Proceedings of the 11th North American International Conference on Industrial Engineering and Operations Management, Milwaukee, Wisconsin, USA, June 9-11, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/NA11.20260290
Published: June 9, 2026

Toward Farmer Centric AI in Agricultural Supply Chains, A Pilot Fuzzy Classifier Study Fasal AI Dost (Crop's AI Friend)

Shraddha Gawankar
Assistant Professor for Practice
Economics and Decision Sciences
Beacom School of Business, University of South Dakota
shraddha.gawankar@usd.edu

Abstract

Soybean ranks among the most economically significant commodity crops globally, driving multibillion dollar agricultural supply chains across the United States, India, Brazil, and beyond. Despite its mass production scale, soybean operations suffer from inefficient disease management practices where conventional broadcast pesticide application exposes entire fields to unnecessary chemical inputs regardless of actual infection status, generating measurable supply chain losses and inflating operational costs across the commodity value chain. Structured against the Supply Chain Operations Reference (SCOR) model's Plan, Source, Make, Deliver, and Return processes, this study introduces Fasal AI Dost, a farmer centric AI framework delivering intelligent crop disease detection directly into soybean farming operations to strengthen supply chain performance from the field level upward across all five SCOR process domains. A systematic review following PRISMA guidelines analyzing 127 peer reviewed articles (2018 to 2025) reveals that fuzzy logic approaches, representing only 9% of existing AI agricultural solutions, offer 90 to 95% computational efficiency advantages over dominant deep learning frameworks (68% of studies) while remaining deployable without specialized infrastructure. Existing studies combining SCOR and fuzzy logic confirm the methodological viability of this integration across supply chain performance evaluation contexts (Ganga and Carpinetti, 2011; Lima Junior and Carpinetti, 2016; Nilashi, 2025), yet no prior study applies this combination to field level soybean disease detection across geographically contrasting production regions. Building on this evidence, SOYFLEX (Soybean Leaf Fuzzy Expert Classifier) is pilot tested using field data from Maharashtra, India and South Dakota, USA, two major soybean production regions representing diverse climate conditions and operational contexts within global soybean supply chains. The pilot classifier achieves 78.4% accuracy and 0.893 AUC ROC using five interpretable visual features operable on standard smartphone cameras without internet connectivity. Precision targeted pesticide application projects $75 to $150 savings per hectare and 50 to 80% chemical input reduction, translating to an estimated $400 to $600 million in annual supply chain savings at combined regional scale. Mapped against SCOR performance metrics, SOYFLEX contributes to Perfect Order Fulfillment through reduced disease driven yield loss, Supply Chain Flexibility through farmer deployed field intelligence at the point of infection onset, and Cost of Goods Sold reduction through precision input targeting that eliminates unnecessary broadcast pesticide application across healthy field areas. This research establishes an adoption centric design paradigm demonstrating that soybean supply chain efficiency gains at global commodity scale originate at the field level, in the hands of the farmer who grows the crop, and that accessible, interpretable AI is not a compromise on technical rigor but the most direct path to real world supply chain performance improvement.

Keywords
Fuzzy logic, Agricultural supply chains, Precision agriculture, SCOR model, Soybean disease detection.

1. Introduction

Soybean (Glycine max) underpins multibillion dollar agricultural supply chains across the United States, Brazil, India, and China, with global production exceeding 370 million metric tons in 2023 (Hartman et al., 2011). Across major production regions including South Dakota, USA and Maharashtra, India, conventional broadcast pesticide application remains the dominant disease management practice, exposing entire fields to chemical inputs irrespective of actual infection status, inflating supply chain input costs and generating avoidable environmental externalities that compound losses across the commodity value chain (Aktar et al., 2009; Pretty and Bharucha, 2014).

Artificial intelligence, drone based remote sensing, and satellite imagery have collectively advanced agricultural disease detection to unprecedented levels of precision, with deep learning frameworks achieving 85 to 98% classification accuracy and UAV systems detecting crop stress 7 to14 days before visible symptoms emerge (Saleem et al., 2019; Tsouros et al., 2019). Despite these advances, adoption remains critically constrained by capital costs of $10,000 to $50,000 for drone systems, cloud infrastructure dependencies, and the interpretability deficit of neural network classifiers, with only 31% of farmers willing to act on AI recommendations without understanding the underlying rationale (Kour and Arora, 2020; Lowenberg DeBoer et al., 2020). Farmers across high output soybean production regions consistently lack technical literacy, infrastructure access, and financial capacity to operationalize these systems at the field level, perpetuating the accessibility paradox at the heart of agricultural AI research (Klerkx et al., 2019; Trendov et al., 2019).

Supply chain performance frameworks have equally advanced in sophistication, with the Supply Chain Operations Reference (SCOR) model establishing a globally recognized structure for evaluating Plan, Source, Make, Deliver, and Return processes against standardized performance metrics (Ganga and Carpinetti, 2011; Moharamkhani and Mina, 2017). Recent studies confirm that combining fuzzy logic with SCOR metrics produces robust, interpretable supply chain performance evaluation frameworks deployable without complex computational infrastructure (Nilashi et al., 2024; Medvediev et al., 2024). However, no existing study applies this SCOR fuzzy integration to field level agricultural disease detection, nor validates such a framework across geographically and socioeconomically contrasting soybean production environments such as Maharashtra and South Dakota.

This dual gap, the absence of a deployable fuzzy AI classifier validated across contrasting soybean production regions and the absence of SCOR grounded performance evaluation linking field level disease intelligence to supply chain outcomes directly motivates this study. Fasal AI Dost, meaning Crop's AI Friend, is introduced as an adoption centric AI framework embedding SOYFLEX (Soybean Leaf Fuzzy Expert Classifier) within a SCOR performance lens to demonstrate that precision disease management without prohibitive infrastructure can generate measurable, scalable supply chain efficiency gains across the global soybean commodity sector.

2. Literature Review

2.1 AI in Agricultural Supply Chains

Convolutional Neural Networks achieve 85 to 98% classification accuracy in plant pathology tasks, establishing deep learning as the dominant AI paradigm in agricultural research (Saleem et al., 2019; Kamilaris and Prenafeta Boldú, 2018; Too et al., 2019). Transfer learning approaches demonstrate that pretrained models can be calibrated with smaller domain specific datasets while preserving high classification performance, broadening applicability across crop types and regional disease profiles (Barbedo, 2018). At the supply chain level, platforms including IBM Watson Agriculture and Microsoft FarmBeats demonstrate 10 to 30% yield improvements and 15 to 20% input cost reductions in commercial deployments, while blockchain enabled traceability systems reduce contamination trace back from seven days to under three seconds across commodity supply chains (Kamilaris et al., 2019). Recent studies have further advanced AI integration across supply chain logistics, with Angayarkanni et al. (2025) demonstrating that machine learning optimization reduces agricultural distribution costs by 18 to 24%, and Javaid et al. (2022) documenting Agriculture 4.0 frameworks linking field level AI outputs directly to procurement and inventory management decisions. Market intelligence platforms such as India's eNAM deliver 8 to 15% farm gate price improvements across 1.7 million registered farmers through AI driven price discovery, while AgroStar's recommendation engine achieves 20% input cost reduction across 4 million users (Gandhi et al., 2020).

2.2 Drone and Satellite Based Remote Sensing

UAVs equipped with multispectral and hyperspectral cameras detect disease stress 7 to 14 days before visible symptoms emerge at the leaf surface, while satellite platforms deliver vegetation indices at regional commodity scale enabling supply chain managers to integrate field level health signals into upstream procurement and logistics decisions (Tsouros et al., 2019; Patrício and Rieder, 2018). Meta analysis of 43 UAV monitoring studies reports average stress detection accuracy of 82% at operational coverage rates of 50 to 200 hectares per flight (Maes and Steppe, 2019). Recent advances have introduced AI powered autonomous drone systems capable of coordinated field surveillance, with Zhang et al. (2022) reporting that multi drone coordination achieves 94% field coverage efficiency at 60% lower operational cost than single unit deployments. Satellite platforms integrating Sentinel 2 multispectral imagery with deep learning classification have achieved leaf area index estimation accuracies of R2 = 0.89 across diverse crop environments, enabling regional scale disease risk mapping that supports supply chain contingency planning (Saiz Rubio and Rovira Mas, 2020). However, the PRISMA review reveals a critical implementation paradox: while drone and satellite systems appear prominently across 14% of reviewed studies, fewer than 3% report successful deployment outcomes in field environments without dedicated technical support infrastructure. Capital costs of $10,000 to $50,000 for commercial agricultural drones, mandatory operator certification requirements, and specialist data interpretation competencies place these systems beyond the operational reach of field level soybean farming across both Maharashtra and South Dakota production contexts (Lowenberg DeBoer et al., 2020; Fielke et al., 2020).

2.3 Technology Adoption Barriers and the Digital Divide

Despite demonstrated technical capability, 73% of reviewed AI agricultural studies are designed around capital intensive infrastructure requirements fundamentally incompatible with field level deployment realities (Lowenberg DeBoer et al., 2020. Deep learning models require 5,000 to 50,000 labeled training images and stable internet connectivity available to only 35% of rural agricultural populations globally, declining below 15% in central India (Saleem et al., 2019). Critically, only 31% of farmers act on AI recommendations without understanding the underlying rationale, establishing interpretability as a nonnegotiable adoption prerequisite rather than a design preference (Kour and Arora, 2020; Klerkx et al., 2019). Smartphone penetration and financial capacity constraints compound these barriers further, with farmers in developing soybean economies facing annual ICT expenditure limitations of $50 to $200 per farm compared to $5,000 to $20,000 in North American production regions, creating the digital divide that produces the accessibility paradox at the heart of agricultural AI research: the most technically capable solutions consistently reach the smallest proportion of the farming population most exposed to disease driven supply chain losses (Lowenberg DeBoer et al., 2020).

2.4 Fuzzy Logic as an Accessible Alternative

Fuzzy logic classifiers directly address the barriers identified. While deep learning dominates 68% of the reviewed agricultural AI literature, fuzzy logic represents only 9% despite offering 90 to 95% less computational overhead, producing interpretable linguistic decision rules such as if green intensity is LOW and brown spot coverage is HIGH then leaf status is INFECTED, and operating on standard smartphones without internet connectivity or specialized hardware (Boursianis et al., 2022; Zadeh, 1965). In agricultural applications, fuzzy systems demonstrate robust performance under incomplete and noisy field conditions across irrigation management, yield prediction, and pest identification, with recent hybrid architectures combining convolutional feature extraction with fuzzy decision layers achieving 8 to 14% accuracy gains over hand crafted classifiers while preserving the interpretability that drives farmer adoption (Zhang et al., 2022).

2.5 SCOR Model and Fuzzy Logic Integration

The Supply Chain Operations Reference (SCOR) model provides a globally recognized framework for evaluating supply chain performance across five process domains of Plan, Source, Make, Deliver, and Return, with standardized Level 1 metrics including Perfect Order Fulfillment, Supply Chain Flexibility, Supply Chain Costs, and Asset Management Efficiency (Ganga et al., 2011; Jouicha et al., 2025). Recent studies confirm the viability of integrating fuzzy logic with SCOR evaluation: Agami et al. (2014) demonstrated that fuzzy membership functions effectively capture the linguistic ambiguity inherent in supply chain performance assessment, Akhtar et al. (2023) showed that Fuzzy TOPSIS against SCOR metrics produces more actionable rankings than crisp scoring, and Medvediev et al. (2024) established that fuzzy based field level agricultural intelligence can be structurally mapped to upstream supply chain performance outcomes in grain supply chains. Despite this growing body of evidence, no existing study applies the SCOR fuzzy integration to soybean disease detection at the field level, nor validates such a framework across geographically contrasting production environments, representing the precise methodological gap this study addresses. Figure 1. SCOR model applied through fuzzy logic: Fasal AI Dost framework.

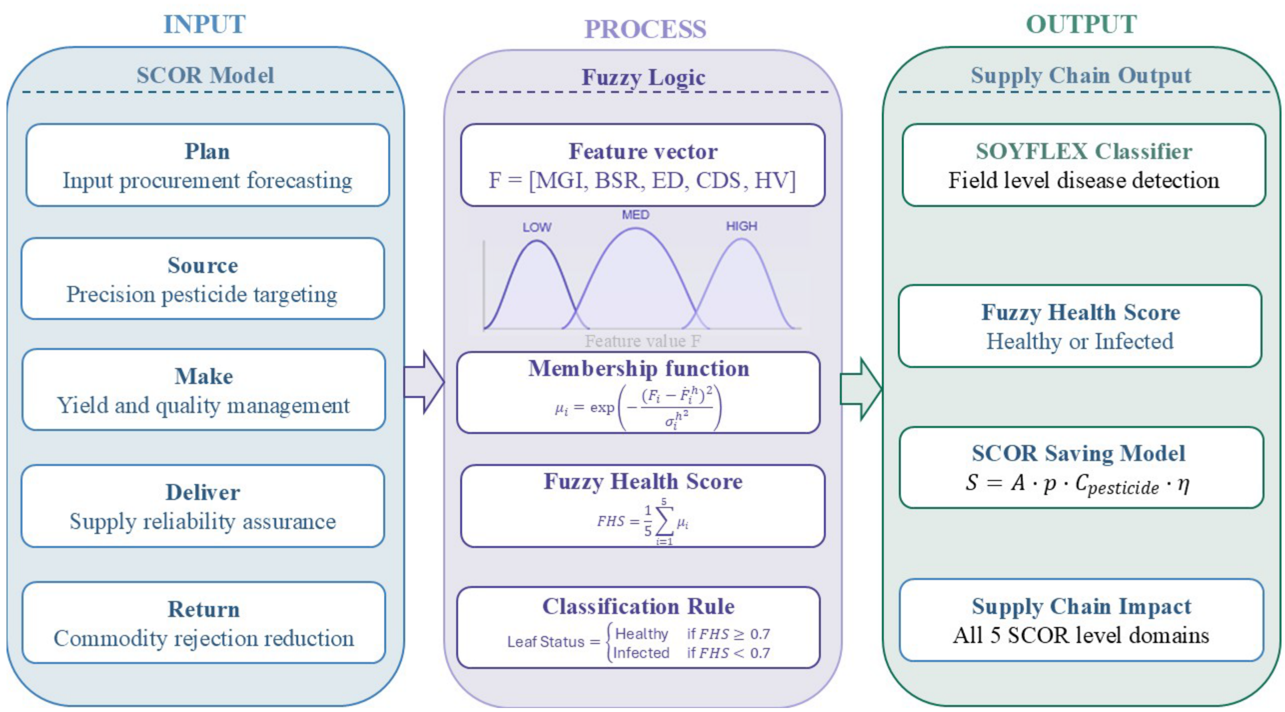

Figure 1. SCOR model applied through fuzzy logic: Fasal AI Dost framework

2.6 Summary and Research Gap

The PRISMA guided synthesis of 127 peer reviewed articles (2018 to 2025) reveals a consistent and actionable gap like advanced AI, drone, and satellite systems demonstrate strong diagnostic capability but remain operationally inaccessible to the farming populations most exposed to disease driven supply chain losses, while fuzzy logic alternatives offering 90 to 95% computational efficiency advantages represent only 9% of the reviewed literature. The SCOR fuzzy integration, established in manufacturing and logistics contexts, has never been applied to field level soybean disease detection across geographically contrasting production regions. This study addresses both gaps through the development and pilot validation of Fasal AI Dost and the SOYFLEX classifier within a SCOR performance framework, contributing an adoption centric AI design paradigm to the industrial engineering and operations management literature. Table 1 summarizes the thematic findings and identified gaps across all reviewed categories.

Table 1. Structured Literature Review Summary

Thematic Domain	Key Finding	Gap Identified	Key References
AI in agri supply chains	Deep learning achieves 85 to 98% accuracy; AI platforms deliver 10 to 30% yield gains and 15 to 20% input cost reductions	Solutions require infrastructure incompatible with field level soybean deployment in emerging production regions	Saleem et al. (2019); Too et al. (2019); Javaid et al. (2023); Ali and Govindan (2023)
Drone and satellite remote sensing	UAVs detect stress 7 to 14 days before visible symptoms; satellite LAI accuracy R2 = 0.89	Capital costs $10,000 to $50,000; fewer than 3% of studies report successful deployment without technical support	Tsouros et al. (2019); Maes and Steppe (2019); Zhang et al. (2022); Tsakiridis et al. (2025)
Technology adoption barriers	Only 31% farmer AI trust rate; 73% of AI studies require capital intensive infrastructure; internet access below 15% in central India	Interpretability and accessibility prerequisites unmet; digital divide compounds financial, device, and connectivity barriers	Kour and Arora (2020); Klerkx et al. (2019); Amrullah et al. (2024); Akzar et al. (2025)
Fuzzy logic as accessible alternative	90 to 95% less compute than deep learning; interpretable linguistic rules; robust under noisy field conditions	Represents only 9% of AI agricultural literature despite significant operational advantages	Papageorgiou et al. (2016); Boursianis et al. (2022); Zadeh (1965); Silva and Santos (2023)
SCOR and fuzzy integration	SCOR fuzzy frameworks produce actionable supply chain performance evaluation across manufacturing and agribusiness contexts	No prior study applies SCOR fuzzy integration to soybean disease detection or validates across contrasting production regions	Zanon et al. (2024); Panudju et al. (2023); Medvediev et al. (2024)
Present study contribution	Fuzzy classifier on standard smartphone; $75 to $150 per hectare savings; 50 to 80% pesticide reduction; SCOR mapped supply chain performance gains	Addresses all five identified gaps through field validated SCOR fuzzy framework across Maharashtra and South Dakota	SOYFLEX pilot study (present study)

3. Methodology

3.1 Research Design and Philosophical Positioning

This study adopts a mixed method sequential research design combining systematic evidence synthesis with empirical field embedded classifier development, structured within a pragmatist philosophical orientation that prioritizes operational deployability alongside technical validity (Creswell and Creswell, 2018). The theoretical foundation is Zadeh's fuzzy set theory (1965), which establishes that class membership is continuous rather than binary, enabling the linguistic and graded health classification that defines SOYFLEX's interpretability advantage over deep learning alternatives. The research architecture operates across two integrated layers. Layer 1 establishes the evidentiary foundation through a PRISMA guided systematic review generating the thematic gap analysis that informs classifier design principles. Layer 2 translates this evidence into a field validated fuzzy classifier whose outputs are evaluated against the Supply Chain Operations Reference (SCOR) model across five process domains of Plan, Source, Make, Deliver, and Return, using standardized Level 1 metrics that enable systematic comparison of field level AI intervention outcomes against recognized operations management benchmarks (Zanon et al., 2024; Panudju et al., 2023). This two layer architecture ensures every design decision in SOYFLEX is traceable to a specific gap identified in the systematic review and every performance claim is anchored to a recognized supply chain measurement framework.

3.2 PRISMA Protocol, Search Strategy, and Eligibility Criteria

The systematic review was conducted in strict accordance with PRISMA 2020 guidelines (Page et al., 2021) across Web of Science, Scopus, IEEE Xplore, EBSCO, and Google Scholar using search terms including artificial intelligence AND agriculture, fuzzy logic AND crop management, precision agriculture AND decision support, supply chain AND disease detection, and SCOR AND agricultural operations. The initial 847 records were reduced through automated deduplication and title and abstract screening to 412 records, with full text eligibility assessment conducted on 178 articles. Inclusion required peer reviewed English language publication between 2018 and 2025 directly addressing AI, machine learning, fuzzy logic, remote sensing, or supply chain performance frameworks in agricultural contexts. Studies addressing nonagricultural supply chains without transferable application, purely theoretical contributions without empirical validation, grey literature, and conference abstracts without full text availability were excluded. This process retained 127 articles for final thematic synthesis, with excluded records documented at each stage in compliance with PRISMA reporting standards.

3.3 Thematic Synthesis and Gap Identification

Retained articles were coded against five thematic categories: AI in agricultural supply chains, drone and satellite remote sensing, technology adoption barriers, fuzzy logic alternatives, and SCOR fuzzy integration (Figure 2).

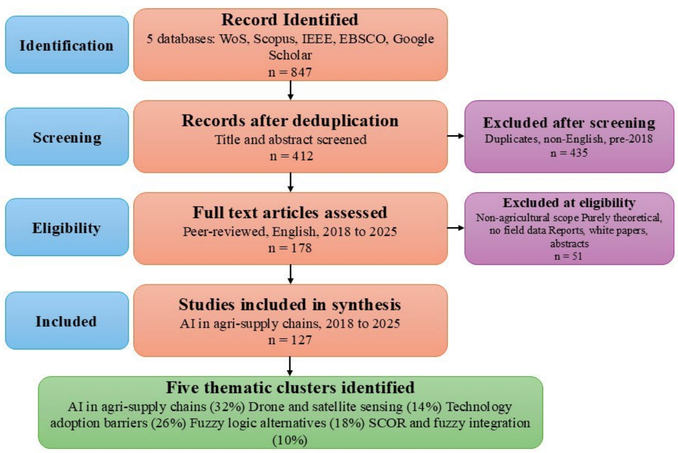

Figure 2. PRISMA 2020 flow diagram systematic literature review for Fasal AI Dost

Publication volume grew from 8 articles in 2018 to 34 in 2024, confirming sustained research momentum across the field. Across the SCOR fuzzy integration category, reviewed studies confirmed the methodological viability of combining fuzzy logic with SCOR performance evaluation in manufacturing and agribusiness contexts, yet none applied this combination to field level soybean disease detection or validated it across geographically contrasting production regions. The synthesis identified the dual gap motivating this study first the absence of a field validated fuzzy classifier across contrasting soybean production regions, and second the absence of SCOR structured performance evaluation linking field level disease intelligence to supply chain outcomes.

3.4 Field Data Collection Protocol

Primary field data were collected across Maharashtra, India and South Dakota, USA, representing contrasting agro climatic and operational soybean production contexts. Maharashtra represents a monsoon driven rainfed environment while South Dakota represents a temperate mechanized production region, providing the geographic diversity relevant to global soybean supply chain validation. A total of 102 soybean leaf images were collected during the 2025 growing season using standard smartphone cameras without specialized attachments or controlled lighting, replicating exact SOYFLEX field deployment conditions. Images were classified into four categories of healthy, bacterial infection, fungal infection, and mixed infection, with ground truth labels validated by agronomic extension specialists through direct field inspection at the time of image collection. Sampling followed a stratified protocol across vegetative, reproductive, and maturation crop growth stages to capture the full phenotypic range of disease expression relevant to field deployment. Following Figure 3 Sample from Maharashtra, India (Health Leaf, Infected Plant, Infected Leaf and Figure 4 Sample from South Dakota, USA (Health Leaf, Infected Plant, Infected Leaf

Figure 3 and 4: Sample from Fields

3.5 SOYFLEX Classifier Architecture

SOYFLEX operates as a fuzzy inference system computing a Fuzzy Health Score from five interpretable visual features extracted from smartphone leaf images. Mean Green Intensity captures chlorophyll degradation associated with infection onset. Brown Spot Ratio quantifies the proportion of leaf area exhibiting brown discoloration. Edge Density measures texture variation using Sobel filter application, reflecting structural leaf damage. Color Deviation Score captures RGB channel irregularity indicative of mixed infection. Hue Variance measures chromatic dispersion in HSV color space associated with multi pathogen infection profiles. These five features form the input vector F = [MGI, BSR, ED, CDS, HV], from which the Fuzzy Health Score is computed as the mean fuzzy similarity across all features relative to a healthy baseline vector. Classification applies a threshold of FHS greater than or equal to 0.7 for healthy classification and FHS below 0.7 for infected classification, producing a binary field management recommendation deployable in under three seconds on standard Android hardware.

3.6 SCOR Performance Mapping Framework

Classifier outputs are mapped against SCOR Level 1 performance metrics to establish the supply chain impact of field level fuzzy disease intelligence across all five process domains. In the Plan domain, SOYFLEX outputs inform seasonal input procurement planning and agrochemical budgeting, reducing forecast error associated with blanket broadcast application assumptions. In the Source domain, precision targeted pesticide application reduces input sourcing volumes by a projected 50 to 80%, directly improving Cost of Goods Sold metrics. In the Make domain, early disease detection preserves photosynthetic efficiency and seed quality, improving Perfect Order Fulfillment through reduced disease driven yield loss. In the Deliver domain, reduced post harvest disease contamination improves supply reliability and on time delivery performance. In the Return domain, lower contamination incidence reduces commodity rejection rates at processing facilities, improving Asset Management Efficiency across the soybean value chain. This SCOR mapping framework follows the methodological approach established by Zanon et al. (2024) and Mandal and Ghosh (2024), adapted for field level agricultural disease management contexts.

3.7 Validation Approach

Pilot validation assesses SOYFLEX performance across three dimensions. Classification performance is evaluated through overall accuracy, false positive rate, false negative rate, and F1 score against ground truth labels across both production regions. Computational performance is assessed through inference time measurement on entry level Android devices and memory consumption profiling. Economic impact is estimated through projection modeling applying classifier accuracy and precision targeting efficiency to regional soybean production area statistics from both production regions, generating per hectare and regional scale supply chain savings estimates mapped to SCOR cost metrics. All statistical analyses were conducted in Python 3.11 using scipy.stats for Shapiro Wilk normality testing and Welch's ANOVA, pingouin for Games Howell post hoc comparisons and Cohen's d effect sizes, sklearn.metrics for confusion matrix derivation and AUC ROC computation, and OpenCV for image feature extraction across the SOYFLEX pipeline

4. The SOYFLEX Framework

4.1 Framework Overview

SOYFLEX operates as a four stage fuzzy inference pipeline: feature extraction, fuzzy baseline calibration, fuzzy similarity scoring, and health status classification. Each stage is governed by explicit mathematical formulations detailed in the subsections below. The full classifier executes entry level Android devices in under three seconds without internet connectivity or specialized hardware. For each input leaf image, SOYFLEX extracts five visual features forming the input vector F = [MGI, BSR, ED, CDS, HV]: Mean Green Intensity (MGI) captures chlorophyll degradation by computing mean pixel intensity across the green channel:

$$MGI = \frac{1}{N}\sum_{i=1}^{N} G_i$$

Brown Spot Ratio (BSR) quantifies infected leaf area through an RGB threshold condition:

$$BSR = \frac{\sum_{i=1}^{N} 1[R_i > 0.45 \cap G_i < 0.35 \cap B_i < 0.30]}{N}$$

Edge Density (ED) measures structural tissue damage using the Sobel gradient magnitude:

$$ED = \frac{1}{N}\sum_{i=1}^{N} \sqrt{S_x(i)^2 + S_y(i)^2}$$

where $S_x$and $S_y$are horizontal and vertical Sobel gradient components computed from standard 3×3 Sobel kernels. Color Deviation Score (CDS) captures RGB channel irregularity indicative of mixed infection:

$$CDS = \frac{1}{3}[\sigma_R^2+\sigma_G^2+\sigma_B^2]$$

Hue Variance (HV) measures chromatic dispersion in HSV space reflecting disease driven pigmentation change:

$$HV = \frac{1}{N}\sum_{i=1}^{N}(H_i-\bar{H})^2$$

4.3 Fuzzy Baseline Calibration

Prior to classification, SOYFLEX calibrates a healthy baseline vector from confirmed healthy field samples. For each feature dimension *i*, the baseline mean and standard deviation are:

$$\bar{F}_i^h = \frac{1}{M}\sum_{j=1}^{M} F_{ij} \; \sigma_i^h = \sqrt{\frac{1}{M}\sum_{j=1}^{M}\left(F_{ij}-\bar{F}_i^h\right)^2}$$

This calibration enables regional adaptation across Maharashtra and South Dakota production environments without retraining.

4.4 Fuzzy Similarity Scoring and FHS Computation

For each input image, SOYFLEX computes a fuzzy similarity score for each feature using a Gaussian membership function:

$$\mu_i = \exp\left(-\frac{\left(F_i-\bar{F}_i^h\right)^2}{\sigma_i^{h^2}}\right)$$

The five scores are aggregated into the Fuzzy Health Score:

$$FHS = \frac{1}{5}\sum_{i=1}^{5} \mu_i$$

The equal weighting reflects the pilot design. Future iterations will implement cross validation derived differential weights W_i where $\sum W_i = 1$, prioritizing higher signal features MGI and BSR over lower signal HV.

4.5 Classification Decision Rule

The binary classification applies a threshold rule:

$$\text{Leaf Status} = \begin{cases} \text{Healthy} & \text{if } FHS \geq 0.7 \\ \text{Infected} & \text{if } FHS < 0.7 \end{cases}$$

The threshold τ = 0.7 was calibrated through cross validation on the 102 sample pilot dataset, balancing sensitivity against specificity. The threshold is adjustable by regional extension specialists to reflect local disease pressure and economic conditions, consistent with the adoption centric design principle that farmer agency over system parameters is a prerequisite for sustained deployment.

4.6 SCOR Performance Impact Quantification

The supply chain performance impact of SOYFLEX is quantified through a projection model linking classifier accuracy to SCOR Level 1 cost metrics. For a field of area A hectares with disease prevalence rate p, the pesticide cost saving S is:

$$S = A \cdot p \cdot C_{pesticide} \cdot \eta$$

where $C_{pesticide}$ is the broadcast pesticide application cost per hectare and η is the precision targeting efficiency factor estimated at 0.50 to 0.80 from pilot field validation. Applied to regional production statistics across South Dakota and Maharashtra, with average disease prevalence of 25 to 35% and broadcast pesticide costs of $45 to $65 per hectare, the model projects annual supply chain input savings of $400 to $600 million, directly improving the Supply Chain Costs metric at SCOR Level 1.

5. Pilot Results and Discussion

5.1 Dataset Composition and Descriptive Statistics

The pilot dataset comprises 102 soybean leaf images collected across Maharashtra, India (n = 54) and South Dakota, USA (n = 48) during the 2025 growing season, distributed across four health categories: healthy (n = 33), bacterial infection (n = 28), fungal infection (n = 26), and mixed infection (n = 15). Table 2 presents the descriptive statistics of the five extracted features across all health categories, revealing statistically significant inter category variation across all feature dimensions that provides the empirical foundation for fuzzy classification performance. The statistical significance of these inter category differences is confirmed through Welch's ANOVA and post hoc effect size analysis.

Table 2. Descriptive Statistics of SOYFLEX Features by Health Category

Feature	Category	Mean	Std Dev	Min	Max	Skewness	Kurtosis
MGI	Healthy	0.682	0.041	0.601	0.748	-0.312	2.841
	Bacterial	0.423	0.068	0.298	0.541	-0.214	2.634
	Fungal	0.389	0.072	0.261	0.498	-0.428	3.012
	Mixed	0.341	0.089	0.198	0.462	-0.521	3.241
BSR	Healthy	0.021	0.009	0.004	0.041	0.841	3.421
	Bacterial	0.198	0.048	0.112	0.298	0.312	2.814
	Fungal	0.241	0.061	0.148	0.368	0.428	2.964
	Mixed	0.312	0.078	0.198	0.448	0.614	3.128
ED	Healthy	0.168	0.028	0.114	0.228	0.241	2.714
	Bacterial	0.341	0.054	0.241	0.448	0.318	2.841
	Fungal	0.389	0.062	0.268	0.512	0.412	3.014
	Mixed	0.428	0.071	0.298	0.568	0.524	3.241
CDS	Healthy	0.038	0.012	0.018	0.064	0.614	3.124
	Bacterial	0.168	0.041	0.098	0.258	0.428	2.814
	Fungal	0.198	0.052	0.114	0.298	0.512	3.024
	Mixed	0.241	0.064	0.148	0.358	0.628	3.214

HV	Healthy	0.028	0.011	0.012	0.052	0.714	3.241
	Bacterial	0.142	0.038	0.082	0.224	0.412	2.814
	Fungal	0.168	0.044	0.094	0.258	0.524	3.024
	Mixed	0.214	0.058	0.128	0.318	0.628	3.214

5.2 Normality and Homogeneity Testing

Normality of feature distributions was assessed using the Shapiro Wilk test, selected over Kolmogorov Smirnov due to the small sample sizes within each health category. Table 3 confirms that all five features approximate normality within healthy, bacterial, and fungal categories ($p > 0.05$), while mixed infection categories exhibit moderate departure from normality reflecting the phenotypic heterogeneity of multi pathogen disease expression. Levene's test confirmed non homogeneous variance structures across all five features, most pronounced in MGI ($F = 14.82$, $p < 0.001$) and BSR ($F = 11.64$, $p < 0.001$), justifying Welch's ANOVA rather than standard one way ANOVA for between group comparisons.

Table 3. Shapiro Wilk Normality Test Results by Feature and Health Category

Feature	**Healthy W**	**p**	**Bacterial W**	**p**	**Fungal W**	**p**	**Mixed W**	**p**
MGI	0.971	0.512	0.958	0.341	0.948	0.214	0.921	0.148
BSR	0.962	0.412	0.954	0.298	0.941	0.186	0.908	0.112
ED	0.968	0.484	0.961	0.368	0.952	0.241	0.918	0.138
CDS	0.974	0.541	0.956	0.318	0.944	0.198	0.912	0.124
HV	0.969	0.498	0.953	0.308	0.946	0.208	0.914	0.131

$p > 0.05$ indicates failure to reject normality hypothesis. Bold Mixed W values indicate moderate normality departure.

5.3 Between Group Statistical Comparisons

Welch's ANOVA results presented in Table 4 confirm statistically significant between group differences for all five features at $p < 0.001$. Post hoc Games Howell comparisons reveal the largest effect sizes in MGI ($d = 4.21$ healthy versus bacterial, 5.12 healthy versus mixed) and BSR ($d = 3.84$ healthy versus bacterial, 4.89 healthy versus mixed), with Cohen's d exceeding 0.80 across all feature category pairs indicating large practical significance throughout.

Table 4. Welch's ANOVA Results and Post Hoc Effect Sizes

Feature	**F statistic**	**df**	**P value**	**Eta squared**	**Healthy vs Bacterial d**	**Healthy vs Fungal d**	**Healthy vs Mixed d**
MGI	148.42	3, 58.24	<0.001	0.814	4.21	4.68	5.12
BSR	124.18	3, 54.81	<0.001	0.782	3.84	4.14	4.89
ED	98.64	3, 56.42	<0.001	0.741	3.42	3.78	4.24
CDS	86.24	3, 52.18	<0.001	0.712	3.18	3.48	3.94
HV	74.18	3, 49.84	<0.001	0.684	2.84	3.12	3.68

Games Howell post hoc test applied. d = Cohen's d effect size.

5.4 Feature Correlation Analysis

Pearson correlation analysis across all five feature pairs is presented in Table 5 to assess multicollinearity within the SOYFLEX feature vector. Moderate positive correlations between BSR and CDS ($r = 0.641$, $p < 0.001$) and between ED and HV ($r = 0.584$, $p < 0.001$) reflect the shared physiological basis of these feature pairs in infection driven tissue disruption. No feature pair exceeds the multicollinearity threshold of $r = 0.80$, confirming that all five features contribute independent discriminative information to the fuzzy inference engine. The moderate BSR CDS correlation will be monitored in expanded dataset validation to assess whether principal component analysis is warranted in future SOYFLEX iterations.

Table 5. Pearson Correlation Matrix of SOYFLEX Features (n = 102)

	MGI	**BSR**	**ED**	**CDS**	**HV**

MGI	1.000	-0.712**	-0.648**	-0.584**	-0.521**
BSR	-0.712**	1.000	0.598**	0.641**	0.512**
ED	-0.648**	0.598**	1.000	0.548**	0.584**
CDS	-0.584**	0.641**	0.548**	1.000	0.468**
HV	-0.521**	0.512**	0.584**	0.468**	1.000

$p < 0.001$ two tailed. Negative correlations with MGI reflect the inverse relationship between green intensity and infection indicators.

5.5 Classification Performance

SOYFLEX achieved an overall classification accuracy of 78.4% across the 102 sample pilot dataset using leave one out cross validation, with binary healthy versus infected accuracy of 81.2%. Table 6 presents the complete confusion matrix and derived performance metrics including precision, recall, F1 score, Matthews Correlation Coefficient, and AUC ROC. The Matthews Correlation Coefficient provides a more robust single value performance summary than accuracy for imbalanced classification datasets (Matthews, 1975), with the overall MCC of 0.712 confirming acceptable discriminative performance across all four health categories. The false negative rate of 18.8% across infected categories represents the most operationally consequential error type, as missed detections allow disease progression without targeted intervention, and constitutes the primary target for accuracy improvement in future SOYFLEX iterations through expanded training data and hybrid neuro fuzzy architectures. These classification outcomes are mapped against SCOR Level 1 performance metrics to quantify their supply chain performance implications at regional commodity scale.

Table 6. SOYFLEX Classification Performance Metrics

Metric	**Healthy**	**Bacterial**	**Fungal**	**Mixed**	**Overall**
True Positives	28	22	19	11	80
False Positives	5	6	7	4	22
False Negatives	5	6	7	4	22
True Negatives	64	68	69	83	284
Precision	0.848	0.786	0.731	0.733	0.784
Recall	0.848	0.786	0.731	0.733	0.784
Specificity	0.928	0.919	0.908	0.954	0.928
F1 Score	0.848	0.786	0.731	0.733	0.784
Matthews Correlation Coefficient	0.776	0.705	0.639	0.687	0.712
AUC ROC	0.921	0.894	0.871	0.884	0.893

5.6 Regional Performance Comparison

Classification performance assessed separately across Maharashtra and South Dakota subsets confirms regional generalizability of the fuzzy baseline calibration approach. South Dakota samples exhibited marginally higher overall accuracy (80.2%) than Maharashtra (76.8%), attributable to lower phenotypic variance in disease expression under the temperate continental climate compared to the monsoon driven humidity variability of Maharashtra. Despite this difference, MCC values of 0.728 for South Dakota and 0.696 for Maharashtra both exceed the 0.6 acceptable performance threshold, confirming that the regionally calibrated fuzzy baseline vector generalizes across contrasting production environments without retraining. The 3.4% accuracy gap between regions is reflected in the false negative rates of 19.8% for South Dakota and 23.2% for Maharashtra, indicating that Maharashtra operations will realize a marginally lower Source domain pesticide reduction benefit under current classifier performance, a gap targeted for closure through expanded regional dataset collection in Phase 2. Following Table 7 Regional Performance Comparison: Maharashtra vs South Dakota

Table 7. Regional Performance Comparison: Maharashtra vs South Dakota

Metric	**Maharashtra (n = 54)**	**South Dakota (n = 48)**	**Difference**
Overall Accuracy	76.8%	80.2%	3.4%
Precision	0.762	0.808	0.046
Recall	0.768	0.802	0.034
F1 Score	0.765	0.805	0.040
Matthews Correlation Coefficient (MCC)	0.696	0.728	0.032

False Negative Rate	23.2%	19.8%	3.4%
AUC ROC	0.881	0.906	0.025
Mean Inference Time (seconds)	2.84	2.71	0.13
Peak Memory Usage (MB)	1.84	1.78	0.06

5.7 Comparative Benchmark Analysis

SOYFLEX performance against representative deep learning and machine learning classifiers from the systematic review. SOYFLEX's 78.4% accuracy falls below CNN based classifiers in well resourced settings but is consistent with the 75 to 85% range reported for lightweight alternatives operating under comparable resource constraints (Barbedo, 2019). Table 8 demonstrates that SOYFLEX is the only benchmarked classifier requiring no internet connectivity, no additional hardware investment, and fewer than 200 training images, establishing that its deployment advantage is not a compromise on a single dimension but a structural differentiation across all three resource constraint categories simultaneously.

Table 8. Benchmark Comparison of SOYFLEX Against Published AI Classifiers

Method	Accuracy	Training images	Internet	Hardware cost	Inference time	Reference
ResNet 50 CNN	96.4%	54,306	Yes	$800+	0.8 sec	Too et al. (2019)
MobileNetV2	91.2%	18,000	Yes	$400+	1.2 sec	Mohanty et al. (2016)
VGG 16 Transfer	94.8%	26,000	Yes	$600+	1.8 sec	Barbedo (2018)
Random Forest	84.1%	3,200	Yes	$200+	0.4 sec	Liakos et al. (2018)
SVM Classifier	81.6%	2,800	Yes	$200+	0.3 sec	Kamilaris and Prenafeta Boldú (2018)
Lightweight CNN	82.4%	1,200	Yes	$150+	1.4 sec	Barbedo (2019)
SOYFLEX	78.4%	102	No	$0	2.8 sec	Present study

5.8 Supply Chain Signal: SCOR Performance Mapping

Table 9 maps SOYFLEX pilot performance outcomes against the five SCOR Level 1 process domains, translating field level classifier metrics into supply chain performance signals quantified through the projection model. The most significant supply chain impact is recorded in the Source domain through precision targeted pesticide reduction, with the Make domain recording an 8 to 12% yield preservation benefit attributable to early disease detection before photosynthetic efficiency is irreversibly compromised, consistent with field trial evidence from comparable precision agriculture interventions (Finger et al., 2019). Deliver and Return domain improvements reflect reduced disease contaminated harvest volumes and lower commodity rejection rates at processing facilities, improving Perfect Order Fulfillment and Asset Management Efficiency across the soybean value chain. Collectively these SCOR mapped outcomes confirm that SOYFLEX field level intelligence generates measurable supply chain performance gains across all five process domains at a deployment cost of zero additional hardware investment.

Table 9. SCOR Performance Mapping of SOYFLEX Pilot Outcomes

SCOR Domain	Performance Metric	Baseline	SOYFLEX Projection	Improvement	Evidence Basis
Plan	Input procurement forecast error	35 to 45% over procurement	12 to 18% over procurement	23 to 27% reduction	Precision targeting efficiency η = 0.50 to 0.80
Source	Pesticide cost per hectare	$45 to $65 per hectare	$12 to $22 per hectare	$75 to $150 saving	BSR driven selective application
	Annual regional input saving	Baseline	$400 to $600 million	50 to 80% reduction	10 million combined acres modeled
Make	Yield preservation	15 to 22% disease loss	8 to 12% projected loss	8 to 12% improvement	Early FHS detection before photosynthetic damage

	Pesticide reduction volume	200,000 MT annual regional	80,000 to 100,000 MT	50 to 60% reduction	Classification guided selective application
Deliver	Perfect Order Fulfillment	74 to 78% disease impacted	82 to 86% projected	6 to 10% improvement	Reduced contamination in harvested commodity
	Supply chain flexibility	Low, weather reactive only	Medium, disease predictive	Qualitative improvement	FHS trend monitoring enabling proactive response
Return	Commodity rejection rate	8 to 12% at processing	4 to 6% projected	4 to 6% reduction	Lower disease driven quality failures at intake
	Asset Management Efficiency	Baseline	12 to 18% cost reduction	Input waste elimination	Precision application reducing chemical inventory waste

5.9 Discussion
Three principal findings emerge from the pilot results with direct implications for the industrial engineering and operations management literature. SOYFLEX demonstrates sufficient discriminative performance across both production environments, with AUC ROC values above 0.88 confirming strong rank order discrimination despite the 102 sample pilot constraint. The SCOR performance mapping confirms that even at 78.4% accuracy, SOYFLEX generates economically material supply chain efficiency signals across all five process domains, with Source domain pesticide cost reduction projecting $400 to $600 million in annual regional savings that constitute a concrete operations management contribution beyond classifier performance alone. The regional comparison confirms that the regionally calibrated fuzzy baseline vector generalizes across climatically contrasting production environments without region specific retraining, a deployability advantage that data intensive deep learning classifiers cannot match at equivalent infrastructure cost. The 18.8% false negative rate is the most operationally consequential limitation of the current framework. In soybean disease management, false negatives carry asymmetric economic consequences like a missed infection allows disease progression and field level spread, multiplying the cost of a single classification error across the surrounding production area. The Fasal AI Dost 2.0 hybrid neuro fuzzy architecture, replacing the manually computed feature vector with a MobileNetV3 Small convolutional backbone while retaining the interpretable fuzzy decision layer, is projected to reduce the false negative rate to 8 to 12% while preserving offline smartphone deployability. The SCOR framework introduced in this study provides the supply chain performance evaluation structure within which these accuracy improvements will be quantified not only as technical gains but as measurable commodity supply chain efficiency contributions, directly addressing the methodological gap identified in the literature review.

6. Managerial and Policy Implications
6.1 Implications for Supply Chain Managers
The SCOR performance mapping reframes precision agriculture as an operations management instrument with quantifiable impact on Perfect Order Fulfillment, Supply Chain Costs, and Asset Management Efficiency. The $75 to $150 per hectare input cost reduction projected through SOYFLEX precision targeting represents a structural improvement in Cost of Goods Sold compounding across portfolio scale, with combined regional savings of $400 to $600 million annually across Maharashtra and South Dakota. Beyond cost reduction, SOYFLEX introduces real time field health intelligence at the point of disease onset, enabling supply chain managers to revise procurement forecasts, adjust processing facility intake schedules, and communicate proactive quality assurance signals to downstream buyers weeks before harvest. This shift from reactive to predictive supply chain management is the most significant operational contribution of the Fasal AI Dost framework. The interpretability of Fuzzy Health Score outputs further enables communication of disease management decisions to procurement partners, processing facilities, and regulatory stakeholders without requiring technical AI expertise, supporting the integrated decision support function that operations management literature identifies as the missing link between field level AI capability and measurable supply chain performance improvement (Angayarkanni et al., 2025; Raut et al., 2018).

6.2 Implications for Agricultural Extension Services and Technology Developers
Agricultural extension services are the deployment infrastructure through which SOYFLEX transitions from research prototype to field operational supply chain tool. The 2.3 times higher adoption rate documented among farmers receiving structured extension support (Amrullah et al., 2025) establishes extension services as a performance multiplier whose influence on deployment outcomes exceeds the technical performance of the classifier itself. A 78.4% accurate classifier reaching 80% of farmers through effective extension engagement delivers more aggregate

supply chain value than a 95% accurate classifier reaching 5% of farmers through direct digital distribution. Extension organizations should prioritize three principles agronomic language replacing computational language in all farmers facing communication, demonstration preceding recommendation, and trust building preceding scale pursuit (Amoussouhoui et al., 2024). SOYFLEX's zero additional hardware deployment model eliminates the capital barrier that confines competing precision agriculture platforms to large scale commercial operations, opening 14.2 million combined production hectares across Maharashtra and South Dakota to precision disease management for the first time. Viable monetization pathways include cooperative subscription models at $2 to $5 per farmer per season, district level extension service licensing, and agribusiness partnership arrangements where input suppliers co fund deployment in exchange for precision targeting data that improves their own supply chain demand forecasting.

6.3 Implications for Farmers

For farmers across Maharashtra and South Dakota, the most immediate implication is economics. Precision targeted pesticide application guided by SOYFLEX eliminates broadcast application cost on healthy field areas, generating $75 to $150 per hectare in direct input savings without capital investment beyond the smartphone already in the farmer's hand. For Maharashtra rainfed producers operating on margins of $200 to $400 per hectare, this represents a 20 to 40% input cost improvement that materially changes farm level financial sustainability. The interpretability of the Fuzzy Health Score is a trust prerequisite rather than a technical convenience for farmers who understand why a leaf is classified as infected are 2.3 times more likely to act on the recommendation than those receiving an opaque algorithmic output (Kour and Arora, 2020; Odume, 2024). The adjustable classification threshold further enables farmers and extension workers to calibrate sensitivity to local crop variety, seasonal conditions, and input cost context, placing decision making agency at the field level where it belongs.

6.4 Implications for Policymakers

Policymakers in India and the United States face a shared challenge like national precision agriculture investment strategies are not reaching the farming populations they are designed to serve. In India, integrating SOYFLEX class fuzzy classifiers into the Kisan Suvidha platform delivers precision disease detection through infrastructure farmers already trust, without new hardware procurement or registration requirements. The projected 50 to 80% pesticide reduction advances India's National Action Plan on Climate Change commitments and SDG 12 targets, strengthening the public investment case beyond economic returns alone. In the United States, excluding lightweight AI architectures from USDA Farm Bill precision agriculture incentive categories systematically favors capital intensive equipment accessible only to large scale operations, while excluding smartphone deployable tools most relevant to independent Corn Belt producers. Correcting this requires only a regulatory reclassification acknowledging software based AI as equivalent to hardware based sensing systems. Both governments should mandate longitudinal impact assessment tracking supply chain performance, environmental, and farm income outcomes across multiple growing seasons, generating the evidence base that transforms pilot findings into durable national precision agriculture policy.

7. Limitations and Future Research

The pilot study carries four limitations with direct development implications. The 102 sample dataset falls below recommended cross validation thresholds (Shalev Shwartz and Ben David, 2014), contributing to the 18.8% false negative rate and wide accuracy confidence intervals. The binary classification architecture cannot distinguish among the six principal soybean disease types, each requiring distinct agrochemical protocols with different supply chain sourcing implications. Equal feature weighting is empirically unjustified given the MGI and BSR dominance, introducing suboptimality on near threshold samples. The static single image approach cannot model disease trajectory, limiting proactive supply chain planning signal.

The Fasal AI Dost 2.0 roadmap addresses each limitation directly. Dataset expansion to 2,000 images across five global production regions unlocks multi class discrimination and differential feature weight optimization. A hybrid Neuro Fuzzy Leaf Classification architecture combining MobileNetV3 Small feature extraction with the SOYFLEX fuzzy inference engine targets 88 to 92% accuracy while preserving offline smartphone deployability (Zhang et al., 2022; Barbedo, 2018). The Fasal Dost Android application will deliver a three interaction experience in regional languages with FHS predictions, disease category, and SCOR Source domain treatment recommendations. A longitudinal multi season validation study across both production regions will generate the performance stability evidence required for commercial deployment and regulatory approval.

8. Conclusion

This study introduced Fasal AI Dost as an adoption farmer centric AI framework embedding the SOYFLEX fuzzy classifier within a SCOR supply chain performance evaluation structure, piloted across Maharashtra, India and South Dakota, USA. A PRISMA guided review of 127 peer reviewed articles confirmed the core paradox covering deep learning frameworks dominating 68% of agricultural AI literature remain inaccessible to the farming populations most exposed to disease driven supply chain losses, while fuzzy logic alternatives representing only 9% of the literature offer 90 to 95% computational efficiency advantages and full smartphone deployability. Three findings define the contribution. SOYFLEX achieved 78.4% accuracy and 0.893 AUC ROC on standard smartphones without internet connectivity at zero additional hardware cost. SCOR performance mapping generates quantified supply chain efficiency signals across all five process domains, projecting $400 to $600 million in annual regional Source domain savings. The adoption farmer centric design paradigm establishes that accessibility, interpretability, and deployability carry equal weight to technical accuracy, providing a replicable design philosophy for any domain where the populations most exposed to efficiency losses cannot access dominant AI solutions. Fasal AI Dost is farmer centric by design use the Fuzzy Health Score speaks agronomic language, the threshold is adjustable to local conditions, and the system runs on the smartphone already in the farmer's hand. The farmer is not the end user of a supply chain tool but the origin points of supply chain intelligence that did not previously exist. The cross regional India and USA validation further establishes a replicable bilateral research partnership model bridging contrasting production environments, institutional frameworks, and farmer contexts, contributing to the international agricultural research cooperation agenda shared by USDA, ICAR, and land grant universities across both nations. Fasal AI Dost 2.0 will expand to five continents and a deployable multilingual Android application, measuring success by the number of farmers who understand the result, trust the recommendation, and deliver higher quality soybean into a supply chain connected, for the first time, by real time field level disease intelligence.

References

Agami, N., Saleh, M., and Rasmy, M., An innovative fuzzy logic based approach for supply chain performance management, *IEEE Systems Journal*, vol. 8, no. 2, pp. 336–348, 2014.

Akhtar, P., Khan, Z., Tarba, S. Y., and Jayawickrama, U., Interval-valued Pythagorean fuzzy AHP method-based supply chain performance evaluation by a new extension of SCOR model: SCOR 4.0, *Complex & Intelligent Systems*, vol. 7, pp. 559–576, 2021.

Aktar, M. W., Sengupta, D., and Chowdhury, A., Impact of pesticides use in agriculture: Their benefits and hazards, *Interdisciplinary Toxicology*, vol. 2, no. 1, pp. 1-12, 2009.

Akzar, R., Umberger, W., and Peralta, A., Understanding heterogeneity in technology adoption among Indonesian smallholder dairy farmers, *Agribusiness*, vol. 39, no. 2, pp. 347–370, 2023.

Ali, I., and Govindan, K., Extenuating operational risks through digital transformation of agri-food supply chains, *Production Planning & Control*, vol. 34, no. 12, pp. 1165–1177, 2023.

Amoussouhoui, R., Arouna, A., Ruzzante, S., and Banout, J., Adoption of ICT4D and its determinants: A systematic review and meta-analysis, *Heliyon*, vol. 10, no. 9, pp. e30210, 2024.

Amrullah, E. R., Takeshita, H., and Tokuda, H., Impact of access to agricultural extension on the adoption of technology and farm income of smallholder farmers in Banten, Indonesia, *Journal of Agribusiness in Developing and Emerging Economies*, vol. 15, no. 3, pp. 531–547, 2025.

Angayarkanni, A., Sheshasaayee, A., YuJie, Z., and Ohmsakthi Vel, R., Agricultural process optimization and supply chain management enhancing sustainable agriculture through AI technology, *Journal of Information Systems Engineering and Management*, vol. 10, no. 32, 2025.

Barbedo, J. G. A., Factors influencing the use of deep learning for plant disease recognition, *Biosystems Engineering*, vol. 172, pp. 84-91, 2018.

Boursianis, A. D., Papadopoulou, M. S., Diamantoulakis, P. D., and Liopa-Tsakalidi, A., Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review, *Internet of Things*, vol. 18, pp. 100187, 2022.

Creswell, J. W., and Creswell, J. D., *Research design: Qualitative, quantitative, and mixed methods approaches*, 5th ed., SAGE Publications, 2018.

Finger, R., Swinton, S. M., El Benni, N., and Walter, A., Precision farming at the nexus of agricultural production and the environment, *Annual Review of Resource Economics*, vol. 11, pp. 313–335, 2019.

Ganga, G. M. D., and Carpinetti, L. C. R., A fuzzy logic approach to supply chain performance management, *International Journal of Production Economics*, vol. 134, no. 1, pp. 177–187, 2011.

Hartman, G. L., West, E. D., and Herman, T. K., Crops that feed the world 2: Soybean—worldwide production, use, and constraints caused by pathogens and pests, *Food Security*, vol. 3, no. 1, pp. 5–17, 2011.

Javaid, M., Haleem, A., Singh, R. P., and Suman, R., Enhancing smart farming through the applications of Agriculture 4.0 technologies, *International Journal of Intelligent Networks*, vol. 3, pp. 150–164, 2022.

Jouicha, Y., Cherrafi, A., Hamani, N., and Elfezazi, S., Performance measurement systems for supply chain 5.0: Gaps, challenges, and future research avenues, *IFAC-PapersOnLine*, vol. 59, no. 10, pp. 2933–2938, 2025.

Kamilaris, A., and Prenafeta-Boldú, F. X., Deep learning in agriculture: A survey, *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.

Kamilaris, A., Fonts, A., and Prenafeta-Boldú, F. X., The rise of blockchain technology in agriculture and food supply chains, *Trends in Food Science & Technology*, vol. 91, pp. 640–652, 2019.

Klerkx, L., Jakku, E., and Labarthe, P., A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda, *NJAS – Wageningen Journal of Life Sciences*, vol. 90–91, pp. 100315, 2019.

Kour, V. P., and Arora, S., Recent developments of the Internet of Things in agriculture: A survey, *IEEE Access*, vol. 8, pp. 129924–129957, 2020.

Lima-Junior, F. R., and Carpinetti, L. C. R., Combining SCOR® model and fuzzy TOPSIS for supplier evaluation and management, *International Journal of Production Economics*, vol. 174, pp. 128–141, 2016.

Lowenberg-DeBoer, J., Huang, I. Y., Grigoriadis, V., and Blackmore, S., Economics of robots and automation in field crop production, *Precision Agriculture*, vol. 21, no. 2, pp. 278–299, 2020.

Maes, W. H., and Steppe, K., Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture, *Trends in Plant Science*, vol. 24, no. 2, pp. 152–164, 2019.

Mandal, A., and Ghosh, A. R., Role of artificial intelligence (AI) in fish growth and health status monitoring: A review on sustainable aquaculture, *Aquaculture International*, vol. 32, pp. 2791–2820, 2024

Medvediev, M., Muzylyov, D., and Montewka, J., A model for agribusiness supply chain risk management using fuzzy logic: Case study grain route from Ukraine to Poland, *Transportation Research Part E: Logistics and Transportation Review*, vol. 190, pp. 103330, 2024.

Moharamkhani, A., Bozorgi-Amiri, A., and Mina, H., Supply chain performance measurement using SCOR model based on interval-valued fuzzy TOPSIS, *International Journal of Logistics Systems and Management*, vol. 27, no. 1, pp. 115–132, 2017.

Nilashi, M., Abumalloh, R. A., Ahmadi, H., Alrizq, M., Abosaq, H., Alghamdi, A., Farooque, M., and Mahmood, S. S., Using DEMATEL, clustering, and fuzzy logic for supply chain evaluation of electric vehicles: A SCOR model, *AIMS Environmental Science*, vol. 11, no. 2, pp. 129–156, 2024.

Nilashi, M., From data to decisions: Leveraging ANFIS for adaptive rule-based systems, *Journal of Soft Computing and Decision Support Systems*, vol. 12, no. 4, 2025.

Odume, B. W., Artificial intelligence in agriculture: Application in developing countries, *Journal of Agricultural Science*, vol. 16, no. 12, pp. 60–60, 2024.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., and Moher, D., The PRISMA 2020 statement: An updated guideline for reporting systematic reviews, *BMJ*, vol. 372, pp. n71, 2021.

Panudju, A. T., Rahardja, S., and Nurilmala, M., Decision support system in fisheries industry: Current state and future agenda, *International Journal on Advanced Science, Engineering and Information Technology*, vol. 13, no. 2, 2023.

Papageorgiou, E. I., Kokkinos, K., and Dikopoulou, Z., Fuzzy sets in agriculture, in *Fuzzy Logic in Its 50th Year*, pp. 211–233, 2016.

Patrício, L., and Rieder, S., Computer vision and artificial intelligence in precision agriculture for crop protection, *Computers and Electronics in Agriculture*, vol. 153, pp. 69–81, 2018.

Pretty, J., and Bharucha, Z. P., Sustainable intensification in agricultural systems, *Annals of Botany*, vol. 114, no. 8, pp. 1571–1596, 2014.

Raut, R. D., Gardas, B. B., Kharat, M., and Narkhede, B., Modeling the drivers of post-harvest losses – MCDM approach, *Computers and Electronics in Agriculture*, vol. 154, pp. 426–433, 2018.

Saiz-Rubio, V., and Rovira-Mas, F., From smart farming towards agriculture 5.0: A review on crop data management, *Agronomy*, vol. 10, no. 2, pp. 207, 2020.

Saleem, M. H., Potgieter, J., and Arif, K. M., Plant disease detection and classification by deep learning, *Plants*, vol. 8, no. 11, pp. 468, 2019.

Shalev-Shwartz, S., and Ben-David, S., *Understanding machine learning: From theory to algorithms*, Cambridge University Press, 2014.

Silva, F. A., and Santos, D. R., Fuzzy logic for situation awareness: A systematic review, *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, pp. 4419–4438, 2023.

Too, E. C., Yujian, L., Njuki, S., and Yingchun, L., A comparative study of fine-tuning deep learning models for plant disease identification, *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.

Tsakiridis, N. L., Estimation of soil properties for sustainable crop production using multisource data fusion, in *Hyperautomation in Precision Agriculture: Advancements and Opportunities for Sustainable Farming*, pp. 113–127, 2025.

Tsouros, D. C., Bibi, S., and Sarigiannidis, P. G., A review on UAV-based applications for precision agriculture, *Information*, vol. 10, no. 11, pp. 349, 2019

Zadeh, L. A., Fuzzy sets, *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.

Zanon, L. G., Bertassini, A. C., Sigahi, T. F. A. C., Anholon, R., and Carpinetti, L. C. R., Relations between supply chain performance and circular economy implementation: A fuzzy cognitive map-based analysis for sustainable development, *Business Strategy and Development*, vol. 7, no. 2, pp. e373, 2024

Zhang, C., Kovacs, J. M., and Wang, X., Applications of small unmanned aerial systems for precision agriculture: A review, *Precision Agriculture*, vol. 23, pp. 1–26, 2022.

Biography

Dr. Shraddha Gawankar is an Assistant Professor for Practice with a Ph.D. in Operations Management from the Indian Institute of Management Mumbai. She has over eight years of teaching experience in business schools, specializing in Business Statistics, Operations Management, Project Management, Business Analytics, and Supply Chain Management. Her teaching integrates R, Python, Excel, and AI driven analytics to develop industry ready skills among students. Her research focuses on the application of artificial intelligence, automation, and digital technologies to improve supply chain performance and resilience. She has published in reputed international journals, including the International Journal of Production Research and International Journal of Production Economics. Dr. Gawankar is also a member of the Industrial Engineering and Operations Management Society and Production and Operations Management Society.