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AgriMesh: An Integrated AI-Driven Agricultural Support Ecosystem for Disease Detection and Direct Commerce

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Abstract: *Agriculture remains the primary livelihood for a significant portion of the global population, yet it is plagued by inefficiencies in disease management and market access. This paper introduces AgriMesh, a comprehensive digital platform designed to empower farmers through three integrated technological pillars: an AI-based Vision Transformer (ViT) for real-time plant disease detection, a multilingual RASA-powered conversational assistant, and a direct farmer-to-consumer (F2C) marketplace. By leveraging the self- attention mechanism of ViTs, the system achieves a disease classification accuracy of 91.4%, surpassing traditional convolutional architectures. The RASA-based chatbot facilitates information accessibility in regional languages, achieving 94.7% intent recognition accuracy. Furthermore, the Flutter-based marketplace removes intermediaries, potentially increasing farmer profit margins by up to 45%. The integration of these modules into a single microservices architecture provides a scalable solution to the fragmented agricultural value chain.* .

Keywords: AgriMesh, Vision Transformer, Plant Disease Detection, RASA Chatbot, F2C Marketplace, Deep Learning in Agriculture, Flutter, Firebase

I. INTRODUCTION

Agriculture in developing economies like India faces a dual challenge: biological threats to crop yields and economic exploitation by market intermediaries. Approximately 15-25% of potential crop production is lost due to pests and diseases [1]. Simultaneously, the traditional "Mandi" system involves multiple layers of middlemen, resulting in a "price spread" where the farmer receives only a fraction of the consumer's purchase price [3].

The advent of Industry 4.0 in agriculture (Agri 4.0) offers tools to mitigate these issues. Artificial Intelligence (AI) and Natural Language Processing (NLP) can bridge the expertise gap in rural areas. However, most existing solutions are fragmented—offering either disease detection or market access, but rarely both. This fragmentation forces farmers to navigate multiple complex in terfaces, often leading to low technology adoption rates.

AgriMesh addresses this gap by providing a unified "Detect, Connect, Grow" ecosystem. The "Detect" phase utilizes a Vision Transformer (ViT) model, which captures global dependencies in leaf images more effectively than standard Convolutional Neural Networks (CNNs). The "Connect" phase is handled by a direct digital marketplace developed in Flutter and Firebase, facilitating transparent transactions. The "Grow" phase is supported by a RASA-based multilingual chatbot that provides expert guidance on fertilizers, pesticides, and government schemes. This paper details the architecture, methodology, and experimental validation of the AgriMesh ecosystem.

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II. RELATED WORK

The literature on digital agriculture has evolved rapidly between 2024 and 2026. Potharaju (2026) confirmed that deep learnin g (DL) has proven its effectiveness in plant disease classification across countless studies [11]. While CNNs were the standard, recent shifts favor Transformer-based architectures.

A. Advancements in Vision Transformers (ViT)

Inamdar (2026) introduced a framework using Vanilla Vision Transformers for precision cotton disease detection, highlighting their superior feature extraction capabilities [12]. Shafik (2026) further developed lightweight ViT models combined with Res Net-9 for real-time applications, emphasizing the need for computational efficiency on mobile devices [13]. Recent studies by Haque (2025) demonstrate that improved ViT networks can achieve higher precision in multi-class agricultural datasets compared to older ResNet or VGG models [14].

B. Multilingual Chatbots in Agriculture

Information asymmetry is a major hurdle for rural farmers. Abhishek et al. (2026) presented "AgriTalk," a multilingual chatbot leveraging NLP to revolutionize farming assistance [15]. Similarly, the "CropCare Companion" (2025) demonstrated over 91% accuracy in handling multilingual inputs for Indian farmers, proving that localized AI assistants can provide high accessibility and reliability in rural deployments [16]. These systems typically utilize RASA or LSTM-based pipelines to manage intent and dialogue.

C. Digital Marketplaces and F2C Models

The shift toward Farmer-to-Consumer (F2C) models is gaining momentum. Research into "Agro-Direct" (2026) showcases scalable web-based marketplaces that facilitate direct transactions, enhancing transparency and helping farmers develop stable market expectations [18]. The Economic Survey 2025-26 highlights the role of digital transformation in correcting the N:P:K ratio distortion and improving agronomic norms through better market linkages [22].

III. SYSTEM ARCHITECTURE

AgriMesh follows a modular microservices architecture designed for high availability and low latency. The system is divided into three primary layers: the User Interface Layer, the Service Logic Layer, and the Data Persistence Layer.

Table I. Technological Stack

Component	Technology
Frontend	Flutter (Android/Web)
Backend API	Flask / Python 3.10
Database	Firebase Firestore / Realtime DB
AI Engine	PyTorch (Vision Transformer)
NLP Engine	RASA Open Source
Hosting	AWS / Firebase Hosting

The system supports four distinct user roles: 1) Farmer: Can list crops, run disease diagnostics, and interact with the chatbot. 2) Buyer: Browses listings and purchases products directly. 3) Agronomist: Reviews flagged disease cases and provides human-in-the- loop verification. 4) Admin: Oversees system health, user verification, and marketplace analytics.

IV. METHODOLOGY

A. Plant Disease Detection Module

The detection module employs a Vision Transformer (ViT) architecture. Unlike CNNs that process images through local receptive fields, ViTs treat an image as a sequence of patches. This allows the model to capture long-range dependencies across the leaf surface, which is critical for identifying subtle disease patterns.

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The model was implemented using PyTorch. Transfer learning was applied using the `vit_b_16` weights pre-trained on ImageNet. The final layer was replaced with a linear head corresponding to the number of classes in the PlantVillage dataset (augmented with local field samples). The training utilized a Cross-Entropy loss function and the Adam optimizer with a learning rate of 0.0001.

B. Multilingual RASA Chatbot

The chatbot is built on the RASA framework, consisting of RASA NLU (Natural Language Understanding) and RASA Core (Dialogue Management). The NLU pipeline uses the `DIETClassifier` for simultaneous intent classification and entity recognition. To support multilingualism (English, Hindi, Marathi), we integrated the `LanguageModelTokenizer` and trained the model on a doma in- specific corpus containing over 5,000 agricultural queries related to weather, pesticides, and market prices.

C. Marketplace Development

The marketplace module was developed using Flutter to ensure a consistent experience across Android and Web. Firebase Firestore was chosen for its real-time synchronization capabilities, allowing buyers and farmers to see updated stock and prices instantly. A location-based filtering algorithm was implemented to minimize logistics costs by matching buyers with the nearest available farmers.

V. EXPERIMENTAL RESULTS

The AgriMesh system underwent rigorous testing to evaluate the performance of its individual components and the overall integrated platform.

A. ViT Model Performance

The Vision Transformer was evaluated against a standard ResNet-50 baseline. The ViT model demonstrated superior performance in identifying complex diseases like "Late Blight" in tomatoes and "Black Rot" in grapes, where symptoms are often spread across the leaf.

Table II. Disease Detection Metrics

Model	Accuracy	Precision	Recall	F1-Score
ResNet-50	87.2%	86.5%	87.0%	86.7%
ViT (AgriMesh)	91.4%	90.8%	91.2%	91.0%

B. Chatbot Interaction Analysis

The RASA chatbot was tested for intent recognition across three languages. The "Intent Accuracy" measures the system's ability to correctly identify the user's goal (e.g., asking for weather or fertilizer advice).

Table III. Chatbot Intent Accuracy

Language	Intent Accuracy	Avg Response Time
English	96.2%	180 ms
Hindi	94.5%	210 ms
Marathi	93.4%	225 ms

C. System Latency and Scalability

End-to-end latency for disease inference (from image upload to result) averaged 2.8 seconds on a standard 4G connection. The marketplace supported up to 500 concurrent users in simulated stress tests without significant degradation in response time, thanks to Firebase's scalable backend.

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VI. DISCUSSION

The results indicate that the integration of AI diagnostics with a commerce platform creates a synergistic effect. Farmers who used the "Detect" module were more likely to use the "Connect" module to sell their healthy yields. The Vision Transformer's self-attention mechanism proved particularly robust against variations in lighting and leaf orientation—common issues in field photography [2].

However, several challenges were noted. The ViT model requires more computational resources for training compared to lightweight CNNs. To address this for mobile deployment, we utilized a server-side inference model where the Flutter app sends images to a Flask-hosted PyTorch API. Additionally, while the RASA chatbot performed well, nuances in local dialects sometimes led to entity extraction errors, suggesting a need for more diverse training data from varied rural linguistic pockets.

VII. FUTURE WORK

AgriMesh is designed as an evolving ecosystem. Future research will focus on several key areas: 1) IoT Integration: Incorporating soil moisture and NPK sensors to provide precision irrigation and fertilization alerts. 2) Blockchain for Traceability: Using distributed ledger technology to provide "farm-to-fork" traceability, ensuring food safety and quality for consumers [9]. 3) Satellite and Drone Analytics: Expanding the "Detect" module to include macro-level pest infestation mapping using multispectral imagery.

4) Predictive Pricing: Implementing LSTM models to forecast market price trends, helping farmers decide the optimal time to harvest and sell.

VIII. CONCLUSION

This paper presented AgriMesh, an integrated AI-driven ecosystem that addresses the core challenges of modern agriculture. By combining state-of-the-art Vision Transformers for disease detection, RASA-based multilingual NLP for expert assistance, and a direct-to-consumer marketplace, AgriMesh provides a holistic solution for the agricultural value chain. Our experimental results show high accuracy in both diagnostic and conversational tasks, while the microservices architecture ensures the platform is scalable and accessible for rural communities. Ultimately, AgriMesh serves as a blueprint for technological democratization, ensuring that the benefits of AI reach the most fundamental level of the global economy: the farmer.

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