Farm and Learn: An Offline Mobile Learning System Integrating AR, AI, and Game-Based Learning for Agricultural Education Among Children

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Abstract—**This study presents Farm and Learn, an offline-first mobile learning system that integrates Augmented Reality (AR), Artificial Intelligence (AI), and Game-Based Learning (GBL) to enhance agricultural education among children in low-connectivity environments. Existing agricultural learning applications often provide isolated functionalities such as visualization or plant recognition, with limited pedagogical integration and insufficient support for rural deployment. To address these limitations, the proposed system combines immersive AR-based exploration, interactive gamified learning activities, and AI-assisted paddy plant growth-stage identification within a unified child-centered educational framework. The architecture adopts a modular offline-first design that enables core learning functionalities to operate without continuous internet access while allowing optional synchronization when connectivity is available. The AI component employs a lightweight YOLOv11n deep learning model validated through prototype inference to assess feasibility for future on-device deployment. The system was developed using Unity and ARCore and evaluated through user acceptance testing involving students, educators, and domain experts. Results demonstrate high usability, strong learner engagement, and improved learning performance, confirming the effectiveness of integrating immersive visualization, intelligent interaction, and gamified reinforcement in educational contexts. The findings highlight the practical potential of offline-first mobile learning platforms to support inclusive agricultural education and provide a scalable foundation for future intelligent educational systems in resource-constrained environments.**

Keywords—Agricultural education; augmented reality; artificial intelligence; child-centered learning; game-based learning; offline mobile learning

I. Introduction

A. Background Information

Agriculture remains a fundamental sector of Sri Lanka's economy and food security [1], yet agricultural education at the primary level continues to face significant challenges in adopting interactive and technology-enhanced learning approaches [2]. Traditional pedagogical practices based on static textbooks and teacher-centered instruction often provide limited opportunities for experiential learning, resulting in reduced engagement among young learners and inadequate exposure to foundational agricultural concepts [3]. This issue is particularly critical in the context of paddy cultivation, a key element of Sri Lanka's rural economy and sustainable food production [4].

Sri Lanka's educational landscape continues to face significant challenges due to a persistent digital divide, even though national internet usage has surpassed 56%. A considerable portion of the population, about 43.7%, remains offline, particularly in rural communities where limited infrastructure and higher poverty levels of around 24.8% restrict access to digital technologies. As a result, many rural schools still depend heavily on traditional teaching approaches with limited exposure to modern digital learning resources. Although mobile technology has become the primary means of connectivity in these regions, access remains uneven and unreliable. Community initiatives such as "Nenasala" telecenters have attempted to bridge this gap by providing shared internet access, but their availability and consistency vary across locations. This situation highlights the importance of designing educational solutions that can operate effectively without requiring continuous internet connectivity [5].

This gap became evident through evaluations of existing school syllabi, classroom observations, and discussions with educators and parents. These stakeholders consistently highlighted the need for modernized, engaging, and visually rich learning materials. Despite the integration of digital resources into general science and geography education, there is a notable absence of purpose-built tools that leverage emerging technologies such as Augmented Reality (AR), Artificial Intelligence (AI), and Game-Based Learning (GBL) for agriculture- focused education at the primary level [6], [7].

Existing digital solutions provide only partial support. For instance, applications such as "FarmAR" offer AR-based visualization of farming equipment but lack structured educational frameworks and curriculum alignment [8]. Conversely, tools such as "Plantix" focus primarily on AI-based plant diagnosis designed for farmers rather than young learners [9]. These applications generally do not provide child-centered learning designs or offline functionality, both of which are essential for deployment in rural and low-connectivity contexts [10].

To address these limitations, this study introduces "Farm and Learn," an offline-first mobile educational system developed using Unity 6, Google ARCore, and Blender 4.3 [11], [12]. The proposed system delivers an immersive learning experience for children aged 10 years and above by integrating modular components, including AR-based exploration of 3D farming equipment, GBL-driven quizzes and interactive activities, and an AI-based plant identification prototype utilizing a YOLOv11n convolutional neural network trained on a custom dataset [13]. Content development was guided by agricultural experts from the Rice Research Station, Labuduwa, while technological implementation was refined in collaboration with academic staff and students from the Department of Software Engineering, University of Kelaniya.

B. Research Problem and Research Questions

Despite the economic and social importance of agriculture in Sri Lanka, primary-level agricultural education continues to face significant limitations related to learner engagement, technological integration, and accessibility. Existing curriculum largely relies on passive, textbook-oriented instruction, which does not adequately support interactive or experiential learning for digitally native students [2]. This pedagogical gap contributes to reduced interest among younger generations in agriculture, particularly paddy cultivation, which remains a critical component of national food security and rural economic sustainability [3].

At the same time, currently available mobile applications in the agricultural domain do not provide comprehensive educational experiences specifically designed for children. While some applications offer isolated capabilities, such as AI-based plant disease detection (e.g., “Plantix”) or AR-based visualization of agricultural objects (e.g., “FarmAR”), these systems typically lack curriculum-oriented learning structures, pedagogical scaffolding, and offline functionality suitable for rural educational deployment. More importantly, existing solutions rarely integrate AR, AI, and Game-Based Learning (GBL) within a unified framework to deliver immersive and holistic learning experiences tailored for young learners [14].

Unlike existing agricultural learning applications that focus on isolated functionalities such as AR visualization or AI-based plant recognition, including systems such as FarmAR [8] and Plantix [9], this work introduces a unified offline-first educational framework that integrates Augmented Reality (AR), lightweight AI-based plant identification, and Game-Based Learning (GBL) within a child-centered learning environment. The proposed system demonstrates how immersive technologies can be combined into modular educational architecture specifically designed for rural and low-connectivity contexts [17], [19], [20]. By integrating AR exploration, AI-driven interaction, and gamified learning within a single platform, this study extends prior work beyond single-purpose agricultural applications toward an integrated and pedagogically aligned learning solution for primary-level agricultural education [23], [25].

Given these limitations, a clear research gap emerges regarding the design and implementation of child-centered, offline-first educational systems that integrate immersive technologies for agricultural learning. Therefore, this study is guided by the following Research Questions (RQs):

- RQ1: Can immersive technologies such as AR, AI, and GBL improve learner engagement and educational outcomes in primary-level agricultural education?
- RQ2: Is it technically feasible to develop a fully offline-first and child-friendly mobile learning system suitable for rural and low-connectivity educational contexts?
- RQ3: Can AI-based visual recognition of paddy plant growth stages be effectively integrated into an interactive educational environment?

To address these questions, this research proposes the development of “Farm and Learn,” an offline-first, context-aware mobile application that combines immersive technologies with pedagogically grounded content. The proposed system aims to increase children’s engagement with agricultural concepts while providing an accessible, scalable, and technologically feasible solution for enhancing agricultural literacy in resource-constrained environments.

C. Significance of the Research

This research addresses a critical gap in primary-level agricultural education by introducing an immersive, technology-enhanced learning solution tailored for children. Despite the centrality of agriculture to Sri Lanka’s economy, the subject receives limited emphasis in early education, with learning resources often restricted to outdated textbooks and static illustrations. This disconnect between traditional teaching methods and the expectations of today’s digitally fluent learners highlights the need for a paradigm shift in educational delivery.

The significance of this project lies in its integration of Augmented Reality (AR), Artificial Intelligence (AI), and Game-Based Learning (GBL) into a unified, modular mobile application [15], [16]. The application not only provides structured agricultural knowledge but also engages learners through interactive visualizations, intelligent plant recognition, and gamified content. Developed using Unity and ARCore, with an AI model trained via Roboflow and implemented in JupyterLab using YOLOv11n, the system demonstrates the viability of deploying advanced educational technology in low-connectivity, rural environments through an offline-first architectural approach.

Beyond its educational objectives, this research contributes to national efforts in promoting food security, rural development, and digital transformation in education. By fostering early interest in sustainable farming and providing access to localized, child-friendly content, the project offers a scalable framework for integrating immersive technologies into primary education, particularly in rural regions.

II. Literature Review

A. Overview of Relevant Literature

Recent advancements in educational technology have increasingly emphasized the integration of immersive tools such as AR, AI, and GBL to enhance student engagement, motivation, and knowledge retention. Studies by Farooq et al. [17] and Kshirsagar et al. [18] demonstrated AR’s effectiveness in simplifying abstract topics and improving test scores among young learners. Similarly, Zulfiqar et al. [19] provided a broad overview of AR’s pedagogical benefits, including enhanced visualization and collaboration.

Game-Based Learning has also emerged as a strong motivational tool. Mohammed and Ozdamli [20] highlighted the effectiveness of badges, leaderboards, and feedback mechanisms in increasing student participation. Additional case studies by Gasca-Hurtado et al. [21] and Triantafyllou and Sapounidis [22] confirmed GBL's psychological and cognitive benefits in structured learning environments.

Artificial Intelligence is increasingly utilized in agriculture, primarily for disease detection and decision support. Studies such as Cheng et al. [23], Paulson and Ravishankar [24], and Paramathma et al. [25] illustrated CNNs' capabilities in image classification and precision agriculture applications. However, these solutions are designed primarily for professional or academic audiences.

Despite these advancements, few systems combine AR, AI, and GBL into a cohesive, offline-first educational solution targeted specifically at children in agriculture-heavy regions. Most tools reviewed are either single-purpose or targeted toward general academic subjects, highlighting a significant gap in subject-specific and age-appropriate technological solutions for agriculture education.

B. Key Theories or Concepts

The development of the "Farm and Learn" application is grounded in a blend of pedagogical and technical frameworks, primarily Constructivist Learning Theory, GBL, and Convolutional Neural Networks (CNNs) in AI.

Constructivist Learning Theory emphasizes experiential learning, wherein learners construct knowledge through direct engagement and contextual exploration. AR supports this theory by offering immersive, spatially- aware interactions. Studies reviewed, including Farooq et al. [17] and Kshirsagar et al. [18] highlighted AR's ability to enhance concept retention, especially when learners manipulate 3D objects within real-world settings.

GBL principles were another prominent framework across the literature. The works of Mohammed and Ozdamli [19] and Triantafyllou and Sapounidis [22] emphasized that interactive elements like feedback, quizzes, and progression tracking enhance student motivation and knowledge retention. In the context of "Farm and Learn," while reward systems like badges are not implemented, GBL is embedded through quiz-based learning and seed sorting mini-games to stimulate engagement and cognitive processing.

On the technical front, CNNs form the backbone of AI-driven plant identification. Literature by Cheng et al. [23] and Paulson and Ravishankar [24] demonstrated the efficacy of CNN-based architectures like VGG16, VGG19, and YOLO in plant classification and real-time inference tasks. The "Farm and Learn" project employs YOLOv11n for lightweight yet accurate plant recognition, trained via transfer learning on a custom dataset using Roboflow and developed in JupyterLab. These theories and frameworks collectively inform the design of the application, ensuring it is educationally grounded, technologically robust, and responsive to the learning needs of children aged 10 and above.

C. Gaps or Controversies in the Literature

Despite growing interest in educational technologies, significant gaps remain in the integrated use of AR, AI, and GBL within agriculture-focused learning particularly for younger audiences in low-resource environments.

Existing AR applications reported in the literature largely concentrate on general subject areas such as early literacy, mathematics, or abstract science concepts, with limited emphasis on agriculture-related knowledge, contextualized local practices, or culturally grounded learning environments [19], [20].

Similarly, while GBL has demonstrated clear benefits in learner motivation and retention, its adoption in agriculture education remains minimal. The reviewed GBL studies predominantly targeted domains like mathematics, accessibility awareness, or computer science, lacking examples tailored to primary-level agricultural education [21], [22]. Many GBL models are also heavily dependent on internet connectivity, real-time multiplayer modes, or reward systems that are less feasible in offline, rural settings.

In the realm of AI, recent literature highlights robust advancements in plant disease detection and smart agriculture using CNNs [23]. However, these systems are typically designed for adult farmers or researchers, with little consideration for integration into educational tools for children [24]. None of the surveyed AI systems offers curriculum-aligned, child-friendly interactions or simplified interfaces suitable for school use.

Moreover, existing educational systems tend to overlook the intersectionality of immersive technologies. Few solutions offer an integrated experience that combines AR exploration, AI-driven interaction, and gamified assessment in a unified learning flow. This fragmented technological landscape presents a missed opportunity to address cognitive and contextual learning needs in agricultural education for children.

The "Farm and Learn" application aims to fill these gaps by offering a unified, offline-first platform tailored for children aged 10 and above. It integrates immersive 3D exploration, real-time AI identification, and interactive games into a localized, age-appropriate framework, thereby addressing both the technological fragmentation and the pedagogical misalignment prevalent in existing literature.

III. Methodology

A. Research Design

The development of the "Farm and Learn" mobile application followed an Agile, user-centered research design to support the multidisciplinary integration of Augmented Reality (AR), Artificial Intelligence (AI), and Game-Based Learning (GBL) within a unified educational platform [26], [27]. The Agile methodology was selected to enable iterative refinement, rapid prototyping, and continuous stakeholder feedback throughout development. Short development cycles allowed progressive implementation and validation of functional modules while ensuring alignment with pedagogical objectives and technical feasibility.

The system was designed as a modular learning framework targeting children aged 10 years and above. Six core components were developed: (1) Learning Module, (2) Augmented Reality Module, (3) AI-Powered Paddy Plant Identification Module, (4) Game-Based Learning Module, (5) User Interface and Navigation Module, and (6) Offline-First Architecture. Each component was independently implemented while maintaining interoperability within the overall application.

B. System Architecture

The overall system architecture of the "Farm and Learn" application adopts a modular offline-first design to ensure reliable operation in low-connectivity educational environments. As illustrated in Fig. 1, the architecture consists of three conceptual layers: the presentation layer, application layer, and storage layer, supported by a future-ready synchronization mechanism.

The presentation layer manages user interaction through a child-centered interface and navigation controller, enabling seamless access to learning functions. The application layer integrates the core learning modules, including instructional content delivery, AR-based visualization, AI-driven plant identification, and game-based activities. Communication between these modules is coordinated through a centralized content delivery mechanism, which dynamically loads resources while maintaining runtime efficiency.

At the foundation of the system, a local storage module contains all instructional assets, multimedia resources, scripts, and assessment logic packaged within the APK during the Unity build process. This design eliminates reliance on cloud services or real-time APIs, ensuring uninterrupted system functionality in rural environments. In addition, a conceptual synchronization layer is included as a future extension to support content updates and learning analytics synchronization when internet connectivity becomes available, without affecting core offline functionality

1) Design rationale: The architectural design was guided by three key considerations: limited rural connectivity, hardware resource constraints of mobile devices, and the requirement to maintain immersive learner engagement. The offline-first strategy ensures accessibility regardless of network availability, while modular separation improves system maintainability and scalability. The centralized content delivery mechanism reduces dependencies among modules and enables independent expansion of system components. Consequently, the architecture balances educational usability, technical performance, and long-term extensibility.

2) Data flow overview: System execution begins at the presentation layer when users interact with learning modules through the application interface. The content delivery mechanism retrieves required assets from the local storage module and executes them directly on the device. User interactions, including scoring and feedback generation, are processed locally to ensure stable performance without internet dependency. When connectivity becomes available, the optional synchronization layer may support future content updates or analytics transfer without affecting core offline functionality.

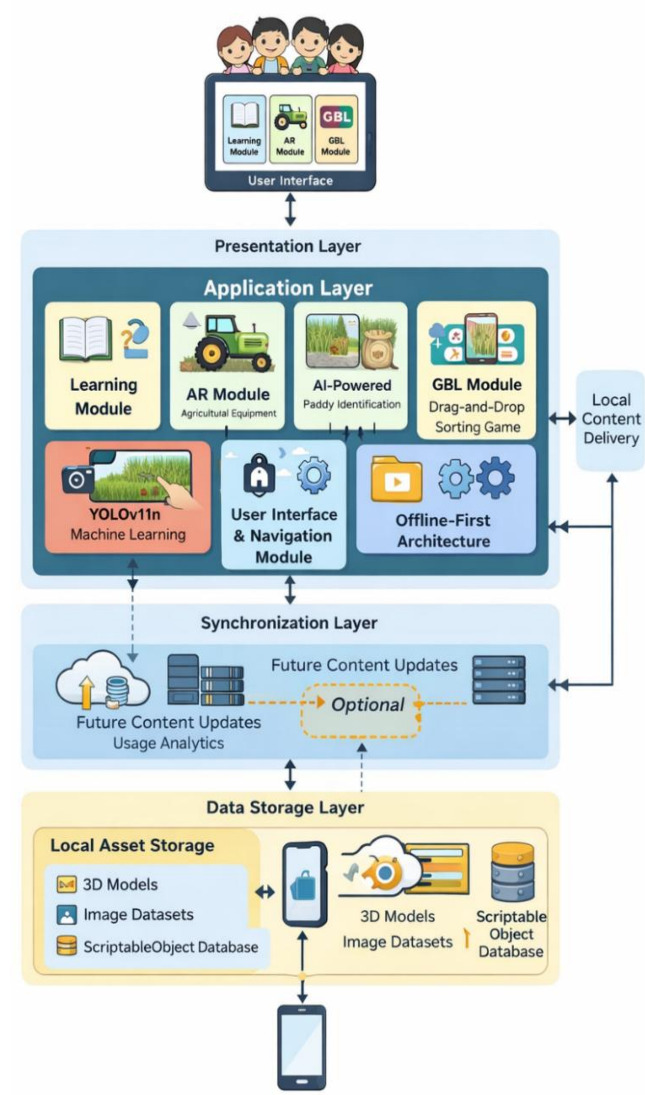

Fig. 1. Overall system architecture of the "farm and learn" application.

3) Architectural contribution: The proposed architecture contributes a lightweight, modular framework for delivering immersive educational experiences in connectivity-constrained environments. Unlike conventional mobile learning systems that rely on continuous cloud connectivity, the proposed design integrates AR visualization, AI-based recognition, and game-based interaction within an offline-first execution model. The separation between presentation, application, and storage layers enables scalable extension of modules while preserving system stability. Furthermore, the inclusion of a conceptual synchronization layer provides architectural flexibility for future cloud-enabled analytics and content updates without restructuring core system components. This architectural approach demonstrates a practical balance between immersive functionality, computational efficiency, and deployment feasibility for rural educational contexts.

C. Module Implementation

1) Learning module: The Learning Module delivers structured instructional content covering the paddy cultivation lifecycle, including land preparation, seed selection, irrigation, pest control, harvesting, and post-harvest practices. The module consists of three pedagogically aligned sub-components: Reading Materials, Interactive Tasks, and Interactive Tests.

a) Reading materials: Implemented using Unity UI Toolkit with scrollable layouts and hierarchical topic navigation, the reading materials incorporate illustrated infographics to reduce cognitive load and improve comprehension among young learners. All assets are optimized for mobile devices and designed for offline use.

b) Interactive tasks: The Interactive Tasks introduce gamified learning activities, such as seed classification using drag-and-drop mechanics. These tasks were developed using Unity's 2D physics engine and event-driven C# scripting to provide immediate visual feedback and reinforce concept application through experiential interaction.

c) Interactive tests: Interactive Tests evaluate learner understanding through multiple-choice quizzes executed entirely on-device. Questions are managed using ScriptableObject-based data structures, enabling scalable expansion without modifying source code. The quiz interface incorporates touch-friendly controls and immediate feedback to support formative learning.

2) Augmented Reality (AR) module: The Augmented Reality (AR) Module was designed to provide immersive and experiential learning by enabling children to interactively explore three-dimensional representations of agricultural equipment such as tractors, ploughs, sickles, and harvesting tools within real-world environments. The module was developed using Unity and Google ARCore, which facilitates markerless plane detection, feature-point mapping, and real-time spatial tracking to accurately position virtual objects on detected surfaces. The AR interaction workflow begins with environment sensing and surface detection, followed by object instantiation and pose alignment to maintain spatial consistency between virtual and physical spaces. Rendering enhancements such as scale normalization, lighting adaptation, and shadow projection are applied to improve visual realism and learner immersion. The overall AR placement and interaction process is illustrated in Fig. 2, which demonstrates the technical flow from surface detection to virtual object placement. Three-dimensional equipment models were primarily developed using Blender and optimized through polygon reduction and texture compression to ensure smooth rendering performance on mid-range Android devices. Once placed, learners can explore virtual farming tools from multiple viewing angles, promoting spatial understanding and exploratory learning behavior. Examples of AR-based farming tool visualization within real-world environments are presented in Fig. 3. In addition, voice narration provides child-friendly explanations to support multimodal learning and improve conceptual comprehension. Although AR functionality requires ARCore-supported hardware, the system preserves educational accessibility by allowing uninterrupted use of the learning and game-based modules when AR support is unavailable.

Fig. 2. ARCore-based surface detection and virtual object placement workflow in the proposed system.

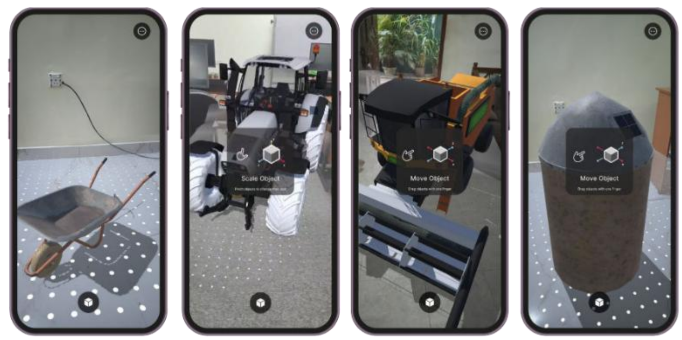

Fig. 3. Examples of AR-based farming tool visualization within the proposed learning system.

3) AI-Powered paddy plant identification module: The AI-powered paddy plant identification module supports recognition of paddy growth stages through deep learning–based image analysis. To validate model feasibility and inference performance while ensuring compatibility with the offline-first system design, the AI component was implemented as a prototype inference layer designed for seamless transition toward fully embedded on-device execution within the mobile application. This staged deployment strategy enables early evaluation of model accuracy while maintaining architectural consistency with the proposed offline learning framework. The module employs a YOLOv11n convolutional neural network optimized for lightweight inference [25]. Training data were collected from the Rice Research Station, Labuduwa, and supplemented with publicly available datasets to improve robustness and generalization. Data annotation and preprocessing were performed using the Roboflow platform, while model training was carried out in JupyterLab using Python with transfer learning from pretrained COCO weights [29], [30]. Hyperparameter tuning was applied to balance detection accuracy and computational efficiency, ensuring readiness for mobile deployment. The system generates annotated predictions indicating paddy detection results and demonstrates the practical feasibility of integrating AI-based plant recognition into child-centered educational learning environments. The trained model is deployment-ready and can be packaged using lightweight mobile inference frameworks to enable fully offline execution within the application without requiring architectural modifications.

4) Game-Based Learning (GBL) module: The GBL Module reinforces learning outcomes through structured gamification strategies designed to increase engagement and motivation among learners. The module includes interactive mini-games and quiz-based assessments that promote concept application and formative evaluation. Activities such as seed-sorting tasks employ drag-and-drop interactions, real-time feedback, and scoring mechanisms to encourage repeated practice and experiential learning. Quiz components provide immediate correctness feedback and summary performance results, supporting knowledge retention while maintaining full offline functionality.

5) User interface and navigation module: The User Interface and Navigation Module coordinates interaction flow across all system components while ensuring accessibility for child users. The interface design emphasizes large touch-responsive elements, simplified iconography, and minimal text usage to reduce cognitive complexity. Navigation is structured around a centralized home interface supported by consistent scene transitions managed through script-based control mechanisms. This design ensures intuitive navigation, session continuity, and seamless movement between learning modules.

6) Offline-first architecture: The Offline-First Architecture was adopted to ensure full system functionality in rural and low-connectivity educational environments. All application assets, including 3D models, images, quiz logic, user interface scripts, audio instructions, and animation resources, are pre-packaged within the APK during the Unity build process, eliminating reliance on cloud services, real-time APIs, or continuous internet access. This design guarantees the uninterrupted availability of learning content, AR-based equipment visualization, and game-based learning activities regardless of connectivity conditions. From a technical perspective, local asset packaging improves performance efficiency and reduces runtime memory requirements, allowing stable execution on Android devices with limited hardware resources. ARCore-specific components, such as plane detection logic and tracking assets, are similarly embedded to maintain spatial interactivity while operating fully offline. Furthermore, the architecture enhances privacy and security by avoiding external data transmission and user account requirements, aligning with child data protection principles such as COPPA [31]. Overall, the offline-first deployment strategy improves accessibility, reliability, and scalability, making the system suitable for deployment across diverse rural educational contexts.

D. Data Collection Methods

A mixed-methods approach combining both qualitative and quantitative data collection was employed to guide the pedagogical design, content development, and technical implementation [32] of the “Farm and Learn” mobile application.

1) Primary data collection: Primary data were collected through field observations, expert consultations, focus-group sessions, and structured questionnaires [7]. Field visits to the Rice Research Station, Labuduwa, enabled the collection of agricultural imagery and contextual farming knowledge used for content design and AI dataset preparation. Structured interviews were conducted to validate the agricultural accuracy, pedagogical relevance, and technical feasibility of the system. Focus-group sessions and pilot testing activities were used to evaluate usability, engagement, and learner interaction with the application. Additionally, questionnaires were administered to capture user perceptions, learning preferences, and accessibility considerations.

2) Secondary data collection: Secondary data were obtained through an extensive review of peer-reviewed literature and academic conference publications related to AR, GBL, and AI in education. Insights from prior research informed the design of system features, pedagogical scaffolding approaches, and evaluation strategies. Additional reference material was sourced from authoritative agricultural databases and publications issued by the Department of Agriculture and other academic institutions to ensure factual accuracy, contextual relevance, and cultural appropriateness of the learning content on paddy cultivation.

E. Sample Selection

Participants were selected using a purposive sampling strategy to ensure representation of the key stakeholder groups relevant to the development and evaluation of the “Farm and Learn” application. The sample consisted of 47 children (students) aged 10–13 years, representing the primary end users of the system, together with 10 educators who evaluated pedagogical alignment and curriculum suitability, and 5 domain experts, including agricultural specialists and technical professionals who validated the accuracy of agricultural content and the technical feasibility of the solution. This multi-stakeholder sampling approach enabled balanced evaluation from learner, educational, and domain-expert perspectives, consistent with pilot studies in educational technology research [7].

F. Data Analysis Techniques

1) Qualitative analysis: A thematic analysis approach was applied to derive insights from user and expert-driven feedback. Focus-group discussions and expert interviews were coded to identify recurring usability patterns, interaction behaviors, and learner engagement characteristics. Survey responses were examined to determine preferred interaction modes and interface expectations among child users. Observational data collected during prototype testing were further used to refine module sequencing, navigation flow, and UI layout based on authentic user interaction with the system.

2) Quantitative evaluation of the AI model: To assess the feasibility and performance of the AI-based paddy-plant identification module, the YOLOv11n-based Convolutional

Neural Network (CNN) was trained and evaluated using annotated image datasets [28]. Model performance was measured using standard machine-learning metrics, including precision–recall curves, confusion matrices, and F1-score calculations [33]. Training and validation metrics were generated in JupyterLab across 100 training epochs using datasets annotated via the Roboflow platform, enabling systematic assessment of detection accuracy and generalization capability.

IV. Results

A. Experimental Evaluation Overview

The performance of the proposed "Farm and Learn" system was evaluated using user acceptance testing (UAT), expert validation, and technical benchmarking [34]. The evaluation involved 47 students, 10 educators, and 5 domain experts, focusing on usability, educational effectiveness, system performance, and AI model feasibility. Quantitative measurements were supplemented with qualitative feedback gathered during pilot deployment sessions.

B. User Acceptance and Educational Evaluation

Table I summarizes the average UAT ratings collected from students, educators, and experts using a five-point Likert scale. The results indicate consistently high acceptance across all stakeholder groups, with average scores exceeding 4.5 for all criteria. Offline accessibility achieved the highest rating (4.90), reflecting the effectiveness of the offline-first architecture in supporting rural deployment conditions. Visual engagement and educational relevance obtained strong scores (4.73), demonstrating the positive impact of immersive and contextually aligned learning content. The lowest relative score was observed for AR interactivity (4.50), suggesting opportunities for future improvements in interaction dynamics and device compatibility. Overall, the consistency of ratings across participants indicates strong agreement regarding usability and educational value.

TABLE I. UAT Evaluation Results (Average Score out of 5)

Evaluation criteria	*Students*	*Educators*	*Experts*	*Average Score*
Ease of Use	4.7	4.8	4.6	4.70
Visual Engagement	4.8	4.7	4.7	4.73
Educational Relevance	4.5	4.9	4.8	4.73
AR Interactivity	4.6	4.4	4.5	4.50
Game-Based Learning Appeal	4.7	4.6	4.4	4.57
Offline Accessibility	4.9	4.7	4.7	4.73
Overall Satisfaction	4.8	4.7	4.7	4.73

C. Learning Engagement and Performance

Observational findings indicated strong learner engagement during AR exploration and game-based activities. Average interaction time increased significantly compared to traditional content-based learning sessions, suggesting that immersive and interactive elements improved sustained attention.

Quiz-based assessments demonstrated progressive learning improvement, with average accuracy increasing from approximately 72% during initial attempts to 88% during repeated interactions. This improvement indicates that immediate feedback and gamified reinforcement contributed positively to knowledge retention.

D. AI Module Performance

The performance of the AI-powered paddy plant identification module was evaluated using standard classification metrics derived from the YOLOv11n model outputs. Table II presents the confusion matrix analysis summarizing the model's prediction results. The model correctly identified 13 Rice Plant instances, while 3 background samples were misclassified as rice plants, indicating strong detection capability with a small number of false positives.

TABLE II. Confusion Matrix Analysis of the AI Module

Predicted class	*True Rice Plant*	*True background*	*Total*
Rice Plant	13	3	16
Background	0	0	0
Total actual	13	3	16

The evaluation dataset contained only positive detections and background samples observed within the same image contexts; therefore, no independent background-only predictions were generated by the model during inference.

Fig. 4 shows stable performance across confidence thresholds, with a peak F1-score of 0.99 at a confidence value of 0.473, indicating a strong balance between precision and recall. Overall model accuracy achieved approximately 81.25%, confirming the feasibility of integrating lightweight AI-based visual recognition into an educational mobile learning environment.

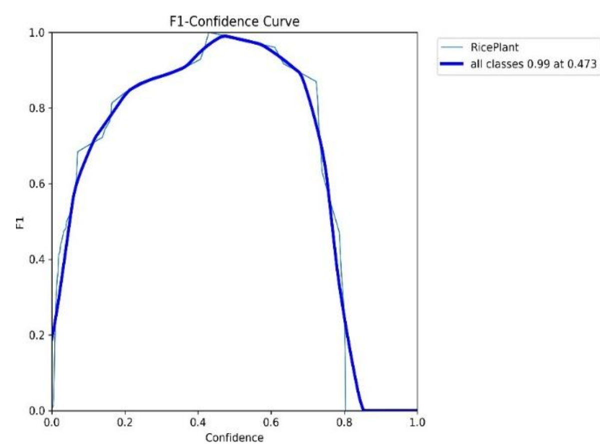

Fig. 4. F1-Confidence curve showing AI model performance for paddy plant identification.

E. System Performance Metrics

To assess technical feasibility, additional system-level performance measurements were collected on mid-range Android devices. Table III summarizes key quantitative metrics related to responsiveness, resource usage, and offline stability.

TABLE III. SYSTEM PERFORMANCE METRICS

Metric	*Observed value*	*Interpretation*
Application package size	~92 MB	Suitable for mid-range devices
Average startup latency	3.2 s	Smooth user experience
AR module loading time	8.1 s	Stable real-time interaction
Battery consumption (30 min session)	6-10%	Efficient mobile operation
Offline synchronization accuracy	100%	No connectivity dependency

The results confirm that the system operates efficiently under offline conditions while maintaining acceptable performance and energy consumption levels.

F. Comparison with Existing Systems

A comparison was conducted between the proposed *Farm and Learn* application and existing agricultural learning systems such as Plantix and FarmAR [8], [9]. As shown in Table IV, while Plantix primarily focuses on AI-based plant recognition and FarmAR emphasizes AR visualization, neither system provides a unified child-centered learning environment with offline educational functionality.

TABLE IV. COMPARISON WITH EXISTING SYSTEMS

Feature	*Plantix*	*FarmAR*	*Farm and Learn*
AR Visualization	No	Yes	Yes
AI-Based Recognition	Yes	No	Yes
Game-Based Learning	No	No	Yes
Child-Oriented Design	No	No	Yes
Offline Capability	No	Partial	Yes

The comparison demonstrates that the proposed system integrates AR, AI, and game-based learning within a single offline-first platform, making it more suitable for primary-level agricultural education in rural contexts.

G. Support for Research Questions

1) RQ1: Supported: The results strongly support this research question. High user acceptance scores across all stakeholder groups (Table I), increased learner interaction time, and improved quiz performance (72% to 88%) demonstrate that immersive and interactive technologies positively influenced learner engagement and knowledge retention.

2) RQ2: Supported: The findings confirm feasibility. Offline accessibility achieved one of the highest evaluation scores (4.73), and system testing demonstrated stable performance without internet dependency, validating the effectiveness of the offline-first architecture for rural educational deployment.

3) RQ3: Supported: The AI module achieved a peak F1-score of 0.99 with an overall accuracy of approximately 81.25%, as illustrated in Table II and Fig. 4. These results confirm that lightweight AI-based plant identification can be successfully integrated into educational mobile systems while maintaining practical performance levels.

Overall, the results affirm the feasibility and pedagogical value of the "Farm and Learn" platform as a scalable, immersive, and inclusive digital tool for enhancing primary-level agricultural education in Sri Lanka, particularly in the domain of sustainable paddy cultivation.

V. DISCUSSION

A. Interpretation of Results

The results suggest that the pedagogical synergy between AR, AI, and GBL contributes directly to engagement and knowledge retention, reinforcing prior evidence on multimodal learning environments. High user acceptance scores and improved quiz performance suggest that interactive and visual learning approaches helped learners better understand agricultural concepts. These findings support previous research indicating that immersive and gamified learning improves motivation and knowledge retention by promoting active participation [17], [19], [20]. Feedback from educators and experts further confirmed that the system maintained both educational relevance and technical feasibility.

B. Conceptual Contribution of AR, AI, and GBL Integration

A key contribution of this work is the combination of AR, AI, and GBL within a single educational framework. Each component plays a complementary role: AR enhances visual and spatial understanding, AI introduces intelligent interaction through plant recognition, and GBL strengthens motivation and reinforcement through interactive activities [17], [23], [25]. Together, these technologies create a balanced learning environment where exploration, feedback, and practice occur simultaneously. This integrated design helps explain the high engagement levels observed during evaluation and demonstrates that multimodal learning approaches may be more effective than isolated technology-driven solutions.

C. Comparison with Existing Literature

Compared to existing platforms such as Plantix and FarmAR [8], [9], the proposed system extends prior approaches by combining multiple immersive technologies within a child-oriented educational framework. While Plantix focuses primarily on AI-based plant recognition and FarmAR emphasizes AR visualization, neither system provides a complete learning environment that integrates structured pedagogy, gamification, and offline usability.

The findings of this study therefore, align with recent research advocating hybrid learning environments that combine visualization, interaction, and intelligent feedback to improve educational outcomes [17], [19]. In addition, the localization of content to Sri Lankan paddy cultivation provides contextual relevance often missing from globally generalized agricultural applications, strengthening both authenticity and learner engagement.

D. Implications and Limitations of the Study

The findings highlight the potential of immersive educational technologies to enhance engagement and accessibility in primary-level agricultural education. The integration of AR, AI, and game-based learning demonstrates how interactive and context-aware digital tools can support learner motivation and experiential learning while remaining technically feasible for rural deployment through an offline-first architectural approach [17], [19], [23]. These results suggest that similar multimodal learning frameworks can be applied to other educational domains requiring practical and visual understanding, particularly in low-resource environments [20], [25].

The proposed system adopts a modular architecture that supports scalability in both content and user expansion. Learning modules, AR assets, and AI components can be extended independently without modifying the core system structure. In addition, the offline-first design reduces server dependency while allowing optional synchronization, enabling gradual deployment across larger educational environments as user numbers and learning content grow.

However, several limitations should be acknowledged. First, AR functionality depends on ARCore-compatible devices, which may restrict accessibility for learners using older or low-end smartphones [18], [19]. Second, the AI-based plant identification component currently operates as a prototype and requires further optimization for full offline deployment using lightweight mobile inference frameworks [23], [25]. Third, the current evaluation emphasizes short-term usability and engagement; therefore, larger-scale and longitudinal studies are needed to examine long-term learning outcomes and system scalability [17], [20].

VI. Conclusion

This study presented the design and evaluation of "Farm and Learn," an offline-first mobile learning application that integrates Augmented Reality (AR), Artificial Intelligence (AI), and Game-Based Learning (GBL) to enhance agricultural education for children. The findings demonstrate that combining immersive visualization, intelligent recognition, and interactive learning activities within a unified framework can improve learner engagement, usability, and perceived educational value, particularly in the context of primary-level agricultural learning [17], [19], [20]. The modular system architecture and offline-first design proved effective for deployment in rural and low-connectivity environments, addressing accessibility challenges commonly identified in educational technology adoption [18], [19].

A key contribution of this work lies in demonstrating the conceptual synergy between AR, AI, and GBL, where each component supports complementary pedagogical functions including experiential visualization, intelligent interaction, and motivational reinforcement [23], [25]. Unlike existing systems that focus on isolated functionalities, the proposed approach provides a child-oriented and contextually localized learning environment tailored to Sri Lankan agricultural practices. The study also shows the feasibility of integrating lightweight AI-based plant recognition within educational applications, supporting future directions for intelligent and adaptive learning tools.

Despite these contributions, certain limitations remain. The AR module depends on ARCore-compatible devices, and the AI component currently operates as a validated prototype inference layer pending final mobile packaging requiring further optimization for full mobile integration. In addition, evaluation focused primarily on short-term usability and acceptance; therefore, future work should include larger-scale longitudinal studies to assess long-term learning outcomes and scalability [17], [20]. Further development could also incorporate multilingual content and advanced adaptive learning features to enhance inclusivity and educational impact. Overall, the study demonstrates that immersive, offline-first mobile learning platforms represent a promising direction for sustainable and accessible agricultural education in resource-constrained environments.

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