallest volume on the disk.

6) Based on the research results, the optimal compression parameters were determined:

– the results of the compression ratio indicators improve with an increase in the size of the channels of parameter R;

– the best values of the compression ratio are achieved by choosing the number of channels in an ordered group, with the limitations of the parameter $10<K<15$;

– the considering the interchannel correlation of the *Cor* parameter shows that the greatest values in the compression ratio of the channel number, with variation of the parameter in the range $0<N<210$;

– the algorithm, considering correlation and grouping at G in [2–10], shows the most effective growth in the compression ratio due to the formed groups of channels and their ordering.

7) The experimental results of the developed algorithms for image compression and its steps are presented in the Fig. 3.

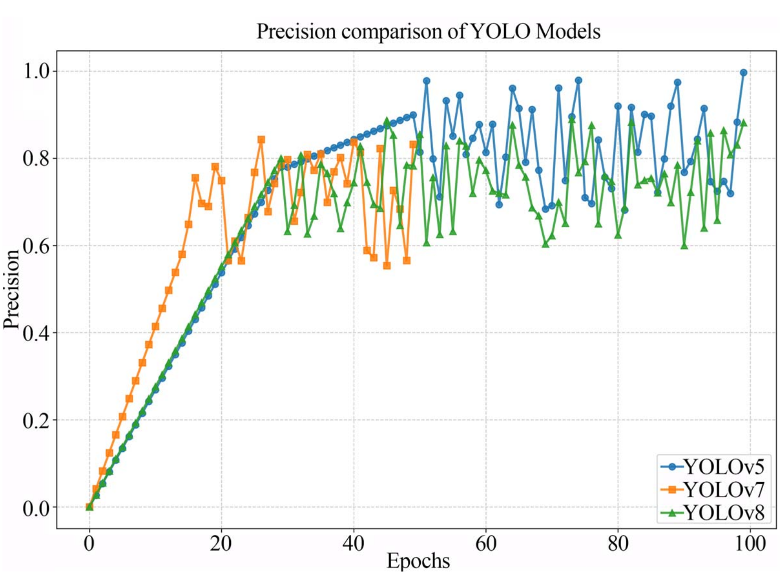

Fig. 3. Conversion algorithms

Fig. 4 is demonstrated the results of the conversion algorithms. There were achieved 3 types of the graphics that are demonstrated the level of the quantitative coefficient from 1 to 15, compression rate D from 0 to 35, and loss level P from 0 to 40. According to these results it was obviously that a blue graphic is more effective because there was used a discreate-math transformation.

Description of the applied approach and method are given below:

1. There was applied the integration of deep learning algorithms in environmental monitoring system provides valuable insights.

2. It was obtained the ability to efficiently detect dead trees can help identify areas affected by deforestation, forest fires, and disease.

3. The assessment of model performance was conducted through a meticulous analysis of a designated test set comprising various images.

4. The test set was served as a standardized benchmark against which the models' capabilities were rigorously evaluated.

5. It was obtained an objective measurement of the models' proficiency in real-world scenarios.

5. 2. The implementation of the different YOLO architecture models for compressed without losses images dataset

This stage is presented the description of the methodology and implementation process of the different YOLO architecture models for compressed without losses images dataset:

1. On the next step it was implemented the YOLO architecture models for already compressed without losses images dataset.

2. In the implementation process it was used an approach based on the divergence in learning rates of the models. The learning rates were tailored differently across the spectrum of models.

3. The detailed breakdown of these learning rate differentials was presented in the accompanying Table 1 of the experimental results.

Table 1

Experimental results of comparing different models' implementation

No.	Name	YOLOv5	YOLOv7	YOLOv8
1	Training time	3600 s	8020.8 s	7596 s
2	Average training time per round	35 s	134 s	70 s
3	Batch size	8	16	8
4	Epochs	100	54	100

4) The selection algorithm.

In the learning process, the method of adaptive learning rate change based on Scheduler (for example, ReduceLROnPlateau or CosineAnnealing) was used. This method reduced the learning rate if the performance of the model (for example, losses on the validation set) did not improve over several epochs. Thus, the selection of the learning rate occurred dynamically depending on the course of training of each model:

– For YOLOv5, the learning rate adapted faster, which ensured fast convergence;

– YOLOv7, due to the larger patch size, required a smoother reduction in the learning rate to avoid learning spikes;

– YOLOv8 demonstrated a balanced change in speed, which allowed for stable performance.

5) The experimental results of this stage are based on the comparation of the YOLOv5, YOLOv7, and YOLOv8 models using a training parameter, and presented below:

– YOLOv5 exhibits the shortest training time and lowest average time per round;

– YOLOv7 shows extended training times and higher times per round due to its larger batch size;

– YOLOv8 offers competitive training times with a moderate batch size.

6) Within an experimental study it was determined that the choice of the model is depends on project priorities and its goal:

– YOLOv5 for fast convergence;

– YOLOv7 for parallelism;

– YOLOv8 for a balanced approach.

7) So, the model performance assessment remains crucial for informed selection to solve those tasks.

The description of the proposed methodology is presented below:

1) To render the evaluation process more visually informative, graphical representations were generated using the matplotlib library.

2) There were applied a well-known evaluation indicator be used, such as the average precision (mAP), the number of parameters (in MB) and the mean detection time (in seconds per sheet) for using YOLO architecture (8):

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i. \tag{8}$$

3) The calculation of AP has been based on integral computation of the PR curve with Precision as the horizontal axis and Recall as the vertical axis.

Here are the precision indicator (P) affects classification ability to samples from a dataset, Recall R reflects the ability to find the positive sample and N represents the number of categories of data. The mAP parameter corresponds to the average AP of all categories.

4) The Precision, Recall and $F1$ score was employed the following formulas (9), (10):

$$R = \frac{TP}{TP + FN}. \tag{9}$$

$$P = \frac{TP}{TP + FN}. \tag{10}$$

5) The parameters P and R were calculated based on the values from the confusion matrix: TP (true positive), FP (false positive) and FN (False Negative). The metric $F1$ score present the harmonic mean precision and recall (11):

$$F1 = 2\cdot\frac{P\cdot R}{P + R}. \tag{11}$$

6) Positive and negative samples have been evaluated by threshold the Intersection over Union (IoU) between the predicted and actual image's regions.

In condition if both IoU parameters exceeding a certain threshold, then it is a positive sample, in other case it is a negative sample.

7) For comparing of outcomes model's results were calculated the average detection speed, which indicate average time the model spends to detect a single image in the validation set.

5. 3. The best model for image compression by comparing features results

Here is determined the best model for image compression by comparing features results based on the experimental results:

1) To compare YOLOv5, YOLOv7, and YOLOv8 object detection models, several performance metrics were evaluated. All metrics results are presented in Table 2.

Table 2

Experimental metrics results of different models

No.	Name	YOLOv5	YOLOv7	YOLOv8
1	Precision	99.7 %	83.2 %	88.2 %
2	Recall	69 %	71.2 %	77.4 %
3	mAP50	87.3 %	85.2 %	87.2 %
4	F1-score	81 %	77 %	82 %
5	Trained model size (in MB)	13.6	71.3	21.5
6	Detection time (in s/sheet)	0.079	0.123	0.052

2) YOLOv5 stands out with the highest precision (99.7 %) but a lower recall (69 %), resulting in a balanced F1-score (81 %).

The metrics presented in Table 2 (Precision, Recall, mAP50, F1-score, trained model size and detection time) were selected as key performance indicators for an objective comparison of the YOLOv5, YOLOv7 and YOLOv8 models. These indicators reflect the ability of models to accurately detect objects (Precision), completeness of predictions (Recall), average accuracy (mAP50), balance between accuracy and completeness (F1-score), as well as efficiency in terms of model size and image processing time.

Precision is important for evaluating how well the model predicted the detected objects with a minimum number of false positives. For tasks related to the detection of objects, such as phytosanitary examination of trees, this is a critical parameter, since accuracy directly affects the probability of false detections.

Recall (completeness) – reflects the ability of the model to detect the maximum number of objects among all possible ones. This indicator is necessary to assess the completeness of detection, which is important in the case of phytosanitary examination, where the passage of infected trees can lead to undesirable consequences.

mAP50 (average accuracy at a threshold of 50 %) is a comprehensive indicator that considers both Precision and Recall. This is a metric traditionally used to evaluate the performance of object detection models, and its inclusion is necessary to ensure a standardized comparison between models.

F1-score is a harmonic mean between Precision and Recall, which allows a more balanced assessment of the model in situations where it is important to take into account both accuracy and completeness. This is important for the tasks of classifying and detecting objects in satellite images.

Model size and detection time – these parameters are necessary to evaluate the effectiveness of the model in real-time conditions and limited computing resources. The smaller model size and fast image processing time are essential for use in field applications such as phytosanitary examination.

3) YOLOv7 offers a competitive precision (83.2 %) and recall (71.2 %), along with an mAP50 of 85.2 % and an F1-score of 77 %.

4) YOLOv8 strikes a balance with precision (88.2 %) and recall (77.4 %), yielding an mAP50 of 87.2 % and an F1-score of 82 %.

5) YOLOv5 has the fastest detection time (0.079 s/img), YOLOv7 has a moderate detection time (0.123 s/img), and YOLOv8 is the most efficient (0.052 s/img).

6) All model classifying results in validation stage presented in figures with an experimental result below (Fig. 4–6).

During the scientific research, the results of comparing the transformed aerospace images using calculated coefficients were obtained.

The output test results suggest the effectiveness of using these studies with adaptive Huffman coding.

The conducted studies of software compression without loss of quality of images for phytosanitary examination of trees in aerospace photography proves superiority over analogues and high performance. Therefore, this approach was applied to create a classification model for the recognition of infected trees based on YOLO.

Below the description of the used research methos and algorithms for the performed experiments is determined:

1) The YOLO architecture design has selected as the optimal solution for creating deep learning classification models.

2) To optimize the neural network training process, the image dataset, sourced from Roboflow, was resized from 1024×1024 to 256×256 using a custom-coded mathematical algorithm.

3) The aerospace images underwent regression transformation, difference transformation, and adaptive entropy coding, achieving a compression ratio of R=8 to the image archive.

4) From image archive already compressed without losses images dataset underwent augmentation leveraging the platform for an enhanced volumetric representation.

5) The expanded corpus it has worked for the subsequent phase of model refinement, encompassing the conversion of dataset information into the YOLO format within the same digital ecosystem.

6) On the next steps, the initial series of JPEG images have divided in an 8:1:1 ratio. As a result, 150, 20, and 22 images have respectively assigned to the training, validation, and test subsets.

7) To collect and increase the training set, augmentation procedures such as image flipping, scaling, and colour dithering were employed it has expanded dataset to the total of 850 images.

8) On the next stage it has performed the model training process.

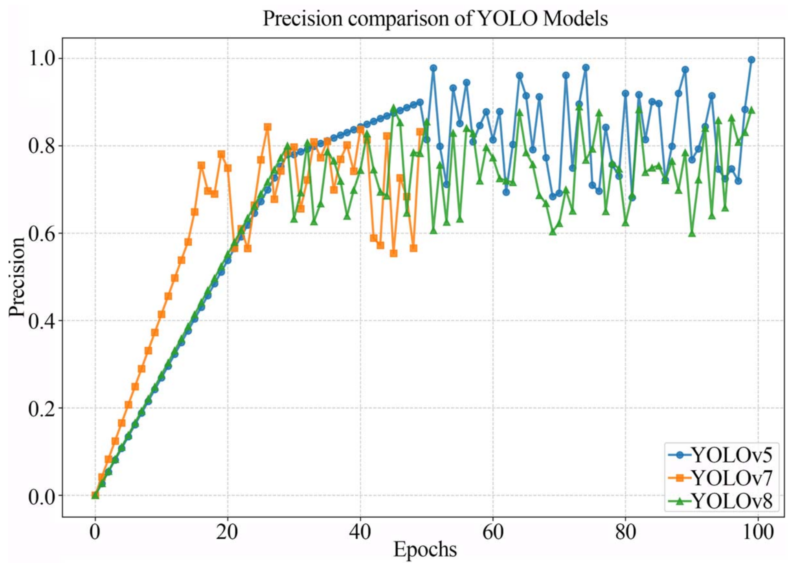

Fig. 4. Models precision comparisons

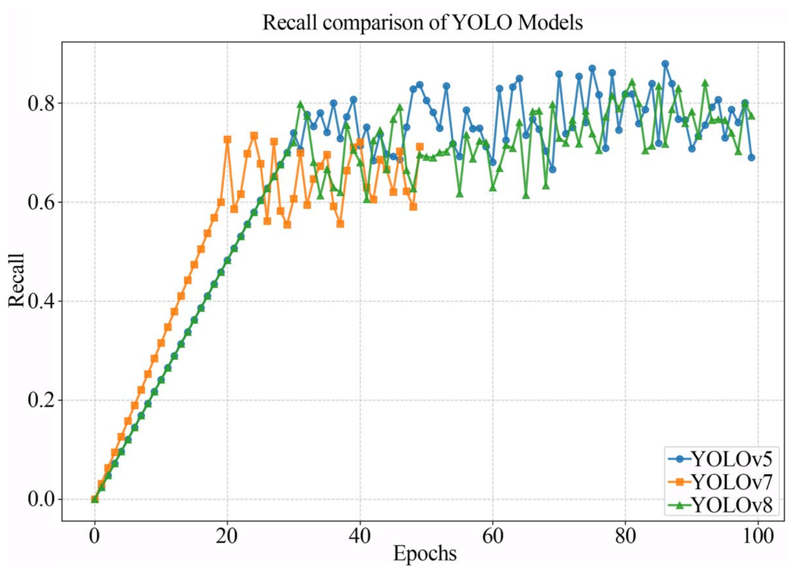

Fig. 5. Models recall comparisons

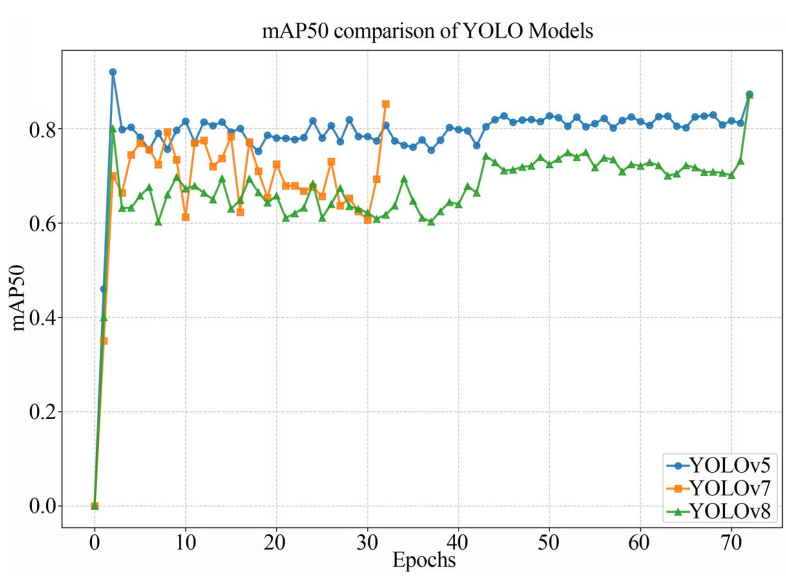

Fig. 6. Models mAP50 comparisons

Within of this training, the spotlight was casted three distinguished models: YOLOv5, YOLOv7, and YOLOv8. These models, known for their advancements in object detection and localization, have selected for training and subsequent comparison.

9) Upon the conclusion of the training phase, an intricate evaluation has conducted, demonstrating the nuances of each model's capabilities, strengths, and weaknesses. This comprehensive assessment served as the linchpin for identifying the model that surmounts its counterparts, emerging as the optimal choice for the current project's objectives.

10) Next, the models underwent training using conventional configurations, forming the foundation for the experimental phase. Within the framework of expanding these models, specific modifications have introduced to enhance the learning process. It is of significance to highlight the deliberate reduction of input photograph resolution to 256×256 pixels.

11) To ensure the preservation of image fidelity amidst the compression process, it has adopted a lossless algorithm for compressing aerospace images.

12) Furthermore, the number of epochs has adjusted. In the case of the YOLOv7 model, a configuration has established wherein 54 epochs have executed. In contrast, the remaining models underwent training over the course of one hundred epochs.

6. Discussion of the study results of experiments based on the proposed methods and approaches

The application of deep learning techniques to classify diseased trees from aerial imagery has important implications for environmental monitoring and forest management. This study examines the use of the You Only Look Once (YOLO) model and its performance in accurately detecting and classifying diseased trees. The results, challenges, and potential future developments in this area are also discussed.

This comprises shrinking satellite and aerial pictures to the storage volume to ease the analysis of the health of the forestry. Fast inference speed images in real time of YOLO have proven to be a powerful tool for object detection, achieving impressive accuracy and real-time performance.

According to the performed experiments and used methods and approaches it is achieved the following study results that is explained below:

1) According the first task of the study it was developed of an algorithm for image compression without losses:

– the developed algorithm is based on the discrete-difference transformations. According to the study experiments, it has allowed to increase the compression ratio to (R=12) that is provided an image compression without losses;

– according to the experiments, it was obtained that algorithm is provided the high precision and high recall scores of 88.2 % and 77.4 % respectively and the high mAP50 of 87.2 % of compression opposite to the existing approaches and methods;

– also, these obtained results have attributabled of the using the mathematical and adaptive compression algorithms to process execute, which were developed to compress the images size by a relatively large amount while preserving quality;

– at the same time, the experimental results are explained by the graphical and computational data that is given in the Fig. 3 and Table 2. The Fig. 3 and Table 2 are demonstrated that the lossless compression it is shown that is faster and achieved high storage efficiency which not only enabled real time detection of diseased trees but also reduced computational time.

Thus, the results of experimental studies of the original algorithms are obtained in comparison with standard and specialized analogues in terms of compression ratio, computational and efficiency presented [4].

These results have proved that a lossless compression algorithm, considering inter-band correlation, using difference-discrete transformations, are superior to other existing algorithms in terms of a set of indicators in particularly, in the speed and quality of compression.

2) It was implemented the different YOLO architecture models for already compressed without losses images dataset:

– in this comparison of YOLOv5, YOLOv7, and YOLOv8 object detection models, several performance metrics were evaluated;

– YOLOv5 stands out with the highest precision (99.7 %) but a lower recall (69 %), resulting in a balanced F1-score (81 %);

– YOLOv7 offers a competitive precision (83.2 %) and recall (71.2 %), along with an mAP50 of 85.2 % and an F1-score of 77 %;

– YOLOv8 strikes a balance with precision (88.2 %) and recall (77.4 %), yielding an mAP50 of 87.2 % and an F1-score of 82 %;

– YOLOv5 has the fastest detection time (0.079 s/img), YOLOv7 has a moderate detection time (0.123 s/img), and YOLOv8 is the most efficient (0.052 s/img);

– selection among these models depends on specific task requirements, with YOLOv5 favored for accuracy and speed, YOLOv7 for well-rounded performance, and YOLOv8 for a balance between precision, recall, and speed;

– all model classifying results in validation stage presented in figures (Fig. 4–6).

The evolution of the models from their standard configurations involved a multifaceted strategy that encompassed resolution reduction, batch size augmentation, epoch count adjustment, and learning rate variation.

These adaptations were orchestrated with the intention of cultivating a deeper understanding of how alterations in these parameters could impact the models' learning dynamics and eventual performance.

3) It was determined the best model by comparing features results during an experimental study:

– each model has exhibited a distinctive results reflective of its unique characteristics and training nuances. It is attributed by the experiment data that are presented in Fig. 5–7;

– the discernible variation in results across models underscores the significance of tailoring training parameters and configurations to optimize performance outcomes that is demonstrated in Fig. 7;

– after a comprehensive analysis of the YOLOv5, YOLOv7, and YOLOv8 object detection models, the YOLOv8 model emerges as the primary choice for this task;

– the well-balanced precision (88.2 %) and recall (77.4 %) of the YOLOv8 are contributed to an impressive F1-score (82 %), indicating a strong trade-off between accurate detections and comprehensive coverage;

– the achieved high mAP 50 (87.2 %) is highlights its reliability across varying IoU thresholds;

– also, the YOLOv8 model stands out with the swiftest detection time (0.052 seconds per image), making it both accurate and efficient model.

So, considering its harmonious blend of performance metrics, YOLOv8 model is recommended as the main selection for a wide array of object detection tasks. Thus, based on the analysis of a study results, the best model by comparing features results during an experimental study was the YOLOv8 model for compression without losses images dataset.

Selection among these models depends on specific task requirements, with YOLOv5 favored for accuracy and speed, YOLOv7 for well-rounded performance, and YOLOv8 for a balance between precision, recall, and speed.

The features of the proposed solutions and the advantages of this study in comparison with similar known ones are presented below:

– the main novelty of the proposed method consists in the fact that the developed image compression algorithm is combined with deep learning-based tree diseases detection models;

– this kind of a compression technique does not reduce the image quality and shrinks the size of the file because of a compression ratio of R=8 compared to other compression methods;

– compared to common approaches that either have the weaknesses in image quality or detection efficiency this study offers more unified approach. For example, it is earlier erasing more image details which in turn affect the detection accuracy or as evidenced in [1];

– however, the method using adaptive entropy coding with regression transformation employed in the research minimizes the loss of data and sustain the detection performance.

There are several limitations in this study which are Inherent:

– first, even though the proposed image compression algorithm is efficient for the high-resolution satellite images, it is not convenient to apply the algorithm for other types of data. For example, the hyperspectral images where lossless compression may be difficult because of the higher complexity of data;

– besides, reproducibility of the method increases with the quality and resolution of the input data which can differ depending on the used satellite or drone for image acquisition;

– its effectiveness also depends on daily repeated conditions of environment. For example, poor lighting, adverse weather conditions or different colors of leaves of trees at different seasons may affect the capacity to detect them;

– additionally, the technical specification of the system is the ability to detect certain tree diseases making it less versatile when it comes to other vegetation challenges or different stress factors such as water or pest stress.

These limitations of this study must be considered when trying to apply it in practice, as well as in further theoretical research on the similar research topics:

– the one main drawback is needs of the large amount of annotated data for training;

– the next is the labeling adequate amounts of high-quality imageries that may proves to be tedious and costly. This might hamper the expansion of the proposed solution into different circumstances;

– to eliminate it in future studies it can be possible using unsupervised learning or transfer learning whereby models trained on similar datasets could be used and fine-tuned with little labeled data;

– the last disadvantage of the described approaches is related to the fact the availability of powerful hardware, or potential delays when transmitting compressed data in real-time might be an issue;

– it is connected to the frame acquisition is synchronized and the frames are processed in real-time, in the case of real-time applications in remote or hard-to-reach areas.

Further work could be devoted to the widening of the range of environments where the resulting algorithm can be used as well as works to different sorts of satellite imagery data:

– extending the method and its application to multispectral and hyperspectral imagery can result in the better recognition of more forms of tree diseases and other stress factors;

– also, the following research could be recommended: deeper analysis of the specifics of YOLOv8 architecture and its further comparison with other deep learning architectures, such as capsule networks; using the combined approach with YOLOv8 and another deep learning model to increase the efficiency of the detection method at the different forest ecosystems;

– analyzing big data obtained from various regions with diverse conditions of the environment would demand a lot of computational power is well as efficient algorithms that can be investigated in future;

– besides, there is also the challenge of making sure that performance and accuracy of the algorithm are depends on the type of tree and the forest kind;

– lack of scalability, limited capabilities for real-time and faster computations along with low flexibility of algorithms would remain critical questions for further developments.

The research novelty and the contribution to the research area are the following:

– it was proposed and developed the new algorithm based on the integration of the deep learning methodologies such as YOLOv8 model with the advanced image compression methods;

– it was designed models based on new image compression algorithm and deep learning techniques for diseases trees detection in aerial imagery;

– the achieved results have showed a substantial increasing positive result in environmental monitoring and forest management;

– the high metrics obtained by the YOLOv8 model provide valuable insights for identifying and assessing dead trees in large areas.

The successful implementation of deep learning in this context represents a significant advance over traditional tree inspection methods.

The speed and accuracy of the model allows for rapid assessment of forest health over a wide area, which is critical for timely intervention and conservation strategies.

Notably, YOLOv8 demonstrates a balanced and superior performance in relation to the other evaluated models.

Despite the challenges remain, the continued research and progress in data collection, model development, and ethical considerations will lead to further improvements and a positive impact on global environmental conservation efforts.

7. Conclusions

1. It was created a new algorithm based on the integration of the deep learning methodologies such as YOLOv8 model with the advanced image compression methods.

Here, the qualitative and quantitative indicators of the research results are next:

– the proposed compression algorithm to the comprehensive image-processing model has produced a compression ratio of R=8;

– the high quality of aerospace image compression without any losses for the data pre-processing was achieved.

2. It was designed the different YOLO architecture models for already compressed without losses images dataset: YOLO v5, YOLO v7, and YOLO v8.

Using these models, it was received the next qualitative indicators of research results:

– YOLOv5 favored for accuracy and speed (99.7 % and 0.079 s/img);

– YOLOv7 for well-rounded performance (83.2 % and 0.123 s/img);

– YOLOv8 for a balance between precision, recall, and speed (88.2 %, 77.4 %, and 0.052 s/img).

3. It was determined the best model by comparing features results.

The qualitative and quantitative indicators of research results here are next:

– the three classification models were constructed and compared (YOLO v5, YOLO v7, and YOLO v8);

– YOLOv8 is one of the greatest (F1-score – 82 %) to classify with high detection a diseased tree (precision – 88.2 % and recall – 77.4 %);

– YOLOv8 is more reliability across varying IoU thresholds (mAP 50 (87.2 %);

– YOLOv8 model has the swiftest detection time (0.052 seconds per image), making it both accurate and efficient model.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research, and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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