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Artificial intelligence tool for cassava viral diseases diagnosis using participatory surveillance in Burkina Faso

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In the area of plant health, there has been little work using participatory approaches to control emerging infectious diseases such as cassava mosaic disease (CMD) and cassava brown streak disease (CBSD). These diseases cause significant yield losses in Sub-Saharan Africa. The current study provided low cost and early detection method of cassava viral diseases surveillance, based on participatory approaches using an AI tool (Plantvillage nuru app). The study involved farmers, agricultural extension agents (AEA), and cassava diseases diagnosis experts. Farmers were made aware of CMD and CBSD damage through a national campaign, while AEA received training to identify CMD, CBSD, and cassava green mite (CGM) symptoms using an AI-based diagnostic tool. Sixty trained AEA, equipped with smartphones running the AI tool, conducted fields surveillance either through visual inspection or with AI tool. The participation rate of the AEA and the diagnostic accuracy of the AI tool and visual assessments were evaluated and compared to experts perception validated by molecular analysis. Workshops and smartphones allocation enhanced AEA participation rate to 60%, and increased surveyed fields number to 132. CMD detection revealed no significant difference between users of AI tool (p -value = 0.709) and visual inspection (p -value = 0.997). The mean scores of CMD detection were $29.83 \pm 12.99\%$ for AI tool, $37.12 \pm 12.78\%$ for experts, and $36.10 \pm 12.74\%$ for molecular analysis among AI tool users. With visual inspection users, the mean scores detection were $46.07 \pm 13.00\%$ for AEA and experts perception, and $43.87 \pm 12.07\%$ for molecular analysis. The AI tool misdiagnosed 5% of CMD as CBSD, but molecular analysis confirmed it as CMD. The CMD infected fields was 31.06%, with a predominantly *African Cassava Mosaic Virus* (93.33%) detected. The results demonstrated that participatory approaches could be effective in the plant pathogens early management.

KEYWORDS

participatory surveillance, artificial intelligence, cassava virus diagnosis, smartphone, Burkina Faso

1 Introduction

Cassava (*Manihot esculenta* Crantz) is a staple food for approximately 800 million people worldwide, including 500 million in Africa (Howeler et al., 2013). Africa accounts for more than half of the global production (FAOSTAT, 2021). However, this production faces several diseases, with cassava mosaic disease (CMD) and cassava brown streak disease (CBSD) being the major biotic threats affecting cassava production in Africa (Legg et al., 2011). The genus Begomovirus and ipomovirus are reported to be the major viruses responsible for CMD and CBSD in Africa (Legg et al., 2014). Yield losses associated with CMD damage reach up to US\$ 2 billion annually in Africa (Patil and Fauquet, 2009). CMD is therefore a real threat to cassava production and food security. Epidemiological studies have shown that its widespread is due to the ignorance of smallholder farmers, who constantly re-use infected cuttings as planting material (Soro et al., 2021), the porosity of borders (Delètre et al., 2021), and the lack of phytosanitary facilities. The lack of diagnostic tools to detect plant viruses at phytosanitary inspection posts has been cited as a reason for cross-border exchange of CMD (Whattam et al., 2021). In Burkina Faso and several African countries where CMD is widespread, disease management is based on classical epidemiology with field surveillance and disease diagnosis. These epidemiological efforts are aimed at promoting virus-free cuttings and resistant varieties, and at sensitizing farmers to adopt good agricultural practices through the efforts of the CENTRAL AND WEST AFRICAN VIRUS EPIDEMIOLOGY (WAVE; <https://wave-center.org/>) program against transboundary plant pathogens (Eni et al., 2021; Soro et al., 2021; Hounigue et al., 2022; Mouketou et al., 2022; Amoakon et al., 2023). However, classical epidemiological studies are subject to high financial costs, require expertise and considerable time to cover large areas and obtain diagnostic results (Calba et al., 2015; Vluggen et al., 2017; Jafar et al., 2024). Therefore, participatory surveillance approaches have been developed to overcome these constraints in the application of classical epidemiology and formal studies (Smolinski et al., 2017).

Participatory surveillance is the use of the bi-directional process of receiving and transmitting of health-related data through community engagement (McNeil et al., 2022). Participatory surveillance takes into account the knowledge of local communities and their involvement in disease control efforts (Catley et al., 2012). This approach has achieved considerable success in animal and human health through the development of Information and Communication Technology (ICT) tools combined with artificial intelligence applications for disease diagnosis and surveillance (Karimuribo et al., 2017; Fornace et al., 2018; Geneviève et al., 2019; Huang and Loschen, 2019; McNeil et al., 2025). Several AI mobile application such as, AgroScout, CropsAI, Crop Doctor, and Plantix were developed based on convolutional neural networks model for plant diseases symptoms recognition (Yadav and Yadav, 2025). In addition to their portability and accessibility on smartphones and ICT tools without the need for an internet connection, they offer the advantages of low-cost and real-time disease diagnosis and monitoring, allowing for the anticipation of alerts and the reduction of the time of the disease spread (Kizito et al., 2013; Gadicherla et al., 2020; Hasan and Haque, 2023). However, in plant health, participatory approaches for monitoring and management of plant pathogens and pests remain underutilized. Nevertheless, several IA-based applications have been designed for the

diagnosis, monitoring, and management of plant diseases, with the particularity of being easily usable by farmers and agricultural extension agents (Fuentes et al., 2017; Johannes et al., 2017; Ramcharan et al., 2019). Among these tools, PlantVillage Nuru is one that has been successfully tested in Sub-Saharan Africa (Mrisho et al., 2020).

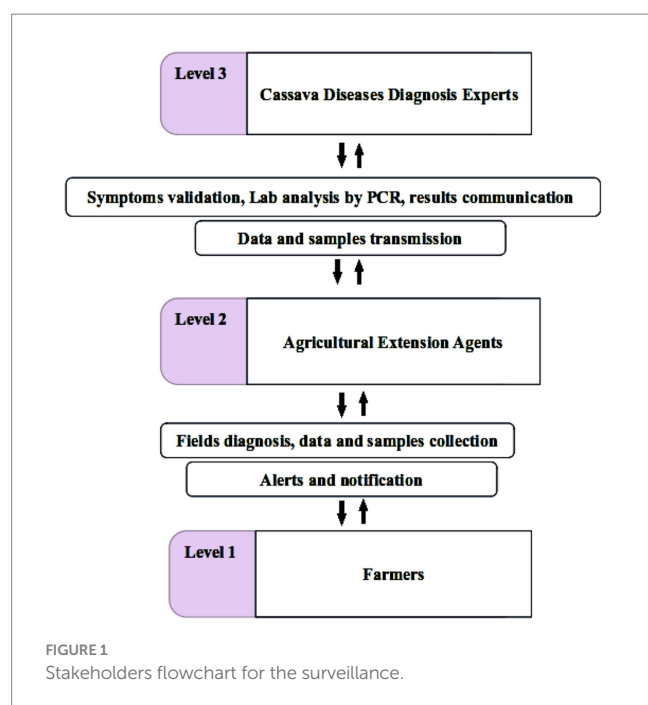
Nuru is a mobile application that can be free downloaded for free from Play Store and operates in real-time without internet (Mrisho et al., 2020). The working principle of the AI tool is based on an image recognition system and has been trained to recognize and detect healthy cassava leaves as well as leaves showing typical symptoms of cassava mosaic disease (CMD), cassava brown streak disease (CBSD), damage caused by cassava mites and brown leaf spot (Ramcharan et al., 2017, 2019). WAVE program contributed to Nuru integration as first line diagnosis tool in Central and West Africa. Since this, the tool help farmers and extension agents in CMD early detection in Benin (Ahoya et al., 2024), Côte d'Ivoire (Adjéi et al., 2024) and Sierra Leone (Saffa et al., 2025). In East Africa, Nuru using for diseases detection allowed farmers to mitigate crop losses (Yadav and Yadav, 2025). In Burkina Faso, cassava viruses diseases management longtime focused on traditional methods engaging only limited personal of researchers for nationals surveillance. Unfortunately, these methods are costly and time consuming, which do not allow early management. Due to financial resources limitations, research personnel and laboratory infrastructures in developing countries, awareness campaigns and trainings with mobile tools engaging farmer and extension agents through participatory epidemiology could enabled early detection and rapid response to disease management (Dhavale et al., 2025).

In view of the above and the vegetative propagation nature of cassava, it seems imperative to involve communities at the grassroots level for awareness of viral diseases and also for participatory surveillance and early warning. The era of ICTs is well suited to support the plant health sector by developing the concept of participatory surveillance. ICTs tools such as AI are positioned as tools that can contribute to improve knowledge of viral diseases and reconnect farmers, breeders, phytosanitary offices, extension agents, researchers and political leaders. In this study, participatory approaches were applied to CMD and CBSD surveillance in Burkina Faso. The participation rate of extension agents was assessed. The diagnostic results of the AI tool, visual diagnosis based on extension agents' perceptions and experts' perception of cassava viral diseases diagnosis in agreement with molecular laboratory analysis were also compared.

2 Material and methods

2.1 Participatory surveillance approach implementation

This study involved cassava farmers, extension agents from the Plant Protection Department of the Ministry of Agriculture, Burkina Faso, and cassava viral diseases experts from WAVE program. The stakeholders were structured to three level following a hierarchical flowchart (Figure 1). The farmers were responsible for recognizing cassava disease symptoms and to reporting fields status to the extension agents. The extension agents were involved in field surveys and collection of cassava leaf samples using the AI tool (Group 1) and visual observations (Group 2). These two groups were established at



the beginning of the study after training. The role of the experts was to validate symptoms status of the collected leaves, before running molecular analysis using polymerase chain reaction (PCR). The accuracy of AI diagnosis and visual assessments performed by extension agents were evaluated and compared with experts visual assessments, which were validated by PCR results as a reference.

2.2 Raising awareness among farmers

Cassava farmers were made aware of the damage caused by CMD and CBSD during a national campaign in April 2022 called “Together, Let us save our cassava.” The main cassava producing areas were visited and farmers were trained to recognize symptomatic leaves. Flyers with typical CMD and CBSD damage and cassava disease management practices were distributed to farmers. During the campaign, audio and visual spots on CMD and CBSD damage and management advice were recorded and aired on national and private TV and radio stations.

2.3 Training of extension agents

In July 2022, the participatory surveillance started with the training of agricultural extension agents (AEA). Sixty AEA were trained. They came from the following regions of Burkina Faso: Boucle du Mouhoun ($n = 8$), Cascades ($n = 8$), Center ($n = 2$), Center-Est ($n = 8$), Center-Ouest ($n = 6$), Center-Sud ($n = 6$), Est ($n = 6$), Hauts-Bassins ($n = 8$) and Sud-Ouest ($n = 8$). Apart from the Center region, all the others are known to be cassava producing areas. The training consisted of the recognition of the typical symptoms CMD and CBSD, the use of the AI tool for plant diagnosis and the management of any disease if fields are infected. The use of the AI tool for real-time diagnosis of CMD and CBSD in cassava fields was also

described. A practical test was carried out in a cassava field infected with CMD. At the end of the training, a WhatsApp platform was created to support participants and keep them in touch. In July 2023, a monitoring and evaluation workshop was organized to equip the sixty extension agents with smartphones (iTél P17 Pro, camera 5 MP Back).

2.4 Sample collection

The two groups of trained AEA conducted cassava fields surveillance and collected leaf samples. The first group used the AI tool as described previously (Mrisho et al., 2020). The second group used visual observation according to their knowledge of the symptoms of CMD, CBSD and CGM. Each group collected leaf samples in paper envelopes and dried them briefly before sending them to the experts. The samples collected were either healthy or suspected to be infected by CMD, CBSD, and CGM symptoms. Information on the region, district, village, collector, sample identity, date of collection and disease were recorded on each envelope. A georeferenced map (Figure 2), showing the sampling locations was generated using QGIS v 3.6.3-Noosa software. The quality and status of the leaf samples received were checked by experts. The leaf samples were then oven dried at 37 °C for dehydration for 72 h and stored at room temperature until nucleic acid extraction.

2.5 Molecular detection of cassava mosaic begomoviruses and cassava brown streak ipomoviruses

Total DNA and RNA were extracted from cassava dried leaves following the CTAB method (Permingeat et al., 1998). The extracted DNA and RNA were eluted in 200 μ L nuclease-free water and their quality checked using a spectrophotometer (NanoDrop 2000, Thermo Fisher Scientific). All DNA and RNA were stored at -20 °C until further use.

Cassava mosaic begomoviruses (CMB) detection was performed in 20 μ L of reaction mixture containing 4 μ L of 1 FIREPol Blend Master Mix (Solis BioDyne, Tartu, Estonia), 0.5 μ L of 10 μ M each forward and reverse primers, nuclease-free water, and 100 ng/ μ L of DNA. The reaction was performed in the Veriti Thermal Cycler (Thermo Fisher Scientific 2017, US) using specific primers (Table 1). The PCR program consisted of an initial denaturation at 94 °C for 15 min, followed by 35 cycles of denaturation at 94 °C for 45 s, hybridization for 45 s, from 55 °C to 70 °C according to the primer, extension at 72 °C for 60 s, and a final extension at 72 °C for 10 min. PCR products were separated by electrophoresis on a 1% agarose gel stained with ethidium bromide (10 mg/mL) in 1X TAE buffer using 100 base pair DNA ladder (Solis BioDyne, Estonia). The gels were visualized under UV light using a Gel Doc™ XR + Molecular Imager from Bio-Rad (ibec®, Institut de bioenginyeria de Catalunya).

For cassava brown streak ipomoviruses (CBSI) detection, cDNAs were prepared using the Revert-Aid cDNA synthesis kit (Thermo Fisher Scientific) according to the manufacturer's instruction. Briefly, first strand cDNA was synthesized using 5 μ g of total RNA, 1 μ L of Oligo (dT)₁₈ primer (10 μ M) and nuclease-free water (11 μ L). The mixture was incubated at 65 °C for 5 min. To the above mixture, 5X

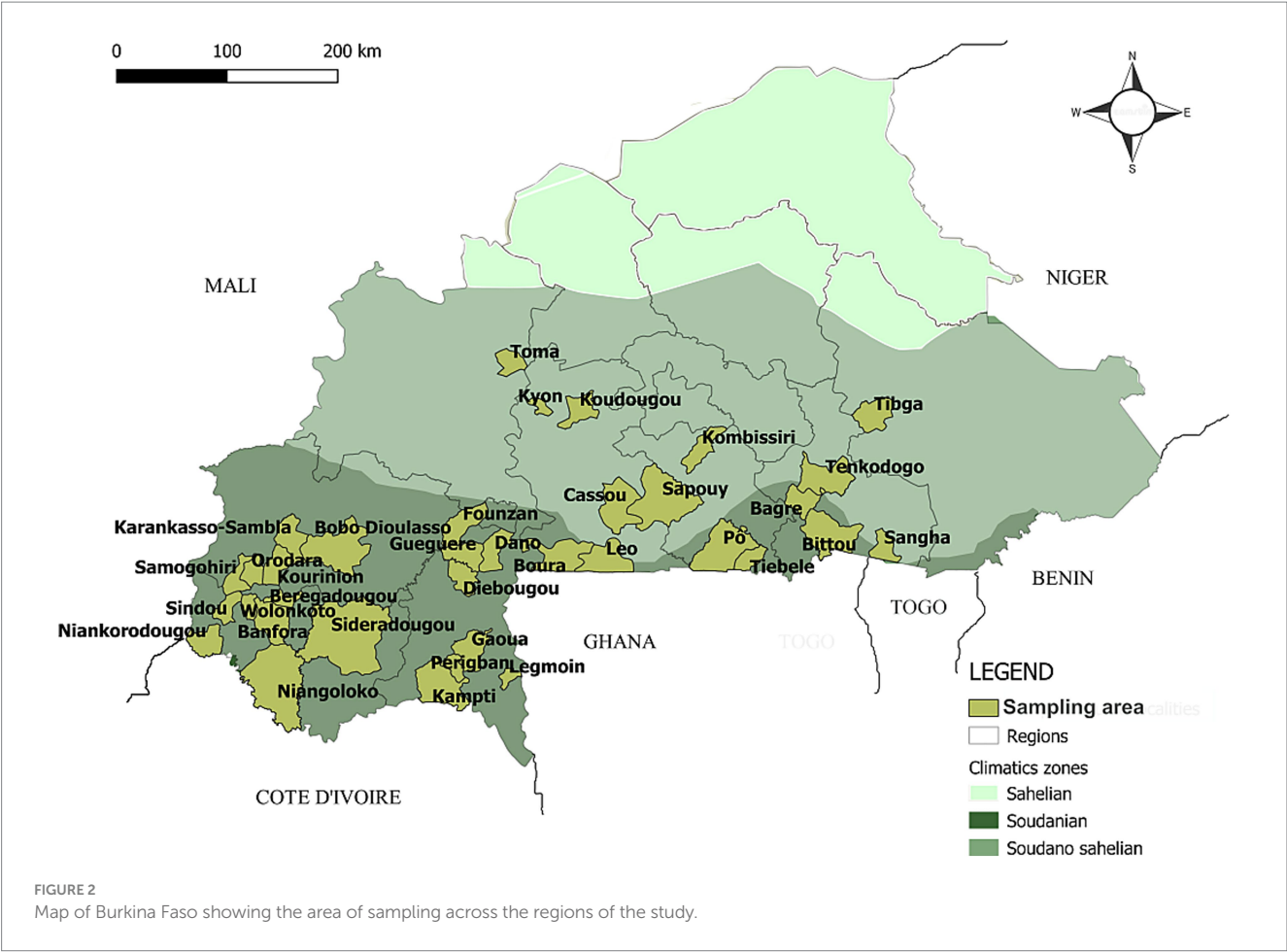


TABLE 1 Primers used for CMB and CBSI detection.

Viruses	Primer name	Primer sequences (5' to 3')	Target region	Size	References
CMB	JSP 001	ATGTCGAAGCGACCAGGAGAT	ACMV DNA-A (CP)	783 bp	Pita et al. (2001)
	JSP 002	TGTTTATTAATTGCCAATACT			
	ACMVBF	TCGGGAGTGATACATGCGAAGGC	ACMV DNA-B (BV1/BC1)	628 bp	Matic et al. (2012)
	ACMVBR	GGCTACACCAGCTACCTGAAGCT			
	ACMV21for	GCAGTGATGAGTTCCCGGTGCG	DNA-A (AC3-AC2-AC1)	552 bp	Matic et al. (2012)
	ACMV21rev	ATTCCGCTGCGCGGCCATGGAGACC			
	JSP 001	ATGTCGAAGCGACCAGGAGAT	EACMV DNA-A (CP)	780 bp	Pita et al. (2001)
	JSP 003	CCTTTATTAATTTGTCACTGC			
	CMBRepF	CRTCAATGACGTTGTACCA	EACMV DNA-A (AC1)	650 bp	Alabi et al. (2008)
	EACMVRepR	GGTTTGACAGAGAACTACATC			
	VNF031/F	GGATACAGATAGGGTTCCAC	EACMV-CM DNA-A (AC2/AC3)	≈ 560 bp	Fondong et al. (2000)
	VNF032/R	GACGAGGACAAGAATTCCAAT			
CBSI	Pri277	GGRCCATACATYAARTGGTT	CBSVs universal	1,670 bp	Apio et al. (2021)
	CBSVDR	GGATATGGAGAAAGRKCTCC			
	CBSVDF2	GCTMGAAATGCGYGGRTAYACAA	UCBSV	437 bp and 343 bp	Apio et al. (2021)
	CBSVDR	GGATATGGAGAAAGRKCTCC	CBSV		

Reaction Buffer, RiboLock RNase Inhibitor (20 U/μl), 10 mM dNTP Mix, RevertAid M-MuLV RT (200 U/μl) were added. The reaction was incubated at 42 °C for 60 min and terminated at 70 °C for 5 min. The resulting cDNAs were used as templates for PCR amplification. The PCR was performed using the universal primer Pri277/CBSVDR to amplify target product of 1,670 bp and the specific primer CBSVDF2/CBSVDR (Apio et al., 2021) to amplify products of 437 bp (UCBSV) and 343 bp (CBSV). The reaction mixture consisted of 20 μL, containing OneTaq Quick-Load 2X Master Mix with Standard Buffer, 20 pmole of each primer at 10 mM, nuclease-free water and 500 ng of cDNA. Amplification conditions were initial denaturation at 94 °C for 30 s, followed by 30 cycles at 94 °C for 30 s, 51 °C for 30 s, 72 °C for 30 s and final extension at 70 °C for 10 min. PCR products were separated by electrophoresis on a 1.2% agarose gel stained with ethidium bromide (10 mg/mL) in 1X TAE buffer. The gel was visualized under UV light.

2.6 Statistical analysis

Data were analyzed using R software v 4.3.1 (R Core Team, 2022). CMD, CBSD, and CGM scores detection distribution across groups were first checked for normality and homogeneity, using Shapiro–Wilk and Bartlett tests, respectively. When the data meet normality and homogeneity assumptions (p -value > 0.05), a one-way analysis of variance (ANOVA) was performed, and means compared using Tukey's HSD *post hoc* test. In contrast, Kruskal–Wallis non parametric test followed by Dunn's test with Bonferroni correction were applied. Differences between groups were considered significant at p -value < 0.05. The boxplots of the scores recorded by each diagnostic method were also drawn.

3 Results

3.1 Extension agents' participation to surveillance

The participation rate of extension agents in this study was assessed by the percentage of participants who surveyed cassava fields, collected samples and sent to the laboratory, in relation to the total number of participants. The overall participation rate of extension agents in cassava field sampling during one year of surveillance (from July, 2022 to June, 2023 without a phone allocated) was 21.67% (13/60). The highest participation rate was recorded in the Cascades region (62.50%, 5/8). In the other regions, the participation rate varied between 12.5 and 25.0% (Table 2). During this period, only 31 cassava fields were surveyed. After the allocation of phones during the second workshop, the number of cassava fields surveyed increased to 132 from July to September 2023. The overall participation rate reached 60% (36/60). Group 1 using the AI tool recorded a participation rate of 36.67% (22/60) and Group 2 using visual observation 23.33% (14/60). With the Exception of the Boucle du Mouhoun and Est regions, where the participation rate remained unchanged at 12.5% (1/8) and 16.67% (1/6) respectively, a significant increase was observed in the other regions (Table 2). The highest rates of 100% were recorded in the regions of Cascades (8/8), Center-Ouest (6/6) and Sud-Ouest (8/8). In the regions of Hauts-Bassins, Center-Est and Center-Sud, the

TABLE 2 Extension agents participation rate across all surveyed regions in 2022 and 2023.

Regions	Participation rate after the first workshop without smartphones in 2022	Participation rate after the second workshop with smartphones allocation in 2023
Boucle du Mouhoun	12.50%	12.50%
Cascades	62.50%	100.00%
Center-Est	25.00%	37.50%
Center-Ouest	16.67%	100.00%
Center-Sud	16.67%	33.33%
Est	16.67%	16.67%
Hauts-Bassins	12.50%	87.50%
Sud-Ouest	12.50%	100.00%
Total	21.67%	60.00%

participation rate was 87.5% (7/8), 37.5% (3/8) and 33.33% (2/6), respectively.

3.2 CMB and CBSI status in collected leaf samples by the group 1 using AI tool

In this group, a total of 65 cassava fields was surveyed to collect 142 leaf samples. Forty (40) leaf samples were recognized as infected with CMD and 102 as apparently healthy according to the perception of Cassava Disease Diagnosis Experts (Figure 3). Molecular analyses by PCR confirmed CMB viruses in 95% (38/40) of symptomatic CMD leaves and 100% (102/102) of apparently healthy were identified as free of CMB virus. Comparing the previous results with the AI tool diagnosis, it was observed that 80% (32/40) of CMD symptomatic leaf samples were diagnosed as CMD by AI tool (Figure 2). However, the AI tool misdiagnosed 15% (6/40) of CMD symptomatic leaves as healthy and 5% (2/40) as CBSI. Nevertheless, the observed symptoms were clearly consistent with CMD. Overall, the AI tool diagnosis was reasonably close to the expert perception of Cassava Disease Diagnosis supported by molecular analysis (Figure 3). Furthermore, all leaf samples subjected to molecular analysis by RT-PCR were negative for CBSI.

3.3 CMB status in leaf samples collected by group 2 by visual observation

In this group, 234 leaf samples were collected from 67 cassava surveyed fields. Sixty-five leaf samples were recognized as infected by CMD and 169 as apparently healthy according to the perception of Cassava Disease Diagnosis Experts. Molecular analysis by PCR confirmed the presence of CMB viruses in 92.31% (60/65) of symptomatic CMD leaves and 100% (169/169) of apparently healthy leaves were found to be free of CMB viruses. Compared to visual observation carried out by Group 2, the latter also recorded 65 leaf samples as CMD infected and 169 as apparently healthy. In summary, the diagnosis based on visual observation was reasonably similar to

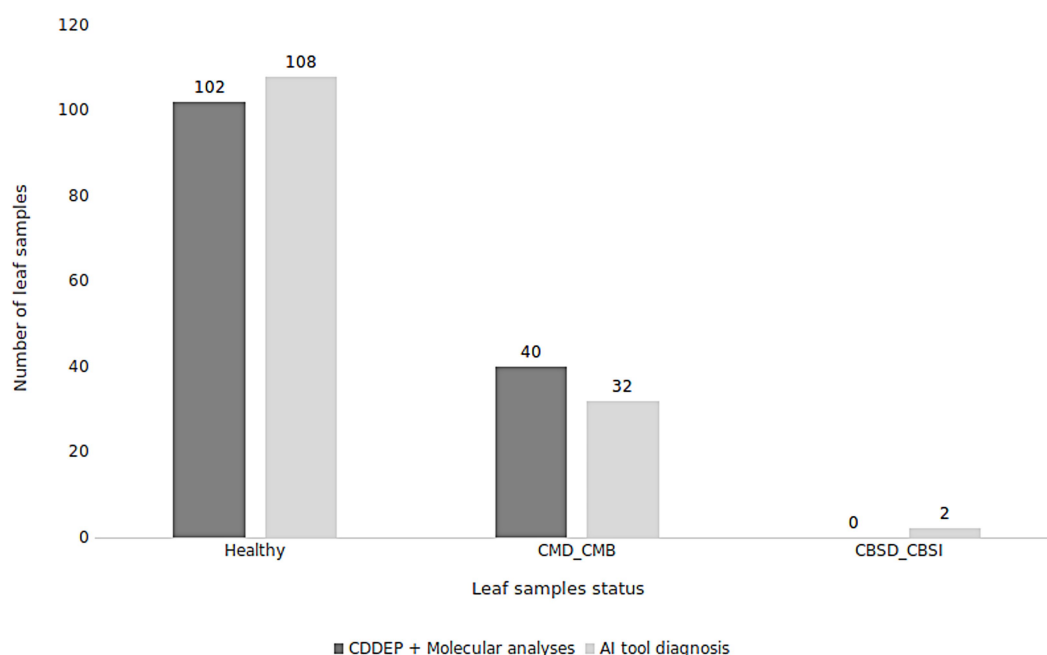


FIGURE 3
CMB and CBSI detection within collected leaf samples.

those observed by Cassava Disease Diagnosis Experts' Perception supported by molecular analysis.

3.4 Accuracy of AI tool, AEAP, and CDDEP to detect cassava diseases

The diagnostic results of the AI tool, the Agricultural Extension Agents' Perception (AEAP) of CMD, CBSD and CGM symptoms recognition compared to Cassava Disease Diagnostic Experts' Perception (CDDEP) and molecular diagnosis were evaluated. For Group 1 AI tool users, AI diagnosis showed no significant difference (p -value = 0.709) in CMD symptoms recognition compared to CDDEP and molecular detection by PCR (Figure 4A). The mean scores (Table 3) for CMD detection were $29.83 \pm 12.99\%$ for AI tool diagnosis, $37.12 \pm 12.78\%$ for expert perception of cassava disease diagnosis and $36.10 \pm 12.74\%$ for molecular detection. In addition, there was no significant difference (p -value = 0.551) in CGM detection between AI diagnosis and CDDEP (Figure 4B). The mean scores for CGM symptom recognition were $6.936 \pm 3.62\%$ for AI diagnosis and $3.746 \pm 3.13\%$ for Cassava Disease Diagnostic Expert Perception (Table 3). Following CBSD symptoms recognition, only AI diagnosis revealed its presence with a mean score of $0.866 \pm 0.866\%$ (Table 3). However, according Experts' Perception of Cassava Diseases Diagnosis supported by RT-PCR testing, no CBSD was present in the collected cassava samples.

In Group 2, which used visual observation based on perception, no CBSD was detected in the fields surveyed. RT-PCR results confirmed these observations. However, no significant difference (p -value = 0.997) was observed for CMD detection. The mean scores of CMD symptoms detection between the extension agents' perception and cassava disease diagnosis experts'

perception ($46.07 \pm 13.00\%$) were similar (Table 3), but higher than the molecular analysis results, which were $43.87 \pm 12.07\%$ (Figure 5A). The CGM symptoms were detected with a mean score of $22.29 \pm 9.03\%$ for extension agents' perception and $22.29 \pm 9.03\%$ for cassava disease diagnosis experts' perception (Figure 5B).

3.5 ACMV prevalence in CMD-infected leaf samples

In the current study, a total of 41 CMD-infected fields were recorded, giving an overall prevalence of 31.06% (41/132). The CMB detected in CMD-infected leaves was *African Cassava Mosaic Virus* (ACMV) in single infections. The prevalence of ACMV in CMD symptomatic leaf samples collected from Group 1 was 95% (38/40) and 92.31% (60/65) for Group 2. The total prevalence was 93.33% (98/105). *East African Cassava Mosaic Virus* (EACMV) was not detected.

4 Discussion

Viruses are a major threat to cassava production in sub-Saharan Africa. Attempts to control these pathogens rely mainly on field inspections and the promotion of good management practices through the use of healthy cuttings. Classical epidemiology, which has been the most widely used strategy to date, is expensive and time-consuming. However, in the field of human and animal health, participatory surveillance is increasingly applied (McNeil et al., 2022), and offers the advantage of warm anticipation and rapid response (Smolinski, 2016).

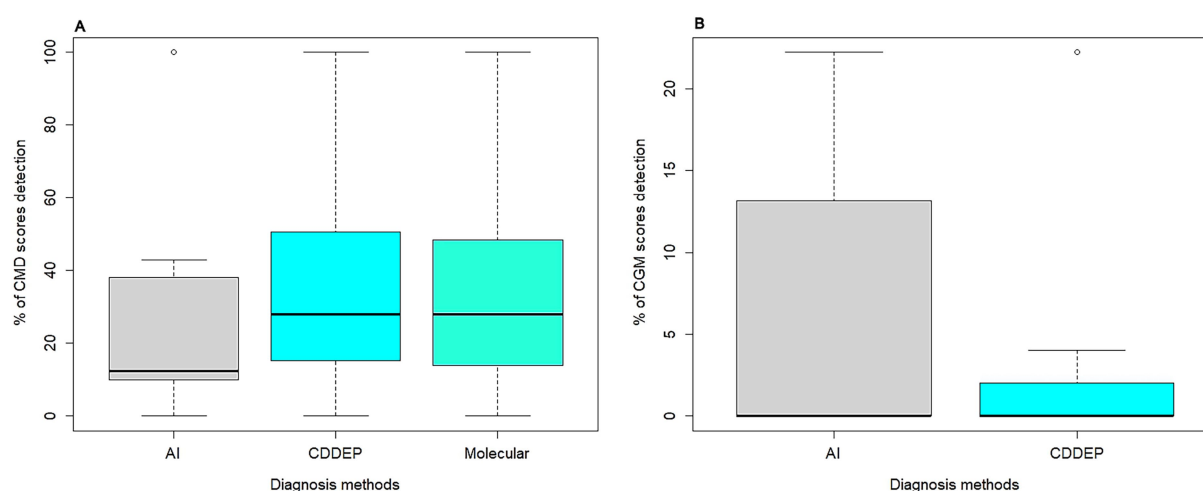


FIGURE 4

(A) Comparison of the ability of AI diagnosis (AI) and cassava disease diagnosis experts' perception (CDDEP) to cassava mosaic disease (CMD) symptoms recognition and confirmed by molecular analysis. The black line within the boxes represents the median, the top and bottom of the box represent the 75th and the 25th percentiles, the whiskers represent the maximum and minimum and the symbol (°) represent the outlier.

(B) Comparison of the ability of AI diagnosis (AI) and cassava disease diagnosis experts' perception (CDDEP) to cassava green mite (CGM) symptoms recognition. The black line within the boxes represents the median, the top and bottom of the box represent the 75th and the 25th percentiles, the whiskers represent the maximum and minimum and the symbol (°) represent the outlier.

TABLE 3 Mean scores of AI diagnosis, CDDEP, AEAP about diseases symptoms recognition and molecular analysis.

	CMD (%)	CBSD (%)	CGM (%)
Mean scores of diagnosis based on AI tool			
AI	29.830 ± 12.99	0.866 ± 0.866	6.936 ± 3.62
CDDEP	37.124 ± 12.78	0	3.746 ± 3.13
Molecular analyses	36.097 ± 12.74	0	nd
P-value	0.709	0.368	0.551
Mean scores of diagnosis based on perception			
AEAP	46.07 ± 13.00	0	22.29 ± 9.03
CDDEP	46.07 ± 13.00	0	22.29 ± 9.03
Molecular analyses	43.87 ± 12.07	0	nd
P-value	0.997	0	1

Recent innovations in ICT have also provided tools, termed “AI tools,” that have contributed significantly to the management of emerging infectious diseases (Brownstein et al., 2023; Sood et al., 2023). Unfortunately, the field of plant health has benefited little from work using participatory approaches and AI tools for the control of plant viral diseases. The present study, based on participatory approaches combined with the use of an AI tool (Nuru), was implemented as an alternative to the classical surveillance and epidemiology of cassava viral diseases in Burkina Faso. The accuracy of the agricultural extension agents and AI tool to detect CMD and CBSD are discussed.

The overall participation rate of agricultural extension agents has been improved after the workshops and mobile phone equipment for

data collection. Previous studies have reported that workshops are a key factor in the success of applying participatory surveillance (Bordier et al., 2021). In fact, the workshop is known to correct any eventual limitations related to the surveillance. It also helps to build confidence among stakeholders, particularly agricultural extension agents. Here, the number of cassava fields monitored increased gradually from 31 to 132 after the workshop. Actually, participants provision with smartphones improves significantly their involvement in diseases surveillance (Orozco et al., 2020). As reported by Dhavale et al. (2025), awareness campaigns and trainings with mobile tools engaging farmer and extension agents through participatory epidemiology enables early detection and rapid response to disease management. Nevertheless, the participation rate remained low in two regions such as Boucle du Mouhoun and Est. The security crisis which affected these regions would have negatively affected the ability of agricultural extension agents to survey fields and collect data. Despite this fact, cassava samples have been collected and sent to the experts of cassava disease diagnosis for laboratory analysis.

Molecular analysis confirmed the presence of CMB within CMD symptomatic leaf samples both samples collected by visual perception and AI tool (Figure 3). AI tool detected accurately symptoms of CMD as well as CGM damages (Figure 4), as reported previously (Mrisho et al., 2020). Although, the accuracy of AI to recognize CMD and CGM symptoms was similar to that of the visual perception of agricultural extension agents, AI tool showed slight precision (80%). These findings agree with Saffa et al. (2025), who reported that AI tool is efficient for the CMD detection like molecular analysis. The current study found that AI tool accurately recognized asymptomatic leaf, which was supported by experts perception and molecular analysis. A similar result was observed by Adjéi et al. (2024), supported that AI tool helped farmers in selecting cassava virus-free cutting in Côte d'Ivoire. Obviously, AI tool misdiagnosed some cassava leaf samples. The CBSD symptoms and healthy leave recorded

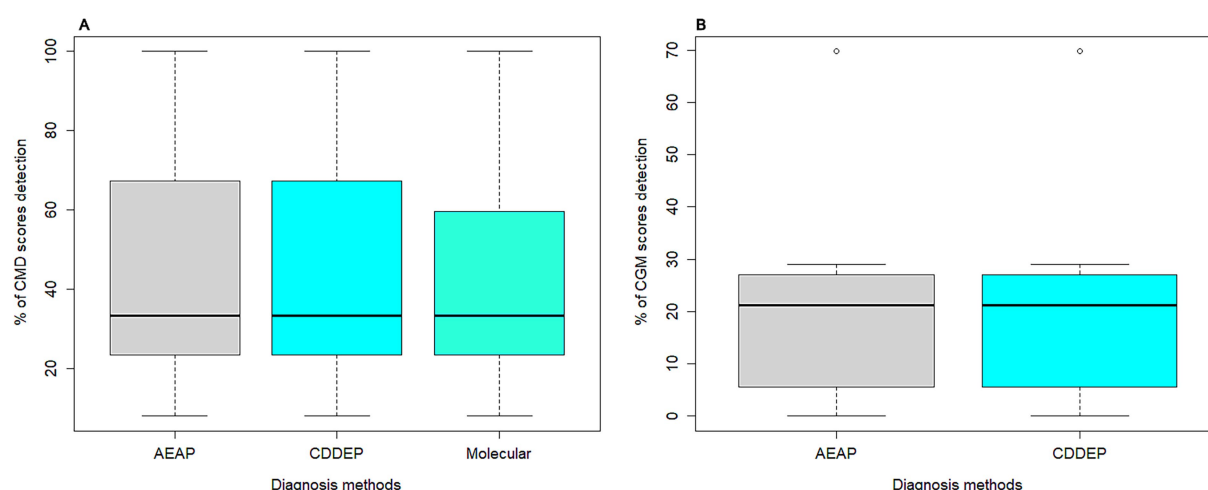


FIGURE 5

(A) Comparison of the agricultural extension agents' perception (AEAP) and cassava disease diagnosis experts' perception (CDDEP) to cassava mosaic disease (CMD) symptoms recognition and confirmed by molecular analysis. The black line within the boxes represents the median, the top and bottom of the box represent the 75th and the 25th percentiles, the whiskers represent the maximum and minimum. (B) Comparison of the ability of agricultural extension agents' perception (AEAP) and cassava disease diagnosis experts' perception (CDDEP) to cassava green mite (CGM) symptoms recognition. The black line within the boxes represents the median, the top and bottom of the box represent the 75th and the 25th percentiles, the whiskers represent the maximum and minimum and the symbols (°) represent the outlier.

with AI tool were clearly matched with CMD and molecular analysis confirmed the presence of CMB in these samples. Low accuracy of CBSD symptoms recognition by AI diagnosis was reported during AI tool development (Ramcharan et al., 2019; Mrisho et al., 2020). On the other hand, it was reported that CBSD is localized only in East and Southern Africa (Tumwegamire et al., 2018), with a high risk of its spreading to West Africa (Legg et al., 2011). CBSD and healthy leave misdiagnose could also be attributed to the low resolution of the camera (5 MP Back) implemented in the smartphones used in the current study as reported by Mrisho et al. (2020). So, AI tool for cassava symptoms diagnosis need to be further improved in CBSD symptoms recognition by providing more similar symptoms to Nuru databases, which could contributed to the tool accuracy. But in the meantime, molecular diagnosis remains the better suited to detecting CBSD.

In the group of visual observation based on perception, each stakeholder (AEAP and CDDEP) was able to identify clearly CMD and CGM symptoms as reported in Figure 5. Agricultural extension agents have a good perception on cassava symptoms recognition. The training organized during the workshop would have strengthened the ability of the extension agents of agriculture to accurately identify the main diseases of cassava. As reported by Mrisho et al. (2020), rigorous training of agricultural extension workers about diseases symptom recognition contributes effectively to improve their perception.

This study revealed that the prevalence of CMD was relatively moderate in the cassava producing regions 31.06% (41/132), showing that CMD is regressing in Burkina Faso comparatively to prevalences observed in 2016 (84.0%) and 2017 (65.9%) (Soro et al., 2021). This regression of CMD prevalence could be to the results of an awareness about CMD damages as well as adoption of good agricultural practices by farmers. However, ACMV in single infection showed high abundance across all surveyed regions 93.33% (98/105). Many reports support that ACMV are the most widespread cassava virus in West

Africa (Pita et al., 2001; Tiendrébéogo et al., 2012; Torkpo et al., 2018; Eni et al., 2021; Soro et al., 2021; Houngue et al., 2022; Amoakon et al., 2023).

The transfer of ICTs to the agricultural sector is increasingly encouraged in order to relieve the efforts of extension agents and farmers (Kalaitzandonakes et al., 2018). When these innovations are suitable for non-specialists such as extension agents and farmers, they improve not only their knowledge, but also help to increase agricultural yields. However, some of these innovations are subjected to easy applicability because of the complexity of their use by extension agents and farmers. Finding in the current study, which involved the use of Nuru through participatory surveillance approaches, are proof of a model of technological innovation that is easily transferable to non-specialists. It will be certainly a powerful tool to maintain the dialog between extensions agents, model farmers and seed multipliers with researchers to monitor the cassava disease and prevent any incursion of CBSD in West Africa.

5 Conclusion

Finding in this study revealed that participatory approaches can be effective for the control of cassava viral diseases. The success of participatory approaches is founded on the training and equipping of grassroots stakeholders such as extension agents and farmers with adapted tools. AI tool diagnosis and visual inspection about CMD detection, performed by extension agents revealed similar results to experts perception supported by molecular analysis. The epidemiological data of this study revealed that CMD is declining in Burkina. However, considering the low ability of AI tool to accurately detect symptoms of the CBSD, an improvement of AI this tool would be essential for cassava's fields diagnosis. AI tool could play a first-line diagnostic role if users are properly trained. AI tool could support

agricultural extension agents' perception about symptom recognition and help to bridge knowledge gap between agricultural extension agents and cassava diagnostics experts for a better management of cassava viral diseases. So, the surveillance and skills of agricultural extension agents must be regularly strengthened by continuous trainings, combined with awareness.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SS: Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing. FT: Conceptualization, Funding acquisition, Project administration, Resources, Supervision, Validation, Writing – review & editing, Writing – original draft. ET: Data curation, Investigation, Writing – original draft, Writing – review & editing. PN: Data curation, Investigation, Methodology, Writing – review & editing, Writing – original draft. FD: Supervision, Writing – original draft, Writing – review & editing. LT: Supervision, Writing – original draft, Writing – review & editing. JP: Funding acquisition, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. AE: Funding acquisition, Project administration, Resources, Supervision, Writing – original draft, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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