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Adopting TOGAF Framework for Sustainable and Scalable Robusta Coffee Leaf Rust Management

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Abstract

Robusta coffee (Coffea canephora) is a globally significant crop. However, managing Coffee Leaf Rust remains challenging due to the reliance on manual detection methods and the lack of structured technological integration. This study proposes a TOGAF-based framework as a scalable and adaptable solution for structuring Coffee Leaf Rust management strategies. The framework leverages enterprise architecture principles to integrate learning algorithms, image detection, and systematic plantation mapping within a structured approach that enhances data organization, rust severity visualization, and predictive analysis. The proposed framework provides a strategic roadmap for integrating technology into Coffee Leaf Rust detection and management by focusing on modularity, scalability, and stakeholder engagement. Unlike existing ad-hoc approaches, this framework is a foundation for future technology-driven solutions, balancing manual practices with structured digital adoption. As no prior research has combined TOGAF with agricultural disease management, this study presents a novel conceptual contribution that could guide future developments in smart agriculture. By adopting this framework, the Robusta coffee industry can move toward proactive, data-driven Coffee Leaf Rust management, fostering long-term resilience and productivity.

Keywords:

Agricultural Technology Integration;
Coffee Leaf Rust;
Coffee Rust Detection;
TOGAF Framework.

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1- Introduction

Coffee has been an essential agricultural product since it was first cultivated in the fifth to eighth centuries in the old Kingdom of Kaffa, now part of Ethiopia [1]. Today, coffee is one of the world's most consumed beverages, with daily consumption exceeding 2.25 billion cups [2]. Two coffee species dominate global production: Robusta (Coffea canephora) and Arabica (Coffea arabica) [3]. Robusta, which accounts for approximately 40% of the worldwide coffee supply [4], is particularly valued for its resilience to heat and climate change, making it an increasingly preferred crop [5]. However, the Robusta supply chain faces significant threats from coffee leaf rust (CLR), a destructive fungal disease caused by Hemileia vastatrix [6].

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CLR was first identified in 1869 in Ceylon (now Sri Lanka) [7], marking the beginning of a global pandemic that would eventually affect nearly all coffee-growing regions. By 1890, the disease had devastated Ceylon's coffee industry, forcing many planters to cultivate tea. The disease spread from Asia to Africa and reached Brazil in 1970 before moving throughout Central and South America [7]. By 1985, CLR had become a primary global concern for coffee producers. The fungus disrupts photosynthesis, leading to significant yield losses and declining coffee quality. Over the years, CLR has triggered large-scale outbreaks, even spreading to previously unaffected regions such as Ecuador and Peru in 2012 [8]. In February 2020, CLR was detected on several islands in Hawaii for the first time, with its source still unknown [9]. Without effective mitigation strategies, CLR could reduce global coffee production by 50% [10], posing a severe risk to coffee-dependent economies.

Beyond its impact on agriculture, CLR has serious economic consequences. The failure to control CLR outbreaks can result in billions of dollars in losses and disrupt the global coffee supply chain. For example, the 2012 CLR epidemic in Central America caused over US$1 billion in losses and left more than 500,000 workers unemployed [8]. Given that Robusta coffee accounts for 40% of global coffee production, future CLR outbreaks represent an economic and social crisis for coffee-producing nations. This highlights the urgent need for improved detection and prediction models to protect farmers' livelihoods and ensure the stability of the global coffee market.

Various management strategies have been implemented to combat CLR, including bioprospecting, plant breeding, chemical-resistant crop development, and agroecological interventions [7, 11-13]. While these approaches have some success in small-scale settings, they have proven ineffective for large-scale plantations due to their labor-intensive nature limited in scalability, and often ineffective in diverse environmental conditions. Recent studies have explored technological solutions such as deep learning models for image-based CLR identification [14], autonomous crawlers for disease detection [15], uncrewed aerial vehicles (UAVs) for aerial surveillance [16], and sensor-based environmental monitoring [17]. While these methods have demonstrated promising results, their real-world applicability remains limited due to the lack of a structured integration framework. For example, deep learning models have shown CLR detection accuracy rates of up to 93.5% [18] yet require large, well-labeled datasets, often unavailable for smallholder farms. UAVs provide high-resolution aerial imaging but cannot detect early-stage rust symptoms in the lower parts of plants. Wireless Sensor Networks (WSNs) can track environmental conditions that influence CLR outbreaks, yet without a centralized system to integrate this data, their predictive capabilities remain underutilized.

A key limitation of these approaches is that they focus primarily on detection rather than prediction. Early detection is crucial, but a more proactive prediction-based approach is necessary to mitigate CLR outbreaks before they escalate. Existing research lacks a comprehensive, scalable, adaptable framework that integrates manual data collection, AI-driven detection, and predictive analytics into a single structured system.

This paper proposes a TOGAF-based framework to address these gaps to integrate CLR detection and prediction technologies into a scalable enterprise architecture. The Open Group Architecture Framework (TOGAF) provides a structured methodology for enterprise architecture, ensuring seamless technology integration while maintaining adaptability for diverse plantation sizes [19]. Unlike standalone AI models or UAV-based detection systems, TOGAF enables a systematic approach to combining manual and digital data collection methods, making it accessible even for smallholder farmers with limited technical expertise. The framework leverages TOGAF's Architecture Development Method (ADM), mainly focusing on aligning CLR management with farm-level decision-making, standardizing data collection, storage, and analysis from deep learning, UAV imagery, and sensor networks, and providing a scalable model that integrates mobile applications, AI tools, and predictive analytics for enhanced CLR management.

This research proposes a hybrid approach integrating manual data collection from farmers, who will document rust severity, deep learning methodologies for image-based rust identification, and WSNs to collect real-time environmental data, such as temperature and humidity, to predict CLR outbreaks. By combining these components, the framework will enhance early detection and predictive capabilities, providing plantation managers and farmers with actionable insights. The TOGAF-based structure eliminates the need for highly specialized technical knowledge, ensuring widespread adoption across diverse coffee-growing regions.

This study is the first to apply TOGAF in agricultural disease management, providing a conceptual framework for integrating AI-driven detection, sensor-based environmental monitoring, and farmer-led manual data collection. By bridging the gap between detection-focused solutions and the need for predictive modeling, this approach offers a scalable and adaptable strategy for CLR management. A TOGAF-based framework can revolutionize coffee disease management, ensuring global coffee supply chain stability and protecting smallholder farmers from economic losses. This research lays the groundwork for future technology-driven agricultural frameworks, fostering a transition from reactive CLR control to proactive, data-driven decision-making.

The paper is structured as follows: Section 2 provides a comprehensive literature review. Section 3 outlines the framework, detailing the application of TOGAF's ADM in designing a scalable and adaptable solution. Section 4 presents a critical discussion of the findings, addressing the framework's strengths and challenges, followed by a conclusion in Section 5.

2- Literature Review

CLR is considered one of the most damaging coffee diseases worldwide [20]. The average rust can start around 4% during the early season and can go up to more than 36% infection for plantation during the harvest [21]. It takes only about 9-11 months for a Robusta coffee tree to be ready for harvesting, which shows that the rust spreads quickly under favourable conditions. Additionally, severe CLR can cause a reduced yield of more than 70% of initial capacity and even plant death [5], underscoring the urgency of effective management strategies.

The economic consequences of CLR are substantial. Coffee is a primary export for many coffee-producing countries, and fluctuations in yield due to CLR outbreaks can disrupt local economies, influence global coffee prices, and contribute to economic instability in regions reliant on coffee production [22]. Historically, CLR outbreaks have triggered significant financial losses; for instance, the 2012 outbreak in Central America cost the region an estimated $500 million and led to substantial job losses, exacerbating poverty and food insecurity in the coffee-growing areas [23].

Traditional CLR management primarily relies on chemical fungicides and disease-resistant coffee varieties. While fungicides offer some control, they incur significant costs, pose environmental risks, and their effectiveness diminishes over time due to evolving fungal resistance [7]. Although disease-resistant varieties show promise, their efficacy is limited by the continuous evolution of CLR strains and the influence of environmental factors [8]. Furthermore, the regular application and substantial resources required for fungicide management present significant economic and logistical challenges for smallholder farmers.

Current manual detection methods primarily focus on identifying the characteristic yellow spotting on the upper leaf surface, a hallmark of CLR infection. These spots gradually develop into lesions that can produce up to 300,000 spores per lesion within three to five months [24]. This manual approach is labor-intensive and time-consuming, particularly given the rapid spread of CLR. Consequently, traditional visual inspection methods are inadequate for large-scale, proactive management, necessitating the development of more effective technological solutions.

2-1- Technology Adoption Needs in Agriculture

In the face of intensifying global competition, technological adoption in agriculture has become paramount. Emerging technologies, including remote sensing, IoT, data mining [25], and AI-powered models, offer promising solutions for crop disease management, enabling early detection and targeted interventions [21]. However, challenges persist, particularly for smallholder farmers who often grapple with limited infrastructure, high costs, and low technological literacy [26]. Complex solutions can be complicated for farmers with limited technical expertise to adopt [27]. Therefore, a practical, scalable, and user-friendly solution is crucial.

Image-based methods for CLR detection have gained traction, with studies like [28] demonstrating the use of UAV-captured images and deep learning to identify CLR with accuracy comparable to manual inspection. However, these methods face challenges like variable lighting, leaf occlusion, and limited UAV spatial perspective. Critically, these approaches lack the predictive capabilities essential for proactive CLR management [29]. Despite achieving high detection accuracy, exceeding 90% in some cases [30, 31], these methods remain limited by their inability to forecast the spread of rust [29].

To address these gaps, a structured framework is necessary for developing practical, scalable, and adaptable technology solutions that align with smallholder farmers' capabilities. TOGAF was selected from a comparative analysis of enterprise architecture frameworks—including ZFEA, DoDAF, and FEAF—due to its adaptability, modular implementation, and seamless integration with modern technologies [19, 32]. Unlike the rigid ZFEA or the security-focused DoDAF and FEAF, TOGAF offers traceability, risk management, and ease of implementation, particularly suitable for smallholder farmers in rural agricultural settings.

2-2- Overview of TOGAF Framework and Its Relevance

Developed in 1995, the TOGAF Framework is a widely used enterprise architecture model. It provides a structured methodology for technology integration and digital transformation [33]. It offers a comprehensive approach for designing solutions that encompass strategic, informational, application, and technological components.

The TOGAF ADM consists of ten phases (see Figure 1) that guide enterprise architecture development [32]. This study applies the first five phases, establishing a structured pathway for detecting and predicting CLR spread in Robusta coffee plantations using historical data. The Preliminary Phase defines stakeholder needs and project scope, while the Architecture Vision Phase sets strategic objectives for CLR management. The Business Architecture Phase ensures alignment with coffee plantation operations, followed by the Information Systems Architecture Phase, which integrates AI-based detection models, sensor data, and predictive analytics. Finally, the Technology Architecture Phase outlines the hardware, software, and infrastructure required for CLR detection systems.

By following TOGAF, the framework ensures structured, scalable, and proactive CLR management, enabling efficient deployment of AI-driven solutions for disease monitoring in coffee plantations.

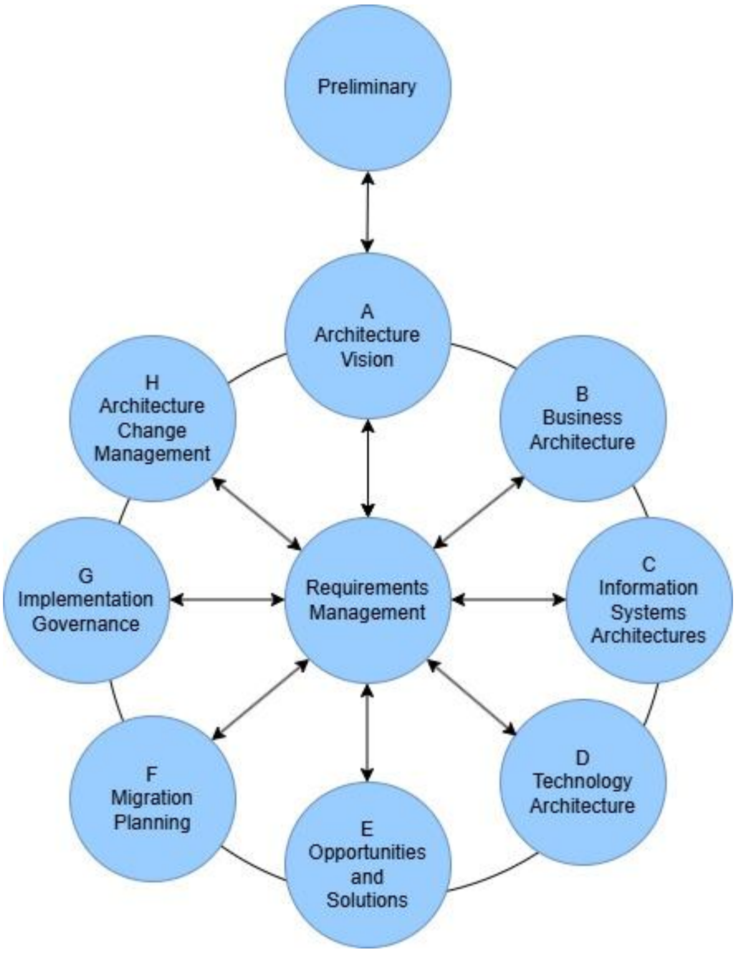

Figure 1. Architecture Development Method of TOGAF by The Open Group

2-3- Theoretical Foundation of the Study

The TOGAF framework, grounded in Enterprise Architecture Theory, provides a systematic methodology for integrating digital solutions, ensuring scalability, interoperability, and strategic alignment with agricultural operations. Unlike other Enterprise Architecture frameworks, TOGAF's adaptability and modular implementation make it particularly suitable for addressing the CLR problem by facilitating structured, data-driven, and scalable technology adoption in agriculture.

By applying Enterprise Architecture Theory and TOGAF, this study establishes a structured pathway for enhancing agricultural efficiency through technology-driven solutions for CLR management. The methodology section will detail how TOGAF's structured approach is applied to optimize AI-driven disease detection and predictive modeling in CLR management.

3- Research Methodology

This study applies the TOGAF framework to develop a structured, scalable roadmap for CLR management, integrating predictive modeling for early disease detection and mitigation in coffee plantations. Rather than focusing on specific machine learning models, the emphasis is on defining architectural phases, data inputs, and integration principles to support predictive capabilities. This methodology remains model-agnostic, ensuring adaptability in AI model selection, data processing techniques, and sensor integration across different plantation environments. Effective CLR management requires structured data collection and system integration. The Technology Architecture Phase defines the data inputs, logical workflows, and infrastructure needed to support deep learning models for CLR prediction, ensuring adaptability to future AI-driven models and varying computational resources.

Figure 2 visually represents the framework's structured layers, demonstrating how sensor inputs feed into AI-driven insights for accurate rust forecasting and intervention planning. The process begins with the Preliminary Phase, which defines the scope of the architecture. The Architecture Vision Phase sets the strategic goals for CLR management, followed by the Business Architecture Phase, which aligns the framework with plantation operations. The Information Systems Architecture Phase structures sensor networks and manual data inputs, while the Technology Architecture Phase establishes the system infrastructure for predictive analytics and forecasting.

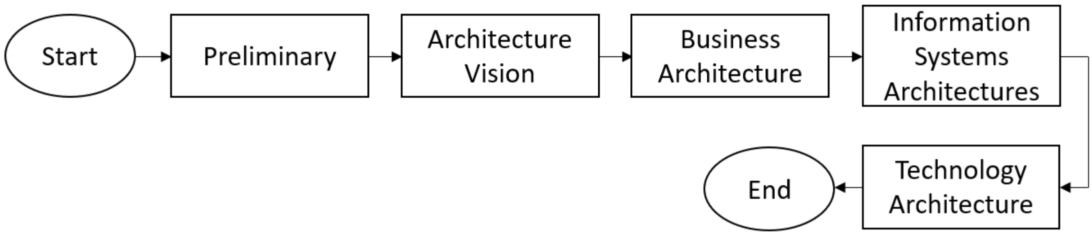

Figure 2. General Flowchart for the Process of Methodology

3-1- Preliminary Phase

In the Preliminary Phase of TOGAF's ADM, architecture principles are established to guide the systematic development of the proposed CLR management solution. These principles are tailored to address the specific needs of farmers, with a focus on adaptability, scalability, and alignment with business objectives, as summarized in Table 1.

Table 1. TOGAF-Aligned Principles for CLR Management

Principle	Statement	Rationale	Implication
Business	Ensure high yield and premium quality Robusta coffee	Standardization enables consistent detection and forecasting, ensuring quality.	Workers must be trained in CLR detection and digital tools to ensure accurate monitoring.
Application	Deliver a flexible, scalable, and cost-effective solution.	TOGAF modularity facilitates rapid development and adaptability for farming needs.	Simplifying and integrating manual and digital systems reduces resistance to adoption.
Data	Ensure high-quality and reliable data collection	Structured data management safeguards data integrity and reliability.	Policies and training minimize data errors and ensure alignment with governance principles.
Technology	Adapt solutions to evolving business needs.	TOGAF's adaptability principle ensures relevance in dynamic agricultural conditions.	Iterative processes support flexible technology implementation tailored to plantation requirements.

The Business Principle focuses on achieving high-yield, premium-quality Robusta coffee through standardized detection processes, supported by worker training in CLR detection and the utilization of digital tools. The Application Principle emphasizes the development of flexible, scalable solutions that leverage TOGAF's modularity, seamlessly integrating manual and digital systems to facilitate adoption. The Data Principle prioritizes collecting reliable, high-quality data, reinforced by structured governance policies and training to minimize errors and support informed decision-making. Finally, the Technology Principle emphasizes adaptability and iterative processes to ensure that technology remains practical and relevant to the evolving needs of plantation management. Overall, the proposed principles emphasize achieving high-quality Robusta coffee through standardized processes, worker training, and digital tools while promoting flexible, scalable solutions, reliable data collection, and adaptable technology to enhance productivity and decision-making in plantation management.

3-2- Phase A: Architecture Vision

This phase addresses the limitations of current manual CLR detection practices by proposing a standardized and scalable system. Existing methods often rely on informal reporting, leading to inconsistent data collection and inefficient monitoring of rust severity. Guided by TOGAF's adaptability, scalability, and business alignment principles, the proposed vision centers around three core components: Rust Severity Classification, Visual Mapping & Color Coding, and Tree Identification System.

The study adopts the rust severity classification scale developed by the Organismo Internacional Regional de Sanidad Agropecuaria (OIRSA) [34], as presented in Table 2. This scale categorizes the severity of leaf rust into four levels, determined by the percentage of the leaf area affected. For instance, a leaf is classified at the highest severity level when rust spots cover over 50% of its surface. Nevertheless, evaluating the severity of individual leaves alone does not provide a sufficiently comprehensive basis for effective monitoring and intervention.

In line with the principle of adaptability, the rust severity classification scale is extended to tree-level assessment (Table 3) by measuring the percentage of infected leaves on a tree. This simplified approach leverages workers' proficiency in visual inspection, ensuring both practicality and scalability across plantations. To improve accuracy and efficiency, the study proposes using a deep learning algorithm for image segmentation, facilitating precise classification and detailed analysis of rust severity.

Table 2. Severity Scale Coffee Leaf of OIRSA

Level	Affected leaf area (spots)
1	1-5%
2	6 – 20%
3	21 – 50%
4	>50%

Table 3. Robusta Coffee Tree Rust Severity Classification

Severity Level	Affected areas
1	1-5%
2	6 – 20%
3	21 – 50%
4	>50%

A colour-coded mapping system (Table 4) further enhances usability by visually representing tree-level rust severity, enabling quick decision-making and effective resource allocation. This system integrates the OIRSA leaf severity classification with the proposed Robusta coffee plant rust severity scale. For example, a tree with more than 50% of its leaves affected, most of which are categorized at severity level 2, would be marked with a red colour and the number '2' for easy identification. This visual system empowers plantation workers to interpret rust severity at a glance, improving the efficiency of monitoring and management efforts.

Table 4. Mapping of Individual Robusta Coffee Plants for Rust Severity by Colors

Colour	Affected Tree areas
Light Green	1-5%
Yellow	6 – 20%
Orange	21 – 50%
Red	>50%

The next step involves developing an efficient and user-friendly tree identification system utilizing a zoning approach with row and column numbering. Tags affixed to tree trunks or roots, accounting for the 2-2.5meter planting distance characteristic of Robusta trees [35], ensure straightforward identification. This method adheres to TOGAF's principle of data governance, promoting scalability while enabling precise tracking and consistent data recording. Building on these foundational elements, Figure 3 depicts the proposed system's operation under standard conditions, showcasing its alignment with established architectural principles. To address TOGAF's Technology Principle of adaptability, Figure 4 presents an enhanced system version, highlighting its flexibility and capacity to integrate future technological advancements.

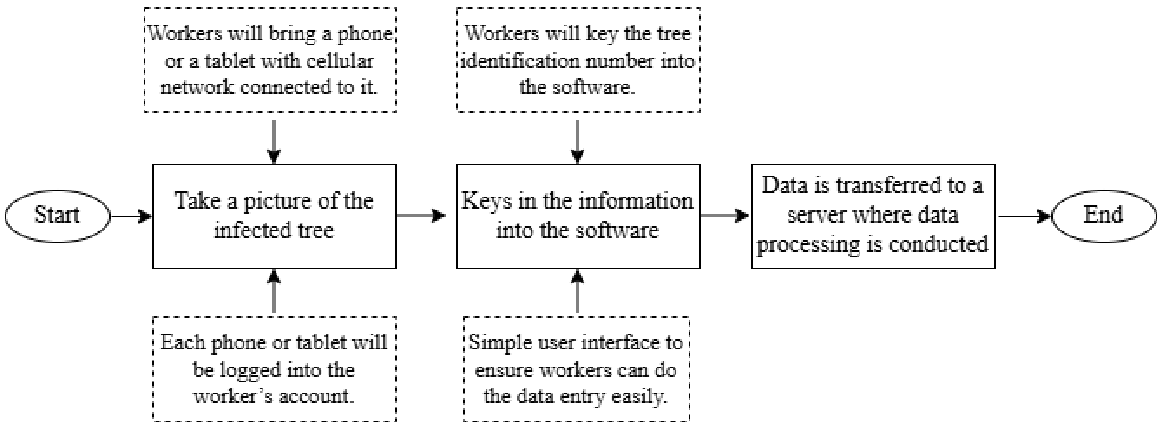

Figure 3. Process Vision on Our Proposed Approach

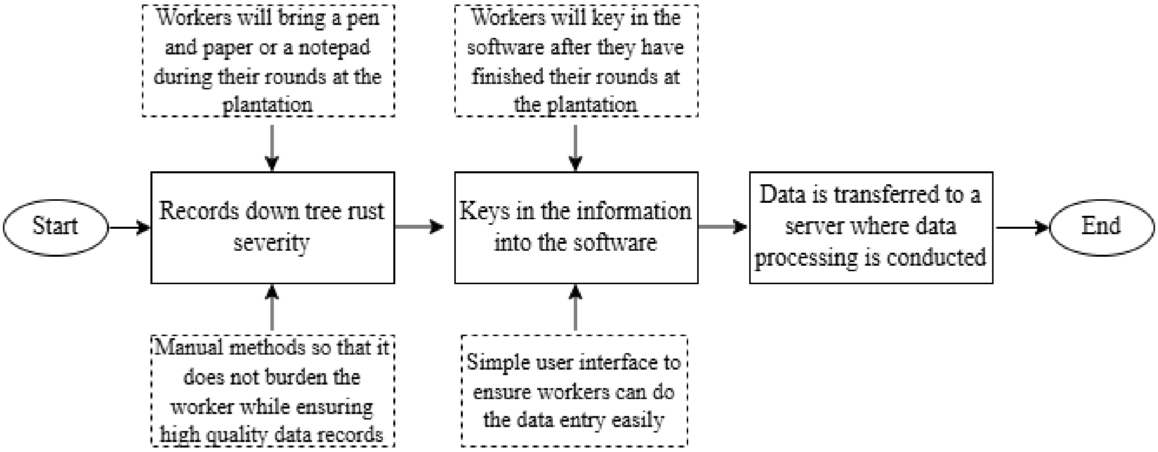

Figure 4. Process Vision on Our Proposed Approach with Adaptability to Change

As illustrated in Figure 3, the proposed process is designed to be straightforward and user-friendly, minimizing any disruption to workers' daily routines. The system saves time, reduces workload, and prevents unnecessary data accumulation by focusing solely on recording infected trees. It is also robust against technological limitations; workers can rely on manual recording methods when devices such as phones or tablets are unavailable. The systematic tree identification system ensures accurate and reliable data collection, even in manual operation. Once the data is entered into the software, a deep learning algorithm processes it to analyze rust severity and generate maps of affected areas. This mapping functionality, shown in Figure 5, delivers actionable insights to support effective plantation management and optimized resource allocation. However, transitioning from traditional manual methods to this hybrid technological solution may pose challenges for farmers, including initial resistance to new digital workflows, concerns over device availability, and difficulties in data entry accuracy. To address these concerns, phased implementation strategies, hands-on training workshops, and simplified user interfaces are incorporated into the system design, ensuring farmers can gradually adapt to new processes without disrupting existing operations. Additionally, incorporating offline functionality and automated data synchronization features will facilitate adoption, particularly in remote areas with limited connectivity.

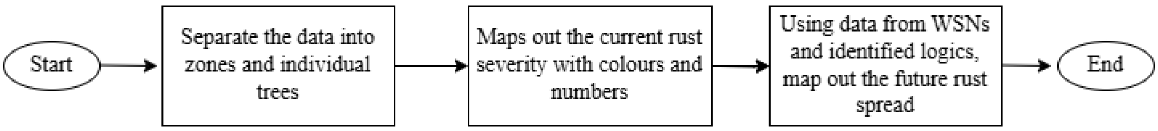

Figure 5. General Flowchart in Software

This proposed system prioritizes efficiency by minimizing data entry requirements. Only infected trees need to be recorded, reducing data storage demands. Furthermore, the system maintains resilience in the face of technological limitations. Manual recording options are available when electronic devices are unavailable. A sophisticated deep learning algorithm will analyze the entered data to assess rust severity and generate maps of affected areas, providing actionable insights for targeted management strategies. This solution leverages the power of data integration, incorporating environmental parameters from WSNs to enhance predictive capabilities, aligning with TOGAF's emphasis on technology alignment.

Key stakeholders in this system include the farmer-owner, who is responsible for defining zones and assigning tasks to workers, and the workers themselves. Workers are tasked with identifying the severity of coffee leaf rust and recording their observations using a standardized color-coding system and a unique numbering system. This structured approach, guided by the principles of the TOGAF's ADM, ensures efficient CLR management and provides the necessary flexibility to adapt to future technological advancements.

3-3-Phase B: Business Architecture

The Business Architecture Phase is crucial for establishing a robust foundation for the rust detection and prediction system. This phase involves thoroughly examining business goals, a comprehensive assessment of current capabilities, and setting clear targets for implementation. By leveraging the TOGAF framework, farmer-owners can strategically optimize disease management, mitigate yield loss, and achieve a scalable and adaptable solution that enhances productivity, improves product quality, and ensures customer satisfaction.

Table 5. Business and IT Capability Assessments for CLR Management (Aligned with TOGAF)

Assessment	Description	TOGAF Principal Alignment
	Business Capability	
Capabilities of the Business	Evaluate plantation infrastructure for zoning and tree tagging; assess worker readiness for system adoption.	Business Alignment: Ensures infrastructure and workforce are prepared for scalability.
Baseline State	Define the starting point for implementation; gradually expand from selected zones to the entire plantation.	Iterative Implementation: Supports phased adoption.
Future State Aspiration	Envision full plantation implementation with ≤5% error margin, leveraging structured training and worker experience.	Long-Term Vision: Establishes measurable success goals.
	IT Capability	
Baseline and Target Maturity of Change Processes	Assess readiness for system implementation, considering plantation size and preparedness; target maturity transition within one week.	Adaptability: Supports readiness and phased deployment.
Baseline and Target Maturity of Operational Processes	Determine the time required for plantation and workforce preparation, leveraging the farmer-owner's operational knowledge.	Scalability: Aligns operational processes with system goals.

The Business and IT Capability Assessments, as outlined in Table 5, provide a structured framework for evaluating the plantation's current readiness and setting achievable implementation goals. These assessments are aligned with TOGAF's core principles, such as modularity, scalability, and adaptability, ensuring that the foundation for an effective rust management system is built upon a solid and adaptable base.

By conducting comprehensive business and IT capability assessments aligned with the TOGAF framework, a solid foundation is laid for a structured and scalable rust management solution. This approach aligns the architecture with immediate operational goals, such as enhanced productivity and optimized resource allocation, and ensures the system's long-term sustainability. Integrating TOGAF's principles guarantees that the solution remains modular, practical, and consistently aligned with the farmer-owner's objectives, facilitating sustainable and efficient CLR management.

3-4- Phase C: Information Systems Architecture

This phase emphasizes the development of a user-friendly software solution to facilitate the efficient recording and management of CLR-related data. The software's input interface is meticulously designed to capture essential information (as outlined in Table 6) while minimizing complexity to ensure seamless adoption by workers.

Table 6. Main Information Needed for the Input

Number	Information	Input
1.	Name. Thank you for reaching out. ID	Text. Thank you for reaching out. Numerical
2.	Date	Date
3.	Zone serviced	Numerical
4.	Rust Infected Robusta Coffee Tree Classification	Severity Colour Choice with numerical

The software enables seamless local data recording on mobile devices such as phones or tablets. This locally stored data is securely transferred to a cloud-based database using various network options, including Bluetooth, Wi-Fi, or other available connections. Each plantation zone is systematically mapped using a structured row-and-column system, ensuring real-time updates accurately reflect field conditions. Figures 6 and 7 visually illustrate this mapping system and its corresponding outputs. To safeguard the security and privacy of collected data, robust encryption techniques are applied during both transmission and storage. Multi-factor authentication (MFA) and role-based access controls (RBAC) further enhance security by restricting unauthorized access, ensuring that only authorized personnel can access sensitive farm data. Regular security audits and adherence to international data protection standards help mitigate potential breaches. To reassure farmers and stakeholders about data privacy, transparent data policies are established, clearly defining data ownership, usage rights, and protection measures. Additionally, anonymization techniques prevent the exposure of individual farm productivity metrics while still allowing for aggregated insights that contribute to industry-wide improvements. By integrating these security measures, the framework maintains data integrity, confidentiality, and trust, fostering widespread adoption among farmers and agricultural stakeholders. This approach not only protects sensitive information but also enhances confidence in technology-driven agricultural management solutions.

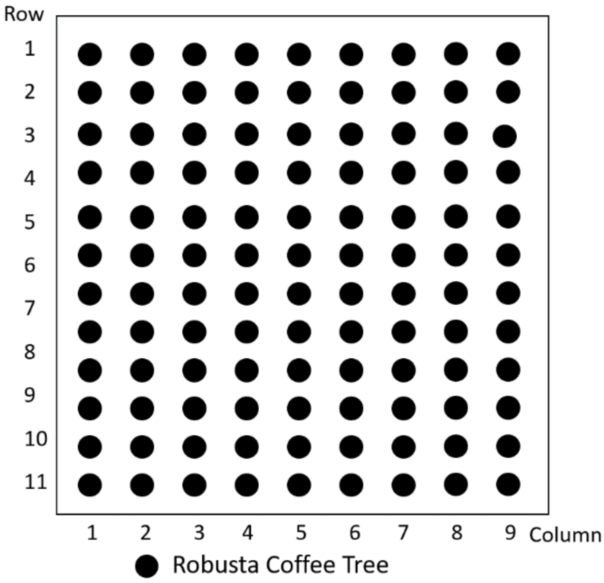

Figure 6. **Mapped Out Robusta Tree Plantation Zones Using Rows and Columns System**

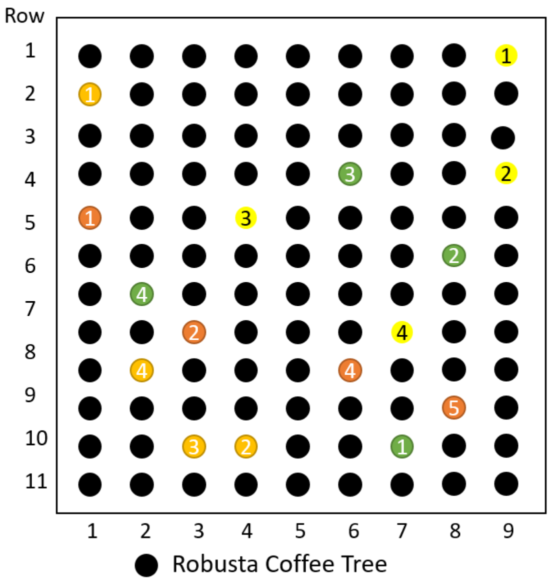

Figure 7. **An Example of Mapped Out Robusta Tree Plantation Zone After a Worker Has Inserted the Inputs**

Figure 7 showcases critical insights, including identifying clusters of infected trees and monitoring rust severity levels using a visually intuitive color-coded system. These insights align with TOGAF's principles of usability and informed decision-making, empowering farmer-owners to prioritize interventions, identify systemic plantation issues, and allocate resources effectively. This system promotes proactive rust management while maintaining scalability and ease of use. The architecture fosters efficient resource allocation, enables continuous plantation health monitoring, and facilitates worker performance assessment, providing a sustainable and practical approach to CLR management.

3-5- Phase D: Technology Architecture

This phase will integrate sophisticated deep-learning algorithms and advanced mapping features to accurately identify and predict the spread of rust-infected trees. It ensures the system's relevance, scalability, and effectiveness by leveraging historical data, incorporating environmental inputs from WSNs, and utilizing robust logical models. This approach aligns with TOGAF's modularity, adaptability, and seamless data integration principles.

The underlying logic of this system is based on the principle that Robusta trees rust primarily spreads to neighboring trees rather than those located at a significant distance. This is because the rust spores travel by wind and are carried out by insects, which makes the spread distance not very big [36]. Therefore, the system uses biological insights, such as the limited spread of rust spores through wind and insects, to form the foundation of its predictive logic. The k-nearest neighbor algorithm is employed to model the spread of rust to neighboring trees. The following rules refine the predictions:

1. Newly infected trees start with the lowest severity classification.
2. Infection severity progresses incrementally over time, with one level of increase observed at each stage.
3. Grouped infections result in an elevation of severity levels for both the affected trees and the initial source of the infection.

Figure 8 visually demonstrates the system's ability to map the propagation of rust, with severity levels indicated by distinct colors and corresponding classification grades.

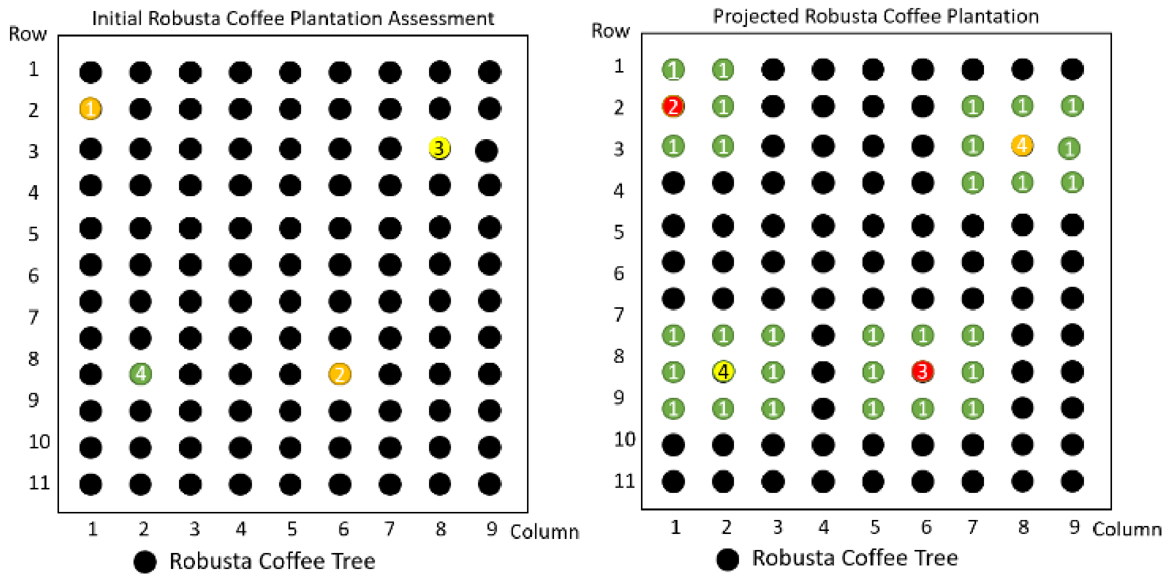

Figure 8. Example of Initial Robusta Coffee Plantation Assessment and Projection of Spread

This visual output empowers farmer-owners to identify high-risk zones within the plantation, enabling them to allocate resources effectively and implement timely interventions for improved rust management. The system is designed as a flexible and adaptable framework, empowering farmer-owners to customize rust severity classifications and incorporate unique plantation-specific parameters while maintaining its core structure. This adaptability ensures the system can effectively address diverse plantation needs and aligns perfectly with TOGAF's emphasis on scalability and user-centered design.

WSNs significantly enhance predictive capabilities by integrating crucial environmental data like temperature, humidity, and wind patterns. This real-time environmental data refines the logic underpinning spread projections. Furthermore, historical data supports predictive capabilities by identifying recurring trends in previously affected areas, enabling proactive interventions. These features, meticulously aligned with TOGAF's data integrity and reuse principles, ensure the system delivers actionable insights that guide immediate responses and long-term strategies for optimizing plantation health. To ensure the predictive analytics component's accuracy and reliability, the system can employ data validation techniques, continuous model training with updated datasets, and cross-referencing with multiple sensor inputs to minimize errors. Additionally, the framework incorporates adaptive machine-learning models capable of adjusting to new environmental conditions and disease progression trends. The system allows for customizable parameter tuning based on localized agricultural data to account for regional differences in climate, soil composition, and farming practices. This ensures that the predictions remain relevant and reliable across diverse coffee-growing regions, improving the accuracy of interventions and the effectiveness of disease prevention strategies.

4- Discussions

Effectively managing Robusta CLR requires a structured, scalable, and data-driven solution that transcends the limitations of existing detection methods. While current image-based systems provide advanced technological capabilities, they face significant challenges, including variability in lighting conditions, occlusions, and limited scalability for large-scale plantations. This study introduces a novel framework, grounded in the TOGAF methodology, that seamlessly integrates deep learning, a systematic tree identification approach, and real-time environmental data inputs. This integrated approach delivers a resilient and adaptive CLR detection and prediction system, improving disease management and enhancing overall agricultural sustainability.

By leveraging TOGAF's ADM and adhering to core principles such as modularity, scalability, and adaptability, this solution transitions CLR management from a reactive to a proactive model, ensuring the long-term health and productivity of coffee plantations. TOGAF's structured methodology ensures seamless alignment between overarching business objectives, specific operational needs, and the system's technological capabilities. The modular design strategically integrates manual methods with advanced technologies, making the system accessible to farmers with varying technological expertise. The implementation of plantation zoning, systematic tree tagging, and the integration of environmental data from WSNs significantly enhance predictive accuracy. This enables stakeholders to efficiently allocate resources, monitor disease progression, and implement timely interventions in high-risk areas. The framework's inherent flexibility supports the customization of rust severity classifications and predictive algorithms, reinforcing TOGAF's adaptability principle and ensuring the framework remains effective across diverse farming environments.

Deep learning algorithms serve as the cornerstone of this system, enabling highly accurate rust severity classification at both the leaf and tree levels. By integrating data from WSNs, such as temperature, humidity, and wind speed, the predictive models continuously refine their accuracy, aligning with TOGAF's principle of data integration. This hybrid approach, which seamlessly combines manual methods with sophisticated prediction systems, minimizes resistance to adoption and encourages widespread implementation. Analyzing environmental parameters alongside image-based disease identification provides a robust decision-making tool that enhances short-term response strategies and long-term plantation health planning.

Despite its numerous advantages, this framework presents several challenges. Acquiring high-quality, consistent data for training deep learning models can be particularly difficult in resource-constrained environments. Furthermore, manual data collection is inherently susceptible to human error, which may affect the accuracy of predictive models. Scalability remains a key concern for large plantations due to the logistical and financial demands of systematic tree tagging and zoning. Selecting appropriate deep learning algorithms, such as Convolutional Neural Networks (CNNs) or transfer learning models, requires rigorous testing to ensure optimal performance across diverse environmental conditions. Additionally, the computational and infrastructure requirements for these advanced models may exceed the available resources of some farmer-owners, necessitating cost-effective solutions such as cloud-based computing or edge AI processing.

The successful implementation of this system hinges on the reliability of the infrastructure supporting the WSNs. These networks may face technical challenges in remote areas, such as equipment failures, inconsistent connectivity, or high maintenance costs. Furthermore, resistance to adopting new technologies, even those with simplified interfaces, poses a significant risk. To mitigate these challenges, comprehensive training programs for farmers and plantation workers are crucial. Awareness campaigns, step-by-step onboarding processes, and community-led demonstrations can facilitate smooth adoption and enhance long-term engagement.

The proposed framework addresses the pressing challenges of CLR management and lays a strong foundation for broader agricultural applications. The system proactively manages recurring outbreaks by integrating historical data and leveraging environmental insights, allowing plantation owners to anticipate and mitigate potential threats before they escalate. This proactive approach is strengthened by the framework's ability to identify long-term disease trends and optimize intervention strategies. Moreover, the system's inherent flexibility allows for adaptation to other crops and agricultural diseases, significantly expanding its potential impact beyond CLR management. By embracing an enterprise architecture-driven approach, this framework is a transformative model for precision agriculture, empowering farmers with actionable insights and fostering a more resilient global coffee supply chain.

5- Conclusion

This study introduces an innovative TOGAF-based framework for managing Robusta CLR, integrating structured enterprise architecture, plantation zoning, and environmental data analysis. By combining manual data collection with advanced technologies, the framework enhances rust detection accuracy, enables predictive analytics, and optimizes plantation management strategies. Its modular and scalable design ensures adaptability across plantations of varying sizes and technological capacities. At the same time, integrating WSNs for real-time environmental monitoring refines predictive models and fosters proactive disease management. Adopting a standardized severity classification system and a color-coded mapping tool enhances data visualization, allowing plantation managers to make informed decisions efficiently. However, implementing this framework presents challenges, including ensuring data consistency, accessibility for smallholder farmers, and scalability for large plantations. Addressing these challenges requires a collaborative, multi-stakeholder approach, where effective knowledge transfer, infrastructure support, and cost-efficient deployment will be crucial for success.

Beyond CLR management, this study highlights TOGAF's broader applicability in agricultural modernization, offering a structured, adaptable model that extends to other crop diseases and plantation systems. This framework-driven approach represents a shift from reactive to proactive disease control, strengthening long-term agricultural sustainability. By integrating enterprise architecture into disease management, this study lays the foundation for data-driven farming, empowering farmers with actionable insights, optimizing resource allocation, and safeguarding the global coffee supply chain from future threats. Through continued research, collaboration, and technological innovation, this approach has the potential to revolutionize agricultural management, ensuring a more sustainable and resilient future for coffee cultivation.

6- Declarations

6-1- Author Contributions

Conceptualization, T.O.K.Z. and K.S.M.A.; methodology, T.O.K.Z. and K.S.M.A.; validation, S.M., B.B., and S.M.; formal analysis, Y.Y.; investigation, T.O.K.Z; resources, K.S.K.; writing—original draft preparation, T.O.K.Z; writing—review and editing, K.S.M.A; visualization, K.S.K.; project administration, Y.Y.; All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6-4- Institutional Review Board Statement

Not applicable.

6-5- Informed Consent Statement

Not applicable.

6-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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