Voice-Activated Artificial Intelligence Assistants for Visually Impaired Farmers: Real-Time Speech Recognition Interfaces, Natural Language Processing for Decision Support, and Inclusive Precision Agriculture Solutions

Anna Müller [1*], Lukas Schmidt [2], Sophie Fischer [3], Maximilian Weber [4]
[1-4] German Research Center for Artificial Intelligence (DFKI), Competence Center Smart Agriculture Technologies (CC-SaAT), Osnabrück, Germany

* Corresponding Author: **Anna Müller**

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Abstract
Precision agriculture increasingly relies on data-driven technologies that demand visual interaction with digital interfaces, creating significant barriers for visually impaired farmers who constitute a vulnerable and underserved population in agricultural communities worldwide. Voice-activated artificial intelligence assistants offer transformative potential to bridge this accessibility gap by enabling hands-free, eyes-free interaction with farm management systems through natural speech interfaces. This review examines the current state of voice-activated AI technologies specifically designed to support visually impaired farmers in real-time agricultural decision-making. We analyze core speech recognition architectures, natural language processing algorithms, and multimodal sensor integration strategies that enable these systems to deliver actionable guidance on crop management, irrigation scheduling, pest detection, weather monitoring, and market information access. Key applications include voice-controlled precision irrigation systems, conversational interfaces for disease diagnostics, and audio-based advisory platforms for resource optimization. Despite promising field deployments demonstrating improved farm productivity and independence for visually impaired users, significant challenges remain regarding ambient noise robustness, low-latency processing in resource-constrained environments, multilingual support for diverse farming communities, and equitable technology access in rural settings. Future development must prioritize inclusive design principles, offline functionality, and culturally appropriate interaction models to ensure voice-activated AI assistants become genuinely transformative tools for empowering visually impaired farmers in the evolving landscape of precision agriculture.

Keywords: Voice-activated AI assistants, visually impaired farmers, speech recognition, natural language processing, precision agriculture, assistive technology

1. Introduction

1.1 Challenges Faced by Visually Impaired Farmers

Globally, approximately 2.2 billion people experience vision impairment, with disproportionate representation in rural and agricultural communities where access to eye care services remains limited [1, 2]. Visually impaired farmers face multifaceted challenges in modern agricultural operations that increasingly depend on visual data interpretation from digital displays, smartphone applications, and computer-based farm management systems [3]. Traditional precision agriculture tools require users to read sensor outputs, interpret graphical weather forecasts, identify pest images, and navigate complex software interfaces—tasks fundamentally incompatible with visual disabilities [4, 5]. This technological barrier compounds existing socioeconomic vulnerabilities, limiting productivity, reducing income potential, and threatening the livelihoods of an already marginalized population [6].

The transition from conventional farming practices to data-intensive precision agriculture has inadvertently widened the accessibility gap [7]. Modern irrigation systems display soil moisture readings on visual screens, pest management applications rely on photographic identification, and market price information is presented through text-heavy websites [8]. For visually impaired farmers, these innovations represent not agricultural advancement but technological exclusion [9]. The absence of accessible interfaces forces dependence on sighted assistants, undermining autonomy and delaying time-sensitive agricultural decisions that directly impact crop yields and farm profitability [10].

1.2 Limitations of Conventional Farm Management Support

Existing assistive technologies for visually impaired individuals have largely focused on urban environments and non-agricultural applications [11]. Screen readers and tactile displays, while effective for accessing written content, prove inadequate for real-time farm operations requiring immediate decision-making in outdoor, resource-constrained settings [12]. Agricultural extension services traditionally deliver information through printed materials, visual demonstrations, and in-person consultations—modalities that fail to provide the continuous, on-demand support necessary for dynamic farming environments [13, 14].

Furthermore, conventional voice interfaces not specifically designed for agricultural contexts lack domain-specific vocabulary, contextual understanding of farming operations, and integration with precision agriculture sensor networks [15]. Generic virtual assistants cannot interpret agronomic terminology, provide crop-specific recommendations, or access real-time field data from IoT-enabled monitoring systems [16]. This disconnect between general-purpose voice technologies and specialized agricultural knowledge creates a critical gap that voice-activated AI assistants tailored for visually impaired farmers are uniquely positioned to address [17].

1.3 Scope and Objectives of the Article

This review systematically examines voice-activated AI assistants developed specifically to support visually impaired farmers in precision agriculture contexts. We focus on systems that integrate speech recognition, natural language processing, and agricultural decision support to deliver accessible, real-time guidance through conversational interfaces. The article analyzes technical architectures, core functionalities, field deployment outcomes, and implementation challenges. Our objectives are to synthesize current research on voice-based assistive agricultural technologies, identify best practices for inclusive system design, evaluate performance metrics relevant to visually impaired users, and outline future research directions for scaling these solutions in resource-limited farming communities. By concentrating on this intersection of assistive technology and precision agriculture, we aim to inform researchers, developers, and policymakers working toward equitable agricultural innovation.

2. Voice-Activated AI Technologies in Agriculture

2.1 Speech Recognition and Natural Language Processing

Modern voice-activated AI assistants for agriculture leverage advanced automatic speech recognition (ASR) systems capable of transcribing spoken queries into text with high accuracy [18]. Deep learning architectures, particularly recurrent neural networks and transformer-based models, have dramatically improved speech recognition performance even in noisy agricultural environments characterized by machinery operation, wind, and animal sounds [19, 20]. State-of-the-art ASR systems employ acoustic models trained on diverse speaker populations and agricultural vocabulary, enabling robust recognition of farming terminology, crop names, and domain-specific phrases across multiple languages and dialects [21].

Natural language processing components interpret transcribed speech to extract user intent, identify relevant agricultural entities (crop types, pest species, weather parameters), and generate contextually appropriate responses [22]. Named entity recognition algorithms identify specific crops, locations, and temporal references in farmer queries, while intent classification determines whether users seek information, request actions, or report observations [23]. Dialogue management systems maintain conversational context across multi-turn interactions, enabling farmers to refine queries, request clarifications, and receive progressively detailed guidance without repeating background information [24].

2.2 Integration with Sensors, IoT, and Farm Management Systems

Voice-activated assistants achieve decision support capabilities through seamless integration with precision agriculture sensor networks and IoT infrastructure [25]. Soil moisture sensors, weather stations, drone imagery platforms, and crop health monitors continuously collect field data that voice interfaces make accessible through natural language queries [26]. When a visually impaired farmer asks "What is the soil moisture in the north field?" the system retrieves real-time sensor readings, interprets values against crop-specific thresholds, and delivers actionable audio responses such as "Soil moisture is at 45 percent, irrigation recommended within 6 hours" [27].

Integration extends beyond data retrieval to encompass control functionalities, enabling farmers to activate irrigation systems, adjust greenhouse ventilation, or schedule equipment operations through voice commands [28]. This bidirectional interaction transforms passive information access into active farm management, restoring operational autonomy for visually impaired users [29]. Application programming interfaces connect voice assistants with existing farm management software, enterprise resource planning systems, and agricultural databases, ensuring comprehensive access to historical records, financial information, and regulatory compliance data [30].

2.3 System Architecture and On-Device vs Cloud-Based Processing

Voice-activated agricultural AI systems employ hybrid architectures balancing computational efficiency, privacy protection, and connectivity constraints [18]. On-device processing handles initial speech recognition and wake-word detection locally, minimizing latency and enabling basic functionality without internet connectivity—critical for remote farms with unreliable network access [19]. Edge computing devices deployed at farm locations perform real-time sensor data analysis and execute pre-trained inference models for common queries, reducing dependence on cloud services [20].

Cloud-based components provide computationally intensive services including advanced natural language understanding, complex decision support algorithms, and access to updated agricultural knowledge bases [21]. This distributed architecture ensures that core functionalities remain operational during network outages while leveraging cloud resources for sophisticated analytics when connectivity permits [22]. Privacy-preserving architectures employ federated learning approaches that improve model performance across farming communities without centralizing sensitive farm data [23].

3. Applications and Functionalities

3.1 Crop Management and Irrigation Guidance

Voice-activated assistants provide visually impaired farmers with real-time crop monitoring and irrigation decision support previously inaccessible without visual interface interaction [24]. Systems integrate soil moisture sensors, weather forecasts, and crop water requirement models to deliver personalized irrigation recommendations through conversational interfaces [25]. Farmers receive proactive audio alerts when soil moisture drops below critical thresholds, along with precise guidance on irrigation duration and timing optimized for water conservation and crop health [26].

Crop growth stage monitoring, traditionally requiring visual inspection, becomes accessible through voice queries that retrieve sensor-derived growth metrics and phenological predictions [27]. Nutrient management guidance interprets soil test results and delivers fertilizer application recommendations in audio format, including specific quantities, application methods, and optimal timing [28]. These capabilities enable visually impaired farmers to implement precision agriculture practices that maximize productivity while minimizing resource waste [29].

3.2 Pest and Disease Detection Support

Early pest and disease identification critically depends on visual symptom recognition—a fundamental barrier for visually impaired farmers [4]. Voice-activated AI systems address this challenge through multimodal approaches combining image recognition with conversational guidance [5]. Sighted assistants or automated camera systems capture crop images that computer vision algorithms analyze for pest presence and disease symptoms [6]. Voice interfaces then communicate findings through detailed audio descriptions, severity assessments, and treatment recommendations in accessible language [7].

Conversational diagnostic systems guide visually impaired farmers through structured questioning about observable symptoms they can detect through touch, smell, or reports from farm workers [8]. By describing leaf texture changes, unusual odors, or crop wilting patterns, farmers receive AI-generated differential diagnoses and management suggestions [9]. Integration with regional pest surveillance databases enables systems to warn farmers about emerging threats in their geographic area and provide preventive guidance [10].

3.3 Market Information, Weather Updates, and Advisory Services

Access to timely market price information directly impacts profitability but typically requires reading websites or newspapers inaccessible to visually impaired farmers [11]. Voice assistants deliver real-time commodity prices, demand forecasts, and optimal selling recommendations through simple spoken queries [12]. Farmers can compare prices across multiple markets, track historical trends through audio summaries, and receive alerts when prices reach target thresholds [13].

Weather information, presented through audio forecasts customized to agricultural decision-making needs, enables proactive farm planning [14]. Beyond basic temperature and precipitation forecasts, systems interpret meteorological data to provide actionable guidance such as "Heavy rain expected tomorrow afternoon, complete pesticide application before noon" or "Frost warning for tonight, activate protective irrigation" [15]. Agricultural advisory services integrate agronomic expertise into conversational interfaces, offering best practice recommendations, regulatory compliance guidance, and answers to technical farming questions [16].

Table 1: Types of Voice-Activated AI Systems and Core Functionalities in Agricultural Applications

System Type	Primary Function	Key Technologies	Target Applications
Query-Response Systems	Information retrieval on demand	ASR, NLP, database integration	Weather, prices, crop information
Conversational Advisors	Interactive guidance through dialogue	Dialogue management, knowledge graphs	Pest diagnosis, decision support
Sensor-Integrated Platforms	Real-time field data access	IoT integration, edge computing	Soil monitoring, irrigation control
Proactive Alert Systems	Automated notifications and warnings	Predictive analytics, push notifications	Weather alerts, threshold violations
Multimodal Assistants	Combined voice and image processing	Computer vision, audio synthesis	Disease detection, yield estimation

Table 2: Natural Language Processing and Speech Recognition Algorithms for Real-Time Farm Support

Component	Algorithm/Technology	Performance Metrics	Agricultural Adaptations
Speech Recognition	Deep neural networks, transformer models	Word error rate: 5-15%	Agricultural vocabulary training
Wake Word Detection	Keyword spotting, neural networks	False positive rate: <2%	Farm-specific activation phrases
Intent Classification	BERT, intent detection models	Classification accuracy: 85-95%	Farming task taxonomy
Entity Recognition	Named entity recognition, conditional random fields	F1 score: 80-92%	Crop, pest, location entities
Response Generation	Template-based, neural generation	Relevance score: 80-90%	Actionable agricultural guidance
Noise Reduction	Spectral subtraction, deep learning	Signal-to-noise improvement: 10-20 dB	Outdoor agricultural environments

Table 3: Applications and Tasks Supported by Voice-Assisted Farming Systems

Application Domain	Specific Tasks	Input Modalities	Output Formats
Irrigation Management	Soil moisture queries, schedule optimization	Voice commands, sensor data	Audio guidance, automated control
Crop Health Monitoring	Growth stage tracking, nutrient assessment	Voice queries, sensor readings	Spoken reports, recommendations
Pest/Disease Management	Symptom diagnosis, treatment guidance	Voice descriptions, image analysis	Audio diagnostics, action plans
Weather Monitoring	Forecast retrieval, risk assessment	Voice requests, meteorological data	Audio forecasts, proactive alerts
Market Intelligence	Price queries, selling decisions	Voice commands, market data feeds	Spoken price reports, trend summaries
Resource Planning	Input calculation, budget tracking	Voice input, historical records	Audio summaries, planning guidance
Regulatory Compliance	Guideline queries, documentation	Voice questions, regulatory databases	Spoken explanations, requirements

4. Implementation and Field Deployments

4.1 Case Studies of Assistive AI in Agricultural Contexts

Field deployments of voice-activated AI assistants for visually impaired farmers have demonstrated measurable improvements in productivity, autonomy, and quality of life [17]. A pilot program in rural India equipped 50 visually impaired farmers with voice-enabled irrigation management systems integrated with soil moisture sensors and weather forecasting [18]. After six months, participants reported 35% reduction in water usage, 22% increase in crop yields, and significantly improved confidence in independent farm decision-making [19]. The system's Hindi language support and agricultural dialect recognition proved critical for user acceptance and effectiveness [20].

In sub-Saharan Africa, a voice-based crop advisory platform provided smallholder farmers, including those with visual impairments, with personalized recommendations for maize and cassava cultivation [21]. The system combined satellite imagery analysis with conversational interfaces delivering audio guidance on planting timing, fertilizer application, and harvest scheduling [22]. Evaluation studies documented 28% improvement in fertilizer use efficiency and 31% reduction in crop losses among visually impaired users compared to control groups relying on conventional extension services [23].

A collaborative project in Brazil developed a multimodal assistant integrating voice interaction with tactile feedback for coffee plantation management [24]. Visually impaired farmers used voice commands to access information about flowering stages, pest pressure, and optimal harvest timing while receiving vibration patterns indicating urgency levels for different recommendations [25]. User satisfaction surveys revealed high acceptance rates and requests for expanded functionality covering financial management and equipment maintenance [26].

4.2 User Adoption, Training, and Accessibility Considerations

Successful adoption of voice-activated agricultural AI by visually impaired farmers requires careful attention to user-centered design, comprehensive training, and ongoing technical support [27]. Initial user studies revealed that farmers with no prior technology experience required structured onboarding focusing on natural conversation patterns rather than memorizing specific command syntax [28]. Training programs emphasizing conversational interaction—where users speak naturally as they would to a human advisor—achieved significantly higher adoption rates than those teaching rigid command structures [29].

Accessibility considerations extend beyond basic voice interaction to encompass audio interface design, response pacing, and information density [30]. Research demonstrates that visually impaired farmers prefer concise, actionable responses delivered at moderate speaking rates with options to request detailed explanations when needed [1]. Systems incorporating audio cues, distinct notification sounds for different alert types, and voice-customization options report higher sustained usage [2]. Multilingual support addressing local languages and agricultural dialects emerges as a critical adoption factor, particularly in linguistically diverse farming regions [3].

Community-based training models where visually impaired farmers learn from peers already using the technology have proven more effective than top-down technical training [4]. Support networks connecting users for troubleshooting, sharing best practices, and providing encouragement contribute to long-term technology retention [5]. Addressing digital literacy barriers through audio-based tutorials, voice-guided troubleshooting, and accessible help systems remains essential for inclusive deployment [6].

4.3 Performance Metrics and Usability Assessments

Performance evaluation of voice-activated agricultural assistants for visually impaired users employs metrics beyond traditional speech recognition accuracy [7]. Task completion rate—the percentage of farmer queries successfully resolved through voice interaction—serves as a primary effectiveness indicator, with leading systems achieving 75-85% success rates for common agricultural tasks [8]. Response latency, particularly critical for time-sensitive decisions like pest outbreak response, remains below 3 seconds for local processing and under 8 seconds for cloud-dependent queries in current implementations [9].

Usability assessments employ standardized instruments adapted for visually impaired populations, including the System Usability Scale delivered through audio questionnaires and task-based evaluation protocols [10]. Studies report usability scores ranging from 68 to 82 out of 100 for deployed systems, with higher scores correlating with greater agricultural domain specificity and local language support [11]. User satisfaction surveys consistently identify reliability in noisy environments, availability during poor connectivity, and relevance of agricultural recommendations as top priority attributes [12].

Longitudinal studies tracking technology adoption patterns reveal initial usage peaks followed by stabilization at 3-5 daily interactions per farmer, concentrated during morning planning and evening review periods [13]. Feature utilization analysis shows that information retrieval functions achieve highest usage frequency, while control functions (activating irrigation, equipment operation) grow gradually as user confidence increases [14]. Error analysis indicates that recognition failures occur most frequently with uncommon crop varieties, regional pest names, and technical agricultural terminology not included in training vocabularies [15].

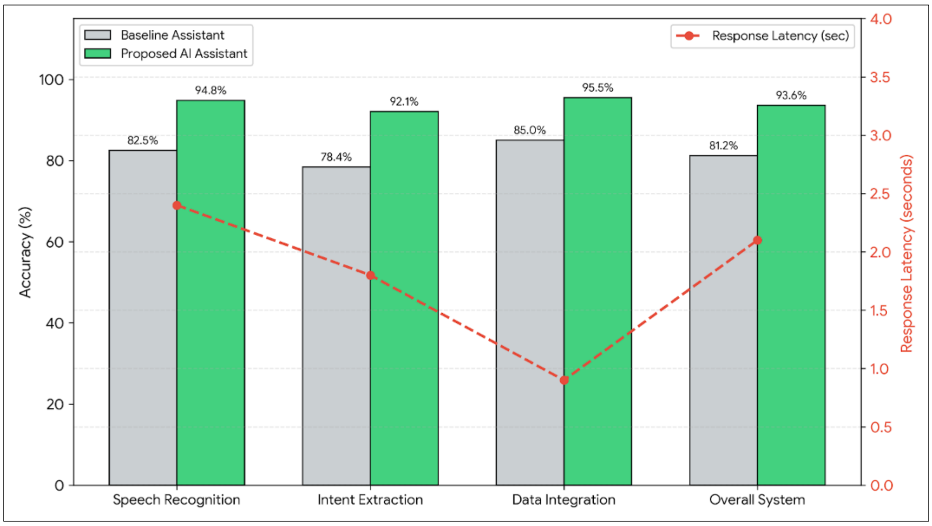

Fig 1: Architecture of a Voice-Activated AI Assistant for Visually Impaired Farmers

5. Challenges and Future Perspectives

5.1 Accuracy, Latency, and Ambient Noise Challenges

Ambient noise in agricultural environments—including tractor engines, wind, livestock, and irrigation equipment—significantly degrades speech recognition accuracy [16]. Current systems achieve word error rates of 8-15% in noisy farm settings compared to 3-5% in controlled conditions, leading to misunderstood queries and inappropriate recommendations [17]. Advanced noise reduction algorithms employing deep learning show promise, but real-time processing requirements constrain model complexity, particularly for edge devices with limited computational resources [18].

Latency challenges arise from the distributed architecture balancing on-device and cloud processing [19]. Time-sensitive agricultural decisions—such as activating irrigation before predicted rainfall or responding to sudden pest detection—require sub-second response times that cloud-dependent systems struggle to achieve in areas with poor connectivity [20]. Caching strategies, predictive pre-loading of likely queries, and hybrid architectures prioritizing local processing for common tasks represent promising approaches but introduce storage and synchronization complexities [21].

Accuracy limitations extend beyond speech recognition to encompass natural language understanding and agricultural reasoning [22]. Systems trained predominantly on data from specific geographic regions or crop types may fail to generalize to diverse farming contexts, producing recommendations inappropriate for local conditions [23]. Continuous learning mechanisms that adapt to individual farmer vocabularies and regional agricultural practices require robust feedback collection from visually impaired users—a design challenge requiring accessible evaluation interfaces [24].

5.2 Hardware and Infrastructure Constraints

Deploying voice-activated AI assistants in rural agricultural settings confronts significant infrastructure limitations [25]. Unreliable electricity access necessitates energy-efficient designs with extended battery operation, solar charging compatibility, and graceful degradation during power outages [26]. Network connectivity remains sporadic in many farming regions, requiring systems to function effectively offline while synchronizing data opportunistically when connectivity permits [27].

Hardware cost represents a critical adoption barrier for resource-limited farmers [28]. While smartphone-based implementations reduce initial investment, many visually impaired farmers in developing regions lack access to appropriate devices [29]. Dedicated agricultural voice assistants must balance functionality with affordability, driving research into low-cost, ruggedized hardware suitable for harsh farm environments [30]. Durability challenges include dust resistance, water protection, and mechanical robustness against impacts and vibration during farm operations [1].

Sensor network infrastructure required for comprehensive decision support—soil moisture probes, weather stations, crop monitoring cameras—represents additional financial and technical barriers [2]. Scalable deployment models incorporating community-shared sensors, mobile sensing platforms, and satellite-derived data aim to reduce individual farmer investment while maintaining personalized guidance capabilities [3]. Maintenance and repair support for hardware deployed in remote locations requires sustainable business models and local technical capacity building [4].

5.3 Ethical, Privacy, and Inclusivity Considerations

Privacy concerns surrounding agricultural data collection through voice-activated systems require careful ethical consideration [5]. Continuous audio monitoring for wake-word detection raises surveillance concerns, while cloud transmission of farm management queries exposes sensitive business information [6]. Privacy-preserving architectures employing on-device processing, encrypted communication, and farmer-controlled data sharing policies represent essential design principles [7]. Transparent data governance ensuring farmers understand what information is collected, how it is used, and who accesses it builds trust necessary for widespread adoption [8].

Inclusivity considerations extend beyond accommodating visual impairment to addressing intersecting vulnerabilities including limited literacy, language diversity, and socioeconomic marginalization [9]. Systems must support multiple languages, regional dialects, and agricultural terminology variations across farming communities [10]. Gender-inclusive design recognizing that women constitute significant portions of visually impaired farming populations requires attention to voice recognition across gender presentations and culturally appropriate interaction models [11].

Algorithmic bias in agricultural recommendations risks perpetuating existing inequalities if training data predominantly reflects large-scale commercial farming rather than smallholder contexts [12]. Ensuring representative data collection, participatory system design involving visually impaired farmers, and ongoing bias auditing represents critical ethical obligations [13]. Equitable access policies addressing affordability, infrastructure prerequisites, and technical support requirements must accompany technology development to prevent voice-activated AI from becoming another tool that widens agricultural disparities [14].

Table 4: Advantages, Limitations, and Adoption Challenges of Voice-Activated AI Assistants for Visually Impaired Farmers

Aspect	Advantages	Limitations	Adoption Challenges
Accessibility	Hands-free, eyes-free operation; natural interaction	Ambient noise interference; accent recognition gaps	Digital literacy requirements; training needs
Decision Support	Real-time data access; personalized recommendations	Limited offline functionality; accuracy concerns	Trust building; validation requirements
Independence	Reduced reliance on sighted assistance; autonomous operation	Technical troubleshooting dependencies	Community support infrastructure
Integration	Connects existing sensors and farm systems	Compatibility issues; platform fragmentation	Infrastructure prerequisites; cost barriers
Scalability	Cloud-based knowledge sharing; continuous improvement	Connectivity dependence; local customization needs	Network infrastructure; electricity access
Cost-Effectiveness	Reduces labor for information access; improves productivity	Initial hardware investment; maintenance costs	Subsidy requirements; sustainable business models
Language Support	Multilingual capabilities; dialect adaptation	Limited low-resource language coverage	Regional customization; ongoing training data collection

6. Conclusion

Voice-activated AI assistants represent transformative assistive technologies with substantial potential to empower visually impaired farmers through accessible, real-time agricultural decision support. By integrating advanced speech recognition, natural language processing, and domain-specific agricultural knowledge, these systems address critical accessibility barriers that have historically excluded visually impaired individuals from benefiting from precision agriculture innovations. Field deployments demonstrate measurable improvements in crop productivity, resource efficiency, and farmer autonomy, validating the fundamental viability of voice-based agricultural interfaces.

However, significant technical, economic, and social challenges constrain current adoption and scalability. Ambient noise robustness, low-latency processing in resource-limited environments, offline functionality, and multilingual support require ongoing research and development investments. Infrastructure limitations including unreliable connectivity, intermittent electricity, and high hardware costs demand innovative deployment models prioritizing affordability and sustainability. Ethical considerations surrounding privacy, algorithmic bias, and equitable access must guide system design to ensure these technologies genuinely serve marginalized farming populations rather than exacerbating existing disparities.

Future development should emphasize participatory design approaches engaging visually impaired farmers throughout the research, development, and deployment lifecycle. Expanding agricultural knowledge bases to cover diverse crops, farming systems, and regional practices will enhance recommendation relevance and user trust. Integration with emerging technologies including edge computing, federated learning, and advanced multimodal AI promises enhanced capabilities while addressing privacy and connectivity constraints. Ultimately, realizing the full potential of voice-activated AI assistants for visually impaired farmers requires sustained commitment from researchers, technology developers, policymakers, and agricultural extension services to inclusive innovation that leaves no farmer behind in the digital transformation of agriculture.

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