Quality inspection of fertilizer granules using computer vision - a review

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Abstract

This research explores the fusion of computer vision and agricultural quality control. It investigates the efficacy of computer vision algorithms, particularly in image classification and object detection, for non-destructive assessment. These algorithms offer objective, rapid, and error-resistant analysis compared to human inspection.

The study provides an extensive overview of using computer vision to evaluate grain and fertilizer granule quality, highlighting granule size's significance. It assesses prevailing object detection methods, outlining their advantages and drawbacks.

The paper identifies the prevailing trend of framing quality inspection as an image classification challenge and suggests future research directions. These involve exploring object detection, image segmentation, or hybrid models to enhance fertilizer granule quality assessment.

Keywords: Quality control, computer vision, machine vision, machine learning, grains, fertilizer granules.

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Introduction

Agriculture plays a vital role in sustaining human existence by providing the necessary food resources. Meeting the increasing global demand for crops has been a long-standing challenge, prompting the exploration of various methods to enhance agricultural productivity. One such approach involves the use of fertilizers, which are natural or synthetic substances containing elements that promote plant growth and vegetation. Among these, mineral fertilizers produced by manufacturing companies, comprising elements like sulphur, nitrogen, phosphorus, and potassium, have gained significant attention [1]. Figure 4 shows samples of Diammonium Phosphate (DAP) fertilizer (Figures 1 and 2), and NPK(S) 15:15:15(10) (Figure 3) mineral fertilizers. The black DAP (Figure 2) contains molasses which serves as a color agent.

To ensure the efficacy of their products, fertilizer manufacturers must guarantee that they meet the specifications of their clients. Fertilizer specifications usually include information about nutrient contents and concentrations, chemical composition, moisture content, particle size distribution, physical condition, solubility, conditioner, special limitations regarding phytotoxic production byproducts or additives, packaging details, methods used in quantifying or qualifying the properties of the fertilizer, and compensations or rebate for deviation from the stated values and conditions [2]. This necessitates the implementation of effective and efficient quality control processes. The physical properties of fertilizer granules, including their shape, size, and density, profoundly impact crop yield in addition to the chemical composition of the granules [3, 4]. While destructive testing methods damage the materials being examined, non-destructive techniques offer a viable alternative. Non-destructive testing involves inspecting materials without extracting samples or causing any harm to them.

In this regard, computer vision algorithms, specifically those for image classification [5, 6, 7, 8] and object detection [9, 10, 11, 12], have emerged as powerful tools for non-destructive quality control. These algorithms extract valuable information from images and videos, enabling accurate analysis. Compared to human inspection, computer vision algorithms for object detection offer several advantages: they provide more objective results, operate at a faster pace, are less prone to errors, and do not suffer from fatigue.

This research aims to provide an overview of the use of computer vision in inspecting the quality of various grains, quality control for fertilizer granules with a focus on granule size, the application of computer vision techniques in assessing the quality of fertilizer granules, as well as an exploration of existing object detection techniques, along with their advantages and disadvantages.

1. Inspection of grain quality using computer vision

This section focuses on exploring how computer vision has been used to examine the quality of various grain types, including rice, corn, wheat, and lentils. The reason for choosing to investigate the application of computer vision in grain quality inspection is that grains bear a close resemblance to fertilizer granules in their physical appearance.

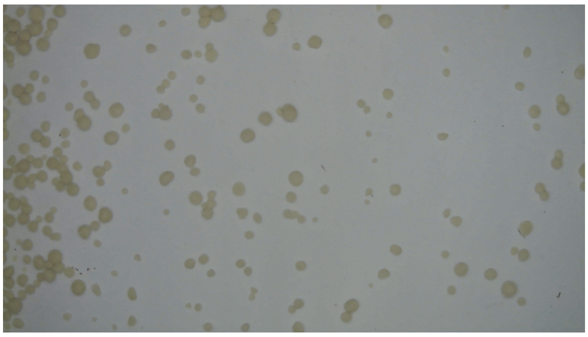

Fig.1. Mineral fertilizer granules. DAP

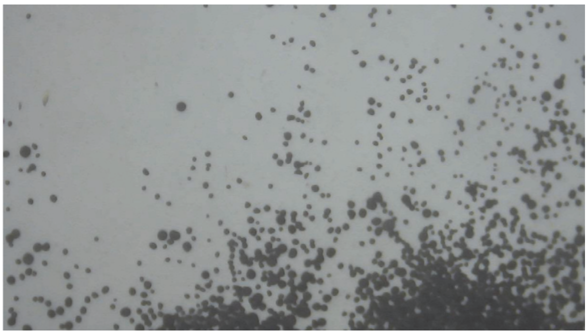

Fig. 2. Mineral fertilizer granules. Black DAP

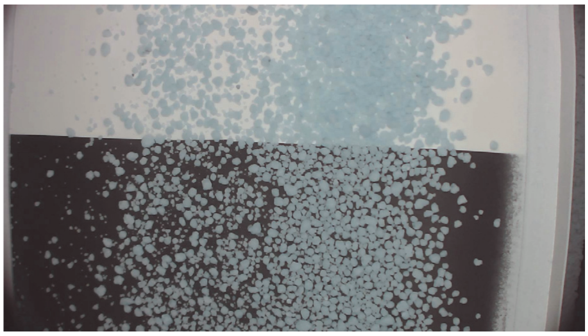

Fig. 3. Mineral fertilizer granules. NPK(S)

Before proceeding, it is necessary to define some terms, such as image classification, object localization, and object detection. Image classification is concerned with assigning labels to images, whereby each image can have only one label. Object localization involves assigning labels, estimating, and drawing a bounding box around a target object in an image. However, object detection focuses on identifying objects of interest in an image and localizing every instance of those objects. While object detection usually considers multiple objects of interest, object localization is mostly concerned with only one object of interest and treats the other pixels contained in the image as background pixels. Essentially, image classification answers the question: "What is in this image?" while object detection answers the questions: "What is in this image? And where are these objects of interest located in the image?"

1.1. Inspection of the quality of rice grains

In the realm of rice quality inspection using computer vision, a series of studies have made significant contributions. Liu et al. [13] devised a method to assess the degree of milling by quantitatively measuring surface lipid concentration. Wan et al. [14] developed an automatic system to classify the quality of rice as sound, immature, cracked, dead, chalky, broken, damaged, and off–type (different variety of rice), while Lloyd et al. [15] compared the performance of an Artificial Neural Network (ANN) based system called GrainCheck with the traditional shaker table method for separating head rice (unbroken rice grain or broken grain that is at least three-fourths of an unbroken grain) from broken rice grains. Yadav and Jindal [16] used image analysis to estimate head rice yield (HRY), and whiteness of milled rice (also known as the degree of milling).

Lan et al. [17] took on fissure detection using a computer vision system composed of a CCD (Charged-coupled Device) camera and Image-Pro Plus software. Van Dalen [18] introduced an efficient method to determine size and quantity, saving substantial time compared to manual analysis.

The utilization of counterpropagation artificial neural networks was explored by Marini et al. [19] to differentiate rice varieties. Guzman et al. [20] deployed multilayer neural networks for grain size and shape identification. Color-based algorithms, such as those by Aggarwal [21], Shantaiya and Ansari [22], and Tated and Morade [23], emerged as effective tools for rice quality assessment.

Kaur and Singh [24] achieved rice grain classification with multi-class SVM. Golpour et al. [25] focused on bulk paddy (unprocessed rice with its hull), brown, and white rice classification using color features and neural networks. Similarly, Azman et al. [26] estimated paddy maturity based on RGB (Red, Green, Blue) color features.

Innovative approaches persisted, such as Anami et al.'s [27] HSI (Hyperspectral Imaging)-based classification, and Singh and Chaudhury's [28] comprehensive analysis involving back-propagation neural networks. The shift towards deep learning was examined by Sun et al. [29], comparing traditional techniques with deep learning for mold recognition in paddy.

1.2. Inspection of the quality of corn grains

Ni et al. [30] designed a system for estimating the size of corn grains using machine vision. The performance of this system was compared with that of a mechanical sieve using a precision round-hole seed sizer, revealing that the machine vision system achieved an average accuracy of approximately 90 %, while the mechanical sieving method yielded an accuracy of about 74%.

In [31], a machine vision system was developed to analyze images of corn grains and determine the projected grain surface area of corn damaged either mechanically or by mold. They achieved 99.5 % accuracy in classifying mechanically damaged grains, and 98.7% accuracy in classifying grains with mold and without mold. Steenhoek et al. [32] implemented a neural network-based computer vision system to classify corn grains as either blue-eye mold damaged, germ damaged, or sound.

Twelve (12) features extracted through image processing were used to classify the grains, and they achieved 89% classification accuracy.

Liu and Paulsen [33] quantitatively determined the whiteness values of 63 corn samples with significant variations in color. Xie and Paulsen [34] developed a machine vision algorithm to recognize and quantify tetrazolium staining in corn. They employed the algorithm to predict damage caused by heat to the viability of corn, based on the temperature of the drying air and the initial corn moisture content. In [35], the authors employed convolutional neural networks based on established pretrained models such as AlexNet, VGGNet, GoogleNet, and ResNet to classify corn seeds as either haploid or diploid. Their results demonstrated that the neural network-based model significantly outperformed machine learning-based methods. Velesaca et al. [36] adopted a deep learning-based approach to classify corn grains as either good, defective, or impure. They utilized the Mask R-CNN model for image segmentation on the dataset, and a custom lightweight neural network to classify the images of the corn grains.

1.3. Inspection of the quality of wheat grains

Zayas et al. [37] examined wheat grain quality by employing a combination of image analysis methods and physical measurements of wheat hardness. Physical properties, such as grain shape and size, were extracted from grain images. Pattern recognition methods were used to classify six variants of wheat grains and 17 variants of soft and hard wheat.

In [38], neural networks were applied to color and texture features of wheat samples for estimating blemishes caused by Fusarium scab infection. Luo et al. [39] utilized morphological and color features from wheat grain images to categorize grains as healthy or damaged, considering six damage categories. The k-nearest neighbor non-parametric classifier yielded the best results when both color and morphological features were utilized instead of solely color features.

Utku [40] proposed a method to select optimal features for distinguishing wheat cultivar images. Ridgway et al. [41] employed an optimized adaptive thresholding algorithm along with median filtering and erosion to detect insects and contaminants in bulk wheat grain during transit.

Dubey [42] evaluated the potential of identifying various wheat grain types using grain morphometry and artificial neural networks. In [43], the authors explored the feasibility of hyperspectral imaging (HSI) to classify wheat grain varieties as Fusarium-damaged, yellow berry, or vitreous.

Zapotoczny [44] developed a method to classify wheat grains utilizing image analysis and 49 texture features. Multidimensional analysis, involving Bayes classifier, Decision Trees, Lazy, Meta, and Discriminatory analyses, was performed to classify various wheat grain types.

Ebrahimi et al. [45] combined the Imperialist Competitive Algorithm (ICA) and Artificial Neural Networks (ANNs) to create a system that identified the best feature sets extracted from wheat grain image samples and robustly classified the grains.

Jirsa and Polisenska [46] employed image analysis to identify Fusarium-damaged wheat grains. A combination of features from the RGB (Red, Green, Blue) and HSL (Hue-Saturation-Lightness) color models was used for classification using linear discriminant analysis.

Olgun et al. [47] classified wheat grains using Dense Scale Invariant Features (DSIFT) and an SVM classifier. Sabanci et al. [48] employed artificial neural networks to classify wheat grains as either bread or durum wheat based on color and texture features extracted from grain images.

1.4. Inspection of the quality of other grains

In addition to rice, corn, and wheat, the application of computer vision and machine learning techniques has extended to the inspection of the quality of other grains, illustrating the versatility of these methods in various contexts.

For lentils, Shahin et al. conducted studies on the utilization of machine learning for quality assessment [49, 50]. In the domain of coffee beans, Huang et al. explored real-time quality inspection using computer vision techniques [51].

The inclusion of oats, barley, and rye into the spectrum of inspected grains has also been explored [52, 53, 54]. The quality inspection of soybeans has garnered attention as well [55, 56, 57, 58].

This comprehensive exploration underscores the broad spectrum of grains subject to quality assessment using advanced technologies, highlighting the potential for increased efficiency and precision in grain processing and production.

1.5. Analysis of reviewed literature on inspection of grain quality using computer vision

Table 1 gives an overview of the number of articles reviewed. It was observed that most of the authors used image processing techniques such as histogram of images, histogram equalization, image binarization, edge detectors such as canny edge detector and sobel filters to mention but a few of the possible image processing techniques. The image processing techniques were mostly used to extract color and texture features from images which were then used to classify the images based on set objectives.

A variety of classifiers were used by the authors ranging from statistical classifiers, naive Bayes, support vector machine (SVM), k-nearest neighbour (kNN), back-propagation neural network (BPNN), deep belief network (DBN), artificial neural network (ANN) to convolutional neural network (CNN). The following abbreviations are used in the tables below: IPT (Image Processing Techniques), Imperialist Competitive Algorithm (ICA), probablistic neural network (PNN), multilayer neural network (MNN), dense SIFT (Scale-invariant feature transform), Statistical Analysis Systems (SAS), SPSS statistical software, partial least squares discriminant analysis (PLS-DA), interval partial least squares discriminant analysis (iPLS-DA), Counterpropagation Artificial Neural Network (CP-ANN).

Tables 2 and 3 provide a summary of the methods used. IPT plays two main roles: image preprocessing and extraction of features used by classifiers to distinguish respective grains. From the tables, it is clear that most of the quality inspection tasks were posed as image classification tasks. Table 4 lists some freely available datasets of granule-like objects.

Tab. 1. Overview of articles reviewed

Grain Type	Number of articles reviewed
Rice	17
Corn	7
Wheat	12
Others	10
Total	46

Tab. 2. Summary of Quality Inspection Method Used (I)

Grain type	Objective	Year	Method used
Rice	Measurement of Rice Degree of Milling [13]	1998	IPT
	Distinguishing between head rice and broken rice grains [15]	2001	ANN
	Determination of degree of milling and head rice yield [16]	2001	IPT
	Classification of the quality of brown rice [14]	2002	IPT + range-selection method implemented as a series of tables
	Detection of fissures in rice grains [17]	2002	IPT
	Determination of the size distribution and percentage of broken rice grains [18]	2004	IPT
	Classification of Italian rice varieties [19]	2004	CP-ANN
	Classification of Philippine rice varieties [20]	2008	IPT + ANN
	Aspect ratio analysis of rice grains [21]	2010	IPT
	Classification of rice grains [22]	2012	IPT + Neural network
	Automatic cleaning of rice [23]	2012	IPT
	Classification and grading of rice [24]	2013	IPT + Multi-class SVM
	Classification of rice varieties [25]	2014	IPT + Neural network
	Estimation of maturity of paddy [26]	2014	IPT + Pearson two-tailed correlation
	Classification of paddy [27]	2015	IPT + ANN
	Classification of rice grains [28]	2016	IPT + naive Bayes, SVM, kNN, BPNN
	Classification of paddy, and recognition of mould colony areas [29]	2016	IPT + SVM, BPNN, DBN, CNN
Corn	Classification of corn grain sizes [30]	1998	IPT + minimum distance clustering classifier
	Classification of corn grains with mold and without mold [31]	1998	IPT + Neural network
	Corn whiteness measurement and classification using machine vision [33]	2000	IPT
	Classification of corn grains damage [32]	2001	IPT + PNN
	Detection of tetrazolium staining in corn [34]	2001	IPT + discriminant functions
	Classification of corn grains as haploid or diploid [35]	2019	IPT + CNN
	Classification of corn grains [36]	2020	Mask R-CNN + CNN

2. Quality control for fertilizer granules

Quality control of fertilizer granules relies on assessing both their chemical and physical properties. While verifying the chemical composition of fertilizer granules presents challenges, evaluating their physical attributes offers a more accessible avenue. Factors such as caking, free-flowing nature, dustiness, moisture content, and stickiness can be visually inspected to ascertain granule quality. Favorable physical characteristics ensure efficient, uniform, and swift application to agricultural fields [2].

In this study, the focal physical attribute under consideration is the granule or particle size. The particle size of a fertilizer granule is defined by its diameter range. This parameter exerts influence over crop yield, granulation processes, blending efficiency, storage conditions, handling practices, and application effectiveness. Maintaining control over fertilizer granule size facilitates rapid disintegration in soil and optimal uptake by crops [2].

Traditionally, particle size analysis involves conducting sieve analysis on a sample using 20 cm diameter sieves. The selection of sieves depends on the desired granule size range for analysis. These sieves are arranged in a stack, with openings progressively enlarging from the bottom to the top. The sample material is placed on the top sieve, and the sieve stack is positioned on a platform capable of controlled shaking. During shaking, each particle migrates through the sieve openings until it encounters a sieve where the openings are too small for passage. After a defined shaking interval, the material on each sieve is individually weighed, enabling the determination of particle size distribution within the sample [2].

Recognizing the rigorous nature of sieve analysis for particle size distribution, the potential exists to develop a computer vision algorithm for quicker and more efficient analysis, bypassing the use of physical sieves. Such an algorithm could also be harnessed to identify impurities and irregularities within the granules. This approach offers an innovative pathway towards enhancing the accuracy and speed of quality control processes for fertilizer granules.

Tab. 3. Summary of quality inspection method used (II)

Grain type	Objective	Year	Method used
Wheat	Classification of wheat grains [37]	1996	IPT + SAS
	Estimation of Fusarium scab infection in wheat [38]	1998	IPT + BPNN
	Classification of wheat grains [39]	1999	IPT + SAS
	Classification of wheat grains [40]	2000	IPT + SPSS
	Detection of insects and other bio-contaminants in wheat grain [41]	2002	IPT
	Classification of wheat grains [42]	2006	IPT + ANN
	Classification of wheat grains [43]	2013	Hyperspectral images + PLS-DA + iPLS-DA
	Classification of wheat grains [44]	2014	IPT + Bayes, Lazy, Meta, Decision Trees, Discriminatory analyses
	Classification of wheat grains [45]	2014	IPT + ICA, ANN
	Classification of wheat grains [46]	2014	IPT + discriminatory equations
	Classification of wheat grains [47]	2016	dense SIFT + SVM
	Classification of wheat grains [48]	2017	IPT + ANN
Other	Classification of soybean [55]	1988	IPT
	Classification of soybean [56]	1999	IPT + discriminant function
	Classification of lentils [49]	2001	IPT + MNN
	Classification of lentils [50]	2003	IPT + statistical classifier
	Classification of five grain types (barley, Canada Western Amber Durum wheat, Canada Western Red Spring wheat, oats, and rye) [52]	2003	IPT + Neural network
	Classification of five grain types (barley, oats, rye, wheat, and durum wheat) [53]	2003	IPT + BPNN
	Determination of seed size uniformity of soybean [57]	2006	IPT + ANN
	Classification of seven grain types (common rice, brown rice, buckwheat, glutinous rice, rough rice, glutinous barley, and common barley) [54]	2011	IPT + BPNN
	Classification of diseases of soybean [58]	2014	IPT + BPNN
	Real-time classification of green coffee beans [51]	2019	IPT + CNN

2.1. Static image analysis methods for particle size analysis

Static image analysis refers to the process of examining and evaluating a still or non-moving image to extract information, identify patterns, or draw conclusions. According to standards set by the ISO (the International Organization for Standardization), to perform static analysis of images, the settings and calibration of the camera need to be determined through a repetitive process to ensure accurate measurement of particle size. It is also advisable for the lighting to be consistent across the entire field of vision and specifically engineered to generate high-contrast images [59].

According to ISO 13322-1 [59], to carryout image analysis, it should be decided if the parameter of interest is the number of particles in each size class or the volume of particles in each size class. The desired accuracy and precision should also be decided before starting the procedure. The procedure for carrying out static image analysis is as follows:

1. The X and Y-axis of the measurement frame of the camera should be calibrated using a certified calibration grid.
2. Incorporate adequate optical magnification to guarantee that the smallest particle intended for measurement occupies a substantial number of pixels, thus supporting the required measurement accuracy.
3. Establish the proper illumination and settings for focusing to achieve optimal image contrast and uniform illumination during image capture.
4. Optimize the particle count within the measurement frame to minimize instances of particles touching each other.
5. Collect adequate number of images from different samples, ensuring they collectively encompass an appropriate total particle count relative to the distribution type and the width of the particle size distribution. Additionally, ensure that these images contain a statistically significant number of the largest particles of the target material.

The main measurement of the particles is the projected area A_i expressed in pixels, then the longest Feret diameter ($x_{Fmax,j}$) and the shortest Feret diameter ($x_{Fmin,j}$) of each particle expressed in pixels. These three values are used to estimate the area equivalent diameter $x_{A,j}$, and the shape descriptor ϕ_i.

$$x_{A,i} = \sqrt{4A_i/\pi}\,, \tag{1}$$

$$\phi_i = x_{Fmin,i} / x_{Fmax,i}\ . \tag{2}$$

The Feret diameter is the measurement of the space between two parallel tangents on opposite sides of a particle's image, whereas the area equivalent diameter is the diameter of a circle that possesses the same area as the particle's projected image [59].

2.2. Computer vision in quality control for fertilizer granules

The production of mineral fertilizers involves the creation of numerous granules, each with unique characteristics [60]. Ensuring that these granules meet the specified customer requirements necessitates consistent quality assessment. Parameters like size, area, and color of the granules demand evaluation, while the production process requires vigilant monitoring to identify anomalies or foreign matter. Various techniques have been employed to gauge the size and color of fertilizers, as elaborated below.

In a study by Yunovidov et al. [60], classical computer vision techniques were harnessed to oversee the particle size of fertilizer granules through a robotic system. This setup comprised three units: a sampling unit, a sample delivery unit, and an analysis unit. The sampling unit received granules from the production line, while the delivery unit uniformly distributed the granules to the analysis unit using vibrations. The analysis unit was equipped with a high-speed camera for capturing granule images, LED (Light-emitting Diodes) lighting for consistent illumination, and software for granule size and color determination. The method encompassed preprocessing granule images, contour detection via edge detection techniques, and size estimation using ellipses. Although granule color was not analyzed in this instance, the authors noted its feasibility. The system's performance was benchmarked against the Camsizer P4 machine, indicating its potential in granulometric composition assessment.

In a subsequent work [61], the same system as described in [60] was enhanced to estimate granule area, size, color, and sphericity. The authors introduced software features, including adaptive equalization and distance separation, for image processing. Moreover, they devised a data recording system to document quality analysis results. This evolved system served as both an indicator for control purposes and a repository for crucial granule properties. Comparative evaluation with the Camsizer P4 machine was also undertaken.

While existing endeavors primarily leveraged traditional computer vision techniques to recognize fertilizer granules and estimate physical attributes, such as size and color, they often overlooked potential anomalies like foreign matter. Thus, this study aims to explore deep learning-based methods for granule and anomaly detection, as well as the estimation of granule size and color. The developed deep learning model will be tailored for operation on central processing units (CPUs), addressing the challenge of efficient functioning typically associated with graphical processing units (GPUs) in deep learning models.

Tab. 4. Some available datasets with granule-like objects

Type of object	Size of dataset	Application
Grains consisting of terrigenous, carbonate, volcaniclastic sand and gravel	409 images	Estimating grain size, and classifying grain shape and population [62]
X-ray tomography images of battery micro- and nanostructures	Approximately 7000 – 19000 particles studied	Segmentation algorithm to identify particles, and calculate the particle size distribution [63]
Rice Image Dataset	75,000 images	Classification of five (5) classes of rice [64]
Dry Bean Dataset	236 images	Classification of seven (7) classes of dry beans [65]
Raisin Dataset	900 images	Classification of two (2) variety of raisins [66]

3. Overview of object detection techniques

An overview of object detection techniques reveals the existence of various computer vision methods for detecting objects in images, which can be broadly classified into traditional computer vision methods and deep learning-based methods. When evaluating object detection algorithms, two key metrics are commonly used: accuracy (for both classification and localization) and speed [67].

Traditional computer vision object detection techniques include the Viola-Jones Detectors [68, 69], Histogram of Oriented Gradients (HOG) feature descriptor [70], and Deformable Part-based Model (DPM) [71]. These methods rely on handcrafted features for object identification and localization such as in document analysis and recognition [72, 73, 74].

In contrast, deep learning-based methods for object detection can be categorized into two-stage detectors and single-stage detectors. Two-stage detectors initially propose potential regions of interest (RoIs) in the input image using a region proposal network (RPN). The RPN generates a set of candidate bounding boxes that may contain objects. In the second stage, the proposed RoIs are classified and refined. This is accomplished by passing the RoIs through a separate network, often a Convolutional Neural Network (CNN), which classifies and precisely localizes objects within each proposed region. On the other hand, single-stage detectors divide the input image into a grid of cells and directly predict object bounding boxes and class probabilities from each cell. Multiple bounding boxes of different sizes and aspect ratios are predicted at each cell to handle objects of various scales. Single-stage detectors are known for their real-time inference speed and efficiency. Although they are generally faster compared to two-stage detectors, they may sacrifice some accuracy and localization precision, particularly for small or heavily occluded objects [67].

Examples of two-stage detectors include the Region-based Convolutional Neural Network (RCNN) [10], Fast RCNN [9], Faster RCNN [75], and Feature Pyramid Networks (FPN) [76]. Some single-stage detectors include You Only Look Once (YOLO) [11, 77, 78], Single Shot MultiBox Detector (SSD) [79], RetinaNet [80], CornerNet [81], and Detection Transformers (DETR) [12].

Table 5 lists the top five (5) object detection models bench marked using the COCO Dataset which is the industry standard dataset for bench marking object detection models.

3.1. Advantages and disadvantages of different techniques

While traditional computer vision object detection algorithms have found applications in areas such as face detection and pedestrian detection, deep learning-based object detection algorithms have gained popularity and consistently outperformed traditional methods due to the following reasons:

1. Improved accuracy: Deep learning algorithms excel at learning intricate features and complex patterns from large-scale datasets. As a result, they achieve higher accuracy in object detection tasks compared to traditional computer vision algorithms.
2. Flexibility and adaptability: Deep learning models can handle a wide variety of object classes and adapt to different environments without the need for hand-crafted features or explicit rule-based algorithms. They possess the capability to learn and generalize from diverse data sources.
3. Robustness to variations: Deep learning algorithms exhibit greater robustness to variations in object appearance, such as changes in lighting, scale, pose, and occlusion. They can learn and represent features at multiple levels of abstraction, enabling better generalization across different instances of an object.
4. Scalability: Deep learning-based object detection algorithms can efficiently handle large-scale datasets and complex scenes. They are capable of processing high-resolution images and detecting objects in real-time, making them suitable for various applications, including video surveillance, visual inspection of manufactured products, autonomous driving, and robotics.

While deep learning-based object detection algorithms offer significant advantages, traditional computer vision algorithms still have their place in scenarios with limited computational resources and where interpretability is crucial. Deep learning algorithms are often considered black-box models.

Tab. 5. Top five (5) real-time object detection models' performance on the COCO dataset

Model	Mean average precision (mAP)	Image size (pixel)
YOLOv8 [82]	37.3 – 53.9	640
YOLOv7 [83]	51.4 – 56.6	640 – 1280
YOLOv6-v3 [84]	37.5 – 57.2	640 – 1280
RTMDet [85]	41.0 – 52.8	640
RT-DETR [86]	46.5 – 54.8	640

4. Research questions

Upon reviewing existing works related to quality inspection of grains and fertilizer granules using computer vision, the central challenge in assessing grain quality has predominantly been framed as an image classification problem. In light of this, it becomes imperative to delve into the following inquiries:

1. Could using state of the art object detection algorithms such as YOLOv8 [82] and YOLOv9 [87] present a superior methodology for the inspection of grain and fertilizer granule quality?
2. Might image segmentation algorithms such as Mask R-CNN [88], Segment Anything Model (SAM) [89], Fast Segment Anything Model [90], or YOLOv8 [82] offer a more effective approach for inspecting the quality of grains and fertilizer granules?
3. Could a hybrid solution that amalgamates object detection and image segmentation emerge as a more optimal approach for assessing the quality of grains and fertilizer granules?

Conclusion

This paper has presented an exploration of existing methods involving computer vision for inspecting the quality of various grains and fertilizer granules, a detailed examination of quality control for fertilizer granules with a specific emphasis on granule size, an overview of object detection techniques, and a discussion on the advantages and disadvantages associated with these object detection methods.

Based on the literature reviewed, it becomes evident that most of the existing methods frame the quality inspection challenge as an image classification problem. To further advance research in quality inspection using computer vision, our future plan involves investigating whether redefining the problem as an object detection task, an image segmentation task, or a hybrid solution that combines both object detection and image segmentation techniques would prove to be a more effective approach for assessing the quality of fertilizer granules. In contrast to classical computer vision methods that necessitate manual feature engineering to differentiate granules from their backgrounds, neural networks offer the capability to automatically extract these distinguishing features. Moreover, neural networks exhibit remarkable versatility, enabling them to be adapted for a wide array of tasks, ranging from image classification and object detection to semantic segmentation. These attributes make a neural network-based approach the preferred choice for addressing the challenge of evaluating the quality of fertilizer granules, as it streamlines the feature extraction process and enhances adaptability to various image analysis tasks.

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