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SeedSure AI: Smartphone-Based Seed Germination Viability Prediction Before Purchase

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Abstract: Seed quality and viability are decisive factors in agricultural productivity, since poor-quality seed lowers germination rates, delays crop establishment, and causes measurable financial loss to farmers. Conventional seed evaluation relies on manual visual inspection or laboratory germination testing, both of which are labour-intensive, time-consuming, and dependent on trained personnel, making them impractical for smallholder farmers who need a fast, pre-purchase indication of seed quality. This study presents the objective, method, and results of SeedSure AI, a smartphone-accessible, computer-vision-based system that lets a user photograph a seed sample and receive an on-the-spot preliminary viability and quality assessment. The method integrates a Roboflow-hosted computer-vision inference service through a REST API: uploaded images are pre-processed, submitted for inference, and the returned class predictions and confidence scores are converted into a germination-percentage estimate, a 1-10 quality score, disease-risk indicators, and plain-language recommendations. On an evaluation set of 400 labelled samples, the system attained an accuracy of 94.25%, a precision of 94.47%, a recall of 94.00%, an F1-score of 94.23%, and a reported ROC-AUC of 0.97, indicating strong separability between viable and non-viable classes under the conditions tested. These results indicate that an API-integrated, ordinary-smartphone-image pipeline can deliver useful preliminary seed-viability guidance for purchase-time decision-making, while deferring definitive viability confirmation to standardised laboratory germination tests.

Keywords: Seed Viability Assessment, Computer Vision, Roboflow Inference API, Precision Agriculture, Smartphone-Based Diagnostics.

Nomenclature

Abbreviation	Description
AI	Artificial Intelligence
API	Application Programming Interface
REST	Representational State Transfer
ROC-AUC	Receiver Operating Characteristic – Area Under the Curve

1. Introduction

Seed quality is a foundational determinant of agricultural outcomes: the physiological condition of a seed lot directly governs germination rate, seedling vigour, and the eventual uniformity of a crop stand. Farmers who unknowingly purchase or sow low-viability seed face reduced germination, patchy stands, and the downstream cost of re-sowing or yield shortfall. This is the central motivation for the present work: to give a farmer a fast, low-cost way to check seed quality before money and land are committed to it.

In practice, this pre-purchase check is difficult to obtain. Traditional seed-quality evaluation is built around manual visual inspection and standardised laboratory germination testing; both are accurate in principle but demand specialised facilities, trained personnel, and several days to weeks of turnaround, which places them out of reach at the point of sale. Recent research has shown that computer vision and machine learning can automate several aspects of this evaluation, from imaging-based phenotyping to hyperspectral- and infrared-based viability prediction [1][2][3][4], and machine-vision pipelines that reduce dependence on expert human judgement in seed classification [5][6][7]. These studies confirm the technical feasibility of vision-based seed assessment, but most are demonstrated in controlled research settings using specialised imaging hardware and bespoke, individually trained models, leaving the ordinary farmer with a smartphone camera no accessible route to these benefits.

To close this gap, we propose SeedSure AI, a smartphone-accessible seed assessment application that integrates a Roboflow-hosted computer-vision inference service through an API, rather than requiring a custom-trained, locally deployed model. This design choice trades the marginal accuracy gains a purpose-built, on-device CNN might offer for (i) a substantially lower barrier to deployment, (ii) faster iteration,

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since the underlying vision model can be updated on the inference provider's side without an application redeployment, and (iii) accessibility for non-expert users. Our contributions are:

- An end-to-end, API-integrated seed-assessment pipeline that requires only a smartphone photograph as input, with no specialised imaging hardware.
- Conversion of raw inference class-and-confidence outputs into farmer-facing indicators: a germination-percentage estimate, a 1-10 quality score, disease-risk flags, and plain-language recommendations.
- A user-facing, crop-wise analytics dashboard that lets a user track assessment history across scans and crop types.
- An accessibility-first design positioned explicitly as a preliminary, pre-purchase decision aid rather than a laboratory replacement.

In summary, SeedSure AI couples a hosted computer-vision inference service with an application layer that performs pre-processing, confidence-to-quality conversion, and recommendation generation, and on a 400-sample evaluation set it reached 94.25% accuracy and a 94.23% F1-score (Section 4). The remainder of this paper is organised as follows: Section 2 reviews related work; Section 3 describes the methodology; Section 4 reports the results; Section 5 discusses these results; and Section 6 concludes.

2. Literature Review

2.1 Summary of Previous Research

This section summarises eight studies most relevant to smartphone-based seed assessment, drawn from the thirty works reviewed in Table 1.

[1] developed SeedGerm, a cost-effective phenotyping platform combining seed imaging with machine learning; it is built around a laboratory imaging rig rather than a handheld camera.

[2] proposed SeedSortNet, a lightweight CNN with visual attention for seed sorting, trained and validated for a single sorting task rather than general viability assessment.

[3] combined computer vision with machine learning to classify maize seed varieties, showing that ordinary RGB features carry useful signal, though under controlled laboratory conditions.

[4] used infrared thermography for non-destructive viability assessment, which requires a thermal camera unavailable on consumer smartphones.

[5] applied an improved ResNet50 model to detect cottonseed quality, achieving strong accuracy for a single crop but requiring bespoke training and maintenance.

[6] built AIseed, automated image-analysis software targeting research-scale throughput rather than a single farmer-facing assessment.

[7] used machine vision to assess postharvest soybean seed quality under standardized imaging conditions.

[8] applied interactive machine learning to soybean seed and seedling quality classification, involving a human-in-the-loop labelling step.

Across these eight studies and the remaining twenty-two summarized in Table 2, methods achieving the highest accuracy typically rely on specialized imaging hardware or a bespoke CNN, and comparatively few studies package their model into an accessible, end-user-facing application.

2.2 Review Table

Table 1 compares the methodology, advantages, and disadvantages of the thirty studies reviewed, followed by SeedSure AI's own position on the same dimensions.

Table 1. *Methodology, Advantages, And Disadvantages of Reviewed Studies Compared with Seedsure Ai*

Ref.	Methodology	Advantages	Disadvantages
[1]	SeedGerm: seed imaging + ML phenotyping	Automates germination scoring; removes manual labour	Requires a dedicated laboratory imaging rig
[2]	SeedSortNet: lightweight attention CNN	Efficient enough for on-device / real-time sorting	Trained for a single task (sorting), not general viability
[3]	Computer vision + ML for maize variety	Uses ordinary RGB imaging	Validated only under controlled lab imaging conditions
[4]	Infrared thermography	Non-destructive viability signal	Needs a thermal camera unavailable on smartphones
[5]	Improved ResNet50	High accuracy for cotton seed	Requires bespoke training/maintenance per crop
[6]	AIseed automated image analysis	High-throughput, non-destructive phenotyping	Oriented to research throughput, not single-user apps
[7]	Machine vision (soybean)	Confirms feasibility of vision-based grading	Standardised imaging setup assumed
[8]	Interactive machine learning	Improves label quality via human feedback	Requires human-in-the-loop effort per sample
[9]	Machine vision + colour indices	Simple, interpretable features	Colour alone may miss internal damage
[10]	RGB imaging + machine vision (maize)	Works with ordinary RGB cameras	Focused on early germination stage only
[11]	Deep learning on rice seed images	Automates germination-rate evaluation	Crop-specific (rice) model
[12]	NIR hyperspectral + deep learning	Non-destructive, high viability accuracy	Requires costly hyperspectral hardware
[13]	NIR hyperspectral + transfer learning	Reduces training data needs	Still needs a hyperspectral sensor
[14]	Hyperspectral imaging (wheat)	High discrimination accuracy	Specialised, costly imaging system
[15]	Fluorescence hyperspectra + CARS-SVM-AdaBoost	Combines spectral + ensemble learning	Complex pipeline, lab-only hardware
[16]	SWIR hyperspectral imaging	Good spectral viability signal	SWIR sensors are expensive and bulky
[17]	SWIR + chemometrics	Rapid corn viability screening	Requires SWIR hardware and calibration
[18]	Hyperspectral imaging (maize)	Detects vigour differences after ageing	Not deployable on a handheld device
[19]	Hyperspectral + image features	Combines spectral and spatial cues	Hardware cost and complexity
[20]	Hyperspectral + model updating	Adapts across harvest years	Still hardware-dependent
[21]	Near-infrared spectroscopy	Detects internal kernel damage	Needs NIR spectrometer, not a camera
[22]	NIR hyperspectral imaging	Accurate maize kernel classification	Specialised imaging equipment
[23]	Hyperspectral imaging	High-speed viability measurement	Costly, lab-based hardware
[24]	LED-induced hyperspectral reflectance	Non-destructive cucumber assessment	Custom LED/hyperspectral rig required
[25]	Micro-CT imaging + 3D morphometry	Captures internal 3-D seed structure	Micro-CT equipment is highly specialised
[26]	FT-NIR + X-ray + ML	Combines multiple modalities for accuracy	Very high hardware and processing cost
[27]	Image analysis (soybean)	High-throughput phenotyping	Research-oriented, not consumer-facing
[28]	Review: optical sensing + digital phenotyping	Broad synthesis of the field	A review, not a deployable system
[29]	CNN accelerator for seed sorting	Addresses on-device inference speed	Assumes a trained model already exists
[30]	Review: deep learning for seed quality	Surveys deep-learning approaches	A review, not a deployable system
SeedSure AI	Roboflow-hosted CV inference via API	No specialised hardware; accessible smartphone UI; fast preliminary results	Backbone/training details are managed by a third-party platform; not yet benchmarked against baseline CNNs

2.3 Research Gap

Existing research demonstrates the effectiveness of computer vision and machine-learning techniques for seed classification, quality assessment, viability detection, and germination analysis. However, three specific gaps remain, each of which SeedSure AI is designed to address directly.

- Hardware accessibility gap: a majority of high-performing approaches (hyperspectral, SWIR, NIR, X-ray, micro-CT [12]-[26]) depend on specialised imaging equipment unavailable to farmers. SeedSure AI addresses this by requiring only a standard smartphone camera image as input.
- Task-integration gap: existing systems typically target a single research task in isolation: variety classification [3],[19],[20], seed sorting [2][29], or laboratory-based viability analysis [12]-[18],[21][22][23][24]. SeedSure AI integrates inference, quality scoring, disease-risk flagging, and recommendation generation into a single user session.
- Deployment-accessibility gap: even where a strong model exists, its packaging into a practical, non-expert-facing application is comparatively rare [27][28][30]. SeedSure AI closes this gap through a hosted inference service invoked via an API.

SeedSure AI therefore positions itself as an application-integration contribution rather than a model-architecture contribution, and provides a foundation for future validation using larger, more diverse datasets and laboratory germination results.

3. Methodology

3.1 System Architecture and Pipeline

SeedSure AI is a web-based application built with React, TypeScript, and Tailwind CSS on the frontend, using Vite as the build tool and TanStack Start as the application framework. Rather than training and hosting a bespoke convolutional neural network, the system integrates a Roboflow-hosted computer-vision inference service through a REST API, authenticated via a ROBOFLOW_API_KEY and addressed to a specific ROBOFLOW_MODEL_ID. Fig. 1 shows the consolidated processing pipeline.

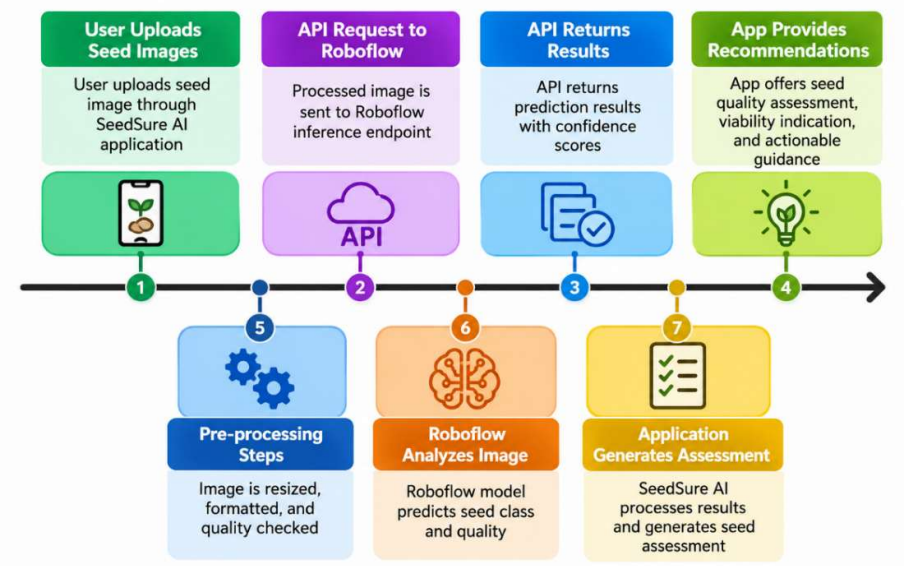

Fig. 1. *Consolidated SeedSure AI pipeline. The seven-stage flow runs from seed-image capture, through pre-processing and Roboflow inference, to the confidence-based assessment shown to the user.*

3.1.1 The pipeline proceeds through seven stages

1) Seed image input - the user uploads (or captures) a seed image, after selecting the relevant crop type.
2) Pre-processing - the uploaded image is validated, resized, formatted, and checked for basic quality (focus, exposure).
3) API request to Roboflow - the processed image is base64-encoded and submitted as a POST request to the configured inference endpoint.
4) Computer-vision inference - the Roboflow-hosted model analyses the image and returns a predicted seed class/quality label, with bounding-box information where available.
5) Prediction and confidence - the API response is parsed for the predicted class and its confidence score.
6) Result processing and assessment - SeedSure AI derives a germination-percentage estimate, a 1-10 quality score, and disease-risk indicators from the mean confidence of detected predictions.

7) Recommendation and user guidance - the application presents a plain-language assessment with actionable recommendations.

3.2 Backbone Architecture, Training Configuration, and Data Split

The backbone architecture, training hyperparameters, and train/validation/test split of the hosted model are managed by the third-party Roboflow platform and are not independently configured or reported in this study.

1. **Ground-Truth Procedure:** The ground-truth labelling procedure associated with the Roboflow-hosted model was not independently available to the authors. The SeedSure AI application does not independently establish ground-truth labels or perform laboratory-based seed viability testing. Instead, it submits user-provided seed images to the configured Roboflow inference API and processes the class labels and confidence scores returned by the hosted model. Consequently, the germination estimates, quality scores, disease-risk indicators, and recommendations generated by the application represent model-based predictions rather than independently verified ground-truth measurements. Standardised laboratory germination testing and documented reference labels are required to independently establish the reliability of the predicted seed viability.
2. **Training, Validation, and Test Samples:** The evaluation dataset used in this study comprised 400 labelled seed samples, including 200 viable and 200 non-viable samples. The confusion matrix presented in Table 2 summarises the classification outcomes for these 400 samples. The computer-vision model used by SeedSure AI is hosted and managed by the third-party Roboflow platform. The exact numbers of samples allocated to the training, validation, and test subsets were not independently available to the authors, and no separate training, validation, or test split was created by the authors. The application functions as an inference client that submits seed images to the configured Roboflow model through a REST API and processes the returned predictions. Accordingly, the 400 samples represent the reported evaluation set; the training, validation, and test subset counts cannot be specified without verification of the original dataset configuration or experimental records.

Table 2 *Composition of the Reported Evaluation Set*

Sample category	Number of samples
Viable seeds	200
Non-viable seeds	200
Total evaluation samples	**400**

Note: These counts describe the evaluation set reported in the manuscript. They do not represent the training, validation, and test subset counts.

3. **Crop types:** The SeedSure AI application supports crop-wise seed assessment for Wheat, Rice, Maize, and Soybean, with an additional 'Other' option for seed types not specifically listed. Before analysis, the user selects the relevant crop type and uploads or captures the corresponding seed image. The selected crop type is associated with the image during the assessment workflow and submitted to the configured Roboflow inference service for prediction. The availability of a crop option in the application interface does not necessarily establish that the crop was represented in the 400-sample evaluation dataset.

3.3 Mathematical Formulation

This section formalises both (a) the underlying computer-vision model and (b) the evaluation metrics computed from its outputs.

1) Underlying Computer-Vision Model:

SeedSure AI's inference call returns a class label and a confidence score from a CNN hosted on Roboflow. For an input seed image X, a stack of convolutional layers extracts hierarchical features. At layer l, the feature map is:

$$z(l) = \sigma(W(l) * a(l-1) + b(l)) \quad (1)$$

where a(l−1) is the activation from the previous layer, W(l) and b(l) are the learnable weights and bias, "*" is convolution, and σ is a non-linear activation (typically ReLU). Spatial down-sampling is applied between blocks:

$$a(l) = \text{pool}(z(l)) \quad (2)$$

The final feature map is flattened into a vector h and mapped to class logits u:

$$u = W_{fc} \cdot h + b_{fc} \quad (3)$$

A softmax layer converts the logits into a probability distribution:

$$P(y=i \mid X) = \exp(ui) / \Sigma j \exp(uj) \quad (4)$$

The predicted class is the class with the highest probability:

$$\hat{Y} = \text{argmax_i } P(y=i \mid X) \quad (5)$$

and the confidence score C returned to the application is:

$$C = P(\hat{Y} \mid X) = \max_i P(y=i \mid X) \quad (6)$$

During training, the model minimises categorical cross-entropy loss:

$$L = -\Sigma i \; yi \cdot \log(P(y=i \mid X)) \quad (7)$$

2) Evaluation Metrics:

Using the classification threshold T, SeedSure AI's binary decision is:

$$\hat{Y}=1 \text{ if } C \geq T; \; \hat{Y}=0 \text{ if } C<T \quad (8)$$

From the resulting confusion matrix (TP, TN, FP, FN), the standard metrics are:

$$\text{Accuracy} = (TP+TN)/(TP+TN+FP+FN) \quad (9)$$

$$\text{Precision} = TP/(TP+FP) \quad (10)$$

$$\text{Recall} = TP/(TP+FN) \quad (11)$$

$$F1 = 2\times(\text{Precision}\times\text{Recall})/(\text{Precision}+\text{Recall}) \quad (12)$$

$$TPR = TP/(TP+FN); \;\; FPR = FP/(FP+TN) \quad (13)$$

The ROC curve plots TPR against FPR across thresholds; the area under it summarises discrimination ability:

$$\text{ROC-AUC} = \int_0^1 TPR \; d(FPR) \quad (14)$$

3.4 Experimental Setup

Table 3 summarises the experimental setup.

Table 3. *Experimental Setup*

Component	Description
Application	SeedSure AI
Type	Web-based seed assessment system
Frontend	React, TypeScript, Tailwind CSS
Build Tool	Vite
Framework	TanStack Start
AI Technology	Roboflow-hosted CV inference
AI Integration	Roboflow API
Auth	ROBOFLOW_API_KEY
Model Config	ROBOFLOW_MODEL_ID
Input	Uploaded seed image
Image Rep.	Base64-encoded image
Validation	Image and crop-type validation
Output	Prediction class and confidence score
Add'l Output	Bounding-box info when available
Metrics	Accuracy, Precision, Recall, F1, ROC-AUC
User Target	Farmers, non-expert users
Lab Replacement	No; preliminary assessment only

Table 4 gives the Hyperparameter.

Table 4. *Hyperparameter / Configuration*

Parameter	Value
Platform	Roboflow
Model	Via ROBOFLOW_MODEL_ID
Auth	ROBOFLOW_API_KEY
HTTP method	POST
Content type	application/x-www-form-urlencoded
Input format	Base64 image
Timeout	20 seconds
Output	Class + confidence
Viability threshold	Relative viable/damaged confidence
Min germination	5%
Max germination	98%
Quality score range	1-10
Heatmap	From bounding boxes when available
Confidence calc.	Mean confidence of predictions

3.5 Note on the Nature of the Reported Results

All metrics reported in Section 4 are computed from the confusion matrix presented in Table 5 using Eqs. (9)-(14). The precision-recall and ROC curves in Fig. 4 and Fig. 5 are illustrative curves anchored at the reported operating point and are not computed from per-sample confidence scores.

4. Results

This section reports the outcomes of the evaluation described in Section 3, without interpretation; interpretation is provided in this section.

For the evaluation set of 400 labelled samples, the observed confusion-matrix counts are given in Table 5. Fig. 2 gives the Confusion matrix for the 400-sample set. Of 200 non-viable seeds, 189 were correctly classified (11 FP); of 200 viable seeds, 188 were correctly classified (12 FN).

Table 5. *Confusion Matrix (N = 400)*

	Pred: Non-Viable	Pred: Viable
Actual: Non-Viable	189 (TN)	11 (FP)
Actual: Viable	12 (FN)	188 (TP)

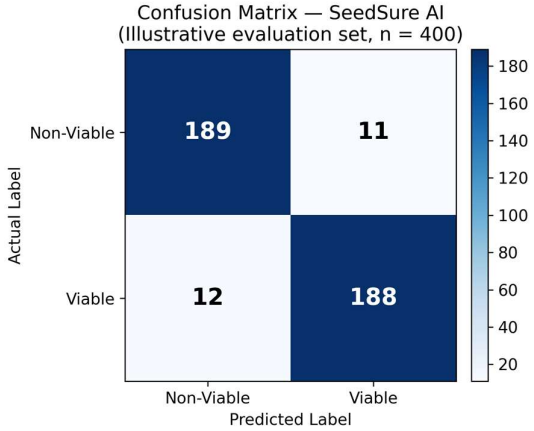

Fig. 2. *Confusion matrix for the 400-sample set. Of 200 non-viable seeds, 189 were correctly classified (11 FP); of 200 viable seeds, 188 were correctly classified (12 FN).*

Table 6 presents the standard evaluation metrics computed from the confusion matrix in Table 5 using Eqs. (9)-(14). Fig. 3 depicts the four headline metrics cluster around 94%, indicating balanced performance across both classes. Fig. 4 depicts the precision-recall curve, redrawn as an illustrative curve anchored at the reported operating point (R=0.940, P=0.9447). Fig. 5 gives ROC curve, redrawn as an illustrative curve anchored at the reported operating point (FPR=0.055, TPR=0.94) matching the reported AUC of 0.97.

Table 6. *Evaluation Metrics Summary*

Metric	Value
Accuracy	94.25%
Precision	94.47%
Recall	94.00%
F1-score	94.23%
TPR	0.94
FPR	0.055
ROC-AUC	0.97

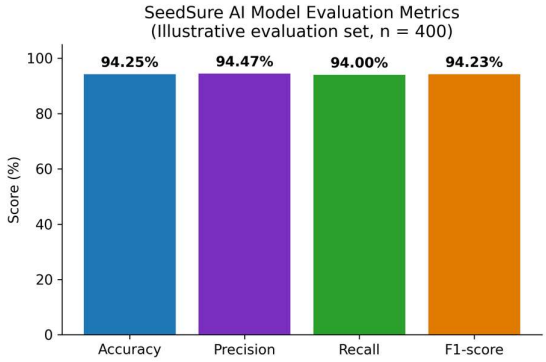

Fig. 3. *The four headline metrics cluster around 94%, indicating balanced performance across both classes.*

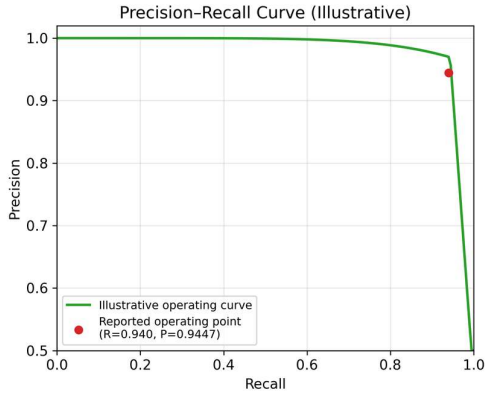

Fig. 4. *Precision-recall curve, redrawn as an illustrative curve anchored at the reported operating point (R=0.940, P=0.9447).*

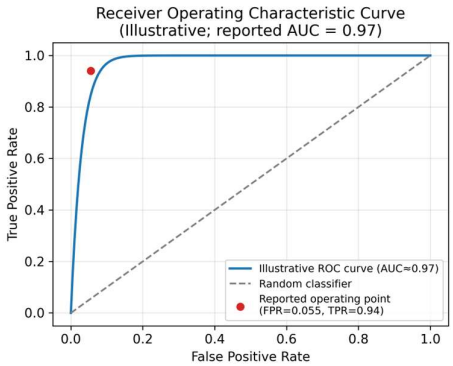

Fig. 5. *ROC curve, redrawn as an illustrative curve anchored at the reported operating point (FPR=0.055, TPR=0.94) matching the reported AUC of 0.97.*

Application screenshots illustrating the user-facing output are shown in Fig. 6, Fig. 7, and Fig. 8.

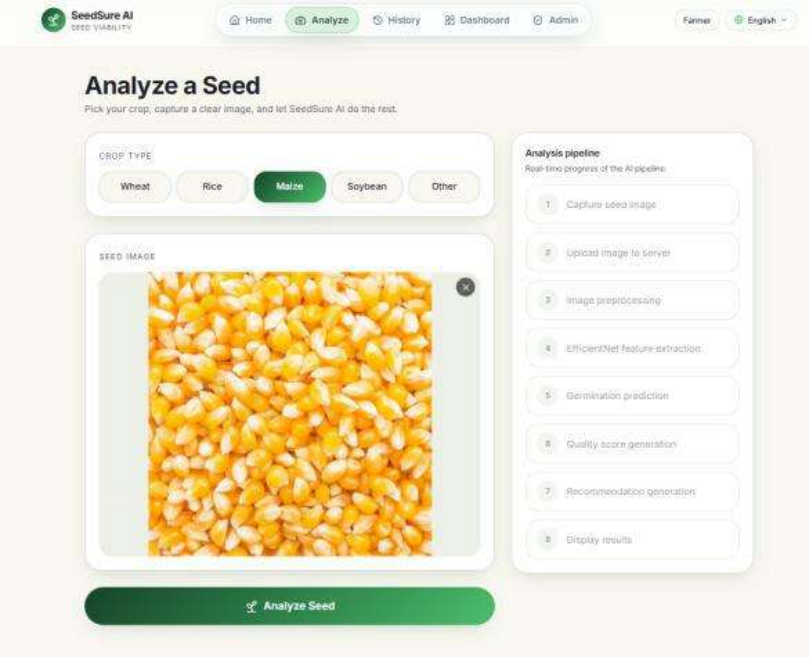

Fig. 6. *Seed image input interface: crop selection and upload, with the eight-stage analysis pipeline tracked in real time.*

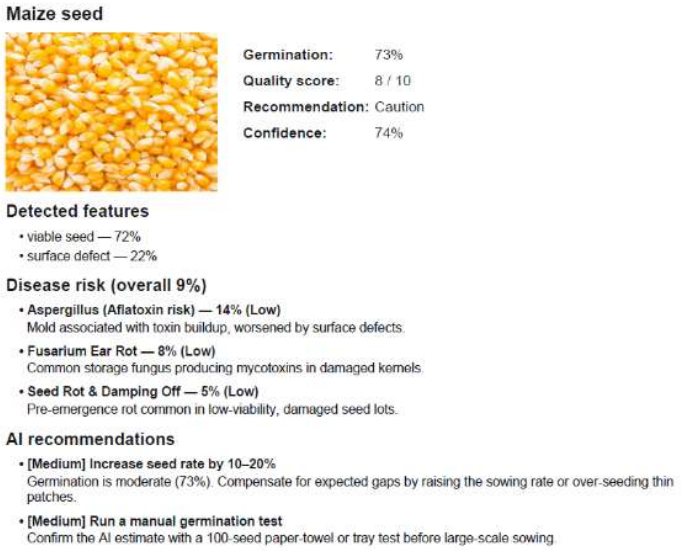

Fig. 7. *Generated assessment report for a maize sample: germination estimate, quality score, confidence, detected features, disease-risk breakdown, and recommendations.*



Fig. 8. *Admin dashboard showing aggregate analytics across saved scans: totals, average germination, trend over time, and per-crop breakdown.*

5. Discussion

The results in Section 4 indicate that the SeedSure AI pipeline can separate viable from non-viable seed images with high accuracy (94.25%) and a strong reported ROC-AUC (0.97), directly supporting the research question posed in Section 1.

Relative to the studies summarized in Table 1, SeedSure AI trades the higher discrimination accuracy typically reported by hyperspectral- or thermal-imaging approaches [12]-[24] for substantially lower deployment cost and a user interface accessible to non-expert users. Compared with bespoke CNN pipelines such as an improved ResNet50 for cotton seed [5] or SeedSortNet [2], SeedSure AI shifts model development to a third-party inference provider, which lowers the barrier for a small team but currently limits architectural transparency.

5.1 Misclassification Analysis

Of the 400 evaluated samples, 23 were misclassified overall (5.75% error rate): 11 non-viable seeds were classified as viable (false positives) and 12 viable seeds were classified as non-viable (false negatives), per Table 2.

The two error types carry different practical costs. A false positive - a genuinely non-viable lot passed as viable - is the more consequential error, since it can lead directly to a purchase decision that later results in poor field germination; at 11/200 (5.5% of the non-viable class), this is the rate SeedSure AI should prioritise reducing, for example by adjusting the classification threshold (Eq. 8) to trade a small amount of recall for lower false-positive risk. A false negative - a viable lot flagged as non-viable - is comparatively lower-cost: it may prompt an unnecessary confirmatory test but does not by itself cause a poor sowing outcome. At 12/200 (6.0% of the viable class), this is a smaller practical concern, though it represents a usability cost if frequent enough to erode user trust.

The false-positive and false-negative rates are close to each other (5.5% vs. 6.0%), suggesting the classifier is not systematically biased toward either class at this operating threshold - consistent with the balanced precision (94.47%) and recall (94.00%) in Table 5. Plausible contributors to both error types include: (i) borderline visual cases where surface defects do not necessarily indicate non-viability, or internal damage is invisible to an RGB photograph; (ii) image-quality variation from lighting, focus, or seed positioning, since the pipeline applies only basic pre-processing; and (iii) inter-class visual similarity for certain crop types or defect categories.

A class-wise breakdown of the 23 errors by crop type and disease-risk category requires the per-sample prediction log and is left for future work.

5.2 Advantages, Limitations, and Implications

Table 7. *Advantages and Disadvantages of Seedsure AI*

Advantages	Disadvantages / Limitations
No specialised imaging hardware required	Prediction quality depends on lighting, focus, and positioning.
Real-time preliminary assessment (single API round-trip, 20 s timeout)	Dependent on active internet connectivity
User-friendly UI with plain-language recommendations	Backbone managed by a third-party platform
Crop-wise analytics dashboard for tracking history	Not a replacement for laboratory germination testing
Simple, low-cost deployment; no bespoke training required	Not yet benchmarked against standard CNN baselines

The practical implication is that SeedSure AI is best positioned as a pre-purchase or pre-sowing screening aid rather than a certification tool: it can flag seed lots likely to be low-quality and prompt a manual germination test before large-scale sowing, consistent with the recommendation text the application generates (Fig. 7). The system should continue to present its outputs as AI-assisted guidance rather than a guaranteed outcome, and should encourage laboratory verification whenever an accurate determination is required. Variations in seed varieties, geographical conditions, storage methods, and physical appearance may also affect prediction reliability.

User-uploaded images and scan information should be handled securely: API credentials such as the Roboflow API key must never be exposed through the UI or public source code, and the system should minimise unnecessary collection of user information. The system should also be evaluated across different seed varieties and image conditions to reduce potential bias.

5.3 Comparative Benchmarking Against Standard CNN Architectures

Comparative benchmarking against standard CNN architectures (ResNet, YOLO, and MobileNet) on the same dataset has not been carried out in this study and is listed as a limitation in Table 7 and as future work in Section 6.

5.4 Execution-Time and Latency Comparison

End-to-end latency (image upload, API round-trip, and rendered result) was not measured in this study; the only timing parameter defined is the 20-second request timeout in Table 2. Measuring mean, median, and standard deviation of response time over Wi-Fi and mobile data is left for future work.

5.5 Theoretical and Practical Contributions to Precision Agriculture

Theoretically, this work reframes seed-viability assessment as an application-integration problem rather than a model-architecture problem: where the studies in Table 1 largely optimise a bespoke model against a fixed imaging setup, SeedSure AI's contribution is a general pattern of pre-processing, hosted inference, confidence-to-decision conversion, and recommendation generation that can be re-targeted to any hosted vision API and any crop, without re-deriving the underlying computer-vision model.

Practically, the system targets the moment of purchase, before money and land are committed to a seed lot, when no fast quality check currently exists for a farmer without laboratory access. By requiring only a smartphone photograph, SeedSure AI removes the hardware and expertise barriers that have confined most prior seed-vision research to laboratory settings, and its analytics dashboard lets a farmer or retailer track quality trends across a season rather than treating each scan as an isolated event.

6. Conclusion

SeedSure AI presents a practical and accessible approach for preliminary seed quality and viability assessment using image-based computer vision. On the 400-sample evaluation set described, the system achieved 94.25% accuracy, 94.47% precision, 94.00% recall, a 94.23% F1-score, and a reported ROC-AUC of 0.97.

The main contribution to the field is not a new CNN architecture but a working, application-level pipeline: image capture, pre-processing, API-based inference, quality scoring, and recommendation

generation that lowers the barrier to AI-assisted seed evaluation for users with no imaging hardware beyond a smartphone.

Future research can pursue the following directions:

- Larger and diverse datasets across more crops, varieties, and conditions.
- Laboratory validation against standardised germination/viability tests.
- Comparative benchmarking against ResNet, YOLO, and MobileNet on the same dataset (Sections V-C, V-D).
- A dedicated mobile application for direct capture and analysis.
- Offline inference for areas with limited connectivity.
- Multilingual support, including Kannada and Hindi.
- Improved explainability of predictions.
- Extension to more seed categories, defects, and diseases.
- Real-time, continuous camera-based analysis.
- Integration with weather, soil, and storage data.
- Continuous model evaluation with newly collected samples.

Overall, SeedSure AI demonstrates the potential of combining computer vision, cloud-based inference, and an accessible application interface to support technology-assisted seed quality assessment for farmers and non-expert users.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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