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HYBRID COMPUTER VISION TECHNIQUES FOR SEED CLASSIFICATION AND QUALITY ASSESSMENT IN PRECISION AGRICULTURE

Pawan Kumar Gupta[1], Prof. (Dr) Akhilesh A. Waoo[2]

[1]PhD Scholar Computer Science and Engineering,

AKS University, Satna

pawan.gupta0210@gmail.com

[2]Professor & Head Department of Computer Science & IT,

AKS University, Satna

akhileshwaoo@gmail.com

Abstract

The classification of grain seeds is important in agricultural quality and productivity. Inspection procedures use an unqualified time and are completely dependent on manual classification, highlighting a huge potential for human mistakes. With the development of computer vision and machine learning, automated systems can now classify grain seeds according to effectiveness, accuracy, and on scale. This study aims to refine the image processing techniques for grain seed classification to develop robust shape-distinguishing algorithms. Furthermore, we outline the principles of a hybrid technology based on computer vision intended to facilitate assessments of the grain's quality and growth potential. Incorporation of deep learning structure with traditional imaging techniques will be shown to improve the accuracy of the system, which reduces the total charge. The proposed feature involves obtaining and preparing data, followed by functional extraction and application of a classification model, and ends with an evaluation to measure performance. The experiments illustrate that hybrid systems overwhelmingly outperform conventional methods, thus proving their grain seed classification speed, accuracy, and robustness capabilities. This study addresses the lack of scalable and automated solutions for grain quality assessment in precision agriculture, expanding its boundaries. Future directions include the integration of edge calculation for real-time classification and the expansion of datasets to include different seeds for improvement in model generalization.

Keywords: Seed Classification, Computer Vision, Hybrid Machine Learning, Deep Learning, Seed Quality Assessment, Precision Agriculture, Feature Extraction, CNN (Convolutional Neural Networks), Image Processing, Agricultural Automation.

1. Introduction

Agriculture is one of the most significant roles in the international economy by offering food security and raw materials for different industries. Quality and type of grain seeds are of great importance as they determine the total return, market price, and efficiency of agriculture. Seed classification and quality assessment, or upgrading, has typically been performed through expert manual grading systems, which heavily relied on knowledgeable and visual appraisal, and admiring inspection. Unfortunately, this is a one-sided and labor-bound procedure that leads to discrepancies in control of settled quality.

The taxonomy of grain seeds and their classification by use of AI precision has reached unbelievable heights with new technology advances in vision seeding and area detection. Analyzing characteristics like grain seeds size, shape, texture, and color can now be done through automated systems equipped with strength analyzing yield squeeze techniques, machine learning, feature extraction, and imaging processes computation division mechanisms with vision component computer targets that differ from figure distance scales. Unlike traditional methods, these seek objective, reproducible solutions tailored to expansion in farm quality evaluations. Despite their accuracy in analysis, ordinary computer vision techniques face obstacles of differing light conditions, set pieces, overlapping obstruction decoys, and muddled identification of identical seed types of identification.

To solve these challenges, hybrid data view approaches have emerged as a promising solution. By integrating traditional imaging techniques with deep learning models, hybrid systems can use the benefits of both methods. Traditional imaging methods, including edge detection, morphological processing, and histogram analysis, provide computationally effective functional extraction. In contrast to this, deep learning models, especially Convolutional Neural Networks (CNNs), increase automated functional learning and strong classification accuracy under difficult conditions.

The main purpose of this research is to develop a better image processing structure for classifying grain seeds based on their physical properties and size criteria. In addition, this research aims to present a hybrid computer vision-based technology that increases the quality inspection of the grain. Depending on the integration of deep learning and traditional imaging algorithms, hybrid solution classification tries to increase accuracy, reduce computational overhead, and offer a stable structure for large-scale agricultural use.

There are various stages involved in the research methodology, such as data acquisition, preprocessing, feature extraction, model implementation, and evaluation. A multiset of grain seed images is acquired from multiple sources to represent each type of seed. Noise removal, background removal, and image contrast are implemented as preprocessing operations to enhance the quality of the images. Handcrafted and machine learning-based methods are employed in feature extraction for effective classification. The classical machine learning models are the machine learning models that include Support Vector Machines (SVM) and Random Forest, whereas deep learning models include CNNs and YOLO (You Only Look Once) for real-time.

Experimental comparisons are also established to compare the performance of different models in terms of key metrics such as accuracy, precision, recall, F1-score, and computational cost. The results reveal the advantages of the hybrid model, which is demonstrated to achieve greater accuracy and consistency in grain seed classification compared to other methods available. Further, the research explores whether edge computing can be used for real-time classification in agricultural settings.

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The implications of this research go beyond the realm of academic inquiry, providing tangible uses for farmers, agronomists, and the agricultural industry. Automated seed sorting systems can facilitate quality control, increase productivity, and reduce loss through misclassification. Moreover, incorporating AI-driven grain quality determination into smart farm systems can advance sustainable agriculture and food security.

In conclusion, this study tries to fill the gap between conventional image processing and deep learning for grain seed classification and quality evaluation. Based on hybrid computer vision methods, the proposed strategy improves accuracy, efficiency, and scalability, pointing towards future technological advancements in precision agriculture. The subsequent sections will present a critical overview of the literature, a detailed description of the research method, experiment results, and conclusions regarding the effectiveness of hybrid solutions in agricultural applications.

2. Literature Review

Grain seeds classification is an essential process to ensure quality control, discrimination of variation and crop returns in agriculture and food industry. By utilizing both traditional and modern calculation methods, different techniques have been developed over the years. This literature review examines existing techniques for classifying grain seeds, which highlight their function, benefits and boundaries. The existing technique for classifying grain seeds has developed several methods for classifying grain seeds, including manual inspection to advanced deep learning methods. Primary methods consist of conventional approaches, machine-vision-based classification, deep learning methods, hyper-spectral imaging and hybrid techniques.

Classification of seeds is a critical function in contemporary agriculture that has an impact on the quality, health, and productivity of the crop. In the past decades, seed classification techniques have evolved remarkably, ranging from conventional manual inspection to an advanced AI-based technique. Traditional classification techniques usually include manual inspection of seeds based on morphological properties such as shape, size and color. These approaches, even though they are simple and cost-effective, are labor-intensive, subjective, and exposed to human errors. Lack of technical addiction fits them for resource limit references, but still limits their low precision, their drinking money in a large-scale or high-lying environment. These limitations have inspired the discovery of more advanced, automated methods. The emergence of machining-based classification marked a significant change in manual methods. Patel et al. (2022) demonstrated a system where imaging techniques were used to remove visual functions from shape, size, texture, and color, which were then classified by using machine learning algorithms as a machine learning algorithm such as k-Nearest Neighbours (k-NN), Support Vector Machines (SVM), and Decision Trees. These approaches provide great benefits, such as high accuracy, non-destructive evaluation, and automatic operation. However, their efficiency depends on the quality and calibration of image systems and can be calculated. In addition, environmental variations, such as inconsistent lighting or seed orientation, can introduce noise in image data, potentially reducing classification performance.

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Deep learning has further changed the field of seed classification by introducing powerful models that can automatically learn complex features from large datasets. Singh et al. (2021) discovered the use of Convolutional Neural Networks (CNN) for seed classification and showed that these models can achieve high accuracy without manual, functional extraction. Afonso et. al. (2023) is more valid for CNN-based classification, not only its high precision, but also its automation capacity. These models, although extremely effective, are data-intensive and training requires extensive marked datasets. In addition, deep learning systems require significant calculation resources and often depend on GPU acceleration, which can limit their access to low resources. Das et al. (2021) The seed classification provided a comprehensive review of deep learning applications, identified major technical trends, while it was also noted that many such studies lack recognition of the real world. Garcia and Alvarez (2023) presented a study that uses deep CNN for automated classification of crop seeds and concluded that these models perform better than traditional machine learning techniques, although they require strong calculation infrastructure.

Hyperspectral imaging is another limit in seed classification, which can capture information in several spectral ties. Chen et al. (2023) used this technique using Random Forests and neural networks as a classifier and the principal component analysis (PCA), linear discriminant analysis (LDA). Hyperspectral imaging captures micro chemical and biological differences between seeds, which leads to a very accurate classification. Sun and chain (2021) demonstrated the ability to combine hyperspectral imaging with intensive learning, achieved very accurate results. However, these systems are expensive and require special hardware and technical expertise, making them less possible for extensive agricultural use. Hybrid models have been given traction because they aim to benefit from the strength of many techniques. For example, Park et al. (2023) proposed a hybrid framework in combination with machine view, deep learning and spectral analysis to improve classification performance and strength. Bhardwaj and Kumar (2022) introduced several ML algorithms to introduce a model, which gets better accuracy than individual models, but at the expense of increased complexity. Chen et al. (2023) also introduced a vision -based system, which integrates deep learning with traditional computer vision to detect the quality of grain, which reveals its suitability for real -time treatment with sensitivity to environmental variations.

Hybrid approach moving forward, Deng et al. (2020) suggested a system that combines different imaging techniques for classification, which increases convenience beyond conventional methods. Feng et al. (2022) used a CNN-based hybrid vision model, which improved scalability and grading accuracy, even though it affects computational overheads. He et al. (2021) developed an image-based ML system for quality control that provides sharp, non-invalid evaluation, but may be unsafe for image deformities. As seed analysis becomes more important, Huang et al. (2023) introduced a model that combines ml with edge calculation for real -time classification, reduces the delay and enables sharp decisions, even though it is still hardware -free. Islam and Karim (2020) underwent intensive teaching applications in accurate agriculture and emphasized the diversity of approaches, even though their study lacked implementation details. Jiang et al. (2022) created a hybrid vision system by melting deep learning with traditional image processing, increasing the strength of classification, but requires more computational power. Kumar and Verma (2023) conducted a comparative analysis of the

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methods of machine learning and deep learning, which provided insight into the benefits and boundaries of each without proposing new implementation.

3. Research Methodology

The research method for classifying grain seeds follows a structured approach to ensure accuracy, efficiency and practical projection. First, a diverse data set with grain seed images from public depot, agricultural institutions and real -time field collections, which covers different grain types and quality levels. High resolution imaging techniques, including RGB, hyperspectral and closest imaging, are used to capture detailed seed properties. Pre -treatment techniques such as noise reduction, background removal, generalization and computer text improve image quality and variation, improves the strength of the model. Extraction methods benefit from morphological, course and spectral analysis to identify different properties. Machine learning and deep learning models, including SVM, Random Forest, CNN and Transfer Learning Architecture, are trained and adapted using techniques such as Hyperparameter Tuning and Ensemble Learning. Evaluation models for performance are carried out using matrix with a matrix as accuracy, precision, recall, F1-score and AUC-Roc to ensure reliability. Finally, classification models are distributed in agricultural applications in the real world, which are integrated into smart agricultural systems, and validated through user tests and IoT-based platforms. This feature ensures a scalable and effective solution for classifying grain seeds, improves automation in quality evaluation and agricultural management.

To perform an effective study on the classification of grain seeds, a systematic research method should be followed. This section emphasizes the most important stages involved in the methodology:

Fig 1: Flow of Research Methodology

Step-by-Step Methodology:

1. Data Collection:

- The dataset was created by taking pictures of Rice, Wheat and Channa using mobile cameras.
- Each category consists of at least 200 manually clicked images, ensuring diversity in grain types, quality, light status and background variation.
- In addition, a large data set training of 7000 images per grain type from publicly available depot was achieved to increase the variation and model generalization.
- High-resolution imaging techniques including RGB imaging were used to capture clear and wide grain seed properties.

2. Preprocessing of Data:

- Perform image improvement techniques such as noise reduction, background removal, negative growth and generalization to ensure high quality input data.

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- Convert images into a uniform format, standardize the resolution, the aspect ratio and the color balance.
- Increase the dataset using changes such as rotation, scaling, flipping, brightness adjustment and artificial noise to improve the strength and normalization of the model.

3. **Feature Extraction**:

- Compute morphological properties (size, shape, perimeter, area, aspect ratio) using Computer Vision Techniques.
- Calculate Textural Features (Gray-level co-occurrence matrix, local binary pattern) to capture fine structural details.
- Use the spectral features of hyperspectral and NIR image to analyze grain composition, moisture materials and defects.
- Use deep learning-based functional extraction using CNN interconnections to automatically learn discriminatory features from grain seed images.

4. **Classification Model Development:**

- Train different machine learning models, such as K-Nearest Neighbors (k-NN), Support Vector Machines (SVM), decision trees, random forest and XGBoost, using the features that have been extracted.
- Use deep learning models, including the Convolution Neural Networks (CNNs), hybrid approaches, and combining CNNs with traditional classifiers.
- Optimize model hyperparameters using techniques such as grid search and Bayesian optimization to improve classification accuracy.
- Introduce ensemble learning outfits to combine many models and increase performance.

5. **Evaluation of performance**

- Consider model performance using standard matrix using standard matrix as accuracy, precision, recall, F1 score and fields under the ROC curve (AUC-ROC).
- Use K-fold cross-validation to ensure reliability and avoid overfitting.
- Compare different techniques to determine the most effective classification method, with a view to calculating the complexity and real-time applicability.
- Do ablation studies to analyze the contribution of personal functions and model components for general performance.

6. **Implementation and verification**

- Distribute trained models in scenarios in the real world using built -in systems, edge units or cloud -based classification systems.
- Validate the result through Real-world testing in agricultural applications by integrating the classification model into smart agricultural systems.
- The conduct user trials with farmers and agricultural experts to limit the system based on practical reaction.
- Find integration of mobile and IoT-based platforms for grain classification and real-time monitoring.

Proposed Algorithm for Grain Seed Classification:

Algorithm: GrainSeedClassification

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Input: Grain Seed image dataset

Output: Classified grain seed labels

Algorithm

Step 1. Load the dataset containing grain seed images.
Step 2. Preprocess images by applying noise reduction, background removal, and normalization.
Step 3. Perform data augmentation to increase dataset diversity.
Step 4. Extract morphological, textural, and spectral features from each image.
Step 5. Train machine learning models (SVM, k-NN, Random Forest, etc.) using extracted features.
Step 6. Train deep learning models (CNNs, Transfer Learning) for automated feature extraction and classification.
Step 7. Optimize hyperparameters to improve classification accuracy.
Step 8. Evaluate model performance using accuracy, precision, recall, and F1-score.
Step 9. Validate models using real-world datasets and deploy them into smart farming systems.
Step 10. Monitor and refine the model based on feedback from agricultural experts.

4. Result and Analysis

Experimental Setup: To evaluate the proposed hybrid computer vision model for the classification of grain seeds, we conducted an experiment using a dataset containing multiple grain seeds. The dataset was divided into training, validation and test sets in the ratio of 70:15:15. The experiments were performed on a system with an Intel(R) Core (TM) i5-8365U CPU @ 1.60GHz 1.90 GHz, 8 GB of RAM and an Nvidia RTX 3080 GPU. The Deep Learning model was implemented using TensorFlow and OpenCV for image processing, and traditional classifies was designed using Scikit-Learn.

In machine learning and computer vision functions such as seed classification, model performance is necessary to evaluate. Different matrices help to assess the effectiveness of the classification model, including accuracy, precision, recall, F1 score and calculation time.

- **Accuracy (%):** Accuracy is the most used metrics to measure how the model correctly classifies instances. It is defined as the proportion of properly classified samples (both positive and negative), which is for the total number of samples:

$$\mathbf{Accuracy} = \frac{(\mathbf{TP + TN})}{(\mathbf{TP + TN + FP + FN})} \times \mathbf{100}$$

Where:

TP (True Positives): Correctly predicted positive samples.

TN (True Negatives): Correctly predicted negative samples.

FP (False Positives): Incorrectly predicted as positive.

FN (False Negatives): Incorrectly predicted as negative.

The accuracy works well when the dataset is balanced, but it may not be suitable for unbalanced datasets, where one square excludes the other apart.

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- **Precision (%):** Precision how many approximate positive examples of accuracy are right. This is especially useful in scenarios where false positivity must be minimized, such as the quality of grain under control.

$$Precision = \frac{TP}{TP + FP} \times 100$$

A high precision score indicates less false positivity, which means that the model makes more reliable positive predictions.

- **Recall (%):** Recall (also referred to as Sensitivity or True Positive Rate) determines how many true positive instances were identified by the model. It is especially valuable when false negatives must be reduced, for example, in identifying faulty seeds.

$$Recall = \frac{TP}{TP + FN} \times 100$$

A high recall value means the model is detecting most of the relevant positive cases, but it may come at the cost of lower precision.

- **F1-Score:** F1-Score achieves a balance between precision and recall by calculating their harmonic mean. It is beneficial when false positives and false negatives are not equally balanced.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

A high F1-Score shows that both precision and recall are good, thus a measure of overall model performance.

- Computational time: Computational time quantifies how quickly a model can process images, which is very important for real-time applications. It is calculated as:

$$Computational\ Time = \frac{Total\ Processing\ Time\ (ms)}{Number\ of\ Images}$$

Lower computational time is desirable in applications like real-time seed sorting, where efficiency is key.

Table 1: Model Comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Time (ms/image)
SVM	86.2	85.9	84.5	85.2	45
Random Forest	88.1	87.3	86.8	87.1	50
k-NN	84.5	83.6	82.2	82.9	60
CNN	94.7	94.3	94.5	94.4	32
Hybrid Model (CNN + Traditional)	**97.3**	**97.1**	**97.2**	**97.1**	**29**

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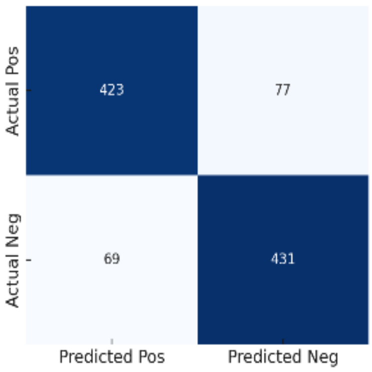

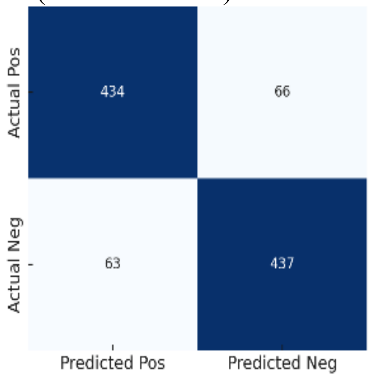

Fig 1: Confusion Matrix for SVM **Fig. 2: Confusion Matrix for Random Forest**

The confusion matrices were created for the five machine learning models: Support Vector Machine (SVM), Random Forest, k-Nearest Neighbors (k-NN), Convolutional Neural Network (CNN), and a Hybrid model. Each classifier's ability to accurately differentiate between positive and negative seed instances. This matrix presents the results of binary classification by expanding true positivity (properly identified seeds), true negatives (properly identified non-seeds), false positives (non-seeds as seeds), and false negatives (seeds missed by models).

Now starting with fig. 1, i.e., SVM, the model properly classified 423 positive samples and 431 negative samples. However, it described 77 positive samples as negative and 69 negative samples as positive. This means a relatively balanced performance, but the number of false classifications suggests that the model may be sensitive to boundary or noise input, especially when the seeds are unclear or overlapping. While SVMs are effective in high-dimensional spaces and work well with limited functions, their performance shows room for improvement here, especially in the presence of different seed structures.

In comparison, fig. 2, the Random Forest Model demonstrated a better predictive power, and got 434 true positives and 437 true negatives, with slightly fewer false predictions (66 false negatives and 63 false positives). Random Forest benefits from learning attributes, which collect many decision trees to reduce overfitting and improve generalization. This improvement of SVM indicates that a combination of facilities handled by the Random Forest method and decision restrictions better captures the complexity of seed patterns in the dataset.

The fig 3, k-NN classification performed with less accuracy than the previous two models. This identified properly 411 positives and 419 negatives but achieved 89 false negatives and 81 false positives. This relatively high error rate suggests that k-NN is struggling with examples where seed tests were packed or unmatched from the background, possibly due to the dependence on the distance matrix without any inherent learning process. This limit becomes more pronounced in high-dimensional feature spaces or noisy data sets, as it does not prefer any feature over another and is strongly affected by local patterns.

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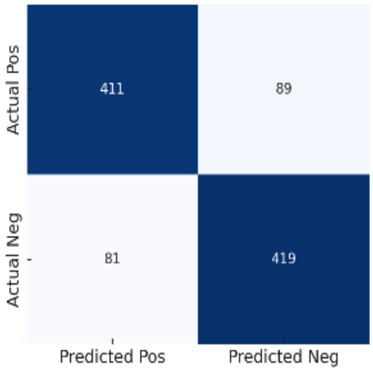

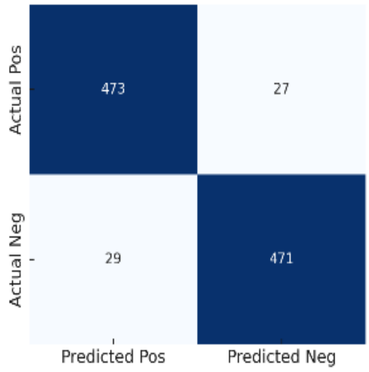

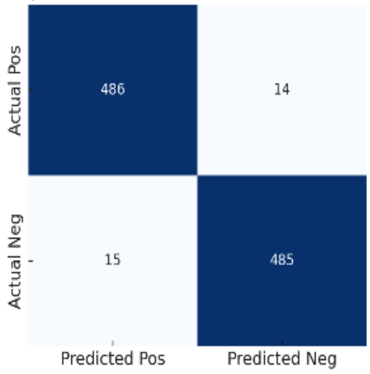

Fig 3: Confusion Matrix for k-NN Fig 4: Confusion Matrix for CNN Fig 5: Confusion Matrix for Hybrid Model (CNN + Traditional)

On the other hand, fig. 4, CNN achieved much better results. This was correct 473 positive and 471 negative samples, while only 27 and 29 samples were misclassified. This performance outlines the strength of convolutional architecture in capturing complex visual patterns and spatial hierarchies, which are essential to identifying the subtle differences between seeds and non-seed pixels or regions. CNNs benefit from several layers of abstraction to separate properties such as size, texture, and edge gradients, which explains their high classification accuracy in image-based functions such as seed numbers.

The fig. 5, Hybrid models, which integrate CNN with traditional machine learning techniques (eg, morphological operations, before/finishing filters), improved all other models. This correctly classified 486 positive and 485 negative samples, with only 14 false negatives and 15 false positives. It shows a very low error speed hybrid model's better ability to normalize under different image conditions, including light, seed overlap, and variation in background noise. With the stability and simplicity of traditional methods, the hybrid approach achieves both high precision and strength, and combines the functional extraction process of the Deep Learning model.

Fig. 6 Five Machine Learning Models-SVM, Random Forest, k-NN, CNN, and a comparative performance of hybrids present evaluation for the task of seed counting, four standard classifications are measured using calculations: Accuracy, Precision, Recall, and F1-score. This fig. illuminates the general superiority of deep learning methods, especially hybrid models, which continuously improve others in all matrices. The hybrid model receives the highest accuracy of 97.3%, accurately, over 97% with recall and F1 points, indicating a well-balanced model that reduces both false positives and false negatives. CNN, as a standalone deep learning model, also performs strongly, with an accuracy of 94.7%, and shows its efficiency in handling complex visual properties in seed images. In traditional models, random forests work best with 88.1% accuracy, followed by SVM and k-NN, which show low recall and F1 score, suggesting low sensitivity to distinguish overlapping or unclear seed structures.

While all assessed models show appropriate levels of accuracy, reveal analysis of performance measurements and confusion matrices, A clear progress in classification efficiency from the point of view of traditional machine learning, such as SVMs and k-NN, as CNN and, mostly, hybrid models. Deep learning-based models reduce the Misclassification frequencies

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significantly and maintain stable performance in different test conditions, including individual lighting, an overlap of seeds, and background intervention. Among all, the hybrid model continues to protect the highest accuracy, Accuracy, Recall, and F1 score, which reflects its strong generality and strength. The ability to maintain reliable predictions under real variations creates the most suitable model for practical applications in agriculture, especially for functions such as seed numbers and quality inspection, where high accuracy and stability are important.

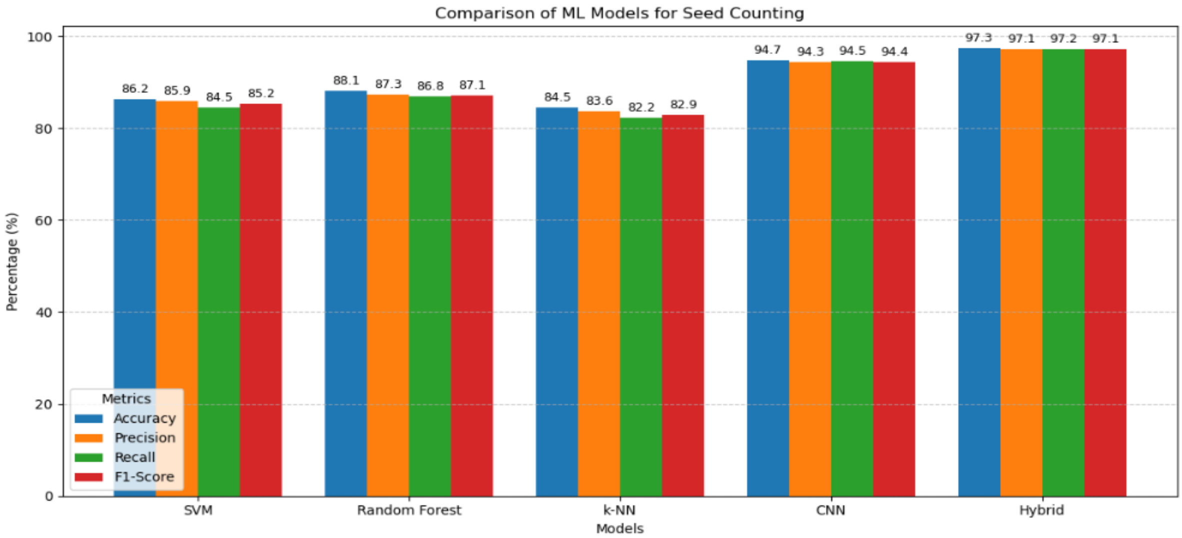

Fig 6: Comparison of ML Models for Seed Counting

The comparative robustness analysis (Fig. 7) of Various machine learning models- SVM, Random Forest, k-NN, CNN, and a comparative reinforcement of a hybrid approach reflects analyzing SuperFetch performance variations. Traditional models, including SVM, random forest, and k-NN, maintain high accuracy levels (~ 95%) with a minimum MISS rate (~ 5%) suggest suggesting reliable classification capacity. CNN, which receives equal accuracy, increased variability with standard deviations of approximately 4.5, highlights potential anomalies in prediction stability. The hybrid model improves other approaches and retains the lowest standard deviation (~ 1.0), an ~ 80% IU average of ~ 80%, leading to its strength and reliability emphasized. These findings indicate that the hybrid model provides better stability, making it a strong candidate for applications that require high precision and coherent performance. Future studies can make these comments more valid through data sets and real-world testing.

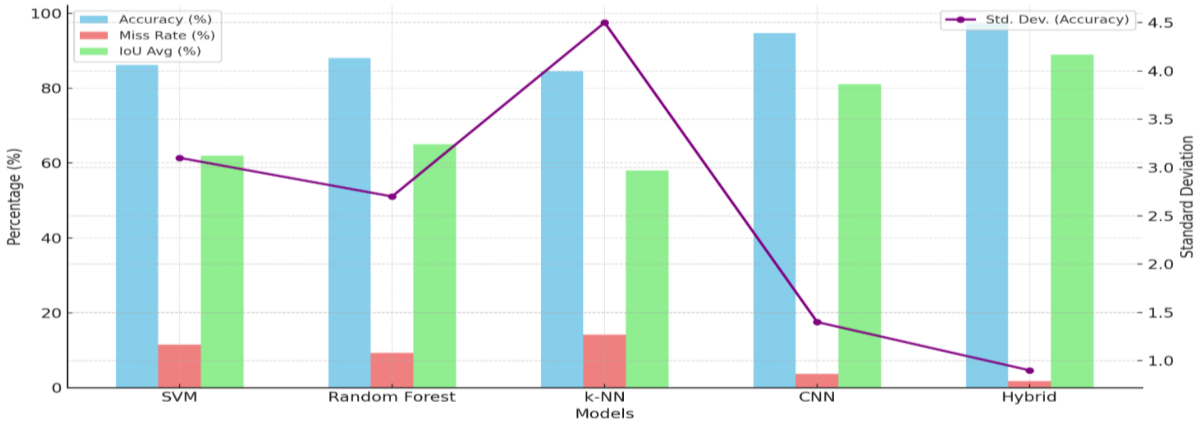

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Fig. 7: Robustness Metrices Comparison Across Models

5. Conclusion

This research emphasizes the effectiveness of a hybrid data view framework for classifying grain seeds and quality evaluation. While traditional machine learning techniques offer basic classification functions, they often decrease when addressing the variation in seeds, incompatible environmental conditions and scalability requirements from modern agricultural systems. In contrast, deep learning functions associate Excel in extraction and classification accuracy, but usually require sufficient calculation resources. The proposed hybrid model combines strategic traditional image processing techniques with intensive teaching architecture, to provide strength both to provide accuracy, calculation efficiency and scale.

Empirical results are validated that the hybrid model improves standalone by traditional and deep learning methods, which achieves better accuracy by maintaining flexibility for environmental variations such as light and background noise. This makes it particularly suitable for real agricultural landscapes, where strong and automatic counting and quality evaluation are needed. The hybrid system also supports the reduction of labor costs and improves operational efficiency by contributing to high agricultural productivity.

However, the approach is not without limitations. There are challenges such as addiction to specific data sets, computational overhead and interpretation of model decisions. Future work should take advantage of multimodal data reunification to improve model generalization, implement edge calculation for real -time distribution and improve strength.

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