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Evaluating Tillage Quality under Varying Speed and Depth Using YOLOv7-Based Image Analysis

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Abstract: Soil tillage is a critical agricultural practice that creates favorable conditions for seedbed preparation and plant growth. This study presents an innovative application of artificial intelligence (AI) in agriculture by employing the YOLOv7 algorithm to classify and assess post-tillage soil surface conditions, a domain underexplored in current research. The integration of mechanical operation parameters with AI-based image classification enables optimization of tillage quality and mitigation of soil compaction, highlighting the novelty of this approach. The study aims to improve the efficiency of moldboard plow operations by examining the effects of tillage speed and depth on soil clod distribution, fuel consumption, and power requirements. The YOLOv7 model was used to analyze soil surface imagery and identify optimal tillage outcomes characterized by minimal soil clod presence. Results indicate that increasing tillage speed and depth led to higher fuel and power consumption. Conversely, smaller soil clod sizes, indicative of better surface quality, were achieved at higher speeds and shallower depths. Model performance demonstrated strong accuracy: recall of 78.5%, precision of 82.0%, and F1-score of 80.2%. The mean Average Precision at 0.5 IoU (mAP@0.5) reached 77.4%, with validation and test set values of 78% and 75%, respectively. These results confirm the effectiveness of YOLOv7 in detecting and localizing soil clods, enabling real-time assessment of tillage quality. The proposed framework supports data-driven decision-making in precision agriculture, enhances operational efficiency, and promotes improved seedbed conditions for optimal crop establishment.

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Keywords: fuel consumption; power consumption; soil clods; tillage; tillage appearance; YOLOv7

使用基于 YOLOv7 的图像分析评估不同速度和深度下的耕作质量

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摘要：土壤耕作是一项重要的农业实践，它为苗床准备和植物生长创造了有利条件。本研究展示了人工智能 (AI) 在农业领域的创新应用，利用 YOLOv7 算法对耕作后土壤表面状况进行分类和评估，而这一领域目前的研究尚不足。机械操作参数与基于人工智能的图像分类相结合，可以优化耕作质量并减轻土壤压实，凸显了该方法的创新性。本研究旨在通过研究耕作速度和深度对土块分布、燃料消耗和功率需求的影响来提高铧式犁的作业效率。YOLOv7 模型用于分析土壤表面图像，并确定以土块数量最少为特征的最佳耕作效果。结果表明，提高耕作速度和深度会导致燃料消耗和功率消耗增加。相反，更高的耕作速度和更浅的耕作深度可以获得更小的土块，这表明地表质量更好。模型性能展现出卓越的准确率：召回率为 78.5%，准确率为 82.0%，F1 得分为 80.2%。0.5 IoU 下的平均准确率 (mAP@0.5) 达到 77.4%，验证集和测试集上的准确率分别为 78% 和 75%。这些结果证实了 YOLOv7 在检测和定位土块方面的有效性，从而能够实时评估耕作质量。该框架支持精准农业中数据驱动的决策，提高作业效率，并促进苗床条件的改善，以实现作物的最佳生长。

关键词：燃料消耗；功耗；土块；耕作；耕作外观；YOLOv7

1 Introduction

Humans have tilled the land for centuries to enhance agricultural productivity. Tillage is considered one of the fundamental field operations in agriculture, as it significantly influences soil structure, environmental conditions, and crop yield. Despite considerable advancements in recent decades, tillage remains a complex process that lacks the precision of an exact science, even though its primary objective is to create an optimal environment for seed germination and plant growth. Under these conditions, the soil must be prepared to allow roots adequate access to air, water, and nutrients, making the assessment of soil fragmentation a critical factor in evaluating tillage quality [1, 2].

Various types of plows are employed in tillage operations, including moldboard plows, which invert the soil; chisel plows, which break up compacted layers without inversion; and rotary plows, which pulverize the soil into fine particles. Selecting the appropriate plow type is essential for improving soil structure and enhancing crop productivity [3].

The size of soil clods after plowing is influenced by tillage depth. Generally, deeper plowing results in larger clods due to reduced fragmentation. Studies have shown that shallower tillage produces smaller clods compared to deeper tillage, indicating an inverse relationship between depth and fragmentation [4]. Deep plowing displaces and mixes a greater volume of soil. As the plow cuts through the soil profile, it generates larger fragments that tend to coalesce into clumps during inversion and rolling. The mechanical action of the plow stretches and separates soil aggregates, leading to significantly larger clod sizes compared to shallow tillage [5].

Tillage speed also affects clod size. Increasing the speed enhances the impact force of the plow blade on the soil, improving its ability to break large clods into smaller fragments. This leads to a higher proportion of fine particles and a more uniform distribution of clod sizes [2, 6]. Nassir [7] found that increasing tillage speed from 0.8 to 1.62 m/s reduced clod size, whereas increasing tillage depth from 22 to 23 cm resulted in larger clods. In summary, clod size is influenced by both tillage speed and depth, as well as by soil moisture, soil type, and the number of tillage passes [8]. Methods to control clod size vary depending on these factors, and adjusting operational parameters can help achieve the desired seedbed texture for specific crops and conditions [9].

At the same time, both tillage speed and depth affect energy and fuel consumption. Higher speeds and greater depths generally lead to increased power and fuel requirements [10]. Olosunde [11] reported a linear relationship between tillage depth and speed with respect to both energy and fuel consumption, highlighting the trade-off between tillage quality and operational efficiency.

Modern agriculture requires precise management of operational parameters, such as tillage depth and speed, to ensure effective soil loosening while minimizing power and fuel consumption. In this context, artificial intelligence (AI) has emerged as a powerful tool for enhancing the efficiency of tillage operations. The integration of computer vision into agricultural practices has advanced significantly, marking a paradigm shift toward precision agriculture and data-driven farm management [12].

A pivotal technological advancement enabling this transformation is the You Only Look Once (YOLO) series of object detection models, renowned for their exceptional speed and accuracy. YOLO's defining feature lies in its single-stage architecture: it divides the input image into a grid and simultaneously predicts bounding boxes and class probabilities in parallel, enabling real-time detection [13]. This departure from traditional two-stage detection methods has significantly accelerated processing speeds without compromising detection accuracy.

The application of YOLO-based models in agriculture holds substantial potential for revolutionizing practices such as crop monitoring [14], disease detection [15], yield prediction [16], and livestock management [17]. The combination of real-time processing, high accuracy, and architectural flexibility makes YOLO variants particularly well-suited to address the dynamic challenges of modern farming.

Ji et al. [18] proposed an innovative method for detecting farmland plow boundaries using RGB-D cameras and the YOLOv5-seg algorithm, achieving 99% recognition accuracy and improved distance estimation. Their results demonstrate the feasibility of autonomous operation for unmanned tillage systems using this advanced technology. Wang et al. [19] employed machine vision techniques to segment farmland boundary images into eight subregions, identifying grayscale jump features and applying robust regression to determine the principal axes of irregular field edges.

Despite these advancements, the application of YOLO models specifically to tillage operations remains underexplored, with limited dedicated research in this domain. This underscores the need for studies that integrate cutting-edge AI technologies with soil science to achieve meaningful improvements in tillage efficiency and soil quality.

The topic of improving soil tillage processes using artificial intelligence (AI) techniques was selected based on a comprehensive assessment of scientific, methodological, and practical criteria to ensure the study's feasibility and originality. First, the research addresses a topic of significant scientific and practical importance: enhancing tillage quality improves seedbed conditions for plant growth while reducing energy and fuel consumption, thereby increasing agricultural productivity and minimizing environmental impact. Second, the study is novel in its integration of advanced image analysis and AI technologies, specifically YOLOv7, into tillage evaluation, contributing new knowledge to precision agriculture and addressing a recognized gap in the literature. Furthermore, the research was deemed technically feasible, with accessible data and appropriate tools for model training and validation. The potential for practical implementation, such as optimizing tillage parameters in real-world operations and supporting resource-efficient farming, further underscores the relevance and applicability of the findings.

Based on these requirements, this study establishes three primary objectives. First, to evaluate the effects of tillage depth and speed on power and fuel consumption, as well as on soil clod distribution. Second, to assess the applicability of image analysis techniques for quantifying the size and spatial distribution of soil clods following tillage. Third, to implement an artificial neural network, specifically the YOLOv7 model, to classify tilled soil surfaces based on soil clod size, thereby identifying optimal combinations of tillage speed and depth. This integrated approach is designed to enhance soil quality, improve seedbed preparation, and support higher crop yields while minimizing power and fuel consumption.

2 Materials and Methods

2.1 Measurement Methodology

The research methodology consists of four main stages designed to evaluate and optimize soil tillage quality through the integration of artificial intelligence (AI) techniques. In the first stage, soil tillage was conducted using a moldboard plow at two speeds (2.5 and 3.5 km/h) and two depths (18 and 25 cm) to examine the effects of these operational parameters on soil clod distribution. In the second stage, images of the tilled soil surface were captured using an iPhone X camera under the defined experimental conditions. These images, representing real-world visual data, were used to train the AI model.

In the third stage, the YOLOv7 model – a state-of-the-art object detection algorithm in computer vision – was trained on the collected dataset to classify soil surface conditions based on clod size and distribution. Finally, in the fourth stage, the trained model was validated using an independent dataset, and its performance was evaluated using standard metrics, including precision, recall, F1 score, and mean Average Precision at 0.5 IoU (mAP@0.5), to assess classification accuracy and reliability.

This methodology represents a synthesis of field experimentation and advanced digital technologies, enhancing the precision of tillage assessment and supporting the optimization of agricultural operations. Figure 1 illustrates the overall experimental and analytical workflow.

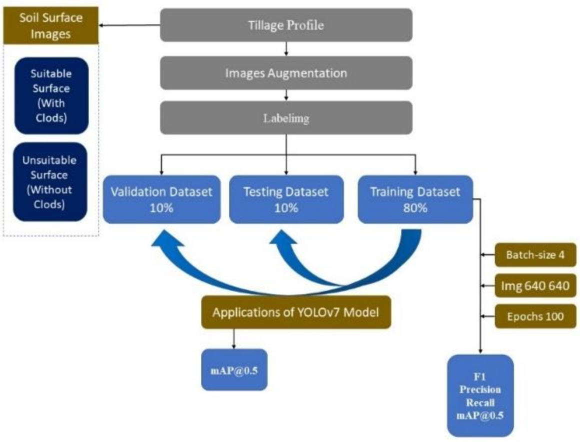


Fig. 1 Measurement methodology diagram. Source: created by the authors

2.2 Field Experiment

The experiment was conducted at the University of Baghdad's Al-Jadriya research fields (33°16′12″N, 44°22′54″E). The soil at the site is sandy, with a moisture content of 18%. To investigate the effects of two operational factors (tillage speed and depth) on soil clod size distribution, power consumption, and fuel usage, the YOLOv7 model was trained to classify soil conditions based on image analysis of captured surface data.

During the trials, an 80 HP 2WD NEW HOLLAND 66S tractor (Turkish production) was used in conjunction with a locally manufactured Iraqi three-moldboard plow produced by the Public Association of Mechanical Trade in Alexandria, Iraq. The plow had a working width of 1.05 m and a total weight of 293 kg. Each test was conducted over a 20-meter pass. The actual configuration of the tractor-plow assembly is shown in Figure 2a.

It was assumed that the primary evaluation metric in this study would be the number of soil clods with a diameter greater than 100 mm [20]. To quantify the number of such clods per square meter, a wooden frame measuring 0.25 m² (0.5 m × 0.5 m) and 10 cm in height was constructed, with its base consisting of a metal sieve. The sieve featured square openings with sides of 100 mm. After sieving a soil sample collected from the tilled field, the number of clods retained on the sieve – those with an equivalent diameter exceeding 100 mm – was recorded for each test. This procedure is illustrated in Figure 2b.

Since the sampling area was 0.25 m², the count was multiplied by four to estimate the number of large clods per 1 m² [21]. Tillage depth was measured directly in the field using a calibrated tape measure, as shown in Figure 2c.

Fig. 2 Field experiment a. Mechanical unit b. Wooden frame c. Depth measuring tape. Source: created by the authors

The fuel consumption after each test was measured based on the fuel shortage inside a 1000 ml measuring cylinder. To calculate the fuel used per unit area, Eq. 1 was used [22]:

$$Fs = (Fca*10) / (Wp * Lp) \qquad (1)$$

where Fs: Fuel consumed per unit area (l/ha), Fca: Field-measured fuel consumed (ml), Wp: Width of the treatment line (m), Lp: Length of the treatment line (m).

The amount of fuel consumed over time (*Fc*) in l/h is calculated on the basis of Eq. 2 [23]:

$$Fc = (Fca / Tp) * 3.6 \qquad (2)$$

where Tp: Operation time (s), 3.6: Conversion factor.

To determine the power used for plowing, a previously developed method [24] was used based on the fuel consumption over time (Fc) as indicated by Eq. 3:

$$P = \frac{Fc}{3600} * \rho_f * \eta_{mec} * LCV * \eta_{th} * \frac{427}{75} * \frac{1}{1.36} \quad (3)$$

where: P: Power consumed by the engine (kW), FC: Fuel consumption over time (l/h), ρf: Fuel density (kg/l) (for diesel = 0.85), LCV: Calorific value of fuel (10,000 kcal/kg), 427: Mechanical thermal equivalent (J/kcal), η_{th}: Engine thermal efficiency of the engine (~35% for diesel engines), η_{mec}: The mechanical efficiency of the motor (~80%).

For training the YOLOv7 model, images were captured in the field immediately after each tillage operation using a 12-megapixel (MP) iPhone X camera mounted perpendicular to the soil surface. The camera was positioned at a fixed height of 1 meter above the ground to maximize the visible soil area per image while maintaining geometric accuracy. A digital lux meter was used to monitor ambient light intensity during image acquisition, ensuring consistent illumination conditions. Light intensity was recorded at approximately 1,000 lux, with a measurement accuracy of ±4%. These standardized imaging conditions were designed to minimize variability and enhance the reliability of the visual data used for model training and validation.

2.3 YOLOv7 Model Structure

The YOLO method is a target detection algorithm based on a neural network. It redefines the task of target detection as a regression problem in computation. The procedure begins by dividing the image into cells in a grid pattern for prediction [25].

The YOLOv7 model was implemented using Python within the Roboflow platform as the development environment, running on a Lenovo laptop equipped with an Intel Core i7 processor (2.3 GHz) and 16 GB of RAM. The dataset consisted of two classes: soil clod appearance (label 0) and no soil clod appearance (label 1). A total of 361 original images were collected, and data augmentation was performed by applying horizontal flipping to double the dataset size, resulting in 722 annotated images.

The LabelImg tool was used to manually annotate the bounding boxes around the tilled soil regions in each image, enabling precise localization of the area of interest. Annotation was conducted to tightly enclose the plowed region while minimizing the inclusion of irrelevant background elements. The dataset was then partitioned into training, validation, and testing subsets, comprising 80%, 10%, and 10% of the images, respectively.

Input images were resized and normalized to 640×640 pixels in RGB format to preserve critical visual features of the soil surface. During model training, the Rectified Linear Unit (ReLU) activation function (Eq. 4) was applied to enhance non-linearity and improve feature extraction. The neural network weights were updated using the gradient descent optimization algorithm to minimize the loss function and improve classification accuracy (Eq. 5) [26]:

$$f(x) = \max(0,x) \quad (4)$$

$$w = w - \eta \nabla L \quad (5)$$

where w: weight, η : learning rate, ∇ L: gradient of the loss function.

The YOLOv7 model structure (Figure 3) illustrates the network output, which is a box showing the appearance of the plowed field and the probability that the land appearance belongs to a particular class.

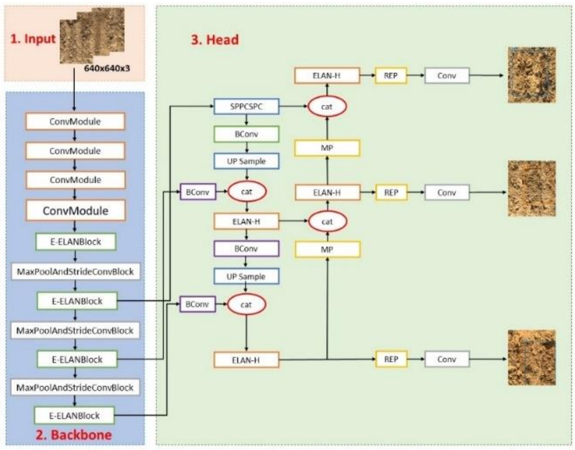


Fig. 3 YOLOv7 network architecture. Source: created by the authors

The YOLOv7 architecture consists of three main components: the input layer, the backbone network, and the detection head, as illustrated in Figure 3. The input layer handles preprocessing of the input images, which are resized and normalized to 640 × 640 pixels in RGB format. The mention of an “orange background” appears to be a misinterpretation or artifact and is not a standard component of YOLOv7 preprocessing; image normalization is performed to preserve essential visual features under varying lighting and environmental conditions.

The backbone network is based on the CSPDarknet53 architecture and includes crossstage partial (CSP) connections designed to enhance gradient flow and feature reuse. It extracts multi-scale spatial features through a series of convolutional and residual blocks. The model employs feature pyramid networks (FPN) and path aggregation networks (PAN) in later stages to improve feature fusion across different scales, enabling robust detection of soil clods of varying sizes.

The detection head is responsible for object localization and classification. It incorporates an auxiliary head for deep supervision during training, which enhances gradient propagation and accelerates convergence. Additionally, YOLOv7 utilizes a dynamic label assignment strategy – known as positive sample matching – that adaptively selects the most suitable anchor boxes during training, improving detection accuracy and training efficiency. The loss function, which combines classification, localization, and confidence losses, is optimized using stochastic gradient descent (SGD) or AdamW, depending on the implementation.

This architecture enables real-time, high-precision detection of soil clods, making it highly suitable for integration into precision agriculture systems.

2.4 YOLOv7 Performance Metrics Overview

In this study, precision was used as one of the key metrics to evaluate the performance of the YOLOv7 model. Precision, defined as the ratio of true positive detections to the total number of predicted positives (i.e., true positives + false positives), is a widely used measure in object detection tasks. A higher precision indicates fewer false detections and greater reliability in classification. However, precision alone does not provide a complete assessment, as it does not account for missed detections.

Therefore, a comprehensive evaluation was conducted using multiple metrics: mean Average Precision at 0.5 IoU (mAP@0.5), recall, and the F1 score. Recall measures the proportion of actual positive instances that were correctly identified by the model, reflecting its sensitivity. The F1 score, which is the harmonic mean of precision and recall, provides a balanced assessment of the model performance, particularly in cases of class imbalance. Together, these metrics offer a robust and multi-dimensional evaluation of detection accuracy and model effectiveness.

The performance measures were calculated as follows: [27].

Precision:

$$P = \frac{TP}{TP+FP} * 100 \quad (6)$$

Recall:

$$\mathrm{R} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} * 100 \quad (7)$$

Average Precision:

$$\mathrm{A} = \int_0^1 \mathrm{P(r)dr} \quad (8)$$

mAP@0.5:

$$\mathrm{mAP} = \frac{1}{n}\sum_{t=1}^{n} API \quad (9)$$

F1 score:

$$\mathrm{F1} = 2\mathrm{x}\frac{\mathrm{PxR}}{\mathrm{P+R}} \quad (10)$$

where TP (True Positive): the number of correct detection of plowing appearance images, FP (False Positive): the number of wrong detection of plowing appearance images, FN (False Negative): the number of non-detection/missing of plowing appearance images, P: precision, R or r: recall.

On the other hand, the loss function was used to evaluate the performance [25]:

$$\mathrm{L_{bbox}} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}} \mathrm{IOU(pred_i, true_i)} \quad (11)$$

where L_{bbox}: bounding box loss, N: number of bounding frames, $pred_i$, and $true_i$: predicted and true frames, respectively.

$$L_{cls} = -\frac{1}{N}\sum_{i=1}^{N}(\log\ y_i(yi^\wedge) + (1-1)\log\ (y_i - yi^\wedge) \quad (12)$$

where L_{cls}: classification loss, yi: true value, yi^: predicted value.

$$L_{obj} = -\frac{1}{N}\sum_{i=1}^{N}(\log\ o_i(oi^\wedge) + (1-1)\log\ (o_i - oi^\wedge) \quad (13)$$

where L_{obj}: objectless loss, oi: the true value of the object's existence, oi^: expected value.

$$L = L_{bbox} + L_{cls} + L_{obj} \quad (14)$$

where L is the total loss function.

2.5 Statistical Analysis

The hypothesis that the experimental distributions of the measured traits across different operators conform to a normal distribution was tested using the Shapiro-Wilk test. This test was applied to assess the normality of the data for each trait. Levene’s test was subsequently used to evaluate the homogeneity of variances, under the condition that the data distribution was consistent with normality. Based on the results of these preliminary tests, parametric or non-parametric analyses were selected accordingly. Specifically, if a trait exhibited a normal distribution and homogeneity of variances, a one-way analysis of variance (ANOVA) was performed. Otherwise, the non-parametric Kruskal-Wallis test was applied. The purpose of these analyses was to determine whether statistically significant differences existed among the operators. All calculations were conducted using the SPSS software package at a significance level of α = 0.05.

3 Results and Discussion

Fuel consumption (*Fs*) under different operating factors was studied. Table 1 shows the important distribution parameters of the fuel consumption (l/ha).

Tab. 1. Distribution parameters of importance for fuel consumption (l/ha) (Processed research data, 2025)

Factors	N	Std. Deviation	Shapiro-Wilk Test		Levene's Test
			W	*P-value*	*P-value*
2.5 km/h	6	11.03	0.88	0.28	0.28
3.7 km/h	6	13.38	0.8	0.056	
18 cm	6	5.56	0.9	0.42	0.006
25 cm	6	11.16	0.68	0.004	

According to the results of the Shapiro-Wilk test to identify compliance with a normal distribution (Table 1), the next two hypotheses were formulated: the null hypothesis (H0), according to which data are normally distributed, and the alternative hypothesis (H1), according to which data are not normally distributed. As per the test result and significance level $p < 0.05$, the null hypothesis (H0) was always accepted if the p value was greater than this value, indicating that the data on the tillage speeds (2.5 and 3.7 km/h) and tillage depth of 18 cm were normally distributed. Conversely, the null hypothesis (H0) was not accepted in favor of the alternative hypothesis (H1) for the plowing depth at 25 cm because it indicated that the data distribution was not normal in this particular case. Additionally, a Levene test was conducted to check the homogeneity of variance across the groups. Between different tillage speeds, homogeneity of variance was observed, but heterogeneity of variance was observed between different tillage depths. Because the parametric test assumptions were not met, a non-parametric Kruskal-Wallis test was used to determine statistically significant differences between the groups, as shown in Table 2. Such practice reflects strict adherence to statistical rules to justify the reliability and validity of the analysis.

Table 2. Results of the significance of group differences in the fuel consumption analysis (l/ha) (Processed research data, 2025)

Factors	N	Mean Rank	*H*	*P-value*
2.5 km/h	6	5.58	0.82	0.36
3.7 km/h	6	7.42		
18 cm	6	4.17	5.36	0.02
25 cm	6	8.83		

The mean ranks presented in Table 2 confirm that fuel consumption increases with an increase in tillage depth and speed. For the variation in tillage depth, the p-value was found to be 0.02 at a 0.05 significance level, which shows that there is a statistically significant difference among the groups. Thus, the alternative hypothesis (H1) that variation in tillage depth significantly affects fuel consumption is verified. In relation to the variation in tillage speeds, the probability value (p) was found to be 0.36, which is above the 0.05 threshold, suggesting that there is no statistically significant difference among the groups. The alternative hypothesis (H1) is thus rejected, and the null hypothesis (H0) that there is no significant influence of variation in tillage speeds on fuel consumption is accepted.

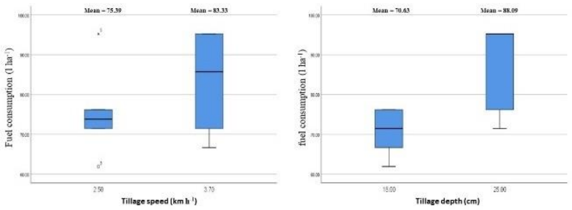


Fig. 4 Mean fuel consumption values at different operating parameters Source: created by the authors

Figure 4 shows that the mean fuel consumption at 2.5 km/h was 75.39 l/ha, while it was 83.33 l/ha at 3.7 km/h. Also, the fuel consumption at the 18-cm depth was 70.63 l/ha, and it was 88.09 l/ha at the 25-cm depth. Fuel consumption increases with increasing tillage speed and depth. Olosunde [11] found a linear relationship between tillage depth, speed, and fuel consumption.

On the other hand, fuel consumption is closely related to the power consumption of the mechanized unit. The speed and depth of tillage affect the power and fuel consumption, where increasing the speed and depth leads to an increase in the power and fuel consumption [10]. Table 3 shows the important distribution measures of the energy consumption (kW).

Tab. 3. Distribution parameters of importance for energy consumption (kW) (Processed research data, 2025)

Factors	N	Std. Deviation	Shapiro-Wilk Test		Levene's Test
			W	*P-value*	*P-value*
2.5 km/h	6	8.86	0.88	0.28	0.017
3.7 km/h	6	15.92	0.8	0.056	
18 cm	6	16.36	0.91	0.49	0.016
25 cm	6	27.2	078	0.04	

The Shapiro-Wilk test results presented in Table 3 attest that the W statistic for all of the variables signifies that the data are normally distributed. At a level of significance of $p < 0.05$, the p values calculated through observation confirmed that the distribution of traits with respect to the tillage speeds of 2.5 and 3.7 km/h, and depth of tillage 18 cm obeyed a pattern of normal distribution, thus enabling the null hypothesis (H0) to be accepted. On the contrary, the null hypothesis (H0) was rejected at a tillage depth of 25 cm because the distribution of the characteristic did not follow a normal distribution. Consequently, the alternative hypothesis (H1) was sustained. With regard to the Levene test, the p-value indicated an absence of homogeneity of variance across different groups that were differentiated based on tillage depth and velocity. The findings in Table 3 indicate that the conditions under which parametric tests can be applied were not fulfilled, thus the necessity to employ the non-parametric Kruskal-Wallis test to establish statistically significant differences among the groups, as indicated in Table 4.

Tab. 4. Results of the significance of group differences in energy consumption (kW) (Processed research data, 2025)

Factors	N	Mean Rank	*H*	*P-value*
2.5 km/h	6	3.9	8.48	0.004
3.7 km/h	6	9.5		
18 cm	6	5.33	1.28	0.25
25 cm	6	7.67		

From the mean rank values in Table 4, energy consumption increased with increasing tillage speed and depth. The probability value at $p<0.05$ for tillage speeds is 0.004, indicating a statistically significant difference; therefore, the alternative hypothesis H1 can be accepted. However, we reject the alternative hypothesis H1 at different tillage depths where the probability value is 0.25, indicating no statistically significant difference.

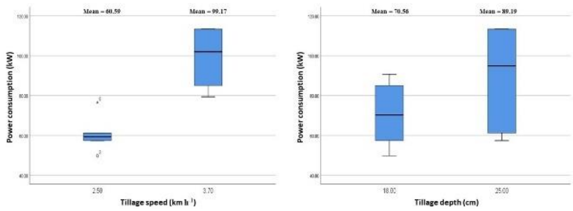


Fig. 5 Mean energy consumption values (kW) at different operating factors. Source: created by the authors

Figure 5 shows that the power consumption, on average, at the tillage speed of 2.5 km/h is 60.59 kW, while the average power consumption at the tillage speed of 3.7 km/h is 99.17 kW. Additionally, the power consumption at the tillage depth of 18 cm is 70.56 kW, while the power consumption at the tillage depth of 25 cm is 89.19 kW. The power consumption increases as the tillage speed and depth are increased.

Both the speed and depth of tillage also affect the volumetric distribution of the soil clods. Table 5 shows the important distribution parameters for the volumetric distribution of the soil clods (clods/m^2).

Tab. 5. Distribution parameters of importance for the volumetric distribution of soil clods (clods/m^2) (Processed research data, 2025)

Factors	N	Std. Deviation	Shapiro-Wilk Test		Levene's Test
			W	*P-value*	*P-value*
2.5 km/h	6	2.06	0.64	0.001	1
3.7 km/h	6	2.06	0.64	0.001	
18 cm	6	2.19	0.68	0.004	0.76
25 cm	6	3.01	0.86	0.21	

The Shapiro-Wilk test results in Table 5 indicate that the W statistics for all parameters support a normal distribution of the data. At the significance level of $p < 0.05$, the null hypothesis (H_0) of normality was retained for most conditions. However, H_0 was rejected at a tillage depth of 25 cm in favor of the alternative hypothesis (H_1), indicating a non-normal distribution under this condition. Similarly, non-normal distributions were observed at tillage speeds of 2.5 and 3.5 km/h and at a depth of 18 cm.

Levene's test was used to assess homogeneity of variances. Based on the p-values, the assumption of equal variances was satisfied across different tillage depths and speeds, indicating stable variance across experimental groups. As shown in Table 5, the key assumptions for parametric testing (normality and homogeneity of variances) were largely met, justifying the use of one-way ANOVA for most variables.

Nevertheless, to ensure methodological consistency and robustness, the non-parametric

Kruskal-Wallis test was applied across all conditions to assess the significance of group differences. This unified analytical approach enhances the reliability of the findings, particularly in cases where normality assumptions were marginally violated (Table 6).

Table 6. Results of the significance of group differences in analyzing the volumetric distribution of soil clods (clods/m^2) (Processed research data, 2025)

Factors	N	Mean Rank	*H*	*P-value*
2.5 km/h	6	8.83	5.98	0.01
3.7 km/h	6	4.17		
18 cm	6	5	2.47	0.11
25 cm	6	8		

According to the values of the mean rank in Table 6, tillage speed increased as the size distribution of the soil clods decreased, and tillage depth increased with the size distribution of the soil clods. The probability value of different tillage speeds at the $p<0.05$ level is 0.01, which indicates a statistically significant difference and, therefore, the alternative hypothesis H1 can be accepted. The probability value for all the tillage depths is 0.11, which is not statistically different; thus, we accept the null hypothesis H0.

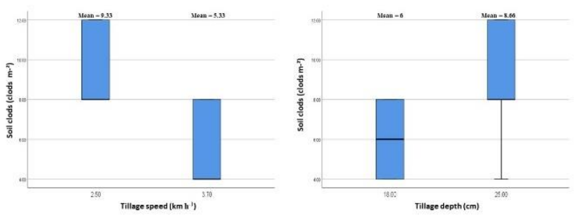


Fig. 6. Mean volume distribution values of soil clods (clods/m^2) at different operating factors. Source: created by the authors

Figure 6 shows the mean soil clod density (number of clods per square meter) under different tillage conditions. At a tillage speed of 2.5 km/h, the mean clod density was 9.33 clods/m^2, compared to 5.33 clods/m^2 at 3.5 km/h. For tillage depth, the clod density was 6.00 clods/m^2 at 18 cm and 8.66 clods/m^2 at 25 cm. These results indicate that soil clod density increases with greater tillage depth but decreases with higher tillage speed. This trend aligns with findings by Nassir [7], who reported that clod volume decreases with increasing tillage speed and increases with greater tillage depth.

Soil clod size distribution significantly affects tillage appearance. Reducing the size of soil clods leads to a finer, more uniform soil surface with fewer large aggregates, thereby improving seedbed quality [20]. The influence of soil clod diameter distribution on tillage appearance is illustrated in Figure 7.

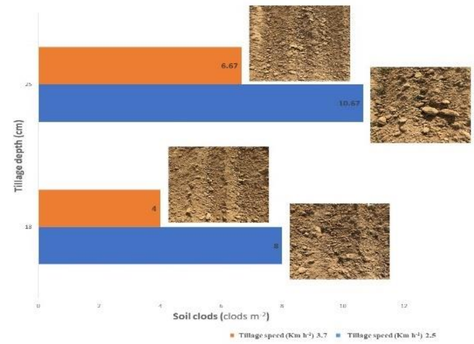


Fig. 7 Effect of the size distribution of soil clods on tillage appearance. Source: created by the authors

Following the plowing operations and field data collection, the raw image dataset was used to train the YOLOv7 model to distinguish between tilled soil with clods and soil with a fine, clod-free surface. Model performance during training is illustrated in Figure 8, which plots three key loss components: box loss, objective loss, and classification loss.

Box loss reflects the accuracy of the predicted bounding box coordinates, measuring the deviation between the predicted and ground-truth box location and size.

Objective loss indicates the model confidence in detecting the presence of an object within a grid cell; lower values suggest improved detection reliability.

Classification loss measures the model ability to correctly assign detected objects to their respective classes (e.g., “soil with clods” vs. “soil without clods”).

The decreasing trend in all three loss metrics across training epochs demonstrates that the model effectively learned to differentiate soil conditions, achieving high accuracy and convergence. Collectively, these metrics provide insight into the model efficiency and robustness in performing real-time soil surface classification for tillage quality assessment.

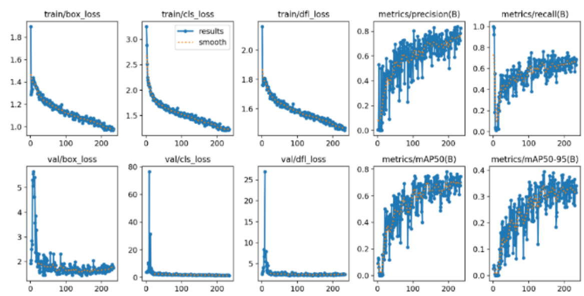


Fig. 8 YOLOv7 model results. Source: created by the authors

Based on the training values in the figure above, it can be said that the model performs well. It gives a recall value of 78.5% and a precision of 82%, while mAP@0.5 gives 77.4%; therefore, the F1 is estimated to be 80.2%. Also, the mAP@0.5 values for testing and validation were 75% and 78%, respectively. For better understanding, we have added a confusion matrix for the positive and negative results (Figure 9). The testing and validation errors are 4 and 3, respectively, which shows that the model has properly classified the look of the soil surface.

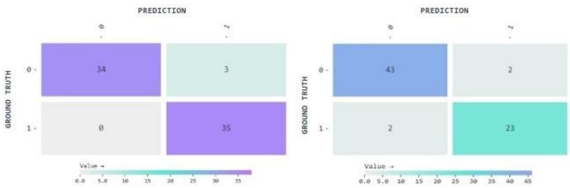
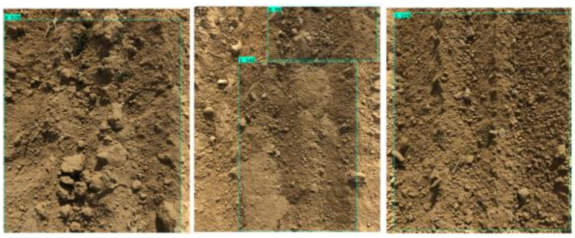


Fig. 9 Confusion matrix a. Test b. Validation. Source: created by the authors

The YOLOv7 model was unable to process higher-resolution images effectively, as soil clods and the surrounding ground often exhibit highly similar shapes, colors, and textures. This visual homogeneity increases the complexity of object detection and reduces the model ability to distinguish clods with high precision. Despite this challenge, the model achieved good accuracy in classifying overall tillage appearance, successfully differentiating between fine, well-tilled surfaces and those with excessive clodding. The classification results are presented in Figure 10, demonstrating the model effectiveness in assessing soil surface quality under real-world field conditions.



a b c

Fig. 10 Determination of the soil surface appearance using the Yolov7 model a. with soil clods b. mixed c. without soil clods. Source: created by the authors

4 Conclusions

The results indicate that increasing tillage speed and depth leads to higher power and fuel consumption, whereas reducing tillage depth and increasing speed results in smaller soil clod sizes and improved soil surface appearance. The YOLOv7 model demonstrated strong performance in classifying tillage quality and identifying clod-free surfaces, achieving a recall of 78.5%, precision of 82.0%, mAP@0.5 of 77.4%, and an F1-score of 80.2%. This study represents the first attempt to develop an image analysis-based method to assist farmers in selecting optimal plowing parameters.

The findings contribute to a practical framework that can be adopted by farmers and agricultural engineers to optimize tillage operations by adjusting plowing speed and depth based on real-time analysis of soil surface characteristics. The study advocates for the integration of AI technologies, such as the YOLOv7 model, as intelligent tools for automated, real-time monitoring of tillage quality. This approach reduces reliance on manual inspection, saves time and energy, and enhances fuel and energy efficiency.

Furthermore, these technologies provide actionable insights into optimal plow operation parameters, promoting favorable conditions for plant growth, increasing agricultural productivity, and reducing both environmental and economic costs of farming operations. For future research, it is recommended to expand the methodology to include additional environmental variables—such as soil type, moisture content, and texture—and to evaluate other AI models to validate and improve classification accuracy. The integration of remote sensing and drone-based imaging could also be explored to capture broader spatial data, further empowering farmers to make data-driven, sustainable agricultural decisions.

Author Contributions

Conceptualization, M.A.J.A., S.A.A., H.A.H. and Ł.G.; methodology, M.A.J.A., S.A.A., H.A.H., Ł.G. and Z.A.A.; software, M.A.J.A.; validation, S.A.A., H.A.H. and Ł.G.; formal analysis, M.A.J.A. and Ł.G.; investigation, S.A.A. and Z.A.A.; resources, M.A.J.A., S.A.A., H.A.H. and Z.A.A.; data curation, M.A.J.A.; visualization, M.A.J.A., S.A.A., H.A.H. and Ł.G.; writing—original draft preparation, both authors contributed equally; writing—review and editing, M.A.J.A. and Ł.G.; supervision, M.A.J.A. and Ł.G.; project administration, M.A.J.A. and Ł.G.. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Declaration

The authors have no affiliations with or involvement in any organization or entity with any financial interest in the subject matter or material of this manuscript.

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