AgriNex AI: Seed Quality Prediction and Cultivation Rental System

Mr. Arpit N. Jawanjal[1], Mr. Jayesh K. Rakhonde[2], Miss. Shital C. Jaiswal[3],
Miss. Pooja G. Jawale[4], Dr. Priyanka A. Chorey[5]
[1,2,3,4,5] *Department of Information Technology, Prof. Ram Meghe Institute of Technology & Research, Amravati*

***Abstract*—Agriculture is a major sector of the Indian economy, and farmers continue to face several challenges such as poor seed quality, reduced crop productivity, high cultivation costs, and limited access to modern agricultural equipment. Traditional methods of seed quality inspection are often time-consuming, dependent on manual observation, and may not provide accurate results. At the same time, purchasing agricultural machinery is expensive, particularly for small and medium-scale farmers. To address these challenges, AgriNex AI: Seed Quality Prediction and Cultivation Rental System is proposed as an AI-based smart agriculture platform that combines seed quality prediction with an agricultural equipment rental service.**

***Index Terms*—Artificial Intelligence, Machine Learning, Seed Quality Prediction, Image Processing, Smart Agriculture, Precision Agriculture, Agricultural Equipment Rental, Crop Productivity, Digital Farming, Farmers, Agricultural Machinery, Sustainable Agriculture.**

I. INTRODUCTION

Agriculture plays a vital role in the economic and social development of India, providing employment and livelihood opportunities to a large population. However, farmers continue to face several challenges that directly affect agricultural productivity and profitability. Poor seed quality, crop diseases, high cultivation costs, limited access to modern agricultural machinery, and dependence on traditional farming practices are some of the major problems faced by small and medium-scale farmers. Among these challenges, the selection of high-quality seeds is particularly important because seed health directly influences germination, crop growth, and final yield. Conventional seed quality assessment generally depends on manual inspection and visual observation, which can be time-consuming and may produce inconsistent results [1].

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and image processing have created opportunities to automate agricultural decision-making processes. Machine learning models can learn visual characteristics from seed images and classify seeds based on their quality. By applying image preprocessing, feature extraction, and classification techniques, an intelligent system can assist farmers in identifying potentially healthy or defective seeds. Such automated prediction can reduce dependence on manual inspection and provide farmers with faster and more consistent information before cultivation [2]. Another major challenge is the high cost of agricultural machinery. Modern cultivation equipment can significantly improve efficiency and reduce manual labour however, purchasing and maintaining such equipment may not be economically feasible for small-scale farmers. Equipment rental provides an alternative solution by allowing farmers to access required machinery without making a large investment. A digital rental platform can connect farmers with equipment providers, allowing them to search for available machinery, place bookings, make online payments, and track their rental activities [3].

To address these challenges, this paper presents AgriNex AI: Seed Quality Prediction and Cultivation Rental System, an integrated smart agriculture platform that combines AI-based seed quality prediction with an agricultural equipment rental service. The proposed system allows farmers to upload seed images through a digital platform, after which the AI prediction module processes the image and generates a seed quality result. The system also

provides an equipment rental module through which farmers can view available cultivation machinery and request equipment based on their requirements [4].

The proposed platform consists of four major components: the Admin Module, Farmer Module, Equipment Provider Module, and AI Prediction Module. The administrator manages users, equipment providers, prediction records, bookings, payments, and system reports. Farmers can register and log in, upload seed images, view AI-generated prediction results, book equipment, make online payments, and track rentals. Equipment providers can add machinery details, manage equipment availability, approve or reject booking requests, and monitor their earnings. The AI module performs image preprocessing, feature extraction, model training, and prediction generation to support automated seed quality assessment [5].

II. LITERATURE ANALYSIS

Several studies have explored the application of Artificial Intelligence and Machine Learning in agriculture to improve productivity and reduce the limitations of traditional farming practices. Long (2021) reviewed the use of AI, spectral imaging, Near-Infrared spectroscopy, image processing, and data analysis for non-destructive seed quality inspection. Their study highlighted the potential of automated image-based techniques for rapid and efficient seed quality assessment. Srinivasaiah (2023) developed a machine learning-based seed quality prediction approach using Convolutional Neural Networks (CNN), where seed images were classified into premium, standard, and regular quality categories. Their results demonstrated the potential of CNN models for automated seed classification, although further improvement in prediction accuracy and dataset diversity was identified as necessary. Hazarika (2025) proposed AgriNex, a smart agriculture framework integrating Large Language Models, UAVs, IoT, semantic mapping, and deep reinforcement learning to improve agricultural data collection, energy efficiency, and resource allocation. Similarly, Hossen et al. presented a systematic literature review of AI applications in agriculture, covering areas such as soil management, disease management, crop monitoring, and weed management. These studies demonstrate the increasing role of AI and ML in developing intelligent agricultural solutions. However, existing research largely focuses on individual agricultural applications, while limited attention is given to integrating AI-based seed quality prediction with practical agricultural resource-access services. Therefore, the proposed AgriNex AI system combines AI-based seed quality prediction with an agricultural equipment rental platform, enabling farmers to obtain intelligent seed assessment while also accessing cultivation machinery at affordable rental costs.

Table I.
Literature Work

Author and Year	Methods	Future Scope
Wei Long, Shasha Jin, Yujie Lu, Liangquan Jia, Xu Huang, Linhua Jiang (2021)	The study reviews AI, spectral imaging, Near-Infrared (NIR) spectroscopy, image processing, and data analysis for non-destructive seed quality inspection. Image denoising, segmentation, dimensionality reduction, and classification techniques are discussed for rapid seed quality assessment.	Improve image denoising and segmentation efficiency, reduce spectral data dimensionality, support more seed varieties, improve model stability and transferability, and develop seed vigor classification using germination images.
Raghavendra Srinivasaiah, Meenakshi,Ravikumar Hodikehosahally Channegowda, Santosh Kumar Jankatti (2023)	The study applies Machine Learning and Convolutional Neural Networks (CNN) for seed quality prediction. A labeled seed dataset is divided into training, validation, and testing sets. The CNN classifies seeds into premium, standard, and regular quality categories. The training accuracy exceeded 97%, while the reported prediction accuracy was 64%.	Improve prediction accuracy, increase dataset size and diversity, support additional seed varieties and quality categories, reduce classification errors, and improve performance on larger real-world datasets.
Ananya Hazarika, Jianlin Guo, Kieran Parsons, Yukimasa Nagai, Takenori Sumi,	The proposed AgriNex system integrates LLM, UAV, IoT, semantic mapping, and Deep Reinforcement Learning. A Semantic Criticality Index (SCI) determines the importance of agricultural sensor data, while a Semantic-	Extend the system to real-world UAV-IoT deployment, improve LLM-based agricultural decision-making, optimize energy consumption, support larger farms,

Philip V. Orlik, Mehdi Rahmati (2025)	Guided Deep Q-Network (SG-DQN) optimizes data collection, resource allocation, and energy consumption.	and integrate applications such as crop monitoring, disease detection, and yield prediction.
Md. Ismail Hossen, Nafiz Fahad, Md. Ridoy Sarkar, Mohammad Ruhani Rabbi (2023)	The study uses a Systematic Literature Review (SLR) to analyze the applications of AI and ML in agriculture. It covers AI applications in soil management, disease management, crop monitoring, and weed management and discusses the role of automation in reducing manual agricultural work.	Focus on farmers' limitations in adopting AI, improve accessibility and usability of AI systems, and develop ML-based solutions for real-world farming. Future applications can include crop prediction, disease detection, seed quality assessment, and precision agriculture.

III. AI/ML IMPLEMENTATION

The AI/ML component of the proposed AgriNex AI: Seed Quality Prediction and Cultivation Rental System is designed to automate the identification of seed quality from uploaded seed images. The implementation uses image processing and machine learning techniques to analyze the visual characteristics of seeds and classify them into predefined quality categories. The objective of this component is to provide farmers with a fast and automated method for preliminary seed quality assessment without depending entirely on manual inspection.

A. Dataset Collection and Preparation

The first stage of the AI implementation is the preparation of a seed image dataset. The dataset consists of images representing different seed conditions and quality categories. Each image is associated with a corresponding class label, allowing the machine learning model to learn the relationship between the visual characteristics of a seed and its quality. The dataset is divided into training and testing subsets. The training data is used to learn the patterns present in seed images, while the testing data is used to evaluate the model's performance on previously unseen images.

B. Image Preprocessing

Before training the model, the collected seed images are preprocessed to ensure that the input data has a consistent format. The images are resized to the required dimensions and converted into a suitable numerical representation. Pixel normalization is applied to reduce variations in image intensity and improve the learning process. Noise and unnecessary background information can also be reduced where required. These preprocessing operations provide standardized input to the machine learning model and help improve prediction consistency.

C. Feature Extraction and Learning

The processed images contain important visual information related to seed quality, including color, shape, size, texture, surface characteristics, and visible defects. These characteristics are used by the AI model to distinguish between different seed categories. Depending on the selected machine learning approach, relevant features may be extracted using image-processing techniques, or the model may automatically learn discriminative features directly from the images using a deep learning architecture.

In a deep learning-based implementation, multiple layers of the model progressively learn increasingly complex patterns from the input images. Initial layers can identify basic visual patterns such as edges and textures, while deeper layers learn more meaningful structures associated with seed appearance and defects. This eliminates the need to manually define every visual characteristic used for classification.

D. Model Training

The preprocessed training images are supplied to the selected machine learning model along with their corresponding labels. During training, the model learns the relationship between image features and seed quality classes by minimizing the difference between the predicted output and the actual class label. The model parameters are updated iteratively during the training process so that the classification error is gradually reduced.

The training process involves multiple iterations over the dataset. The performance of the model is monitored during training to identify overfitting and ensure that the model learns generalized patterns rather than memorizing the training images. Appropriate training and validation strategies are used

to select a model that provides reliable classification performance.

E. Model Testing and Evaluation

After training, the model is evaluated using test images that were not used during the training process. This allows the system to determine whether the learned model can correctly classify unseen seed images. Standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score are used to measure the effectiveness of the implemented model.

Accuracy measures the overall proportion of correctly classified samples, while precision indicates how accurately the model identifies samples belonging to a particular quality class. Recall measures the model's ability to identify relevant samples correctly, and the F1-score provides a balance between precision and recall. These metrics provide a more comprehensive evaluation than accuracy alone.

F. Seed Quality Prediction

Once the model has been trained and evaluated, it is integrated into the AgriNex AI application. When a farmer uploads a seed image, the image passes through the same preprocessing pipeline used during model training. The processed image is then provided to the trained model for inference. The model analyzes the visual characteristics of the input image and generates a prediction corresponding to one of the predefined seed quality categories.

The prediction result is returned to the application and displayed to the farmer through the user interface. This enables the farmer to obtain an automated preliminary assessment of the uploaded seed without performing a complete manual inspection.

G. AI Integration with the Application

The trained AI model is connected with the application through the AI prediction component. The applicationmanages image uploading, input validation, preprocessing, model execution, and presentation of the prediction result. The prediction information can also be stored in the system database along with relevant user and prediction details, allowing administrators to monitor prediction records and generate reports.

The complete AI workflow can therefore be represented as:Seed Image Upload → Image Preprocessing → Feature Extraction/Feature Learning → Trained ML Model → Classification → Seed Quality Prediction → Result Display

Through this implementation, AgriNex AI integrates artificial intelligence into a practical agricultural application and provides farmers with automated image-based seed quality assessment. The AI component can be further improved by increasing dataset size and diversity, applying data augmentation, tuning model parameters, and retraining the model with additional real-world seed images.

IV. WORKING METHODOLOGY

The working methodology of the proposed AgriNex AI: Seed Quality Prediction and Cultivation Rental System integrates Artificial Intelligence, image processing, machine learning, database management, and an online equipment rental mechanism into a single platform. The system is designed to provide farmers with automated seed quality assessment while also enabling them to access agricultural equipment on a rental basis. The overall working process consists of user authentication, seed image processing, AI-based prediction, prediction result management, equipment search and booking, payment processing, and rental tracking.

A. User Registration and Authentication

The process begins with user registration and authentication. Farmers and equipment providers create accounts by providing the required information. The system validates the submitted details and stores the user information securely in the database. After successful registration, users can log in to access the functionalities available according to their respective roles. The administrator has additional privileges to manage users, equipment providers, bookings, payments, and system records.

B. Seed Image Upload

After authentication, the farmer can access the seed quality prediction functionality. The farmer uploads an image of the seed through the application interface. The system validates the uploaded file and checks whether the image satisfies the required format and input conditions. The uploaded image is then forwarded to the AI prediction pipeline for further processing.

C. Image Preprocessing

The uploaded seed image undergoes preprocessing before being provided to the trained AI model. The image is resized according to the input requirements of the model and converted into an appropriate numerical representation. Pixel values are normalized to maintain consistency between training images and newly uploaded images. Where necessary, noise and irrelevant background information are reduced to improve the quality of the input. The processed image is then prepared for feature extraction or direct model inference.

D. AI-Based Seed Quality Prediction

The preprocessed image is provided to the trained machine learning model. The model analyzes the visual characteristics of the seed and identifies patterns learned from the training dataset. Features such as color, shape, texture, size, and visible surface defects contribute to the classification process. The model generates a prediction corresponding to the predefined seed quality categories.

The prediction workflow is represented as:

Seed Image → Preprocessing → Feature Extraction/Feature Learning → Trained ML Model → Classification → Quality Prediction

The resulting prediction is returned to the application and displayed to the farmer. This provides an automated preliminary assessment of the uploaded seed and reduces dependence on manual visual inspection.

a. Prediction Result Storage

After the AI model generates the prediction, the result can be associated with the farmer and the uploaded image and stored in the application database. The stored information allows the system to maintain a history of prediction activities. Administrators can use these records to monitor system usage, review prediction information, and generate relevant reports.

b. Equipment Provider and Equipment Management

The second major functionality of the system is the agricultural equipment rental service. Equipment providers can register and add details of their available machinery, including equipment name, type, description, rental price, and availability information. The administrator can verify equipment providers and monitor the equipment listed on the platform.

Equipment providers can update the availability of their machinery according to their current rental status. This ensures that farmers are able to view equipment that is available for booking and reduces the possibility of duplicate or conflicting bookings.

c. Equipment Search and Booking

Farmers can browse the available cultivation equipment through the rental module. The system displays relevant equipment information so that farmers can select machinery according to their cultivation requirements and budget. After selecting suitable equipment, the farmer submits a booking request by specifying the required rental details.

The system checks the availability of the selected equipment before processing the request. The booking information is stored in the database and made available to the respective equipment provider. The provider can review the request and approve or reject it based on equipment availability.

d. Online Payment and Rental Tracking

After a booking is approved, the farmer can complete the required online payment through the system. Payment-related information is recorded for transaction management. Once the booking and payment process is completed, the farmer can track the rental status through the application.

Equipment providers can also monitor their active and completed bookings and view their earnings. This provides transparency between farmers, equipment providers, and the administrator.

e. Admin Monitoring and Management

The administrator acts as the central management component of the system. The admin can manage registered users, verify equipment providers, monitor AI prediction records, manage equipment-related activities, monitor bookings and payments, and generate system reports. Administrative monitoring helps maintain the reliability and proper operation of the platform.

f. Overall System Workflow

The complete working methodology of AgriNex AI can be summarized as follows:

User Registration/Login → Farmer Dashboard → Seed Image Upload → Image Preprocessing → AI/ML Prediction → Display Prediction Result

For equipment rental, the workflow is:
Equipment Provider Registration → Equipment Listing → Availability Management → Farmer Searches Equipment → Booking Request → Provider Approval/Rejection → Online Payment → Rental Tracking

Thus, the proposed methodology combines AI-based seed quality prediction with a digital agricultural equipment rental service. The integration of these functionalities provides farmers with intelligent decision support as well as affordable access to cultivation machinery through a single platform.

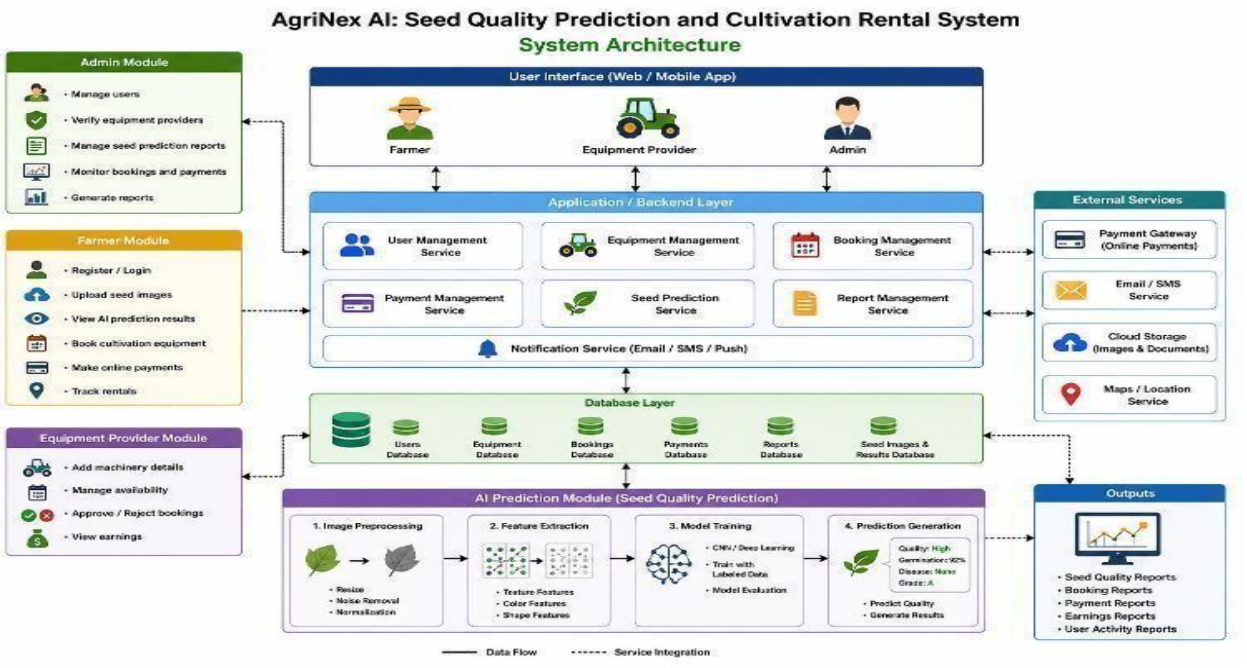

Figure 1. System Diagram

V. RESULTS AND DISCUSSION

The implementation of the proposed AgriNex AI: Seed Quality Prediction and Cultivation Rental System demonstrates the practical application of Artificial Intelligence and Machine Learning for seed quality assessment along with a digital platform for agricultural equipment rental. The developed system provides farmers with an automated mechanism for analyzing seed images and obtaining quality predictions, while the rental module provides access to cultivation equipment without requiring farmers to purchase expensive machinery.

A. AI Model Results

The AI-based seed quality prediction component processes the seed image provided by the farmer and generates a predicted quality category. During the implementation, the seed images are preprocessed before being supplied to the trained machine learning model. This ensures that the input provided during prediction is consistent with the data used during model training.

The performance of the implemented model is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. Accuracy represents the overall percentage of correctly classified seed images. Precision indicates the proportion of predicted samples belonging to a particular class that are actually correct, while recall represents the ability of the model to identify samples belonging to the respective class. The F1-score provides a balanced measure of precision and recall.

The evaluation results demonstrate the capability of the trained model to identify visual patterns associated with different seed quality categories. However, model performance can vary depending on factors such as image quality, lighting conditions, background, seed orientation, dataset size, and similarity between different seed classes.

B. Seed Prediction Results

The developed system successfully accepts seed images through the farmer interface and passes them through the implemented AI prediction pipeline. After processing the image, the system generates a prediction and displays the result to the farmer. This reduces the time and effort required for preliminary seed inspection compared with completely manual visual examination.

The prediction process also demonstrates the importance of maintaining consistency between the training and prediction environments. Images uploaded by users must undergo the same preprocessing operations used during model development. Differences in image dimensions, lighting, background, or image quality may affect prediction performance.

C. System Functionality Results

Apart from the AI component, the implemented system provides separate functionality for farmers, equipment providers, and administrators. Farmers can register and log in, upload seed images, view prediction results, search for agricultural equipment, submit rental requests, make payments, and track rental activities. Equipment providers can add machinery details, manage equipment availability, process booking requests, and monitor their rental activities.

The administrative component provides centralized management of users, equipment providers, prediction records, bookings, payments, and reports. The integration of these modules allows the system to operate as a unified agricultural platform rather than as an isolated seed prediction application.

D. Discussion

The results indicate that AI-based image analysis can be used as a practical decision-support mechanism for preliminary seed quality assessment. The major advantage of the proposed approach is the automation of visual analysis, which can reduce dependence on manual inspection and provide results through a digital interface. The system can be particularly useful for farmers who require quick information about the apparent quality of seeds before cultivation.

At the same time, the AI prediction should be considered an automated preliminary assessment rather than a complete laboratory-based seed certification process. The reliability of predictions depends heavily on the quality, size, diversity, and labeling accuracy of the training dataset. Images captured under different lighting conditions, backgrounds, camera qualities, and seed orientations may introduce variations that can influence model predictions.

The equipment rental component complements the AI functionality by addressing the economic limitations associated with agricultural machinery. Instead of purchasing expensive equipment, farmers can access machinery through the rental platform according to their requirements. This can potentially reduce initial cultivation expenses and improve access to modern agricultural tools.

Overall, the implementation demonstrates the feasibility of combining AI-based seed quality prediction and digital agricultural equipment rental within a single system. The proposed platform provides a foundation that can be further improved by increasing the size and diversity of the seed image dataset, applying advanced deep learning techniques, improving image preprocessing, incorporating additional seed quality classes, and continuously retraining the model using real-world agricultural data.

Result

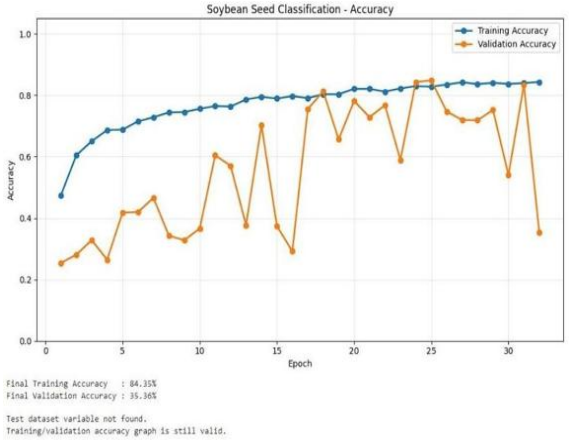

Fig 2. Soybean Seed Classification - Accuracy

This graph plots the Training Accuracy (blue line) and Validation Accuracy (orange line) over 33 epochs.

- Training Accuracy (Blue): The model learns steadily. It starts around 48% and rises smoothly, eventually plateauing at roughly 84.35% by the end of the training. This indicates the model is

fitting the training data well.

- Validation Accuracy (Orange): This line is highly volatile. It fluctuates wildly between roughly 25% and 80% throughout the epochs. While it trends slightly upward early on, it fails to stabilize. notably, there is a huge drop at the very end (Epoch 33) down to roughly 35.36%.
- Analysis: This is a classic sign of overfitting. The model has memorized the training data but is unable to generalize the patterns to new, unseen data (the validation set). The large gap between the final training accuracy (84%) and validation accuracy (35%) confirms the model is not reliable for real-world predictions in its current state.

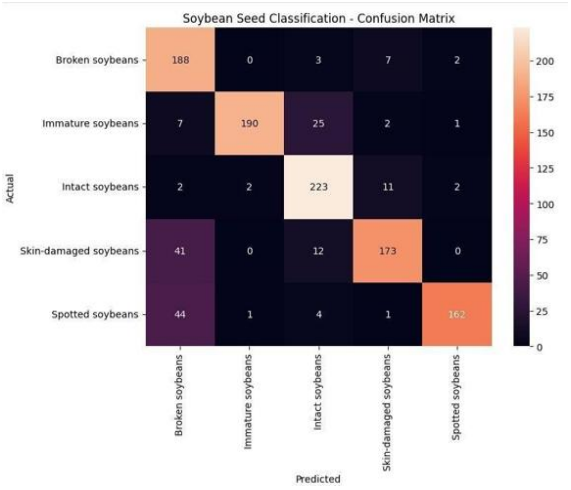

Fig 3. Soybean Seed Classification – Confusion Matrix

This heatmap breaks down exactly where the model is succeeding and failing across the 5 classes of soybeans. The diagonal numbers (the light squares) represent correct predictions.

- Strong Classes:
  - Intact soybeans: This is the model's best category. It correctly identified 223 samples.
  - Immature soybeans: Correctly identified 190 samples.
  - Broken soybeans: Correctly identified 188 samples.
- Weaknesses & Errors:
  - Skin-damaged soybeans: The model correctly identified 173, but it misclassified 41 of them as "Broken soybeans."
  - Spotted soybeans: The model correctly identified 162, but it misclassified 44 of them as "Broken soybeans."
- Key Insight: The model seems to have a bias toward predicting "Broken soybeans." When it sees a "Skin-damaged" or "Spotted" seed, it frequently mistakes them for broken ones. Additionally, there is confusion between "Immature" and "Intact" seeds (25 misclassifications).

VI. CONCLUSION

The proposed AgriNex AI: Seed Quality Prediction and Cultivation Rental System provides an intelligent and integrated solution for addressing important challenges faced by farmers. The system utilizes Artificial Intelligence, Machine Learning, and image processing to analyze seed images and predict their quality. By automating the initial seed inspection process, the system reduces dependence on manual examination and provides farmers with quick and accessible information for making better seed selection decisions.

The combination of AI-based seed quality prediction and agricultural equipment rental makes AgriNex AI a comprehensive smart agriculture platform. It provides intelligent decision support while also improving farmers' access to modern cultivation resources. The proposed system can contribute to reducing cultivation costs, improving resource utilization, and encouraging the adoption of technology-driven farming practices.

Future improvements can focus on increasing the size and diversity of the seed image dataset, incorporating advanced deep learning models, improving prediction accuracy, supporting additional seed varieties and quality classes, and integrating real-time agricultural data such as soil conditions, weather information, and crop requirements. The equipment rental module can also be extended with location-based equipment recommendations, real-time availability, and intelligent pricing. These enhancements can further strengthen AgriNex AI as an effective AI-enabled platform for smart and sustainable agriculture.

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