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A MACHINE VISION SYSTEM FOR QUALITY-BASED GRAIN CLASSIFICATION USING MACHINE LEARNING

This Grain quality control directly affects the efficiency of grain processing, the stability of product parameters, and the economic outcomes of storage and cleaning operations. In industrial practice, visual inspection and manual sampling remain widespread, yet these approaches are time-consuming and sensitive to human subjectivity, especially when large grain volumes must be assessed continuously. This study addresses the need for an automated, objective, and scalable solution for grain quality classification that can operate in real time under conveyor-based conditions.

The purpose of the research is to develop and experimentally validate a machine vision system that classifies grain by quality and supports operational decisions for fractional separation and cleaning. The work focuses on achieving reliable defect recognition while maintaining processing speed suitable for production environments. The research tasks include designing an image acquisition setup, forming a labeled dataset of grain images, implementing supervised classification models, and evaluating both classification accuracy and computational performance.

An experimental test stand was built to simulate conveyor transportation of grain, enabling controlled variation of belt speed and illumination conditions. A dataset of wheat, corn, and barley was formed using laboratory image capture, followed by manual labeling into three quality categories based on visible defects and damage severity. Image preprocessing and augmentation were applied to increase variability in orientation and photometric conditions and to improve model robustness. Two machine learning approaches were implemented for comparative evaluation: a deep learning image classifier and a kernel-based classifier using handcrafted visual descriptors. Performance was assessed using overall classification accuracy, confusion-matrix-based error analysis, and average processing time per image across different conveyor speeds.

The experimental evaluation demonstrates that the deep learning approach achieves higher classification accuracy on test data, while the kernel-based classifier provides faster inference with a moderate reduction in accuracy. Error analysis shows that the most frequent misclassifications occur between adjacent quality categories, indicating the importance of borderline-class data coverage and improved labeling consistency. The obtained processing time per image indicates that the proposed system can support real-time operation for moderate grain flow rates, with acceptable performance degradation at higher conveyor speeds due to motion-related image distortions.

The scientific novelty of the work lies in the integrated experimental assessment of quality-based grain classification under controlled conveyor conditions with simultaneous consideration of accuracy and throughput. The practical significance is the feasibility of deploying the system as a component of automated grain cleaning and separation lines, enabling consistent quality monitoring and decision support for industrial processing.

Keywords: *Machine vision, grain classification, machine learning, support vector machine, image processing, grain sorting.*

Formulation of the problem. In the grain-processing industry, grain quality is one of the key factors influencing profitability and the competitiveness of products [1]. To ensure high quality, continuous monitoring of grain characteristics such as shape, size, color, and the presence of damage or foreign impurities is necessary [2]. Traditional methods of quality assessment (for example, manual sampling and visual analysis) are relatively subjective and labor-intensive, making them less suitable for large volumes of grain in industrial-scale operations.

Modern machine vision technologies make it possible to automate the process of detecting defects in grains and to classify individual grains according to various characteristics [3]. At the same time, the use of machine learning algorithms (in particular deep learning) offers the potential to increase classification accuracy and to adapt the system to new conditions or types of grain crops [4]. In this study, we propose integrating a machine vision system with machine learning algorithms to automate the fractional separation and cleaning of grain, which will help improve the final product's physico-mechanical properties.

Analysis of recent research and publications. Automated grain quality assessment has been a focal point of agricultural research for over a decade, evolving from simple statistical models to complex autonomous systems. Comprehensive surveys of the field highlight that computer vision-based classification has become the gold standard for ensuring food security and processing efficiency [1]. Recent advancements have specifically emphasized the integration of hyperspectral imaging with deep learning, allowing for multiscale sensing that goes beyond human visual capabilities [2].

The evolution of object detection algorithms has significantly impacted the speed and accuracy of grain analysis. Improved versions of real-time detection frameworks, such as YOLOv5, have demonstrated high efficiency in identifying wheat grain quality [3], while similar deep learning architectures have been successfully adapted for the classification of various soybean seeds [4]. For more specialized tasks, such as detecting damage in milled rice, researchers have utilized high-magnification datasets combined with deep convolutional neural networks (CNNs) to achieve superior granularity in classification [5]. These methods are not limited to rice; they have also proven effective for the fast classification of barley grains, showing the versatility of CNN-based approaches across different crop types [6].

Beyond simple classification, predicting specific quality parameters like the breakage rate of kernels remains a critical industrial challenge. Recent studies have combined machine vision with diverse machine learning algorithms to predict maize kernel damage with high precision [7]. To handle complex scenes where grains may overlap or vary significantly in orientation, region proposal-based CNNs have been introduced to improve localization and classification accuracy [8]. This progress is further supported by high-throughput phenotyping methods that leverage transfer learning to adapt models to specific seed characteristics with minimal retraining [9].

Digital imaging has also opened new avenues for comprehensive quality assessment, particularly in rice production, where deep learning helps evaluate various quality indices simultaneously [10]. This includes the detection of specific biological threats, such as mildew, which is now possible using optimized convolutional networks [11]. For specialized crops, such as colored rice, custom inspection systems have been developed to account for unique spectral and morphological features [12]. Furthermore, cognitive spectroscopy has emerged as a powerful tool for variety classification, offering a non-destructive alternative to chemical analysis [13].

A significant bottleneck in industrial application is the analysis of bulk grain. Researchers have addressed this by implementing deep learning segmentation techniques that can process images of grain masses to predict overall market quality [14]. The reliability of these models depends heavily on the availability of high-quality data; hence, the creation of annotated kernel image databases has become a fundamental contribution to the research community [15]. These resources allow for a more nuanced understanding of the frontiers of grain analysis, particularly in the context of grading and quality standardization [16].

Innovative training strategies have also been explored to overcome the scarcity of labeled industrial data. For instance, the use of synthetic datasets to train instance segmentation networks has shown promise in crop seed phenotyping [17]. In practical harvesting scenarios, real-time sensing of impurities using decision-tree algorithms and image processing has been integrated into combine harvesters to provide immediate feedback [18]. For processing lines, online detection technologies for broken kernels have been developed to maintain high throughput without sacrificing accuracy [19].

Recent trends focus on making these systems more efficient and deployable. Lightweight models, such as improved versions of YOLOv8, offer a balance between detection speed and resource consumption, which is vital for edge computing in silos

[19]. Advanced hyperspectral analysis continues to push the boundaries of what can be detected, offering deeper insights into the internal properties of wheat crops [17-19]. These technologies are now being integrated into specific machine vision systems designed for grain separation, ensuring that quality control happens dynamically during the cleaning process.

In this context, the present work contributes by experimentally evaluating a machine vision system that combines CNN and SVM approaches under controlled conveyor-based conditions, with particular emphasis on accuracy, processing speed, and industrial applicability.

Task statement. The purpose of this paper is to develop and experimentally validate a machine vision system enhanced by advanced machine learning methods for real-time grain quality classification, with a focus on high-accuracy defect detection, efficient processing speed, and scalability for industrial use.

Our objectives include:

1) To develop a prototype of a machine vision system capable of accurately detecting defective grains and grains of different quality categories.

2) To compare the effectiveness of various machine learning algorithms (primarily convolutional neural networks (CNN), and support vector machine (SVM).

3) To assess the performance speed of the prototype system and its potential scalability to real industrial environments.

Research methodology. The research methodology employs an experimental approach that integrates machine vision techniques with supervised machine learning algorithms for the classification of grain quality. The objective is to evaluate the feasibility of automated grain quality assessment under conditions that closely simulate real industrial conveyor-based processing.

The proposed methodology consists of four main stages:

1) construction of an experimental image acquisition setup;

2) formation and preprocessing of a labeled image dataset;

3) implementation and training of machine learning models (CNN and SVM);

4) evaluation of classification accuracy and processing speed.

To simulate industrial grain transportation conditions, a laboratory test stand with a conveyor belt was developed. The stand enables the controlled acquisition of images of grains in motion. The hardware configuration includes:

Illumination System: LED light sources providing uniform illumination with a color temperature of 5000 K to minimize shadows and highlights.

Image Acquisition: An industrial CMOS camera with a resolution of 1920 × 1080 pixels, capturing frames at 60 FPS.

Computing Platform: A workstation equipped with an NVIDIA RTX 2060 GPU (6 GB VRAM), an Intel Core i7-10700 processor, and 16 GB of RAM. Software implementation was performed using Python with TensorFlow and OpenCV libraries.

The conveyor belt speed was adjustable from 0.1 to 0.5 m/s, allowing the assessment of motion blur effects on classification accuracy.

A dedicated image dataset was created for three grain crops: wheat, corn, and barley. A total of 5,000 original images were captured. Grains were manually categorized by experts into three quality classes:

1) high quality: Intact grains without visible defects;

2) Medium quality: Grains with minor mechanical damage or slight discoloration;

3) Low quality: Grains with significant defects, including cracks, mold, or foreign impurities.

To enhance the model's ability to generalize, data augmentation was applied (rotation ±15°, horizontal/vertical flips, and brightness adjustment). This expanded the dataset to 15,000 images, partitioned into training (70%), validation (15%), and test (15%) sets. All images were resized to 128 × 128 pixels to standardize the input for the neural network.

A dedicated image dataset was created for training and evaluating machine learning models. The dataset includes images of three grain crops: wheat, corn, and barley, collected under controlled laboratory conditions.

Approximately 5,000 original images (Fig. 1) were acquired, with roughly equal representation of each crop. During image acquisition, grains were manually categorized into three quality classes:

1) high quality: intact grains without visible defects;

2) medium quality: grains with minor damage or slight discoloration;

3) low quality: grains with significant defects, including cracks, mold, or foreign inclusions.

Fig. 1. Example grain image

Each image was manually labeled according to its quality class. In cases where multiple grains appeared in a single frame, image segmentation methods (thresholding and contour detection) were applied to extract individual grain images.

To increase dataset diversity and improve model generalization, data augmentation techniques were applied, including rotation within the range of -15° to +15°, horizontal and vertical flipping, and random adjustments of brightness and contrast. After augmentation, the final dataset contained approximately 15,000 grain images, which were divided into training (70%), validation (15%), and test (15%) subsets.

To classify grain quality, two machine learning approaches were implemented and compared: a convolutional neural network (CNN) and a support vector machine (SVM).

Convolutional Neural Network. The CNN architecture was designed to strike a balance between classification accuracy and computational efficiency. The input images were resized to 128 × 128 pixels and normalized before training. The network consists of three convolutional layers with 3 × 3 kernels and 32, 64, and 128 feature maps, respectively. Each convolutional layer is followed by a 2 × 2 max-pooling layer. The extracted features are processed by two fully connected layers with 256 and 64 neurons, followed by a final output layer with three neurons corresponding to the three quality classes.

ReLU activation functions were used in hidden layers, while Softmax activation was applied in the output layer. Model training was performed using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss. The network was trained for 50 epochs with a batch size of 32.

Support Vector Machine. For comparison, an SVM classifier with a radial basis function (RBF) kernel was implemented. Feature vectors were extracted from grain images using classical computer vision descriptors, including Histogram of Oriented Gradients (HOG), color histograms, and Local Binary Patterns (LBP).

The SVM hyperparameters were selected empirically: the regularization parameter was set to C = 1, and the kernel parameter was set to $\gamma = 0.01$.

Other classification methods, such as Random Forest and k-nearest neighbors (k-NN), were tested preliminarily; however, the primary analysis focuses on CNN and SVM due to their widespread use in image-based classification tasks.

Evaluation Metrics

Model performance was evaluated using quantitative metrics relevant to both classification accuracy and real-time processing requirements (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \quad (1)$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

In addition, confusion matrices were used to analyze misclassification patterns between adjacent quality classes. Processing speed was measured as the average time required to process a single image (or individual grain) at different conveyor speeds, providing an estimate of system throughput under real-time conditions.

Research results. To assess the effectiveness of the proposed machine vision system, the convolutional neural network was trained and evaluated on the constructed grain image dataset. The objective was to classify grains into three quality categories (high, medium, and low) based on visual characteristics.

The dataset consisted of approximately 15,000 grain images after augmentation and was divided into training (70%), validation (15%), and test (15%) subsets. During training, model parameters were updated using backpropagation on the training set, while validation data were used to monitor generalization performance and detect overfitting.

The CNN was trained for 50 epochs using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. Classification accuracy and loss were monitored simultaneously on the training and validation sets.

Fig. 2 illustrates the evolution of training and validation accuracy over the training epochs. The results show a rapid increase in accuracy during the first 15-20 epochs, followed by gradual convergence. Training accuracy increased from approximately 70% to 95-96%, while validation accuracy stabilized at approximately 92-93%. After 30–40 epochs, both curves exhibited saturation behavior, indicating that the model had converged.

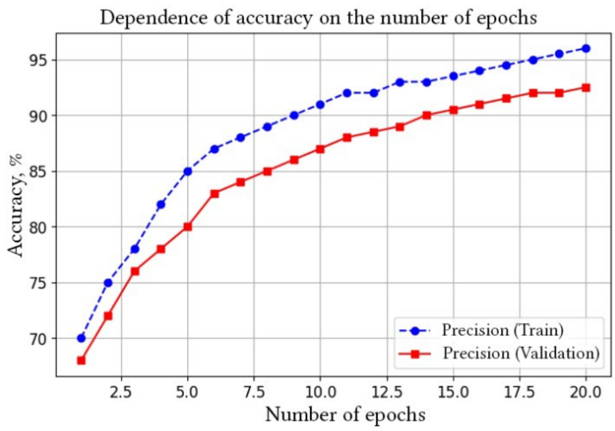

Fig. 2. Example chart of training accuracy (blue curve) and validation accuracy (red curve) vs. the number of epochs, illustrative data

Comparative Analysis of Classification Accuracy and Processing Speed. To evaluate the trade-off between classification accuracy and computational efficiency, the performance of the CNN was compared with that of a support vector machine using an RBF kernel. The evaluation was conducted on the independent test set comprising approximately 2,250 grain images.

The comparative results are summarized in Table 1.

Table 1

Comparison of accuracy and average processing time per image

Algorithm	Configuration	Accuracy (%)	Average processing time (ms)
CNN	3 conv layers, LR=0.001	93.8	5.8
SVM (RBF)	C = 1, γ = 0.01	91.2	2.2

The CNN achieved higher classification accuracy (93.8%) compared to the SVM (91.2%), confirming the effectiveness of deep learning for visual grain quality assessment. However, this improvement in accuracy comes at the cost of increased processing time. On average, the CNN required approximately 5.8 ms per image, while the SVM processed images in approximately 2.2 ms.

Despite the higher computational cost, the CNN processing time remains acceptable for conveyor systems with moderate grain flow rates, where real-time operation typically allows several milliseconds per grain.

Error Analysis Using a Confusion Matrix. To gain deeper insight into classification performance beyond overall accuracy, a confusion matrix was analyzed for the CNN model. This approach enables the identification of systematic misclassifications between quality categories. When classifying grain into three quality categories (labelled "High," "Medium," and "Low"), it is essential not only to measure overall accuracy but also to understand which classes the model confuses most frequently. For this purpose, a confusion matrix is typically used.

Purpose of the Confusion Matrix. A confusion matrix is an N×N matrix, where N is the number of classes. Here N=3. The element CM[i,j] indicates the number of samples that actually belong to class i but were predicted by the model to belong to class j. With this, one can:

- easily spot the most frequent sources of errors (for example, if "High" quality grains are often misclassified as "Medium");
- measure classification accuracy for each class individually (rather than a single overall percentage);
- plan how to improve the model - by collecting additional data or adjusting hyperparameters - if certain classes "underperform."

Below is an example code snippet that illustrates building a confusion matrix (Fig. 3)

We obtained the following confusion matrix (Table 2):

Table 2

Confusion Matrix for three grain quality classes

	Predicted High	Predicted Medium	Predicted Low
Actual High	700	25	8
Actual Medium	40	610	35
Actual Low	15	30	787

The results indicate that grains of high quality are most often confused with medium-quality grains, while low-quality grains are classified with higher reliability. Specifically, 700 high-quality samples

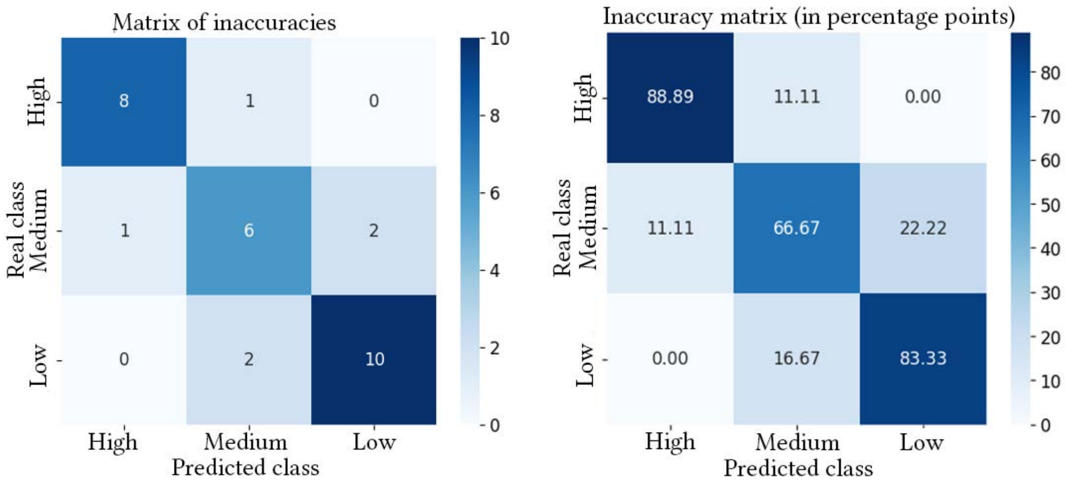

Fig. 3. Confusion Matrix for three grain quality classes

were correctly identified, with a limited number misclassified as medium (25 cases) or low quality (8 cases). Medium-quality grains exhibited the highest confusion rate, particularly with high-quality grains (40 cases) and low-quality grains (35 cases). Low-quality grains showed the best classification performance, with 787 correct predictions.

The observed confusion between high and medium quality categories reflects the presence of subtle defects that are visually indistinguishable. In contrast, low-quality grains typically exhibit pronounced defects such as cracks or mold, which are more easily detected by the model.

System Throughput at Different Conveyor Speeds. Additional experiments were conducted to evaluate the robustness of the classification system under varying conveyor speeds. The goal was to assess how increased grain velocity affects both classification accuracy and processing throughput. The results are presented in Table 3.

As conveyor speed increases, a gradual decrease in classification accuracy is observed for both models. This effect is primarily attributed to reduced exposure time and an increased likelihood of motion blur. Nevertheless, even at the highest tested speed of 0.5 m/s, the CNN maintained accuracy above 92%, demonstrating robustness suitable for many industrial grain processing applications.

The experimental results demonstrate that convolutional neural networks provide superior classification accuracy for grain quality assessment compared to classical machine learning approaches, while still meeting real-time processing requirements under typical conveyor conditions. Although the SVM offers faster processing, its lower accuracy may limit its applicability in scenarios where precise defect detection is critical.

The confusion matrix analysis reveals that the most challenging classification task is distinguishing between high- and medium-quality grains, indicating that further improvements could be achieved through enhanced data augmentation, refined labeling of borderline cases, or the use of more advanced CNN architectures.

Overall, the results confirm the feasibility of deploying the proposed machine vision system for automated grain quality classification in conveyor-based industrial environments.

Conclusions. The experimental results confirm that convolutional neural networks provide high classification accuracy for grain quality assessment, but at the cost of increased computational complexity. In contrast, the support vector machine approach demonstrates significantly lower computational requirements and faster processing, although its classification accuracy is approximately 2–3% lower than that of the CNN.

The choice of a classification model should therefore be determined by specific operational constraints. In scenarios where classification accuracy is critical and sufficient computational resources (e.g., a GPU) are available, CNN-based solutions are preferable. Conversely, for small- and medium-scale operations with limited hardware capabilities or for applications requiring extremely high throughput, SVM-based or hybrid approaches may offer a more practical compromise between speed and accuracy.

The quality of the training data plays a decisive role in classification performance. In the present study, dataset labeling relied on a combination of manual sorting and automated segmentation, which may introduce labeling inaccuracies, particularly for borderline quality classes. Increasing the diversity of training data - by incorporating images captured under different lighting conditions, conveyor speeds, and grain varieties - could further improve model robustness.

An important practical aspect is integrating the proposed machine vision system into a fully automated grain processing line. Such integration requires synchronization with conveyor speed sensors, mechanisms for removing nonconforming grain, and feedback loops for adjusting sorting and cleaning parameters. Addressing these system-level challenges is essential for successful industrial deployment.

Based on the conducted experimental study, the following conclusions can be drawn:

The proposed convolutional neural network achieved classification accuracy exceeding 93% on the test dataset, demonstrating the feasibility of automated separation of high-, medium-, and low-quality grains using machine vision techniques.

Table 3

Dependence of accuracy and average processing time on conveyor speed

Conveyor Speed (m/s)	CNN (Accuracy, %)	SVM (Accuracy, %)	Grains per second	Throughput (grains/s)*
0.1	94.1	91.5	100	~100 (CNN), ~250 (SVM)
0.3	93.2	90.1	300	~280 (CNN), ~450 (SVM)*
0.5	92.5	88.7	500	~420 (CNN), ~500 (SVM)*

**Throughput values depend on hardware configuration and GPU parallelization capabilities.*

The support vector machine provides significantly faster processing, but with a reduction in classification accuracy of approximately 2-3% compared to the CNN. This highlights a clear trade-off between accuracy and computational efficiency.

Classification performance is strongly influenced by imaging conditions, particularly illumination quality and conveyor speed. Under more demanding operating conditions, advanced data augmentation techniques and high-speed imaging become critical to maintaining reliable performance.

With high classification accuracy and acceptable processing throughput, the proposed system is suitable for implementation in grain elevators, processing plants, and agricultural enterprises. The approach can be extended to additional grain types and integrated more deeply into automated sorting lines.

Future research will focus on developing a comprehensive control system for fractional grain separation, utilizing machine vision outputs to regulate conveyor speed, grain flow direction, and cleaning mechanisms (e.g., sieves and air channels). Further work will also address system scalability for higher throughput and the automatic detection of specific defect types, such as mold or insect damage.

Bibliography:

1. Velesaca H. O., Suárez A., Mira J., Sappa, A. Computer vision based food grain classification: A comprehensive survey. *Computers and Electronics in Agriculture*. 2021; 190: 106287. DOI: https://doi.org/10.1016/j.compag.2021.106287.

2. Shuai L., Chen H., Luo S. A research review on deep learning combined with hyperspectral imaging in multiscale agricultural sensing. *Computers and Electronics in Agriculture*. 2024; 217: 108577. DOI: https://doi.org/10.1016/j.compag.2023.108577.

3. Zhao W., Liu S., Li X., Han X., Yang H. Fast and accurate wheat grain quality detection based on improved YOLOv5. *Computers and Electronics in Agriculture*. 2022; 202: 107426 DOI: https://doi.org/10.1016/j.compag.2022.107426

4. Huang Z., Wang R., Cao Y. Deep learning based soybean seed classification. *Computers and Electronics in Agriculture*. 2022; 202: 107393. DOI: https://doi.org/10.1016/j.compag.2022.107393.

5. Moses K., Miglani A., Kankar, P. K. Deep CNN-based damage classification of milled rice grains using a high-magnification image dataset. *Computers and Electronics in Agriculture*. 2022; 195: 106811. DOI: https://doi.org/10.1016/j.compag.2022.106811.

6. Shah S. A. Automatic and fast classification of barley grains from images: A deep learning approach. *Smart Agricultural Technology*. 2022; 2: 100036. DOI: https://doi.org/10.1016/j.atech.2022.100036

7. Fan C., Wang W., Cui T., Liu Y., Qiao M. Maize Kernel Broken Rate Prediction Using Machine Vision and Machine Learning Algorithms. *Foods.* 2024; 13(24): 4044 DOI: https://doi.org/10.3390/foods13244044.

8. Aukkapinyo K., Sawangwong S., Pooyoi P., Kusakunniran W. Localization and Classification of Rice-grain Images Using Region Proposals-based Convolutional Neural Network. *International Journal of Automation and Computing*. 2020; 17(2). Pp: 233–246. DOI: https://doi.org/10.1007/s11633-019-1207-6

9. Yang S., Zheng L., He P. et al. High-throughput soybean seeds phenotyping with convolutional neural networks and transfer learning. *Plant Methods*. 2021; 17: 50. DOI: https://doi.org/10.1186/s13007-021-00749-y.

10. Kurade M. B. A Digital Imaging and Deep Learning-Based Approach for Rice Quality Assessment. *Foods*. 2023; 12(6): 1273. DOI: https://doi.org/10.3390/foods12061273.

11. Chen S., Xiong J., Guo W., Bu R., Yang Z., Zheng Z., Lin R. Colored rice quality inspection system using machine vision. *Journal of Cereal Science*. 2019; 88. Pp:87–95. DOI: https://doi.org/10.1016/j.jcs.2019.05.010.

12. Onmankhong K., Ma T., Inagaki T., Sirisomboon P., Tsuchikawa S. Cognitive spectroscopy for classification of rice varieties. *Infrared Physics & Technology*. 2022; 123: 104100. DOI: https://doi.org/10.1016/j.infrared.2022.104100.

13. Ashtiani S. H. M., Walker A., Panozzo J. Deep learning segmentation in bulk grain images for prediction of grain market quality. *Food and Bioprocess Technology*. 2022; 15: 114–128. DOI: https://doi.org/10.1007/s11947-022-02840-1.

14. Lin Y., Fan J., et al. An annotated grain kernel image database for classification and detection. *Scientific Data.* 2023; 10: 642. DOI: https://doi.org/10.1038/s41597-023-02660-8.

15. Ahmed S. B., Ali S. F., Khan A. Z. On the frontiers of rice grain analysis, classification and quality grading: A review. *IEEE Access*. 2021; 9. Pp:160779–160796. DOI: https://doi.org/10.1109/ACCESS.2021.3130472.

16. Toda Y., Okura F., Ito J. et al. Training instance segmentation neural network with synthetic datasets for crop seed phenotyping. *Commun Biol* 3, 173 (2020). https://doi.org/10.1038/s42003-020-0905-5.

17. Chen J., Lian Y., Li Y. Real-time grain impurity sensing for rice combine harvesters using image processing and decision-tree algorithm. *Computers and Electronics in Agriculture*. 2020; 175: 105591. DOI: https://doi.org/10.1016/j.compag.2020.105591.

18. Zidi F., Ouafi A., Bougourzi F., Distante C., Taleb-Ahmed, A. "Advancing wheat crop analysis: A survey of deep learning approaches using hyperspectral imaging". arXiv preprint. 2025; arXiv:2505.00805. DOI: https://doi.org/10.48550/arXiv.2505.00805.

19. Stepanenko S., Kuzmych A., Kharchenko S., Borys A., Dnes V., Volyk D., Kalinichenko R. A machine vision approach for grain quality control during separation. *Journal of Engineering Sciences*, Vol. 12(1), pp. E9–E17. https://doi.org/10.21272/jes.2025.12(1).e2

Кузнєцов Д.І., Музика І.О., Іващенко О.Р. СИСТЕМА МАШИННОГО ЗОРУ ДЛЯ КЛАСИФІКАЦІЇ ЗЕРНА ЗА ЯКІСТЮ З ВИКОРИСТАННЯМ МАШИННОГО НАВЧАННЯ

Контроль якості зерна безпосередньо впливає на ефективність його переробки, стабільність параметрів продукції та економічні показники операцій зберігання й очищення. У промисловій практиці досі широко застосовуються візуальний контроль і ручний відбір проб, однак ці підходи є трудомісткими та чутливими до суб'єктивного людського фактору, особливо за необхідності безперервної оцінки великих обсягів зерна. У даному дослідженні розглядається потреба в автоматизованому, об'єктивному та масштабованому рішенні для класифікації якості зерна, здатному працювати в режимі реального часу в умовах конвеєрного транспортування. Метою роботи є розробка та експериментальна валідація системи машинного зору для класифікації зерна за якістю та підтримки оперативних рішень щодо фракційного розділення й очищення. Основна увага приділяється досягненню надійного розпізнавання дефектів за збереження швидкодії, придатної для виробничих умов. До завдань дослідження належать проєктування системи отримання зображень, формування розміченого набору зображень зерна, реалізація моделей керованого навчання та оцінювання точності класифікації й обчислювальної ефективності. Для імітації конвеєрного транспортування зерна було створено експериментальний стенд, що забезпечує контрольовану зміну швидкості стрічки та умов освітлення. Набір даних пшениці, кукурудзи та ячменю сформовано на основі лабораторного отримання зображень із подальшою ручною розміткою за трьома категоріями якості відповідно до видимих дефектів і ступеня пошкодження. Для підвищення стійкості моделей застосовано попередню обробку зображень та аугментацію з метою збільшення варіативності орієнтації та фотометричних умов. Для порівняльного аналізу реалізовано два підходи машинного навчання: класифікатор зображень на основі глибокого навчання та ядерний класифікатор із використанням ручних візуальних дескрипторів. Оцінювання проводилось за показниками загальної точності класифікації, аналізу помилок на основі матриці невідповідностей та середнього часу обробки одного зображення за різних швидкостей конвеєра. Результати експериментальних досліджень показують, що підхід на основі глибокого навчання забезпечує вищу точність класифікації на тестових даних, тоді як ядерний класифікатор демонструє швидшу інференцію за помірного зниження точності. Аналіз помилок свідчить, що найбільш часті хибні класифікації виникають між суміжними категоріями якості, що вказує на важливість кращого охоплення прикордонних класів і підвищення узгодженості розмітки. Отримані значення часу обробки одного зображення підтверджують можливість роботи системи в режимі реального часу за помірних потоків зерна, при допустимому зниженні продуктивності на вищих швидкостях конвеєра через спотворення зображень, спричинені рухом. Наукова новизна роботи полягає в комплексній експериментальній оцінці класифікації зерна за якістю в контрольованих конвеєрних умовах із одночасним урахуванням точності та пропускної здатності. Практична значущість полягає в можливості впровадження запропонованої системи як складової автоматизованих ліній очищення та сепарації зерна, що забезпечує стабільний контроль якості та підтримку прийняття рішень у промисловій переробці.

Ключові слова: *машинний зір, класифікація зерна, машинне навчання, метод опорних векторів, обробка зображень, сортування зерна.*

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