DOI: https://doi.org/10.15276/aait.09.2026.02
UDC 378.147:004.6:331.5

A machine vision system for real-time grain quality classification using machine learning

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ABSTRACT

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. 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 and manual labeling into three quality classes based on visible defects and damage severity. Image preprocessing and augmentation were applied to increase variability and improve robustness. Two supervised approaches were implemented for comparative evaluation: a deep learning image classifier and a kernel-based classifier using handcrafted visual descriptors. The experimental results demonstrate that the deep learning approach achieves higher classification accuracy, while the kernel-based classifier provides faster inference with a moderate reduction in accuracy. The most frequent misclassifications occur between adjacent quality categories, indicating the importance of borderline-class coverage and labeling consistency. Processing time measurements confirm the feasibility of real-time operation for moderate grain flow rates, with performance degradation at higher conveyor speeds due to motion-related image distortions. The scientific novelty lies in the integrated experimental assessment of classification accuracy and throughput under controlled conveyor conditions. The practical significance is the feasibility of deploying the system as a component of automated grain cleaning and separation lines.

Keywords: Machine vision; grain classification; machine learning; support vector machine; image processing; grain sorting

For citation: **Kuznietsov D. I., Muzyka I. O., Ivashchenko O. R. "A machine vision system for real-time grain quality classification using machine learning".** ***Applied Aspects of Information Technology*****. 2026; Vol.9 No.1: 25–36. DOI: https://doi.org/10.15276/aait.09.2026.02**

INTRODUCTION

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.

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.

RELATED WORKS

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 [20]. Advanced hyperspectral analysis continues to push the boundaries of what can be detected, offering deeper insights into the internal properties of wheat crops [21]. 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 [22].

Methodologically, the field continues to weigh the benefits of different approaches. Comparative analyses between traditional machine learning and deep learning show that while CNNs often lead in accuracy; traditional methods still offer advantages in terms of interpretability and lower computational overhead [23]. To further refine performance, specialized architectures like GC_DRNet have been proposed for variety recognition [24]. Finally, the move toward quantized neural networks represents the latest stage in this evolution, enabling efficient, high-speed classification on industrial hardware with limited memory resources [25].

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

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.

Experimental Setup

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.

Dataset Overview

A dedicated image dataset was created for training and evaluating machine learning models for grain quality classification. 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. To ensure representativeness across grain crops and quality categories, the dataset was formed with approximately equal representation of the three grain types (wheat, corn, barley). Each image sample was manually assigned to one of three quality classes (High, Medium, Low) based on visible defect severity criteria described above. The final dataset composition before augmentation is summarized in Table 1.

Table 1. **Distribution of the original dataset by crop type and quality class (before augmentation)**

Crop type	High quality	Medium quality	Low quality	Total
Wheat	520	600	520	1,640
Corn	510	620	530	1,660
Barley	495	625	580	1,700
Total	1,525	1,845	1,630	5,000

***Source*: compiled by the authors**

Fig 1. **Example grain image**
***Source*: compiled by the authors**

The maximum class ratio in the original dataset was approximately 1:1.2 (High vs Medium), which we treat as moderate imbalance.

After augmentation (rotation, flipping, brightness/contrast changes applied only to the training set), the total number of samples increased to approximately 15,000 images. This distribution reflects realistic industrial conditions, where Medium-quality samples tend to dominate due to minor mechanical damage or slight discoloration being more frequent than severe defects.

A moderate class imbalance was observed due to naturally lower occurrence of heavily defective grain samples during acquisition. To compensate for this imbalance during model training, class weights were applied in the CNN loss function, and stratified sampling was used when splitting the dataset into training, validation, and test subsets to preserve class proportions across all partitions.

During image acquisition, grains were manually categorized by experts into three quality classes based on visible defects:

1) high quality: intact grains without visible defects;

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

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

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.

In cases where multiple grains appeared in a single frame, segmentation was performed using intensity thresholding and contour detection to isolate each grain, followed by cropping into individual samples. When grains overlapped or were in close contact, segmentation errors such as merged contours or incomplete boundaries could occur. These cases were treated as a potential source of classification error because incorrect boundaries reduce the visibility of fine surface defects and alter shape descriptors. To reduce this impact, segmented objects were filtered using geometric constraints (area, aspect ratio), and images with ambiguous or strongly overlapping grains were excluded during dataset preparation. As a result, segmentation-related artifacts were minimized and were not the dominant source of classification error compared to borderline class similarity.

To increase dataset diversity and improve model generalization, data augmentation techniques were applied, including rotation within −15° to +15°, horizontal and vertical flipping, and random adjustments of brightness and contrast. After augmentation, the dataset size increased to approximately 15,000 grain images.

To prevent data leakage, dataset splitting was performed before augmentation at the level of source frames. All segmented grains originating from the same captured frame were assigned to the same subset (training, validation, or test). Augmentation was applied only to the training set, while validation and test subsets contained non-augmented samples. The final dataset was divided into training (70%), validation (15%), and test (15%) subsets using stratified sampling to preserve class distribution across subsets. All images were resized to 128 × 128 pixels to standardize CNN input.

Minor deviations in class frequencies were observed during labeling; therefore, class weights were applied during CNN training to minimize potential bias and improve learning stability.

Machine Learning Models

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).

ISSN 2617-4316 (Print)
ISSN 2663-7723 (Online)

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

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.

In addition to overall accuracy, model performance was evaluated using precision, recall, and F1-score computed for each quality class. To provide robust aggregated estimates across the three classes, macro-averaged and weighted-averaged F1 scores were calculated. These metrics provide a more complete assessment than accuracy alone, especially in grain quality classification where borderline cases between adjacent classes may lead to asymmetric misclassification patterns.

RESEARCH RESULTS

To assess the effectiveness of the proposed machine vision system, the convolutional neural network (CNN) described in Section 3.3 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 shows the training history of the CNN model, including training and validation accuracy over 25 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.

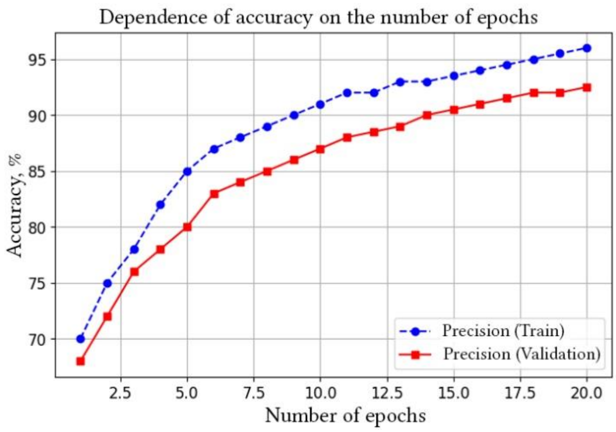

Fig 2. **Training and validation accuracy of the CNN model over 50 epochs**

***Source*: compiled by the authors**

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 (SVM) 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 2.

Table 2. **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

***Source*: compiled by the authors**

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 are examples of confusion matrix visualization for the three grain quality classes (Fig. 3 and Fig. 4).

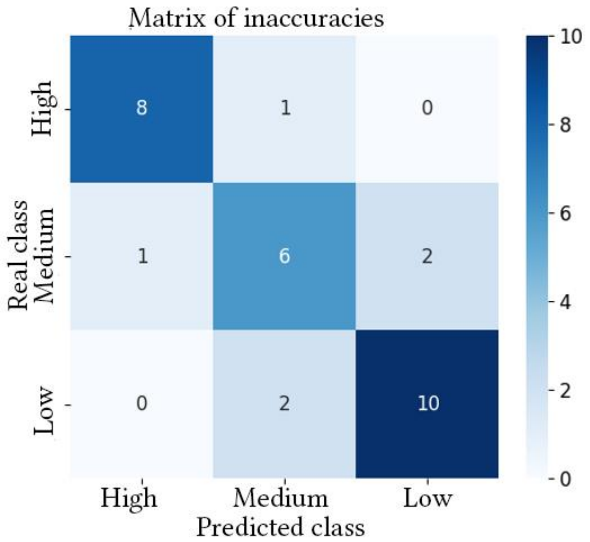

Fig. 3. **Confusion matrix visualization for three grain quality classes (example A)**
***Source*: prepared by the authors**

We obtained the following confusion matrix (Table 3).

The class-wise precision, recall, and F1-score values derived from the confusion matrix are shown in Table 4. The results confirm consistently strong performance across all three classes, with F1-scores above 0.90. The macro- and weighted-averaged scores indicate stable classification quality and confirm that model performance is not driven by a single dominant class.

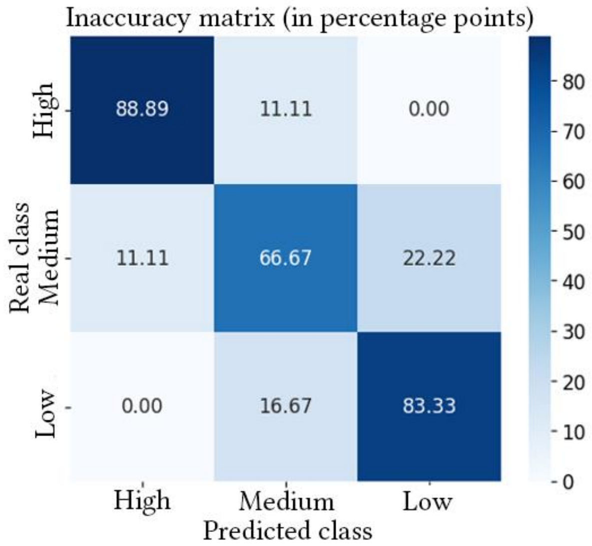

Fig. 4. **Confusion matrix visualization for three grain quality classes (example B)**
***Source*: prepared by the authors**

Table 3. **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

***Source*: compiled by the authors**

Table 4. **Class-wise precision, recall, and F1-score for CNN classification**

Class	Precision	Recall	F1-score
High	0.927	0.955	0.941
Medium	0.917	0.891	0.904
Low	0.948	0.946	0.947
Macro average	0.931	0.930	0.931
Weighted average	0.933	0.933	0.933

***Source*: compiled by the authors**

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 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.

In addition to aggregated evaluation on the combined test set, model performance was assessed separately for each grain crop (wheat, corn, and barley). This analysis is important because different crops exhibit distinct surface texture patterns, shape variability, and defect appearance, which may affect classification difficulty. The per-crop results for the CNN and SVM models are summarized in Table 5.

The results demonstrate stable performance across all three crops, with the CNN consistently providing higher accuracy and macro-F1 than the SVM. Slightly lower performance was observed for corn, which can be explained by the presence of visually subtle borderline defects that increase confusion between adjacent quality categories.

Table 5. **Classification performance by crop type (test subset)**

Crop type	CNN Accuracy (%)	CNN Macro F1	CNN Weighted F1	SVM Accuracy (%)	SVM Macro F1
Wheat	94.2	0.941	0.943	91.7	0.915
Corn	92.6	0.923	0.925	89.8	0.894
Barley	94.6	0.946	0.947	92.1	0.918
Average (overall)	93.8	0.931	0.933	91.2	0.909

***Source*: compiled by the authors**

The per-crop evaluation confirms that the proposed models maintain stable classification performance across wheat, corn, and barley. The CNN demonstrates consistently higher accuracy and macro-F1 values than the SVM for all crop types, indicating stronger generalization under varying visual grain characteristics. A slightly lower performance for corn suggests that defect patterns in corn kernels may present more borderline cases between adjacent quality classes (High vs Medium), which increases misclassification probability. Overall, the results indicate that crop-specific texture and morphology affect classification difficulty, but do not compromise the feasibility of the proposed approach for multi-crop industrial deployment.

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.

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 6.

Table 6. **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

***Source*: compiled by the authors**

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 influence of conveyor speed on image quality was evaluated by visual inspection of representative frames captured at each speed regime (0.1–0.5 m/s), focusing on typical motion artifacts such as edge smearing and loss of fine surface texture that are important for defect recognition. In the current prototype, no dedicated motion compensation methods were applied (e.g., strobe illumination, synchronized triggering, short exposure optimization, or algorithmic deblurring/filtration), so the reported accuracy values reflect baseline performance under continuous LED lighting conditions. The obtained results indicate that the CNN model remains robust at belt speeds up to 0.5 m/s, with accuracy above 92%, and supports real-time operation for moderate industrial grain flows. For higher-throughput processing lines operating at higher belt speeds, reliable classification would require high-speed image acquisition solutions (shorter exposure time, strobed illumination, or synchronized capture) to reduce motion blur and preserve surface defect visibility.

The stability of grain classification in industrial deployment depends not only on the selected model but also on image acquisition conditions and surrounding environment. While the laboratory setup ensured uniform LED illumination, real production lines may exhibit non-uniform lighting distribution, specular reflections from grain surfaces, shadows from mechanical elements, and gradual illumination drift over time. These factors reduce the visibility of fine defects (cracks, discoloration, mold traces), directly affecting classification confidence.

Another important factor is the degree of grain overlap in the camera field of view. When grains partially occlude each other, the segmentation stage may produce merged contours or incomplete boundaries, leading to loss of defect regions and distortion of geometric descriptors. Such cases increase the probability of confusing “High” and “Medium” classes, where differences are subtle. Finally, environmental artifacts such as dust, small debris, and surface contamination can introduce additional texture patterns and reduce color consistency, especially under side illumination, which negatively impacts both handcrafted descriptors (HOG/LBP, color histograms) and CNN-based feature extraction.

For this reason, industrial-scale deployment should include measures for acquisition robustness (controlled illumination enclosure, periodic lens cleaning, and dust-reduction mechanisms), as well as expanded dataset coverage with samples collected under variable illumination, different overlap degrees, and contamination conditions.

Summary of Findings

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.

In future work, the segmentation and object extraction stage may be improved using modern object detection architectures from the Ultralytics YOLO family (latest versions), which provide robust grain localization under complex conditions such as partial overlap, background clutter, and variable illumination. Integrating YOLO-based detection with the proposed quality classification pipeline may increase stability in real industrial environments without compromising real-time throughput.

DISCUSSION

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

Comparison with published results and experimental conditions. Many studies on grain quality classification report high accuracy under laboratory conditions, typically relying on static images and controlled illumination. In such settings, CNN-based models often exceed 90% accuracy. However, direct benchmarking remains challenging because datasets differ significantly in grain variety, number of classes, labeling criteria, imaging setup, and preprocessing pipelines.

In the present work, image acquisition was performed under controlled conveyor-based conditions with adjustable belt speed (0.1-0.5 m/s), which introduces motion blur and exposure constraints not present in most static datasets. Despite these factors, the proposed CNN model achieved 93.8% accuracy on the test set, while maintaining an inference time of 5.8 ms/image, supporting real-time processing for moderate flow rates. The observed accuracy decrease with higher conveyor speed aligns with expected motion-related distortions reported in machine vision systems for industrial quality control.

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,

ISSN 2617-4316 (Print)
ISSN 2663-7723 (Online)

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.

Although the experimental prototype used an RTX 2060 GPU to ensure stable real-time performance, the proposed approach can be adapted for deployment on edge devices without a dedicated GPU. For such scenarios, lightweight CNN architectures (e.g., MobileNetV2/MobileNetV3 or EfficientNet-B0/EfficientNet-Lite) may be used as drop-in replacements for the baseline CNN while maintaining competitive accuracy. In addition, inference efficiency can be improved through model compression techniques such as pruning and post-training quantization (e.g., FP16/INT8), or quantization-aware training, which reduces memory footprint and computational load. Practical deployment options include converting the trained model to TensorFlow Lite or ONNX format and performing optimized CPU inference via TFLite delegates or ONNX Runtime. For higher throughput industrial lines, embedded platforms such as NVIDIA Jetson modules can provide accelerated inference at low power consumption. These optimizations represent an important direction for future work to increase scalability and applicability in industrial grain processing environments.

Industrial deployment scenarios and line integration. In a practical grain-processing facility, the proposed machine vision system can be integrated into the sorting and cleaning line as an online inspection module. The camera unit is installed above the conveyor after the cleaning stage (or before final sorting), and classification results are transferred to the line controller (PLC/industrial PC) with synchronized timestamps from the conveyor speed sensor or encoder. Based on model output, the system can actuate downstream separation mechanisms such as pneumatic air jets, mechanical diverters, or reject gates to remove low-quality grains or foreign inclusions into a separate channel.

From a hardware perspective, stable real-time operation requires an industrial camera with sufficient frame rate, controlled illumination, and a computing platform capable of performing inference within the conveyor cycle time. For moderate throughput lines, CPU or edge inference is feasible; for higher flow rates, GPU/accelerated platforms (e.g., NVIDIA Jetson or workstation-class GPU) are recommended to maintain low latency.

The control logic may operate in different modes:

1) monitoring mode, where the system reports quality metrics and alarms without active sorting;

2) semi-automatic mode, where separation is enabled only when confidence thresholds are met;

3) fully automatic closed-loop mode, where classification statistics are used to dynamically adjust technological parameters (conveyor speed, cleaning intensity, and separation thresholds) to stabilize product quality.

CONCLUSIONS

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

Effectiveness of CNN-based classification. 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.

Trade-off between accuracy and computational efficiency. 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.

Influence of imaging conditions. 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.

Industrial applicability and scalability. 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.

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Conflicts of Interest: The authors declare that they have no conflict of interest regarding this study, including financial, personal, authorship or other, which could influence the research and its results presented in this article

Received 24.12.2025
Received after revision 12.02.2026
Accepted 18.02.2026

DOI: https://doi.org/10.15276/aait.09.2026.02
УДК 378.147:004.6:331.5

Система машинного зору для класифікації якості зерна в режимі реального часу з використанням машинного навчання

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АНОТАЦІЯ

Контроль якості зерна безпосередньо впливає на ефективність його переробки, стабільність параметрів продукції та економічні результати процесів зберігання й очищення. У промисловій практиці візуальний огляд і ручний відбір проб залишаються поширеними, однак ці підходи є трудомісткими та чутливими до суб'єктивного фактора, особливо за необхідності безперервного оцінювання великих обсягів зерна. Дослідження спрямоване на вирішення потреби в автоматизованому, об'єктивному та масштабованому підході до класифікації якості зерна, здатному працювати в режимі реального часу в конвеєрних умовах. **Метою роботи є** розробка та експериментальна валідація системи машинного зору, що класифікує зерно за якістю та підтримує прийняття технологічних рішень щодо фракційного розділення й очищення. Для моделювання конвеєрного транспортування зерна створено експериментальний стенд, який забезпечував контрольовану зміну швидкості стрічки та умов освітлення. Сформовано датасет зображень пшениці, кукурудзи та ячменю шляхом лабораторної зйомки з подальшим ручним маркуванням на три класи якості залежно від видимих дефектів і ступеня пошкоджень. Застосовано попередню обробку та аугментацію зображень для підвищення варіативності й стійкості моделей. Для порівняльного аналізу реалізовано два підходи навчання з учителем: класифікатор зображень на основі глибокого навчання та ядерний класифікатор із використанням ручних візуальних дескрипторів. **Експериментальні результати** показують, що підхід глибокого навчання забезпечує вищу точність класифікації, тоді як ядерний класифікатор має швидший час інференсу за помірного зниження точності. Найчастіші помилки класифікації виникають між суміжними категоріями якості, що підкреслює важливість покриття прикордонних випадків і узгодженості розмітки. Вимірювання часу обробки зображень підтверджують можливість роботи в режимі реального часу для помірних потоків зерна, при цьому зі зростанням швидкості конвеєра спостерігається погіршення показників через викривлення зображень, пов'язані з рухом. **Наукова новизна** полягає в інтегрованій експериментальній оцінці точності класифікації та пропускної здатності за контрольованих конвеєрних умов. Практична значущість визначається можливістю впровадження системи як компонента автоматизованих ліній очищення та сепарації зерна.

Ключові слова: машинний зір; класифікація зерна; машинне навчання; метод опорних векторів; обробка зображень; сортування зерна

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