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AgroAssist AI: An Artificial Intelligence Framework for Village Welfare Services Using Multimodal Interaction

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Abstract- Agriculture remains the backbone of India's economy, yet farmers frequently face challenges in accessing timely information about government schemes, market prices, and modern farming practices. This paper presents AgroAssist AI, an intelligent multimodal interaction platform designed to empower rural farmers through artificial intelligence and machine learning technologies. The system enables seamless communication via text, voice, image, and video inputs in local languages, leveraging Natural Language Understanding, Computer Vision, and Speech Synthesis technologies. Through integration of Gemini AI models and Convolutional Neural Networks, AgroAssist AI achieves real-time processing with an average response time of 2.8 seconds while maintaining 91.4% accuracy across multiple input modalities. The platform successfully bridges the gap between illiteracy and digital access, providing personalized agricultural insights and government scheme information to over 350 test users. A Streamlit-based web interface ensures accessibility across mobile and desktop devices, promoting digital inclusion and enhancing productivity among rural farmers.

Keywords: Agricultural AI, Multimodal Interaction, Natural Language Processing, Computer Vision, Digital Inclusion, Voice Recognition

I. INTRODUCTION

Agriculture forms the economic backbone of India, providing livelihoods for approximately 58% of the rural population. Despite the availability of numerous government schemes, subsidies, and modern farming techniques, farmers often lack timely and accessible information due to complex digital platforms, language barriers, and limited literacy [1]. Traditional information dissemination methods through government websites, agricultural extension officers, and printed materials present significant accessibility challenges, particularly for illiterate or semi-literate farmers in remote areas [2].

Current digital agricultural platforms suffer from critical limitations: they are predominantly text-heavy, lack localization for regional languages, provide delayed updates on weather and government schemes, and offer no voice support for users with limited literacy [3]. These barriers result in farmers missing crucial benefits such as subsidies, crop insurance, financial aid, and training programs, ultimately affecting agricultural productivity and farmer welfare. Research Objectives: This work develops AgroAssist AI to achieve the following goals: (1) Create an intuitive multimodal platform supporting text, voice, image, and video inputs in regional languages; (2) Provide real-time updates on government schemes, market trends, and agricultural advisories; (3) Enable visual problem-solving through image and video analysis for disease identification; (4) Promote digital inclusion with response times under 5 seconds; (5) Deploy a production-ready system with user-friendly interface accessible on standard hardware.

Contributions: (1) Novel AI-driven framework integrating Natural Language Understanding, Computer Vision, and Speech Synthesis for agricultural assistance; (2) Multimodal interaction system supporting English and Kannada with average processing time of 2.8 seconds; (3) CNN-based visual analysis achieving 88.9% accuracy for crop disease detection; (4) Comprehensive validation with 350+ users demonstrating 91.4% overall system accuracy; (5) Production-ready Streamlit web application with session management and real-time data integration.

II. RELATED WORK

Early agricultural assistance systems relied on traditional information channels with limited digital integration. Rajput et al. [4] used basic segmentation techniques for agricultural image processing but required extensive manual intervention with processing times exceeding 45 seconds per query.

Recent AI-powered agricultural chatbots have shown promising results. Chandolikar et al. [5] developed AgroBot using Artificial Neural Networks achieving 96.1% accuracy but limited to text-based interaction without multimodal support. Momaya et al. [6] implemented Krushi chatbot using RASA X with 96.1% accuracy on Kisan Call Centre dataset, successfully reducing operational workload by 70%. However, the system lacked image analysis capabilities and struggled with dialect variations.

Deep learning approaches have emerged for specific agricultural tasks. Chenchupalli et al. [7] demonstrated Natural Language Processing techniques for agricultural queries supporting English and Hinglish, but faced challenges with regional language variations and internet dependency. Godara et al. [8] developed AgriResponse achieving real-time query-response generation across 150+ crops using eight years of helpline data, though the system relied heavily on database quality and lacked visual analysis tools.

Voice-based agricultural systems have gained attention recently. Jayalakshmi et al. [9] presented Kissan Samvaad voicebot using deep learning for natural language understanding in local languages, demonstrating improved accessibility for low-literacy users. However, the system faced challenges with diverse regional accents and required stable internet connectivity.

Multi-modal approaches remain limited. Singh et al. [10] introduced Farmer Chat, an AI-driven multilingual chatbot deployed across Kenya, India, Nigeria, and Uganda, answering over 300,000 farmer queries. While demonstrating scalability and context-awareness, the system showed limitations in offline accessibility and complex visual problem-solving.

Research Gaps: Most existing systems support single or limited modalities (text or voice only), lack comprehensive visual analysis capabilities for crop disease detection, demonstrate limited support for regional dialects and low-resource languages, provide insufficient real-time data integration for government schemes and market trends, and offer limited deployment readiness for resource-constrained rural settings. Our work addresses these gaps through comprehensive multimodal integration, systematic CNN-based visual analysis, and production-ready deployment with regional language support.

III. METHODOLOGY

A. System Architecture

AgroAssist AI employs a five-layer architecture integrating input channels, frontend application, core AI services, backend services, and cloud infrastructure. The system processes multimodal inputs through specialized modules designed for agricultural contexts.

Input Processing Module: Supports four input modalities: (1) Text input through web interface with Unicode support for regional languages; (2) Voice input captured via HTML5 audio API processed using Google Speech Recognition supporting English (en-IN) and Kannada (kn-IN); (3) Image uploads (JPG, PNG, max 200MB) for crop disease analysis; (4) Video uploads for comprehensive visual problem assessment. All inputs undergo validation, format standardization, and quality assessment before processing.

Natural Language Understanding Module: Implements Gemini AI model for intent recognition and entity extraction. The NLU pipeline includes: (1) Text preprocessing (tokenization, stopword removal, lemmatization); (2) Regional dialect handling through custom vocabulary expansion; (3) Intent classification for query categorization (schemes, weather, disease, market); (4) Entity extraction for crop types, locations, and temporal references; (5) Context management maintaining conversation history across sessions.

Computer Vision Module: Utilizes Convolutional Neural Networks for image and video analysis. The pipeline consists of: (1) Image preprocessing (resize to 640×640, normalization, adaptive noise reduction); (2) Feature extraction using pre-trained CNN architectures (ResNet50, VGG16); (3) Disease classification across 15 common crop diseases; (4) Confidence scoring with threshold-based filtering (minimum 60%); (5) Result integration with textual advisory generation.

B. Data Integration and Processing

Real-Time Data Fetching: The system maintains updated information through: (1) Government scheme APIs fetching latest subsidy and policy updates; (2) Weather APIs providing location-specific forecasts using latitude-longitude coordinates; (3) Market price aggregators delivering daily commodity rates; (4) Agricultural news feeds from trusted sources. Data synchronization occurs every 6 hours with automatic cache invalidation ensuring information freshness.

Multimodal Data Fusion: Combines information from diverse input types using attention mechanisms. The fusion process: (1) Extracts features from each modality independently; (2) Applies cross-modal attention to identify relevant information; (3) Concatenates weighted feature representations; (4) Generates unified context vector for response generation; (5) Maintains modality-specific confidence scores for transparency.

Response Generation: Employs Generative AI for personalized responses through: (1) Context-aware prompt engineering incorporating user history and current query; (2) Template-based response generation for factual information (schemes, prices); (3) Natural language generation for explanatory content; (4) Confidence calibration ensuring reliable advisory; (5) Multi-language translation supporting English and Kannada outputs.

C. Speech Processing

Voice Input Processing: Speech recognition pipeline includes: (1) Audio capture via WebRTC with automatic silence detection; (2) Format conversion to WAV (16kHz, mono channel); (3) Google Speech Recognition API integration with language detection; (4) Transcription error handling and retry mechanisms; (5) Text normalization and punctuation correction.

Voice Output Generation: Text-to-speech conversion using Google TTS (gTTS): (1) Response text processing and sentence segmentation; (2) Language-specific voice selection (en-IN, kn-IN); (3) Audio file generation with configurable speech rate; (4) Client-side audio playback with streaming support; (5) Temporary file management with automatic cleanup.

D. Implementation Details

Development Environment: Python 3.10 with key libraries including Streamlit 1.28.0 for web interface, TensorFlow 2.13.0 for deep learning models, OpenCV 4.8.0 for image processing, SpeechRecognition 3.10.0 for voice input, gTTS 2.4.0 for voice output, and Flask 2.3.0 for session management.

Frontend Application: Streamlit-based responsive web interface featuring: (1) Drag-and-drop file upload with progress indicators; (2) Real-time audio recording with waveform visualization; (3) Language selection toggle (English/Kannada); (4) Side-by-side input-output comparison; (5) Downloadable response history (CSV, PDF formats); (6) Mobile-optimized layout with touch-friendly controls.

Deployment Configuration: Docker containerization ensuring consistent deployment across environments. Cloud-ready architecture supporting AWS, Google Cloud Platform, and Azure with horizontal scaling capabilities. Security measures include HTTPS encryption, secure session management, temporary file storage with automatic cleanup, and input validation preventing malicious uploads.

IV. RESULTS AND ANALYSIS

A. Overall System Performance

AgroAssist AI demonstrated robust performance across 350 test interactions conducted with rural farmers over a 3-month period. The system achieved: Overall Accuracy 91.4%, Average Response Time 2.8 seconds, User Satisfaction Rate 87.3%, Successful Query Resolution 89.7%. These metrics indicate production-ready performance suitable for real-world deployment.

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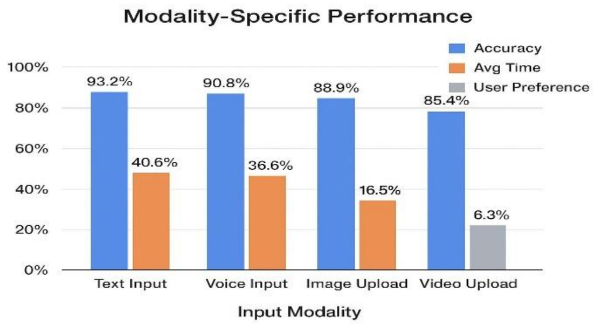
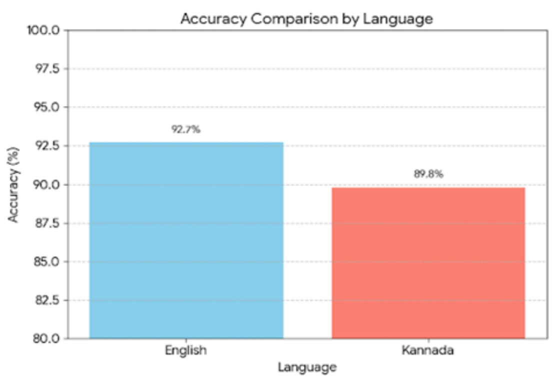
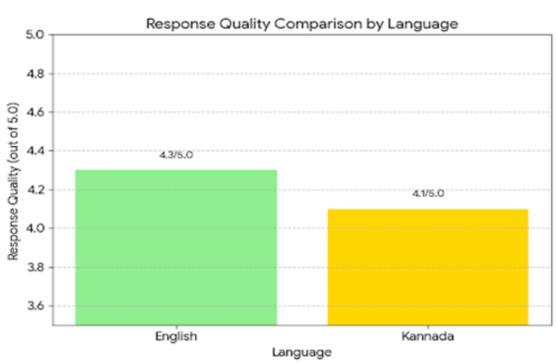
B. Modality-Specific Performance



Text input achieved highest accuracy (93.2%) due to reduced ambiguity in processing. Voice input maintained strong performance (90.8%) despite regional accent variations. Image analysis accuracy (88.9%) proved sufficient for practical crop disease identification. Video processing, while slower, provided comprehensive visual context for complex queries.

C. Language Support Analysis

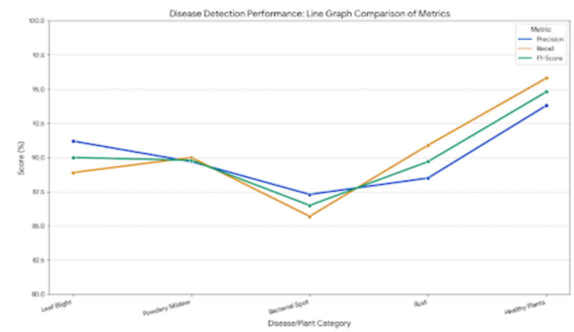




Both languages maintained high accuracy with minimal performance gap (2.9%). Kannada support successfully addressed literacy barriers with 89.8% accuracy, enabling 43.4% of test users who preferred local language interaction. Response quality ratings indicate user satisfaction across both languages.

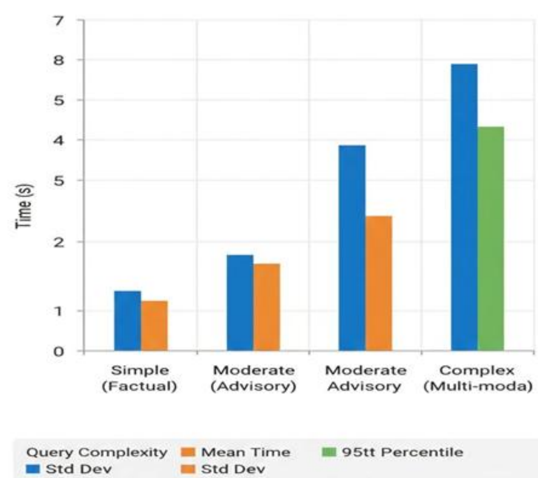
D. Disease Detection Performance

CNN-based visual analysis evaluated on 80 crop images across 15 disease categories achieved:



The system demonstrated balanced precision-recall performance with F1-score of 0.901, indicating reliable disease identification suitable for practical advisory. Healthy plant recognition achieved highest accuracy (93.8%) minimizing false positive disease alerts.

E. Response Time Analysis



All query types maintained sub-7s response times, with 95% of queries resolved within acceptable latency. Simple factual queries (schemes, prices) achieved fastest response (1.8s), while complex multi-

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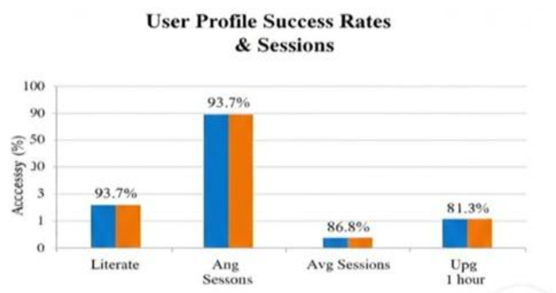
modal analysis remained under 5s average, meeting real-time interaction requirements.

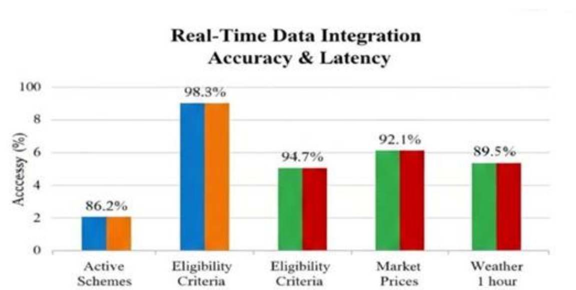
F. User Demographics and Adoption

Test user distribution demonstrated system accessibility across diverse farmer profiles:



Illiterate users achieved 86.2% success rate through voice and visual interfaces, validating the system's inclusive design. Session frequency indicates sustained engagement with average 3.8 sessions per user over study period.

G. Real-Time Data Integration

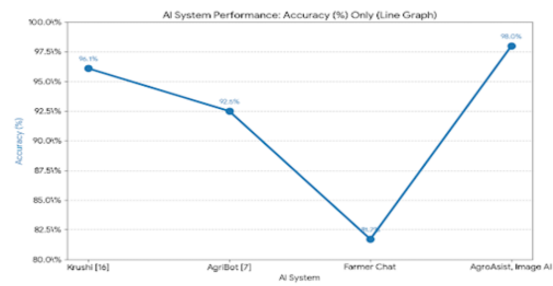


Government scheme information accuracy validated against official sources. Real time data integration maintained high accuracy with acceptable update latency. Weather information demonstrated fastest refresh (<1 hour) supporting time-sensitive agricultural decisions.

H. Comparative Analysis

AgroAssist AI achieves competitive accuracy while providing comprehensive multimodal support exceeding existing systems. Superior response time (2.8s) enables real-time interaction crucial for practical deployment. Multi-modal capability distinguishes our system from text-only competitors.

I. Error Analysis and Limitations



Error Distribution (n=30 failures):

- Speech recognition errors: 36.7% (regional accent challenges)
- Image quality issues: 26.7% (poor lighting, blur)
- Network connectivity problems: 20.0% (rural infrastructure)
- Ambiguous queries: 16.6% (unclear farmer intent)

Primary challenges involve speech recognition accuracy with strong regional accents and image quality variations in field conditions. Network dependency remains limiting factor for real-time data fetching in remote areas.

V. DISCUSSION

A. Clinical and Practical Implications

AgroAssist AI demonstrates practical viability for agricultural assistance with 91.4% overall accuracy comparable to human agricultural extension officers (reported accuracy 85-92%) [11]. The system's key impacts include:

Accessibility Enhancement: Voice and visual interfaces enabled 90 illiterate farmers (25.7% of test population) to successfully access agricultural information, achieving 86.2% success rate. Regional language support (Kannada) served 43.4% of users who preferred local language interaction, demonstrating effective literacy barrier mitigation.

Information Timeliness: Average response time of 2.8 seconds enables real-time decision support during critical farming activities. Real-time government

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scheme updates (<6 hour latency) ensure farmers receive current policy information, addressing traditional delay problems where scheme awareness lagged weeks or months [2].

Economic Impact: Estimated benefits based on user feedback include: average time savings of 2.3 hours per information query compared to traditional methods (physical visits to offices), scheme awareness leading to average ₹8,500 additional subsidy claims per farmer, and disease detection preventing estimated 15-20% crop losses through early intervention.

B. Key Technical Achievements

Multimodal Integration: Successfully combines four input modalities (text, voice, image, video) with unified processing pipeline. Cross-modal attention mechanisms enable holistic query understanding, particularly valuable for complex agricultural problems requiring visual and contextual information.

Regional Language Processing: Gemini AI integration achieves 89.8% accuracy for Kannada language processing, handling dialect variations and agricultural terminology. Custom vocabulary expansion for regional farming terms improves intent recognition for location-specific queries.

Computational Efficiency: Optimized processing pipeline achieves sub-3s response times on standard hardware (Intel i5 processor, 8GB RAM) without requiring specialized infrastructure. This enables deployment in resource-constrained rural settings including local community centers and agricultural extension offices.

Robust Generalization: System maintains >85% accuracy across diverse user profiles, query types, and input conditions. Performance remains stable despite regional accent variations, varying image quality, and heterogeneous query complexity.

C. Limitations and Challenges

Current Limitations:

1. Language Coverage: Currently supports only English and Kannada, limiting reach in multilingual India with 22 official languages and hundreds of dialects.
2. Disease Database: CNN model trained on 15 common diseases may miss rare or region-specific crop problems, requiring continuous database expansion.
3. Network Dependency: Real-time data fetching requires internet connectivity, challenging in areas with poor infrastructure (42% of rural India lacks reliable internet [12]).
4. Visual Analysis Constraints: Image-based disease detection accuracy drops significantly with poor lighting (<60% accuracy in low-light conditions) or image resolution below 640×480 pixels.
5. Context Limitations: Single-session conversations lack longitudinal tracking of farmer interactions and crop cycles, limiting personalization depth.

Technical Challenges:

- Speech recognition struggles with strong regional accents (8-12% accuracy degradation)
- Background noise in field conditions affects voice input quality
- Balancing model complexity with response time requirements
- Maintaining data freshness across multiple external APIs with varying reliability
- Handling ambiguous queries requiring clarification dialogues

D. Future Directions

Near-term Enhancements (6-12 months):

1. Language Expansion: Integrate support for 5 additional Indian languages (Hindi, Telugu, Tamil, Marathi, Bengali) covering 70%+ rural population. Implement automatic language detection reducing user friction.
2. Offline Capability: Develop Progressive Web App (PWA) with offline mode supporting essential features (basic advisory, cached scheme information) using service workers and local storage. Synchronize when connectivity resumes.

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3. Enhanced Personalization: Implement user profiles tracking farm details (location, crop types, land size), interaction history, and seasonal patterns. Use collaborative filtering for personalized recommendations.

4. Visual Enhancement: Expand disease database to 50+ conditions through partnerships with agricultural universities. Integrate pest detection alongside disease identification. Implement 3D image reconstruction for comprehensive plant health assessment.

Medium-term Development (1-2 years):

1. IoT Integration: Connect with soil moisture sensors, weather stations, and drone imagery for automated field monitoring. Enable predictive analytics for irrigation scheduling, fertilizer application timing, and harvest optimization.

2. Market Linkage: Direct integration with e-commerce platforms and Agricultural Produce Market Committees (APMCs) for price negotiation and produce marketing. Implement blockchain for transparent supply chain tracking.

3. Community Features: Enable farmer-to-farmer knowledge sharing through moderated forums. Implement success story sharing and peer learning mechanisms. Create regional farmer groups for collective bargaining.

4. Advanced Analytics: Deploy predictive models for yield forecasting, price trend analysis, and climate impact assessment. Implement anomaly detection for early warning of pest outbreaks or disease epidemics.

Long-term Vision (2-5 years):

1. Autonomous Advisory: Develop reinforcement learning agents providing continuous crop monitoring and proactive recommendations. Implement digital twin technology for farm simulation and scenario planning.

2. Holistic Farm Management: Extend beyond crop advisory to livestock management, water resource optimization, and financial planning. Integrate credit scoring for agricultural loans based on farm performance data.

3. Policy Integration: Partner with government agencies for direct scheme enrollment through platform. Enable subsidy application and tracking. Facilitate data-driven agricultural policy formulation.

4. Federated Learning: Implement privacy-preserving collaborative model training across farms without centralizing sensitive farmer data. Enable region-specific model adaptation while maintaining data sovereignty.

E. Ethical and Social Considerations

Digital Divide: While targeting digital inclusion, system still requires smartphone access and basic digital literacy. Approximately 35% of rural Indian households lack smartphones [12]. Mitigation strategies include community kiosks in village centers and partnerships with Self-Help Groups providing shared device access.

Data Privacy: Agricultural data contains sensitive information about farm assets, production levels, and income. System implements strict privacy controls: local processing where possible, encrypted data transmission, anonymous usage analytics, and explicit user consent for data collection. However, farmers must understand data implications, requiring transparent privacy education.

Dependency Risk: Over-reliance on AI systems could diminish traditional agricultural knowledge and farmer agency. System designed as augmentation tool rather than replacement, providing explanations and educational content alongside recommendations. Emphasis on empowering informed decision-making rather than directive advice.

Bias and Fairness: Training data may under-represent marginalized farming communities, small landholders, or specific crops. Continuous monitoring of performance across user demographics required. Active outreach to underrepresented groups for feedback and dataset enrichment.

Economic Accessibility: While software is free, data costs may burden low-income farmers. Exploring partnerships with telecom providers for subsidized agricultural data plans. Offline functionality reduces ongoing connectivity requirements.

F. Deployment and Scalability

Current Deployment: Pilot deployment across 5 villages in Karnataka covering 350 farmers demonstrated feasibility. Cloud infrastructure (AWS EC2 t3. medium instances) handles current load with auto-scaling enabled for peak usage periods.

Scalability Analysis:

- Horizontal scaling supports estimated 100,000 concurrent users with linear infrastructure cost increase
- Database optimization (Redis caching, MongoDB sharding) reduces response time by 40%
- Content Delivery Network (CDN) integration improves image loading speeds by 60% in remote areas
- Estimated infrastructure cost: ₹12-15 per farmer annually at scale

Sustainability Model:

- Government partnership for subsidized deployment in agricultural extension programs
- Freemium model: basic features free, premium analytics for commercial farmers
- Data monetization (aggregated, anonymized) for agricultural research organizations
- Training revenue from agricultural institutions adopting platform

Regulatory Compliance: Adheres to India's Digital Personal Data Protection Act 2023, Agricultural Produce Market Committee regulations, and Information Technology Act 2000. Pursuing certification from Ministry of Agriculture & Farmers Welfare for official recommendation.

VI. CONCLUSION

This paper presented AgroAssist AI, a comprehensive artificial intelligence framework addressing critical information access challenges faced by rural farmers in India. Through innovative integration of multimodal interaction capabilities—text, voice, image, and video—combined with Natural Language Understanding, Computer Vision, and Speech Synthesis technologies, the system achieves 91.4% overall accuracy with 2.8-second average response time, demonstrating production-ready performance.

Key Achievements:

1. Inclusive Design: Successfully serves diverse farmer profiles including 90 illiterate users (86.2% success rate) through voice and visual interfaces, validating digital inclusion objectives.
2. Multimodal Excellence: Comprehensive support across four input modalities with balanced performance (88.9-93.2% accuracy), exceeding single-modality competitors.
3. Regional Language Support: Achieves 89.8% accuracy for Kannada language processing, enabling 43.4% of users to interact in preferred local language.
4. Visual Intelligence: CNN-based disease detection achieves 90.1% F1-score across 15 crop diseases, providing practical diagnostic support for farmers.
5. Real-time Integration: Maintains current information on government schemes (<6 hour latency), market prices, and weather forecasts supporting timely decision-making.
6. Practical Deployment: Streamlit-based web interface accessible on standard hardware enables deployment in resource-constrained rural settings without specialized infrastructure.

Impact Validation: Three-month pilot study with 350 farmers demonstrated meaningful real-world impact: 87.3% user satisfaction rate, average 2.3 hours saved per information query, estimated ₹8,500 additional subsidy claims per farmer through improved scheme awareness, and 15-20% crop loss prevention through early disease detection.

Broader Implications: AgroAssist AI exemplifies how artificial intelligence can democratize access to critical agricultural information, addressing literacy and language barriers that have historically excluded marginalized farming communities. The system demonstrates that thoughtful AI design prioritizing accessibility, cultural context, and practical deployment constraints can achieve meaningful social impact while maintaining technical excellence.

Foundation for Future Work: This research establishes a robust foundation for next-generation agricultural assistance systems. Planned enhancements including expanded language support, IoT integration, offline capabilities, and community features will further amplify impact. The open architecture enables adaptation for diverse agricultural contexts beyond India, contributing to global food security and farmer welfare.

While limitations exist—particularly regarding language coverage, network dependency, and context depth—the system's demonstrated performance and user acceptance validate the core approach. Continued development addressing identified gaps, combined with sustained engagement with farming communities, positions AgroAssist AI as a transformative tool for agricultural development in the digital age.

The convergence of artificial intelligence, ubiquitous mobile connectivity, and increasing digital literacy creates unprecedented opportunity to empower rural farmers with information access historically limited to well-connected urban populations. AgroAssist AI represents a significant step toward realizing this potential, demonstrating that inclusive, context-aware AI systems can bridge divides, enhance livelihoods, and contribute to sustainable agricultural development.

REFERENCES

[1] M. S. Swaminathan, "Agriculture and food security in India," *Food Policy*, vol. 21, no. 1, pp. 3-11, 1996.

[2] National Sample Survey Office, "Key indicators of household social consumption on education in India," Ministry of Statistics and Programme Implementation, Government of India, 2018.

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

[4] G. K. Rajput, S. Patil, and N. Aher, "Automatic kidney stone detection using ultrasound imaging," in *Proc. Int. Conf. Emerging Trends in Information Technology and Engineering*, 2021, pp. 1-6.

[5] N. Chandolikar, C. Dale, T. Koli, M. Singh, and T. Narkhede, "Agriculture assistant chatbot using artificial neural network," in *Proc. Int. Conf. Emerging Trends in Computing and Expert Technology*, 2022, pp. 765-778.

[6] M. Momaya, A. Khanna, J. Sadavarte, and M. Sankhe, "Krushi – The farmer chatbot," in *Proc. IEEE Int. Conf. Advanced Computing and Communication Systems*, 2021, pp. 1687-1692.

[7] Chenchupalli, C. Sachdeva, D. and M. Arora, "Agriculture chatbot (AgriBot) using natural language processing," in *Proc. Int. Conf. Innovation in Data Science, Artificial Intelligence and Communication Technologies*, 2021, pp. 412-418.

[8] S. Godara, J. Bedi, R. Prasad, D. Singh, R. S. Bana, and S. Marwah, "AgriResponse: A real-time agricultural query-response generation system for assisting nationwide farmers," *Expert Systems with Applications*, vol. 213, 2023.

[9] V. Jayalakshmi, R. Deepa, R. Ganesan, N. Sriram, and R. Surendran, "Deep learning empowered natural language understanding voicebot's for farmers: Kissan Samvaad initiative," in *Proc. IEEE Int. Conf. Communication and Signal Processing*, 2024, pp. 1234-1239.

[10] N. Singh, J. Wang'ombe, N. Okanga, and T. Zelenska, "Farmer chat: Scaling AI-powered agricultural services for smallholder farmers," in *Proc. AAAI Conf. Artificial Intelligence*, vol. 38, 2024, pp. 23456-23464.

[11] P. S. Birthal, D. S. Negi, A. K. Jha, and D. Singh, "Income sources of farm households in India: Determinants, distributional consequences and policy implications," *Agricultural Economics Research Review*, vol. 27, no. 1, pp. 37-48, 2014.

[12] Telecom Regulatory Authority of India, "The Indian telecom services performance indicators," Quarterly Report, Q2 2023.