

KrushLiLINK: AN AI-POWERED SMART NURSERY SELECTION, SEEDLING BOOKING, AND CROP HEALTH ADVISORY PLATFORM

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Abstract—Small and marginal farmers typically rely on scattered information sources while choosing the planting material, locating a suitable nursery, diagnosing crop diseases, and purchasing agricultural input. Previous works in digital agriculture have demonstrated crop recommendation, soil analysis, disease recognition, agricultural marketplaces, and farmer-assistant systems, but these features are usually offered as stand-alone applications or limited research prototypes. This paper presents KrushiLiLINK, an AI-powered platform connecting farmers with nurseries and agricultural input suppliers through an end-to-end system. The platform enables farmers and nursery owners to browse, book, manage, and locate seedlings and agricultural input while implementing a machine-learning recommendation system for recommending nurseries based on crop, location, land size, quantity, budget, season, and available agricultural parameters. The paper introduces a novel crop-health module allowing a farmer to upload an image of a crop leaf, process the input with a CNN or transfer-learning-based classifier to identify crop diseases, and cross-reference the problem with a treatment knowledge repository. The platform then recommends local fertilizer/agri-input shops and their products in case inventory information is available on the marketplace. The paper describes the system design, recommendation model, crop disease detection pipeline, data model, research gap, and an evaluation methodology relying on accuracy, precision, recall, F1, recommendation relevance, response time, and usability. The work focuses on a decision-support system, which should not be mistaken for a diagnostic tool, as treatment recommendations should be evaluated by cross-referencing with crop-specific guidelines, formulation instructions, regulatory rules, and agricultural expert advice.

Index Terms—smart agriculture, nursery recommendation, seedling booking, machine learning, crop recommendation, plant disease detection, convolutional neural network, fertilizer recommendation, geolocation, agricultural marketplace, decision support system.

I. INTRODUCTION

Agriculture is highly reliant on critical but fragmented decisions about what to grow, what to buy/sell, and how to maintain the crop's health. These decisions are scattered between local nurseries, agricultural input shops, farmers' experience, extension services, and now online. It becomes hard for a farmer to act on the best available information if they find a great recommendation for a seedling but have to research in parallel where to pick it up, if it is available, if there is a disease, and where to buy the right pesticide.

Recent work has shown that leveraging machine learning and IoT can recommend crops based on their growing conditions, while image-based deep learning can identify crop diseases

from images. Agricultural digital marketplaces also highlight the need for direct connections between buyers and sellers. At the same time, each solution addresses only a particular aspect of the overall agricultural life-cycle. KrushiLiLINK takes a farmer-centric view to the agricultural life-cycle and addresses the key decisions in turn: choosing which planting material to use, comparing and booking it from nurseries, maintaining the crop and its health, responding to disease recommendations, and finding nearby suppliers of agricultural inputs. The proposed solution focuses on key crops for the local context: sugarcane, chilli, tomato, cabbage, cauliflower, onion, and potentially others. It introduces a web-based decision support and marketplace application with roles for farmers and nursery owners and a separate interface for agricultural-input suppliers. Emphasis is placed on critical factors that influence farmers' decisions: variety, cost, availability, proximity, ratings, quantity, and delivery/collection options.

The major contributions of this work include (1) farmer-nursery platform for discovering, comparing, and booking seedlings; (2) recommendation layer for selecting between varieties of planting material; (3) crop disease detection module based on image recognition; (4) treatment knowledge base linked to the detection module and local agri-input shop discovery; and (5) unified data model and evaluation framework that can be implemented in the form of a final-year engineering prototype.

II. RELATED WORK

Research in smart agriculture is moving from rule-based and sensor-assisted decision systems to machine-learning recommenders, computer-vision disease diagnosis, and integrated farmer-assistance platforms. A recent review of crop recommendation systems highlights machine learning, deep learning, IoT, ensemble methods, and feature engineering as directions, and emphasizes the need for feedback-based and integrated decision support [1].

For crop selection, Balaji et al. developed a precision agriculture recommendation system using IoT and machine learning with soil and environmental variables including N, P, K, pH, temperature, humidity, and land type; Random

Forest was reported as the strongest model among the compared approaches [2]. A separate IEEE study on seed suggestion combines IoT sensing and machine-learning techniques to recommend suitable seed varieties from environmental and soil-related conditions [3]. These studies establish the feasibility of data-driven planting recommendations but do not provide the complete nursery booking workflow proposed in KrushiLINK.

Explainability is another important direction. Kumar and Kumar proposed an XAI-based crop recommendation framework using soil nutrient profiles and historical yields and reported high validation performance while emphasizing transparency of model decisions [4]. KrushiLINK can adopt the same principle by presenting the key factors that influenced a recommendation rather than displaying only a predicted crop or variety.

Disease recognition research demonstrates that leaf images can be classified using deep learning. Bhargava et al. reviewed computer vision, deep learning, few-shot learning, and diagnosis techniques for plant leaf diseases [5]. Rahman et al. developed a real-time plant-leaf disease system using multiple CNN architectures and PlantVillage-derived data and integrated the best-performing models into web/mobile applications that provide treatment suggestions [6]. An IEEE study on image-based cucumber disease detection used pretrained ResNet50, MobileNetV2, and EfficientNet-B0 models with weighted ensemble averaging and Grad-CAM visualization [7]. These works support the feasibility of KrushiLINK's proposed disease-scanning module, while the present system focuses on linking disease output with localized agricultural-input discovery.

Agricultural marketplaces provide the commercial layer required after recommendation. Selvam et al. proposed an agricultural product-selling platform supporting direct interaction, payments, logistics, ratings, and reviews [8]. CropCart integrates crop advisory, disease diagnosis, weather prediction, voice assistance, and e-commerce [9]. Agri Assist similarly combines crop recommendation and a farmer-query chatbot using an ensemble model and Flask-based web interface [10]. KrushiLINK differs in its emphasis on nursery-level planting-material discovery and booking, followed by crop-health assistance and nearby input-shop discovery.

An important recent IEEE study, Smart Soil Nutrient Monitoring and Crop Suggestion Analysis System using IoT, integrates NPK sensing, temperature/humidity measurement, ThingSpeak visualization, alerts, and crop suggestions [11]. Together, these studies demonstrate strong individual components but leave an implementation-oriented gap in a single platform that connects planting-material selection, nursery inventory/booking, crop disease image analysis, disease-specific recommendations, and local agricultural-input discovery.

TABLE 1: SUMMARY OF RELEVANT RESEARCH AND IDENTIFIED GAPS

Study	Core Focus	Key Evidence	Gap Relevant to AgroSprout
Crop	ML/DL/IoT	Identifies	Does not

recommendation review [1]	recommenders	major methods and future directions	implement nursery discovery/booking plus crop-health procurement.
Balaji et al. [2]	IoT + ML crop recommendation	Uses soil and environmental variables	No nursery marketplace or disease-to-shop workflow.
Kumar & Kumar [4]	XAI crop recommendation	Adds transparency to recommendations	Focuses on crop selection rather than end-to-end farmer services.
Bhargava et al. [5]	Plant disease AI review	Summarizes CV/DL disease detection	Review; no integrated farmer commerce layer.
Rahman et al. [6]	Real-time leaf disease detection	Multiple CNN models and treatment suggestions	No nursery booking or local shop discovery.
Selvam et al. [8]	Agricultural marketplace	Direct trade, payments, logistics, ratings	No AI planting/disease recommendation layer.
CropCart [9]	Integrated digital agriculture	Advisory + disease + weather + e-commerce	Different platform scope; nursery-centric seedling booking is not the focus.
Agri Assist [10]	AI farmer assistant	Crop recommender + chatbot	No nursery inventory/booking and disease-to-local-shop integration.

III. RESEARCH GAP AND PROBLEM DEFINITION

The literature suggests that the primary technological components required for smart agricultural decision support individually exist. Thus, the research gap is not in the creation of crop recommenders or plant disease detection methods. Rather, the gap is in limited interoperation of such capabilities in a nursery-centric procurement workflow. Crop recommenders generally end with a prediction, agricultural marketplaces generally begin at product listing, and disease-detection systems commonly end with diagnosis or treatment suggestions. A farmer still has to move between services to obtain planting material and manage their crop-health decisions.

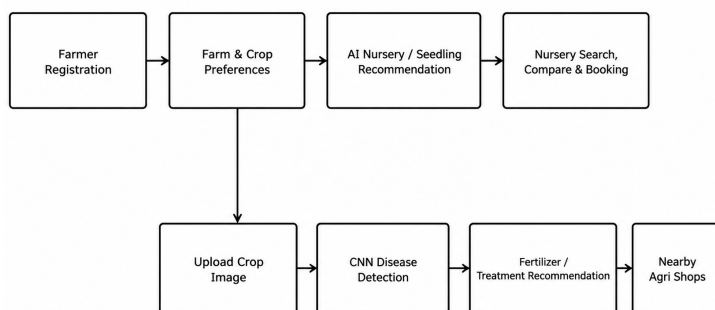
KrushiLINK defines the problem thus: given a farmer's crop intent, location, land size, quantity, budget, and available agricultural parameters, how can a digital platform rank suitable seedlings, connect the farmer to nurseries with relevant inventory, support it for booking, and subsequently assist with image-based disease identification and localized

agricultural-input discovery? The proposed solution treats recommendation, discovery, transaction, diagnosis, and procurement as connected stages of one decision-support workflow.

The project does not claim that a photograph can replace laboratory or field diagnosis. Image classification can be affected by lighting, camera quality, background, disease stage, cultivar, and visually similar symptoms. Thus, the disease module is designed to return a predicted class with confidence and an advisory status, while recommending that uncertain cases be verified by a qualified agricultural professional.

IV. PROPOSED SYSTEM

KrushLINK has been segregated into five thematic levels: farmer interaction, nursery marketplace, recommendation intelligence, crop-health intelligence, and location-aware agricultural services. Farmers can register and set their crop/farm preferences. Nursery owners can maintain seedling catalogues, variety information, prices, stock, availability, and service radius. A recommendation engine will rank the seedlings based on farmer and agricultural attributes. After growing the crop, the crop-health module takes an image and predicts the disease class. A knowledge base aligns the disease class with suitable treatment categories and prevention guidance. Finally, the geolocation module can retrieve nearby fertilizer/agri-input shops and can be filtered by distances, product availability, and ratings if inventory data is present.



The core user roles are Farmer, Nursery Owner, and Fertilizer/Agricultural Input Supplier. The Farmer can search, filter, compare, select quantity, book seedlings, upload crop images, view disease results, and locate nearby input shops. The Nursery Owner can create/update a nursery profile, manage seedling varieties, pricing, stock, availability, and booking status. The input supplier can maintain shop details and, where supported, product inventory. An administrator layer can moderate accounts, catalogue records, reports, and inappropriate listings.

Fig. 1. End-to-end KrushiLINK workflow from seedling selection to crop-health support.

V. METHODOLOGY

V.1 Nursery Recommendation Approach

The recommendation component is designed to identify nursery options according to the requirements provided by the farmer.

Let fig. 1. KrushiLINK End-to-End Farmer Workflow be a farmer's requirement vector denoted as:

$$[R = \{C, V, Q, B, L, S\}] \quad (1)$$

where

(C) = Crop type

(V) = Required seedling variety

(Q) = Required quantity

(B) = Budget

(L) = Farmer location

(S) = Season

Each nursery can be represented using:

$$[N = \{V_a, Q_a, P, L_n, R_n\}] \quad (2)$$

where

(V_a) = Available varieties

(Q_a) = Available quantity

(P) = Price

(L_n) = Nursery location

(R_n) = Nursery rating or other nursery attributes

The system can calculate a suitability score based on matching factors such as variety availability, quantity availability, geographical proximity, price compatibility, and nursery attributes. A general scoring formulation is represented as:

$$[Score(N) = w_1(V_m) + w_2(Q_m) + w_3(L_m) + w_4([P]_m) + w_5(R_m)] \quad (3)$$

where

(V_m) = Variety match

(Q_m) = Quantity match

(L_m) = Location or distance match

([P]_m) = Price compatibility

(R_m) = Nursery-attribute match

$(w_{(1)} - w_{(5)})$ = configurable weights assigned to the matching factors

The matching values can be normalized to a common scale before calculating the final score. The weights can be adjusted during system evaluation according to farmer requirements and experimental observations.

V.2 Geospatial Search

The geospatial component helps the farmers in finding out the nursery based on the location from them. The farmer's location and the nursery's registered location can be represented by the geographical coordinates.

The distance between the farmer and a nursery can be represented as:

$[d = \text{Distance}(L_f, L_n)]$ (4) where (L_f) is farmer's location and (L_n) is nursery's location.

The calculated distance can be fed into the nursery matching process so that the nursery around the farmer can be identified and ranked.

V.3 Requirement Matching

V.3 Requirement Matching

The requirement-matching process involves comparing the farmer requirements against the information maintained about the nurseries. Some of the important factors to consider when matching requirements are

- Required crop or plant type
- Seedling variety
- Required quantity
- Nursery inventory
- Price compatibility
- Geographical proximity
- Seasonal availability

Nursery attributes

Nurseries that satisfy the specified requirements can be identified and ranked based on their suitability score. Requirement matching can be initially done using rule-based or weighted scoring approaches and can be further enhanced through machine learning if sufficient data about the nurseries, inventory, and procurement become available.

V.4 Crop Disease Detection

The proposed disease module would follow an image-classification pipeline, comprising image acquisition, validation, resizing, normalization, (optional) background/leaf preprocessing, CNN inference, confidence estimation, and advisory generation. I think that transfer learning, using a light-weight architecture, such as MobileNetV2 or EfficientNet-B0, would be appropriate for an initial prototype, as it exploits pretrained visual features, thus reducing the training burden. The model should be trained and validated using an stringent train/validation/test protocol. The use of PlantVillage data would provide an initial proof of concept, but I think that the model should also be validated with field images, as the controlled conditions of the PlantVillage dataset might not generalize to field conditions.

I would structure the output as a disease class, with associated confidence, crop, symptoms or image indicators, and a status. I think that a low confidence threshold should emit a warning message, such as 'image quality or disease evidence insufficient; upload higher-resolution image or consult expert.' This way, not every input would generate a diagnostic claim, thus reducing liability.

V.5 Data Model

TABLE II: CORE DATA ENTITIES

Fig. 2 Three-Layer KrushiLINK System Architecture

TABLE III: PROPOSED TECHNOLOGY

Layer	Proposed Technology	Role
Frontend	React native, Expo SDK 57, Expo router, Next.js & React	Farmer, nursery, supplier dashboards and booking UI.
Backend	Python Flask + REST API	Authentication, business logic, ML inference and APIs.
Database	Firebase cloud Firestore	Users, catalogues, bookings, scans, treatments and shop data.
ML Recommendation	Random Forest / XGBoost + ranking rules	Seedling/crop suitability and personalized ranking.
Disease Detection	CNN transfer learning; MobileNetV2/EfficientNet-B0	Leaf image disease classification.

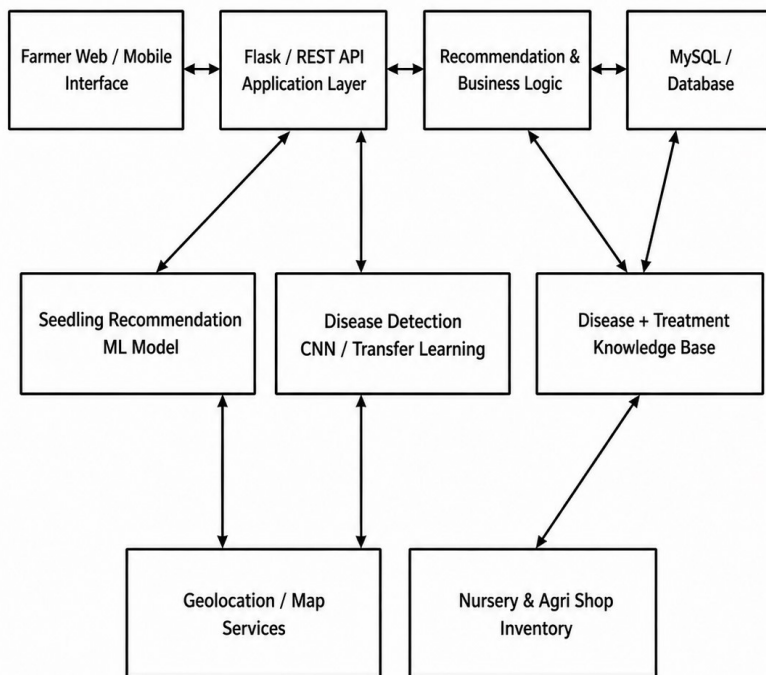


Image Processing	OpenCV + TensorFlow	Resize, normalization and model input preparation.
Location	Browser Geolocation + mapping API	Nearby nursery and agri-input shop discovery.
Deployment	Cloud/server deployment	Web access and scalable inference.

V.6 Disease-to-Fertilizer/Treatment Recommendation

Entity	Important Attributes	Purpose
Farmer	farmer_id, location, land_size, budget, crop_preferences	Stores user profile and recommendation context.
Nursery	nursery_id, owner_id, location, rating, service_radius	Represents seedling supplier.
Seedling	seedling_id, crop, variety, price, stock, quality	Catalogue and inventory item.
Booking	booking_id, farmer_id, nursery_id, item_id, quantity, status	Stores seedling reservations.
Disease Scan	scan_id, farmer_id, crop, image_path, predicted_class, confidence	Stores AI crop-health history.
Treatment	disease_id, crop, treatment_type, product_category, notes	Knowledge base for disease-specific advice.
Agri Shop	shop_id, location, contact, rating, inventory	Stores nearby fertilizer/input supplier data.

The treatment engine is kept separate from the CNN.

The classifier determines the disease; a knowledge base of curated disease and crop combinations links to treatment categories, prevention measures, and product attributes. This allows the agricultural recommendations to be independently updated without retraining the image model. The knowledge base could include chemical treatment categories, biological/organic options, prevention measures, formulation names, crop applicability, safety notes, etc. Product availability is separately managed by the supplier inventory layer.

The platform should not be determining the amount (weight/volume) of fertilizer or the dosage of a given pesticide from the image; that should be determined by the product-label, crop stage, and agricultural recommendations. The system is therefore built as a recommendation and informational layer, and not as an autonomous prescribing engine.

V.7 Nearby Fertilizer/Agricultural Input Shop Discovery

After determining the disease, the user's approximate geolocation is used to query for nearby agricultural-input shops, which can be ranked by distance, rating, open status, and whether they carry any of the recommended treatments. Map integration could be done through a geolocation/map service. A shop card would show the name, distance (or address), phone, categories available, rating, and navigation. This closes the loop for the user from diagnosis to procurement.

VII. EVALUATION FRAMEWORK

Given that the KrushiLINK system is a prototype under final-year research development, it is important to differentiate the evaluation of the model from the performance of the system. The paper does not assert experimental accuracy for an implementation that has not been measured before; instead, we propose the following protocol for implementation of the completed prototype.

V.1 Disease Model Metrics

For the disease classifier, accuracy, precision, recall, F1-score, confusion matrix, per-class support, and inference time should be reported. If class imbalance is present, macro-averaged precision/recall and F1-score should be included. A held-out field-image set should be used alongside benchmark data to estimate generalization error. The IEEE/Elsevier literature shows that high benchmark accuracy is possible, but real-world conditions can be substantially more challenging, so controlled-dataset performance should not be presented as field-level diagnostic accuracy [5]–[7].

V.2 Recommendation Evaluation

Seedling recommendations can be evaluated using Precision@K, Recall@K, ranking relevance, budget constraint satisfaction, availability constraint satisfaction, and farmer acceptance of top recommendations. A small expert-labelled validation set can be created by asking agricultural-domain reviewers to identify acceptable seedlings for representative farmer profiles, making the evaluation more meaningful than reporting only one machine-learning classification score.

V.3 Platform Evaluation

System-level measures should include average API response time, disease-inference latency, successful booking completion rate, search/filter response time, recommendation generation time, and usability feedback. Functional test cases should cover farmer registration, role-switching, nursery catalogue management, booking, image upload, disease prediction, treatment retrieval, nearby-shop search, and failure cases such as unavailable inventory or low-confidence disease predictions.

Seedling recommendation	Precision@K, relevance	Expert-labelled profiles	Top-K relevance rate
Nursery search	Response time, filter correctness	Functional/API tests	Successful query cases
Booking	Completion/error rate	End-to-end test cases	Transaction logs
Shop discovery	Distance/ranking correctness	Known-location test cases	Correct nearby ordering
Usability	Task completion + user rating	Pilot user study	Structured feedback

TABLE IV: PROPOSED VALIDATION MATRIX

Module	Primary Metric	Validation Method	Target Evidence
Disease detection	Precision, Recall, F1, Accuracy	Held-out test set + field images	Per-class confusion matrix

VIII. DISCUSSION

The chief virtue of KrushiLINK is the continuity of farmer workflow. A crop recommendation is more actionable for the farmer if they can immediately discover a nursery, compare available seedlings, and book the required quantity. Similarly, disease detection is more useful to the farmer when the system links to an understandable treatment knowledge base and nearby input suppliers. This integration turns isolated predictions into a series of decisions and actions.

The literature also indicates that system integration must be balanced against reliability. Crop recommendation models can excel on curated datasets, but regional differences, changing weather, soil variability, and incomplete inputs may limit generalization [1], [2], [4]. Disease classifiers face additional challenges from lighting, leaf orientation, background clutter, cultivar differences, and visually similar symptoms [5] – [7]. Consequently, AgroSprout should record confidence, expose uncertainty, and preserve human verification.

A second consideration is data freshness. Nursery stock, fertilizer availability, prices, and shop opening status fluctuate. These values should therefore be treated as live or periodically refreshed business data rather than static ML features. The recommendation engine can combine stable suitability information with dynamic availability and distance constraints. This hybrid architecture is more befitting for the marketplace than relying on a single predictive model.

A third consideration is responsible agricultural guidance. Disease detection and treatment recommendation can have economic, environmental, and safety ramifications. The proposed architecture therefore keeps the disease model and treatment knowledge base separate, supports advisory disclaimers and avoids generating unsupported dosage instructions. The system should favor verified product information and allow farmers to consult qualified agricultural experts for uncertain or serious cases.

IX. LIMITATIONS AND FUTURE WORK

The proposed study has a few limitations. Firstly, the initial disease module uses public benchmark datasets with images that are different from photographs in the real field. Secondly, the project catalogue has an initial focus on a limited set of crops that can be expanded once reliable regional data has been collected. Thirdly, shop inventory integration relies on the suppliers' participation and data freshness. Fourthly, the recommendation model needs representative labelled data to avoid overfitting on a particular geography or crop distribution. Finally, a student prototype cannot establish agronomic effectiveness without field trials and expert validation.

The future work will include the collection of Maharashtra-specific field images, multilingual farmer assistance (in Marathi/Hindi/English), explainable disease predictions with the help of visual heat maps, severity estimation, weather-aware timing of treatments, synchronisation with supplier inventory, demand forecasting

for nursery owners, farmer feedback loops, and offline/low-bandwidth support. The system can also support government scheme information and verified agricultural advisories. A later research phase can investigate multimodal recommendation with the joint usage of soil, weather, image, and historical crop data.

X. CONCLUSION

KrushiLINK is an innovative concept of an integrated AI-based smart agriculture solution, which binds the nursery selection and seeding booking stages with the crop-health assistant and agri-input shop discovery. The idea combines the multi-criteria recommendation system, nursery inventory and booking, classification of crop diseases based on imaging, treatment-disease associations, and geo-localized discovery of fertilizer and agri-input shops. The separate aspects of such a system have been proven viable and functional in the research. The idea of KrushiLINK itself is focused on the end-user, which is the farmer, and builds its interface around the decision-making process they have to engage in. The evaluation framework proposed by the research does not claim to have achieved positive results by incorporating the planned prototype measurements, which are yet to be made, into the results section. After the development and testing phases that would use the local region's data and expert opinions, AgroSprout would be able to serve as an accessible digital assistant while also enabling more research into the topic of localized explainable AI and serving as a basis for future multimodal solutions in precision agriculture.

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