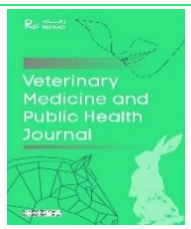
www.refaad.com

Veterinary Medicine and Public Health Journal (VMPH)

Journal Homepage: https://www.refaad.com/Journal/Index/7

E-ISSN 2707-7195 | P-ISSN 2707-7187

Vol. 7, No. 3, 2026, pp. 153 - 166



Smartphone-integrated Microscopy and Deep Learning for Early Mold Screening in Cinnamon: A Scoping Review of Transferable Evidence and Validation Requirements

Dr. Sana Mohamed Alkhateeb[1*], Dr. Emran Mustafa Alshatnawi[1], Dr. Maysaa Mohammad Rasheed[1], Dr. Rani Radi Alhaj Alakhras[1]

[1] Jordan Food and Drug Administration, Jordan.

* Corresponding Author: Sana Alkhateeb (Eng.sana2016@gmail.com)

Original Research Article

https://doi.org/10.31559/VMPH2026.7.3.5

Received: 6 Sept 2026

Revised: 27 Oct 2026

Accepted: 2 Nov 2026

How to cite this article: Alkhateeb, S. M, et al. (2026). Smartphone-integrated Microscopy and Deep Learning for Early Mold Screening in Cinnamon: A Scoping Review of Transferable Evidence and Validation Requirements. *Veterinary Medicine and Public Health Journal*, 7 (3), 153-166.

https://doi.org/10.31559/VMPH2026.7.3.5

This file is licensed under a *Creative Commons Attribution 4.0 International*

Abstract:

Objectives: To map direct and transferable evidence for smartphone-integrated microscopy and deep learning as a low-cost approach to early mold screening in cinnamon and to identify requirements for end-to-end validation.

Methods: This PRISMA-ScR-informed scoping review searched PubMed/MEDLINE and IEEE Xplore on 5 September 2026 and examined backward citations. Screening, charting, and narrative transferability appraisal were performed by one reviewer. The two-database, English-language search and unretrieved reports limit completeness.

Results: The documented aggregate flow comprises 786 record appearances (369 PubMed, 370 IEEE Xplore, and 47 backward-citation appearances), 29 duplicates removed, 757 records screened, 168 reports sought, 62 not obtained, 106 full texts assessed, 24 exclusions, and 82 included publications. The evidence domains were portable microscopy (n = 38), fungal-image analysis (n = 24), food-mold recognition (n = 5), and spice/cinnamon contamination (n = 15). Published examples support component feasibility, but only a subset of individual-study outcomes could be independently rechecked in this revision.

Conclusion: Among the retrieved and mapped studies, no report was identified that prospectively validated a complete culture-referenced, sample-level smartphone workflow for pre-visible mold growth in cinnamon. Smartphone microscopy remains a candidate triage technology, not a substitute for culture, taxonomic confirmation, or separate mycotoxin analysis.

***Keywords*:** *cinnamon; deep learning; food safety; mold detection; smartphone microscopy.*

1 Introduction

Cinnamon is marketed as bark, chips, and powder and passes through harvesting, drying, storage, milling, transport, repackaging, and retail. Low water activity usually restricts fungal proliferation but does not establish sterility. Airborne spores or fragments can enter from soil, dust, drying surfaces, equipment, and handling. Fungal presence, viability under specified culture conditions, active growth, and chemical toxin residues are different endpoints. Spice surveys have recovered Aspergillus, Penicillium, Rhizopus, Mucor, and other fungal taxa, while separate chemical surveys have detected aflatoxins and ochratoxin A in certain spice markets (El-Kady et al., 1995; Elshafie et al., 2002; Garcia et al., 2018; Hashem & Alamri, 2010; Mandeel, 2005; Nordin et al., 2022).

These facts show that a dry, visually acceptable product can still be fungal or toxin-laden. Cinnamon is also a hard matrix to visualize. Bark is fibrous, fissured and heavily pigmented; powder contains irregular fragments whose edges and branching patterns may look like fungal structures at low optical resolution. Essential oil components, particularly cinnamaldehyde-rich fractions, may inhibit some fungi but antimicrobial activity does not imply sterility and can't be taken to guarantee every product, lot, and storage condition. Aflatoxin B1 has been reported in imported cinnamon, and more general spice research has shown that contamination differs with origin, processing, packaging and storage, and not just product identity (Demirhan & Demirhan, 2023; Safavizadeh et al., 2022).

Microscopic recognition of a spore, hypha, or fungal fragment may indicate fungal material but does not, by itself, prove viability or active growth. The absence of visibly growing mold also does not rule out pre-existing mycotoxins: toxins formed during earlier fungal activity may persist after growth has ceased or viable fungi are no longer recoverable. Conversely, fungal presence does not establish toxin production. In this review, 'fungal-presence screening' means detecting potentially fungal optical structures; a stronger claim of 'pre-visible growth screening' requires prospective evidence of viable growth and paired longitudinal visual assessment. Culture provides a viability-related reference under specified incubation conditions and permits recovery of fungal isolates, while molecular assays may support identification. Mycotoxin status requires separate validated chemical or immunochemical testing. These reference approaches require equipment, consumables, trained personnel, and quality assurance that can be difficult to sustain in resource-constrained inspection settings.

Deep learning can alleviate manual interpretation of data by learning discriminative patterns from annotated data. In mycology, convolutional networks, object detectors and vision transformers have been used to classify microscopic fungal images, localize fungal structures and identify spores as well as colonies (Gümüş, 2024; Koo et al., 2021; Sun et al., 2016; Zieliński et al., 2020). Picek et al. (2022) addressed macroscopic fungi recognition and therefore provides contextual evidence for artificial-intelligence methods rather than validation of microscopic mold detection.

Recently, food-focused work has extended this concept to early bread mold and multi-food smartphone microscopy (Pham et al., 2026; Treepong & Theera-Ampornpunt, 2023). However, the evidence is not yet abundant for the full target application. A model that identifies mature mold from clean food in a curated image set is not an early-detection system. Similarly, a microscope that can resolve parasites or blood cells does not necessarily resolve sparse fungal elements against cinnamon particles. There must be a chain of evidence of repeatable sampling, sufficient optical contrast, culture-linked labels, appropriate definition of pre-visible growth, independent training and evaluation lots, robustness on different phones and product forms and decision thresholds for screening.

Failure at any link in this chain can make image-level performance appear stronger than sample-level performance. Accordingly, this scoping review asks: What direct and transferable evidence supports smartphone-integrated microscopy and deep learning as a low-cost approach to early mold screening in cinnamon, and which validation gaps remain? The objectives were to map primary evidence across four related domains, identify technical and methodological limitations, distinguish direct evidence from transfer by analogy, and define minimum requirements for future end-to-end studies.

Operational endpoint hierarchy: (1) optical structures suggestive of fungi, (2) culture-confirmed viable propagules at a matched sampling time, (3) culture- or time-series-confirmed growth before an independently blinded visual threshold, and (4) analytically measured

mycotoxins. Evidence for one tier is not automatically evidence for the others.

2 Methods

2.1 Review design and reporting approach

We conducted a scoping review with critical narrative synthesis, guided by the PRISMA extension for scoping reviews (PRISMA-ScR; Tricco et al., 2018). The population/context comprised cinnamon, other culinary spices, or technically relevant imaging specimens; the concepts were portable optical acquisition, automated fungal-image interpretation, food-mold recognition, and fungal or mycotoxin contamination. Heterogeneous designs precluded a shared estimand or meta-analysis. No prospectively registered protocol was provided. Appendix C gives an item-by-item reporting checklist, including unresolved documentation gaps.

2.2 Information sources and search strategy

The original search was reported as completed on 5 September 2026 in PubMed/MEDLINE and IEEE Xplore, without start-date restrictions. PubMed employed an English-language filter; IEEE did not, although screening was restricted to English-language reports. These two databases were chosen to span biomedical/ microbiological imaging and engineering/computer-vision literature, not because they exhaust food science, agriculture, or analytical chemistry. Food-specific indexes (for example, Scopus, Web of Science, CAB Abstracts, FSTA, and AGRICOLA) were not systematically searched; therefore, missed multi-spice surveys and non-indexed conference reports are plausible. Google Scholar and individual publisher platforms were omitted from the reported rerun because record-level export and reproducible deduplication had not been documented. This design limits comprehensiveness rather than establishing that evidence outside these sources is absent.

Seven platform-specific searches addressed smartphone microscopy, automated fungal-image analysis, food-mold recognition, and cinnamon contamination (exact historical strings and yields in Appendix A). PubMed contributed 369 appearances, IEEE Xplore 370, and backward checking of the 47 previously cited publications contributed 47 appearances, producing the stated total of 786 before deduplication. These 47 are citation-search appearances, not 47 verified additional unique references: the supplied materials do not preserve source-level overlap or demonstrate which citations were genuinely new after deduplication. Exact PubMed title/abstract restrictions, including the cinnamon requirement in search D, are relatively insensitive to multi-spice studies that omit 'cinnamon' from the title or abstract. Appendix A therefore distinguishes the executed historical strategy from proposed sensitivity searches; proposed strings were not run and must not be incorporated into the original flow counts.

2.3 Eligibility criteria

Eligible primary reports addressed at least one prespecified evidence domain: (i) portable/smartphone microscopy, (ii) automated microscopic fungal or spore analysis, (iii) food-surface or food-microscopy mold recognition, or (iv) fungal or mycotoxin contamination in cinnamon or culinary spices. Inclusion in domains (i)–(iii) did not imply that a study tested cinnamon. For domain (iv), a multi-spice survey was eligible as direct cinnamon evidence only when a cinnamon sample, subgroup, or cinnamon-specific quantitative finding could be verified; surveys without extractable cinnamon results are contextual related-spice evidence and cannot substantiate cinnamon-specific prevalence. The original full-text screening counted nine exclusions for unavailable cinnamon-specific findings. Where the supplied study list does not support confirmation of a cinnamon subgroup, the entry is expressly marked 'cinnamon-specific extraction not verified' in Table S1 rather than being presented as direct cinnamon evidence. Distant clinical/material studies are retained only as component-transfer analogues when they show a specific technique (e.g., calibrated mobile optics, optical texture discrimination, device-based automation, specimen-level reference pairing); they provide no evidence about cinnamon biology.

2.4 Study selection and data extraction

The manuscript reports 786 record appearances, 29 duplicates, 757 unique records screened, and 589 title/abstract exclusions. Of 168 reports sought, 62 were not obtained and 106 were assessed in full text. The reported 24 full-text exclusions comprised no extractable cinnamon-specific result (n = 9), matrix/imaging/validation mismatch (n = 6), non-eligible target (n = 4), non-eligible sensing method (n = 3), and lack of biological validation for a smartphone microscope (n = 2), leaving 82 included publications. These counts reconcile arithmetically.

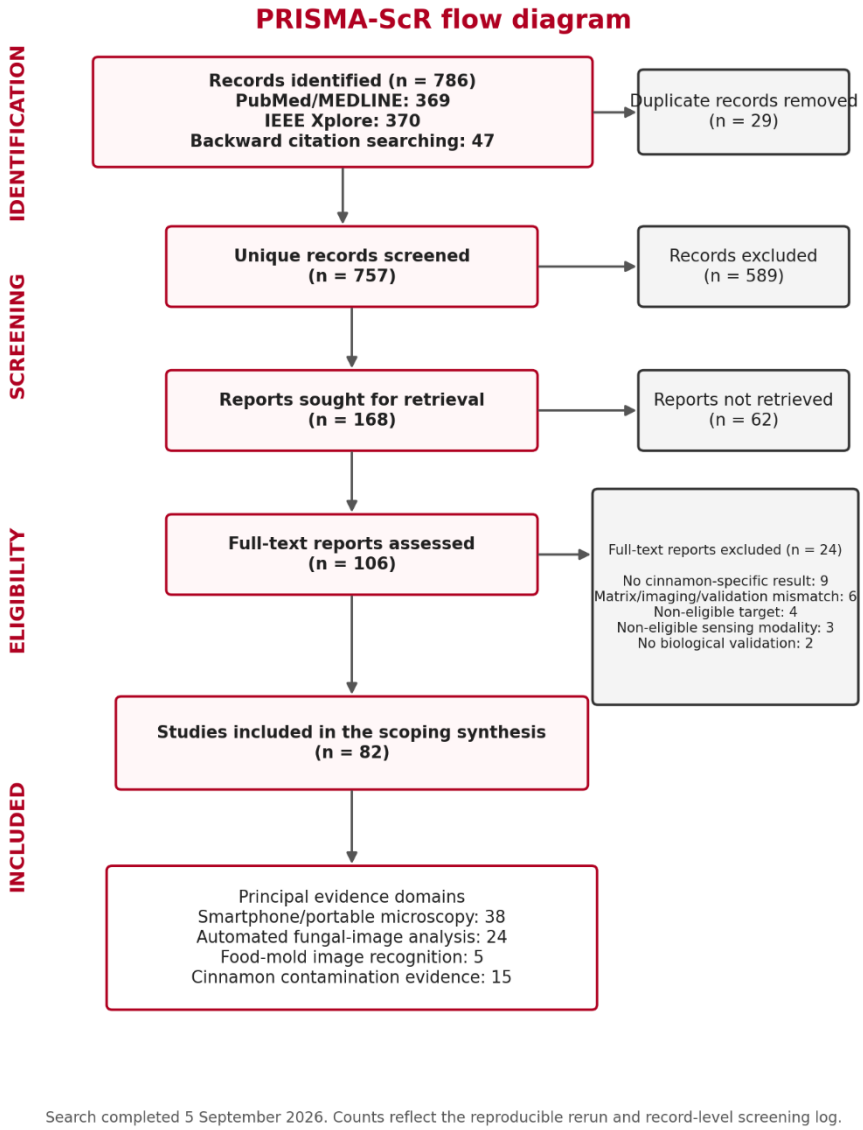


Figure 1: PRISMA-ScR flow diagram for the reproducible search and screening process.

2.5 Methodological appraisal and transferability assessment

No pooled methodological score was calculated because designs, biological targets, reference standards, and units of analysis varied substantially. Instead, the reported appraisal domains were (a) specimen representativeness, (b) independence and credibility of labels/reference tests, (c) time-matched imaging and reference testing, (d) validation at image versus specimen/lot level, (e) risk of correlated-data leakage, (f) handling of ambiguous or unreadable fields, and (g) external applicability to cinnamon. The qualitative appraisal identified recurring concerns: portable-optics studies frequently target nonfood specimens; many fungal classifiers use curated microscopy and cannot establish viability; macroscopic food-mold datasets can overrepresent obvious disease; and spice chemistry or culture surveys do not assess smartphone decision accuracy. These are domain-level observations, not a verified study-by-study frequency estimate. Table S1 assigns a transparent transferability qualification to each entry and flags fields that could not be checked from the submitted materials; counts of studies at each risk level should not be inferred from these missing fields.

2.6 Evidence synthesis

The 82 entries are retained in their original four principal domains for traceability: portable microscopy (n = 38), automated fungal-image analysis (n = 24), food-mold image recognition (n = 5), and spice/cinnamon contamination (n = 15). For evidential interpretation, three non-interchangeable levels apply: D-direct cinnamon evidence with an explicit cinnamon-specific result; R-related food or spice evidence without an

independently verified cinnamon endpoint; and C-component-only transfer from imaging, algorithmic, or biomedical studies. D establishes contamination relevance, not smartphone diagnostic validity; R informs matrix-specific challenges, and C informs individual technical capabilities. The 15 domain-(iv) entries must not all be construed as verified cinnamon-specific reports. Table S1 documents the provisional evidence tier and the reason for transfer.

3 Results

3.1 Characteristics of the evidence base

The original inventory comprises 82 publications (portable microscopy, 38; fungal-image analysis, 24; food-mold recognition, 5; spice/cinnamon contamination, 15). These are bibliographic-domain counts, not counts of independently validated cinnamon diagnostic systems. Among directly checked examples, Treepong and Theera-Ampornpunt (2023) evaluated 1,495 white-bread and 1,488 whole-wheat microscopic images using a 50× smartphone clip-on lens and reported image-level F1 scores of 0.9948 and 0.9972; however, their endpoints were visually labeled bread-image classes rather than paired culture-confirmed cinnamon lots. Jubayer et al. (2021) analyzed 2,050 moldy-food images and reported 98.1% precision, 100% recall, and 99.6% average precision for YOLOv5, again without a cinnamon sample-level endpoint. Pham et al. (2026) released 4,941 annotated food-microscopy images across 11 foods, supplying useful cross-matrix and device evidence but no verified cinnamon cohort. The full table distinguishes independently checked numerical values from details not extractable from the submitted review.

Table 1: Evidence map of the 82 included primary studies and their relevance to cinnamon screening.

Evidence domain	Included studies	Contribution to the review question	Limitation for cinnamon translation
Smartphone or portable microscopy	38	Establishes low-cost optics, illumination, acquisition control, and automated portable workflows.	Most studies concern biomedical or laboratory targets rather than cinnamon particles and sparse fungal structures.
Automated fungal-image analysis	24	Shows feasibility for fungal classification, localization, segmentation, or spore counting.	Curated datasets, image-level splitting, and limited external validation constrain transferability.
Food-mold image recognition	5	Demonstrates image-based recognition on foods or grains, including early or localized mold detection.	Macroscopic growth and controlled contamination often make the task easier than pre-visible retail cinnamon screening.
Spice/cinnamon contamination evidence	15	Reports fungal or toxin findings in culinary spices; cinnamon-specific endpoints vary by study.	These studies establish hazard relevance, not diagnostic accuracy of smartphone microscopy.

3.2 Smartphone microscopy as a low-cost imaging platform

Early mobile-microscopy studies showed that a phone camera can be used as the detector for compact bright-field and fluorescence systems. Breslauer et al. (2009) demonstrated the clinical significance of mobile-phone microscopy in global health applications and Smith et al. (2011) emphasized the phone as a platform for device development and education. Zhu et al. (2011) enabled wide-field fluorescence in a phone attachment, Tapley et al. (2013) presented the field diagnosis technique with mobile digital fluorescence microscopy for tuberculosis. These studies demonstrate the hardware feasibility of portable microscopy with no equivalent to benchtop microscopy for every target. But low cost does not eliminate optical discipline.

Bogoch et al. (2013) used mobile-phone microscopy for helminth diagnosis and Switz et al. (2014) showed an accessible configuration based on a reversed phone-camera lens. Skandarajah et al. (2014) did quantitative mobile imaging and highlighted the need for system characterization, not just nominal magnification. Phillips et al. (2015) extended mobile imaging with multi-contrast acquisition and computational refocusing. These issues are critical for the uneven and highly textured cinnamon matrix: a fixed geometry, well-calibrated field of view, reproducible lighting, and the chosen focus quality are all needed. A portable microscope can also be used for interpretation. D'Ambrosio et al. (2015) combined a mobile microscope with an automated system to measure blood-borne parasites.

Koydemir et al. (2015) combined phone-based fluorescence imaging with machine learning for automated parasite detection, and Pirnstill and Coté (2015) integrated polarization in a mobile

microscope for malaria diagnosis. Rivenson et al. (2018) used deep learning to enhance mobile-phone microscopy images computationally. These works show that portable acquisition, image enhancement, and automated interpretation can be integrated, but do not directly validate food-mold screening.

For cinnamon, the most useful lesson is that the phone is part of the measurement chain. Camera model, sensor processing, compression, focus behavior, white balance, lens alignment, illumination and distance to the sample can all change the learned signal. A classifier trained on one phone may associate fungal status with the rendering pipeline of that device. Cross-device validation and acquisition standardization are not optional engineering refinements; they are prerequisites for claims of portability.

3.3 Deep learning for fungal morphology and spore recognition

Computer vision has been applied to fungi on several biological scales. Sun et al. (2016) used conventional and deep learning to detect mold colonies on unhulled paddy showing the separation of fungal growth from a complex agricultural substrate. Zieliński et al. (2020) classified fungal images, Koo et al. (2021) localized superficial fungal infection using a region-based convolutional network, and Gümüş (2024) investigated vision transformers for microscopic fungal classification. Picek et al. (2022) focused on macroscopic citizen-science fungi recognition and thus context-based rather than microscopic information. These studies confirm that learned models can represent fungal morphology in a context where class balance, preparation, image scale, and taxonomic composition of the training data are important.

Spore-oriented studies help define transferable algorithms but do not establish biological early growth. Crespo-Michel et al. (2023) introduced grapevine spore micrographs, Li et al. (2023) analyzed cucumber gray-mold spores, Javidan et al. (2024) examined tomato pathogen spores, and Zhou et al. (2024) and Zhang et al. (2024) applied object detectors to rice-blast and wheat-scab spores. Soltani Nezhad et al. (2024) addressed Trichoderma spore classification, while Huang et al. (2023) used transfer learning for laboratory filamentous-fungus identification. Their contributions concern microscopic object localization and classification; a detected spore need not be viable or indicate active growth, and none supplies prospective culture-referenced cinnamon-lot evidence.

These results demonstrate feasibility, not interchangeability. Most plant-pathogen studies start with enriched spore preparations or slides on which the target occupies a significant portion of the field. Cinnamon screening instead involves sparse organisms, opaque particles, fibers, oils, dust, and possibly mixed taxa. Species-level classification may not be realistic and therefore not necessary for an initial screen. A good first target to be identified would be binary or triage-based detection of fungal structures at the sample level followed by culture, taxonomic identification, and toxin analysis. The literature also points out a validation hazard: images are not independent when they come from the same plate, sample, colony, time series, or acquisition session. A random image-level split may lead to nearly identical fields in development and test sets, and a model can learn background, preparation, or device signatures from them. For cinnamon, every image from the same commercial lot and experimental unit should be stored in one partition. External validation should be done with new lots, a later acquisition period, and ideally with more phones and operators.

3.4 Food-mold recognition and the meaning of early detection

Food-specific studies close some of the translational gap. Sun et al. (2016) investigated mold colonies on paddy, linking fungal recognition to a commodity surface. Treepong and Theera-Ampornpunt (2023) studied bread mold using smartphone microscopic images and convolutional networks and framed the task as early detection. Pham et al. (2026) introduced MobileMold, a smartphone-microscopy dataset from various foods, phones, and clip-on microscopes. The broadening of the matrices and hardware is important because it can also test whether learned features stay stable, both with the background and acquisition system.

An operational distinction is necessary: a visible microscopic spore may be dormant but viable, nonviable, or a fragment, and none by itself proves active growth. Here ‘fungal-presence screening’ denotes fungal-like optical structures and ‘pre-visible growth screening’ requires prospective demonstration of culture-linked growth preceding a blinded, independently assessed macroscopic threshold. A culture-positive sample may have no detectable structures in the sampled fields. Valid early-growth testing requires matched sampling and culture, blinded visual

assessments, time-indexed observation, and predefined field-to-sample aggregation. Fungal microscopy does not determine chemical toxin status.

Food-mold classifiers also face spectrum bias: extreme positive examples and pristine controls make image recognition easier than inspection of cinnamon with fibers, dust, glare, yeasts, nonviable fragments, mixed molds, and ambiguous fields. Evaluation should distinguish image-level labels from independent sample/lot diagnoses, with predefined aggregation and an indeterminate outcome when necessary. Negative microscopic fields do not establish either culture negativity or toxin absence.

3.5 Cinnamon and spice contamination evidence

The biological rationale for screening is supported by decades of spice surveillance. El-Kady et al. (1995) described the natural occurrence of mycotoxins in spices in Egypt, and Martins et al. (2001) investigated aflatoxins in spices sold in Portugal. Elshafie et al. (2002) reported fungi and aflatoxins in spices in Oman, Mandeel (2005) reported fungal contamination in imported spices, and Hashem and Alamri (2010) identified potential mycotoxin-producing fungi in spices sold in Saudi Arabia. The presence of xerophilic and storage molds in spices does not exclude contamination before or after distribution. There have been a number of microbiological and chemical studies in this field; Özbey and Kabak (2012) investigated co-occurring aflatoxins and ochratoxin A; El Mahgubi et al. (2013) investigated the distribution and toxicity of Aspergillus section Flavi in Moroccan spices; and Koohy-Kamaly-Dehkordy et al. (2013) examined the retail microbiological quality of spices in Tehran.

Hammami et al. (2014) compared fungal and aflatoxin assessments in marketed spices, while Prelle et al. (2014) investigated co-occurrence of aflatoxins and ochratoxin A in Italy. Jeswal and Kumar (2015) confirmed several mycotoxins in Indian spices by mass spectrometry, and Garcia et al. (2018) investigated spice fungi and the mycotoxigenic potential of selected Aspergillus isolates. Recent surveys have shown that the issue is still relevant.

Akhtar et al. (2020) investigated exposure to aflatoxins from branded and non-branded spices in Pakistan, and Iha et al. (2021) studied aflatoxins and ochratoxin A in Brazil. Nordin et al. (2022) characterized fungi and mycotoxigenic potential in spices used in Malaysian cuisines, while Ogur (2022) examined dried spices from retail and household settings. Demirhan and Demirhan (2023) employed a multi-mycotoxin method, and Mir et al. (2024) investigated fungal contamination and heavy metals. Wakhungu et al. (2024) investigated mycoflora and ochratoxin A in culinary herbs and spices in Kenya, and Gialluisi et al. (2025) studied major mycotoxins in products sold in Italy. Results in different periods and regions indicate that dry appearance alone does not guarantee microbiological or chemical safety.

The original inventory listed 15 records under the cinnamon-contamination domain, but some are wider culinary-spice reports, and their cinnamon-specific denominators are not independently verified. For direct cinnamon evidence, Safavizadeh et al. (2022) analyzed 40 imported cinnamon samples by HPLC and found aflatoxin B1 in seven (17.5%; range 0.59–5.8 μg/kg). Elshafie et al. (2002) studied 105 samples of seven spices, including cinnamon, and recovered 20 fungal species across their surveyed samples; the cinnamon-specific isolate count is not established here. Therefore only explicitly reported cinnamon-specific results can support direct-cinnamon estimates, while other spice surveys contribute related-food context. Neither chemical findings nor culture surveys validate smartphone-microscope diagnosis.

3.6 Cross-cutting methodological limitations

Table 2: Cross-cutting evidence-transfer threats and safeguards for future cinnamon studies

Domain	Risk to interpretation	Minimum safeguard
Reference standard	Labels based on visible appearance or expert image review can reproduce human perception rather than biological truth.	Pair every imaging time point with culture; use molecular identification where taxonomic claims are made.
Sampling	A few attractive microscopic fields may not represent a heterogeneous cinnamon unit.	Use systematic fields across predefined regions and aggregate decisions at sample or lot level.

Data leakage	Fields from the same unit, colony, plate, or time series may occur in both development and test data.	Partition by source lot and biological unit before image generation or augmentation.
Device dependence	Phone rendering, compression, focus, and illumination can become unintended class cues.	Lock acquisition settings where possible and validate on additional phones, operators, and sessions.
Spectrum bias	Obvious positive images and pristine controls overstate performance for borderline retail samples.	Include naturally contaminated material, difficult negatives, mixed taxa, and indeterminate fields.
Temporal claim	The word early may be used without comparison to blinded unaided inspection.	Define pre-visible status prospectively and evaluate image, culture, and visual status at matched times.
Taxonomic claim	Morphologically similar fungi cannot always be separated in low-resolution images.	Restrict the model claim to screening unless isolate-level identification is independently confirmed.
Mycotoxin inference	Mold presence is sometimes interpreted as toxin presence or absence.	Use separate validated chemical assays and avoid toxin claims from microscopy alone.
Explainability	Saliency maps can be visually persuasive without proving causal or biological reasoning.	Use blinded expert review, artifact challenges, and counterfactual tests as supporting—not definitive—evidence.

4 Discussion

4.1 Principal findings

The retrieved evidence supports a technically plausible but unvalidated screening concept: phone-based optics can image relevant biological structures, fungal-image classifiers can recognize patterns, food studies demonstrate some modality integration, and spice surveys establish background contamination risks. In the studies retrieved and mapped for this review, we did not identify prospective sample-level, culture-referenced validation of pre-visible fungal growth in cinnamon. This is a statement about the reviewed evidence, not a universal assertion that no such study exists. Unavailable reports, two-database coverage, and limited independent verification restrict confidence in completeness.

The most defensible intended use is triage. A low-cost tool could flag lots that need culture, taxonomic identification, moisture investigation, or mycotoxin testing. It could also support longitudinal storage monitoring by standardizing image capture at high-risk points. It should not certify a lot as toxin-free, replace statutory microbiological methods, or identify species unless those claims have been separately validated.

4.2 A translational framework for cinnamon

Table 3: Minimum evidence chain for an end-to-end cinnamon screening study.

Component	Requirement
Intended use	Define the output as a screening or triage decision and specify who acts on it.
Representative lots	Include bark and powder from independent vendors, origins, batches, packaging types, and storage histories.
Paired reference	Link each imaged sampling unit and time point to culture; add independent taxonomic confirmation for organism-level claims.
Pre-visible endpoint	Use blinded standardized visual inspection and matched time points to establish whether algorithmic positivity precedes visible growth.
Acquisition control	Calibrate field of view, illumination, focus, and sampling geometry; record phone, lens, operator, and session metadata.
Independent partitioning	Keep every field, replicate, and time point from a source lot in one data partition.
External evaluation	Test locked software on new lots, phones, operators, and a later acquisition period without threshold revision.
Sample-level decision	Prespecify how multiple microscopic fields are aggregated and how unreadable fields are handled.
Deployment assessment	Report acquisition burden, consumables, offline operation, maintenance, training needs, and confirmatory workflow.
Post-deployment control	Monitor drift, device updates, false-negative investigations, and periodic comparison with reference methods.

Before any performance claim, future studies should define the intended triage decision, a representative lot-level sampling frame, matched reference tests, blinded visual time points, predefined field-to-sample aggregation, and independent evaluation on new lots. These requirements are consolidated in Table 3; image-level classifier performance must not be presented as a substitute for them.

4.3 Low cost, usability, and implementation

Low cost is a part of the whole system and not just the cost of a clip-on lens. The total resource burden is the phone or dedicated handset, optical attachment, illumination, sample holders, cleaning materials, calibration target, operator time, quality control, software maintenance, data storage, confirmatory tests and the consequences of wrong decisions. A reusable attachment may still be economically attractive but cost claims should be transparently reported for the intended setting and should distinguish capital items from per-sample consumables.

Usability also impacts validity. An operator may choose visually suspicious fields, focus on different locations, or contaminate the attachment between samples. So a guided application should enforce a certain sequence of sampling steps, focus and illumination checks in real time, preserve the original images and withhold the model result until all fields are complete. Offline inference might be preferable in the event of a poor connection or if product images are commercially sensitive. Updates should be made and validated instead of deployed in secrecy.

The best initial deployment is a supervised pilot in which smartphone results do not independently release or reject a product. Discordant cases can then be compared to culture and toxin testing, as appropriate. This design creates an error library that reflects the local cinnamon supply and shows if fibers, glare, debris or non-target organisms drive false decisions.

4.4 Implications for research and practice

The most informative next study is a prospective, lot-independent evaluation with paired culture, a defined visual endpoint, and separate toxin analysis when indicated. Researchers should publish complete acquisition metadata, locked decision thresholds, selection/exclusion decisions, and a usable audit trail for unreadable images. Table 3 states the minimum validation chain; repeating these requirements in multiple sections does not add evidence.

For laboratory practice, a positive smartphone screen would trigger the appropriate confirmatory workflow; a negative screen must not be used to waive legally required testing, replace approved sampling plans, or certify toxin absence. Decisions to rely on a negative result would require local evidence on false-negative rates and clinical/regulatory acceptability for that exact use. A fungal-like optical structure, a culture-positive sample, pre-visible growth, species identification, and analytically confirmed mycotoxin are distinct outcomes.

For developers, domain shift should be addressed when designing and evaluating the model. Cinnamon bark and powder should be treated as distinct visual strata. Origins, harvest conditions, milling grades, packaging formats, phones, and operating system camera updates can affect image distributions. If a system goes beyond the research environment, performance monitoring and periodic reference testing will be necessary.

4.5 Strengths and limitations of the scoping review

The review's main strength is the explicit linkage among portable optics, algorithmic recognition, food-matrix difficulty, microbiological reference testing, and contamination evidence. The submitted manuscript provides aggregate PRISMA counts and 82 named study entries with identifiers, but the cited full record-level screening log was not included with the available materials.

Major limitations are single-reviewer screening and charting; no supplied preregistered protocol; English-language eligibility; restricted database scope and narrow title/abstract strings; 62 unretrieved full texts for which individual retrieval attempts are undocumented; and incomplete original charting fields. The absence of source-level deduplication and exclusion records prevents independent reconstruction of the reported flow or confirmation that backward citations introduced unique new studies. Detailed extraction was independently checked only for selected accessible primary sources in this revision; Table S1 marks all remaining data gaps as requiring source verification.

4.6 Future research agenda

The immediate research priority is one preregistered or prospectively specified cinnamon study that evaluates a frozen algorithm against culture and blinded unaided inspection at matching sample/time units. It should report

separate performance for fungal presence, viable growth, and early pre-visible growth, with separate chemical testing if toxin-related claims are contemplated.

Once the primary endpoint is established, secondary studies should test independent lots, phones, operators, time periods, and product forms, and measure acquisition failures and implementation burden. Explainability methods should be treated as supporting diagnostics rather than proof of biologically meaningful model attention.

A staged translational pathway—analytic feasibility, locked sample-level diagnostic evaluation, external replication, supervised field implementation, and drift monitoring—is appropriate; none of these stages can establish mycotoxin status without a separate validated assay.

5 Conclusions

Among the 82 publications included in this review's supplied evidence map, we found component-level technical feasibility but no independently verified prospective validation of a complete culture-referenced, sample-level smartphone microscopy and deep-learning workflow for pre-visible fungal growth in cinnamon. This conclusion is limited to the retrieved and examined evidence and is weakened by the absent full screening log, unavailable reports, and incomplete extraction details. A portable screen could eventually help prioritize confirmatory testing, but it should not be used to certify microbiological or mycotoxin safety or replace culture, taxonomic confirmation, or validated chemical analysis.

6 References

Akhtar, S., Riaz, M., Naeem, I., Gong, Y. Y., Ismail, A., Hussain, M., & Akram, K. (2020). Risk assessment of aflatoxins and selected heavy metals through intake of branded and non-branded spices collected from markets of Multan city of Pakistan. *Food Control,* 112, 107132. [DOI]

Armstrong, M., Harris, A. R., D'Ambrosio, M. V., Coulibaly, J. T., Essien-Baidoo, S., Ephraim, R. K. D., Andrews, J. R., Bogoch, I. I., & Fletcher, D. A. (2022). Point-of-Care Sample Preparation and Automated Quantitative Detection of Schistosoma haematobium Using Mobile Phone Microscopy. *The American journal of tropical medicine and hygiene,* 106(5), 1442–1449. [DOI]

Bao, H., Luo, J., Li, J., Zhang, H., & Zhou, H. (2023). *Automatic detection of stored grain fungal spores based on deep learning*. In 2023 International Conference on Network and Information Systems for Computers (pp. 127–131). IEEE. [DOI]

Bogoch, I. I., Andrews, J. R., Speich, B., Utzinger, J., Ame, S. M., Ali, S. M., & Keiser, J. (2013). Mobile phone microscopy for the diagnosis of soil-transmitted helminth infections: A proof-of-concept study. *American Journal of Tropical Medicine and Hygiene,* 88(4), 626–629. [DOI]

Bogoch, I. I., Koydemir, H. C., Tseng, D., Ephraim, R. K. D., Duah, E., Tee, J., Andrews, J. R., & Ozcan, A. (2017). Evaluation of a Mobile Phone-Based Microscope for Screening of Schistosoma haematobium Infection in Rural Ghana. The *American journal of tropical medicine and hygiene,* 96(6), 1468–1471. [DOI]

Breslauer, D. N., Maamari, R. N., Switz, N. A., Lam, W. A., & Fletcher, D. A. (2009). Mobile phone based clinical microscopy for global health applications. *PLOS ONE,* 4(7), e6320. [DOI]

Cho, S., Islas-Robles, A., Nicolini, A. M., Monks, T. J., & Yoon, J. Y. (2016). In situ, dual-mode monitoring of organ-on-a-chip with smartphone-based fluorescence microscope. *Biosensors & bioelectronics,* 86, 697–705. [DOI]

Cighir, A., Bolboacă, R., & Lenard, T. (2025). OpenFungi: A Machine Learning Dataset for Fungal Image Recognition Tasks. *Life (Basel, Switzerland),* 15(7), 1132. [DOI]

Coulibaly, J. T., Silue, K. D., Armstrong, M., Díaz de León Derby, M., D'Ambrosio, M. V., Fletcher, D. A., Keiser, J., Fisher, K., Andrews, J. R., & Bogoch, I. I. (2022). High Sensitivity of Mobile Phone Microscopy Screening for Schistosoma haematobium in Azaguié, Côte d'Ivoire. *The American journal of tropical medicine and hygiene,* 108(1), 41–43. [DOI]

Crespo-Michel, A., Alonso-Arévalo, M. A., & Hernández-Martínez, R. (2023). Developing a microscope image dataset for fungal spore classification in grapevine using deep learning. *Journal of Agriculture and Food Research,* 14, 100805. [DOI]

D'Ambrosio, M. V., Bakalar, M., Bennuru, S., Reber, C., Skandarajah, A., Nilsson, L., Switz, N., Kamgno, J., Pion, S., Boussinesq, M., Nutman, T. B., & Fletcher, D. A. (2015). Point-of-care quantification of blood-borne filarial parasites with a mobile phone microscope. *Science Translational Medicine,* 7(286), 286re4. [DOI]

de Haan, K., Ceylan Koydemir, H., Rivenson, Y., Tseng, D., Van Dyne, E., Bakic, L., Karinca, D., Liang, K., Ilango, M., Gumustekin, E., & Ozcan, A. (2020). Automated screening of sickle cells using a smartphone-based microscope and deep learning. *NPJ digital medicine,* 3, 76. [DOI]

Demirhan, B., & Demirhan, B. E. (2023). Analysis of multi-mycotoxins in commonly consumed spices using the LC-MS/MS method for assessing food safety risks. *Microorganisms,* 11, 1786. [DOI]

Diederich, B., Wartmann, R., Schadwinkel, H., & Heintzmann, R. (2018). Using machine-learning to optimize phase contrast in a low-cost cellphone microscope. *PloS one*, 13(3), e0192937. [DOI]

Du, Y., Liang, Y., Li, P., Xu, Y., Zhen, X., Li, L., Huang, M., Zhan, Y., Li, G., Wu, Z., Anson, C. H. F., Zhou, C., Aimaierjiang, A., Chen, J., Tang, K., Guo, Y., Guo, Z., Bian, J., & Lai, D. (2026). Automatic classification of kidney stone components based on smartphone microscopy and the GoogLeNet model. *BMC urology,* 26(1), 73. [DOI]

El Mahgubi, A., Puel, O., Bailly, S., Tadrist, S., Querin, A., Ouadia, A., Oswald, I. P., & Bailly, J.-D. (2013). Distribution and toxigenicity of Aspergillus section Flavi in spices marketed in Morocco. *Food Control,* 32(1), 143–148. [DOI]

El-Kady, I. A., El-Maraghy, S. S., & Mostafa, M. E. (1995). Natural occurrence of mycotoxins in different spices in Egypt. *Folia Microbiologica,* 40, 297–300. [DOI]

Elshafie, A. E., Al-Rashdi, T. A., Al-Bahry, S. N., & Bakheit, C. S. (2002). Fungi and aflatoxins associated with spices in the Sultanate of Oman. *Mycopathologia,* 155, 155–160. [DOI]

Fozouni, P., Son, S., Díaz de León Derby, M., Knott, G. J., Gray, C. N., D'Ambrosio, M. V., Zhao, C., Switz, N. A., Kumar, G. R., Stephens, S. I., Boehm, D., Tsou, C. L., Shu, J., Bhuiya, A., Armstrong, M., Harris, A. R., Chen, P. Y., Osterloh, J. M., Meyer-Franke, A., Joehnk, B., … Ott, M. (2021). Amplification-free detection of SARS-CoV-2 with CRISPR-Cas13a and mobile phone microscopy. *Cell,* 184(2), 323–333.e9. [DOI]

Garcia, M. V., Parussolo, G., Moro, C. B., Bernardi, A. O., & Copetti, M. V. (2018). Fungi in spices and mycotoxigenic potential of some Aspergilli isolated. *Food Microbiology,* 73, 93–98. [DOI]

Ghetia, T., Kaur, I., Kumar, Y., Mink, & Simrat. (2025). *Automated fungi classification using deep learning-based approaches with explainable AI*. In 2025 12th International Conference on Computing for Sustainable Global Development (pp. 1–5). IEEE. [DOI]

Gialluisi, K., El Darra, N., Nicoletti, M. G., Solfrizzo, M., & Gambacorta, L. (2025). Natural occurrence of main mycotoxins in herbs and spices commercialized in Italy. *Foods,* 14, 1889. [DOI]

Goh, M. M. R., Zou, L., Tan, Y. E., Tan, M. G., Goh, H. L., & Yip, B. K. L. (2025). FungAI—A clinically oriented two-stage artificial intelligence framework for microscopic fungal species identification. IEEE Access, 13, 205457–205471. [DOI]

Gümüş, A. (2024). Classification of microscopic fungi images using vision transformers for enhanced detection of fungal infections. *Turkish Journal of Nature and Science,* 13(1), 152–160. [DOI]

Hammami, W., Fiori, S., Al Thani, R., Ali Kali, N., Balmas, V., Migheli, Q., & Jaoua, S. (2014). Fungal and aflatoxin contamination of marketed spices. *Food Control,* 37, 177–181. [DOI]

Hashem, M., & Alamri, S. (2010). Contamination of common spices in Saudi Arabia markets with potential mycotoxin-producing fungi. *Saudi Journal of Biological Sciences,* 17(2), 167–175. [DOI]

Hossain, M., Islam, M. K., Uddin, M., Jahan, F., Chowdhury, M. S. A., & Ahadullah, M. (2026). Explainable deep learning techniques for microscopic fungi classification using a learnable threshold-based ReLULeaky activation function and transfer learning. *Journal of pathology informatics,* 22, 100683. [DOI]

Huang, T.-S., Wang, K., Ye, X.-Y., Chen, C.-S., & Chang, F.-C. (2023). Attention-guided transfer learning for identification of filamentous fungi encountered in the clinical laboratory. *Microbiology Spectrum,* 11(3), e04611-22. [DOI]

Iha, M. H., Rodrigues, M. L., & Briganti, R. C. (2021). Survey of aflatoxins and ochratoxin A in spices from the Brazilian market. *Brazilian Archives of Biology and Technology,* 64, e21210244. [DOI]

Indira Priyadharshini, M., Pavithra, R., Mahalakshmi, M., Mohanapriya, S. U., & Jasiya Yasika, S. (2024). *AI-powered fungal detection in dried chilli: A deep learning approach*. In 2024 4th Asian Conference on Innovation in Technology (pp. 1–4). IEEE. [DOI]

Islam, S. M., Sazzad, M. S. H., Ahamed, M. F., Ahmed, M., Nayon, S. I., Islam, T., Ayon, S. S., Haider, J., Abdullah-Al-Wadud, M., & Islam, S. M. R. (2025). Microscopic image dataset of fungal spores for computer vision applications in Tectona grandis and other taxa. *Scientific data,* 12(1), 2017. [DOI]

Javidan, S. M., Banakar, A., Asefpour Vakilian, K., Ampatzidis, Y., & Rahnama, K. (2024). Diagnosing the spores of tomato fungal diseases using microscopic image processing and machine learning. *Multimedia Tools and Applications*, 83, 67283–67301. [DOI]

Jeswal, P., & Kumar, D. (2015). Mycobiota and natural incidence of aflatoxins, ochratoxin A, and citrinin in Indian spices confirmed by LC-MS/MS. *International Journal of Microbiology,* 2015, 242486. [DOI]

Jubayer, F., Soeb, J. A., Mojumder, A. N., Paul, M. K., Barua, P., Kayshar, S., Akter, S. S., Rahman, M., & Islam, A. (2021). Detection of mold on the food surface

using YOLOv5. *Current research in food science*, 4, 724–728. [DOI]

Kasamsumran, N., Ittichaiwong, P., Chinudomporn, C., Veerakanjana, K., Karoopongse, E., & Pora, W. (2025). AI-assisted web application for leukocyte abnormality counting with YOLOv11 and smartphone microscopy. *IEEE Access*, 13, 89079–89107. [DOI]

Koo, T., Kim, M. H., & Jue, M.-S. (2021). Automated detection of superficial fungal infections from microscopic images through a regional convolutional neural network. PLOS ONE, 16(8), e0256290. [DOI]

Koohy-Kamaly-Dehkordy, P., Nikoopour, H., Siavoshi, F., Koushki, M., & Abadi, A. (2013). Microbiological quality of retail spices in Tehran, Iran. Journal of Food Protection, 76(5), 843–848. [DOI]

Koydemir, H. C., Feng, S., Liang, K., Nadkarni, R., Benien, P., & Ozcan, A. (2017). *Automated detection and enumeration of waterborne pathogens using mobile phone microscopy and machine learning*. In 2017 Conference on Lasers and Electro-Optics (pp. 1–2). IEEE.

Koydemir, H. C., Göröcs, Z., Tseng, D., Cortazar, B., Feng, S., Chan, R. Y. L., Burbano, J., McLeod, E., & Ozcan, A. (2015). Rapid imaging, detection and quantification of Giardia lamblia cysts using mobile-phone based fluorescent microscopy and machine learning. *Lab on a Chip*, 15(5), 1284–1293. [DOI]

Kühnemund, M., Wei, Q., Darai, E., Wang, Y., Hernández-Neuta, I., Yang, Z., Tseng, D., Ahlford, A., Mathot, L., Sjöblom, T., Ozcan, A., & Nilsson, M. (2017). Targeted DNA sequencing and in situ mutation analysis using mobile phone microscopy. *Nature communications*, 8, 13913. [DOI]

Li, C., Huang, D., & Zhou, H. (2026). YOLO-RBSD: an efficient and accurate rice blast spore detector based on improved YOLOv8. *Plant methods*, 22(1), 34. [DOI]

Li, K., Zhu, X., Qiao, C., Zhang, L., Gao, W., & Wang, Y. (2023). The gray mold spore detection of cucumber based on microscopic image and deep learning. *Plant Phenomics*, 5, 0011. [DOI]

Lin, L., Solano, A. V., Gonzales, F., Torrico, M. C., Illanes, D., Díez, N., Bermejo-Peláez, D., Dacal, E., Vallés-López, R., Pastor, L., Mancebo-Martín, R., Ledesma-Carbayo, M. J., Luengo-Oroz, M., Rubio, J. M., & Flores-Chavez, M. (2026). Artificial intelligence algorithm for real-time detection and counting of Trypanosoma cruzi parasites using smartphone microscopy. *PLoS neglected tropical diseases*, 20(5), e0012955. [DOI]

Liu, Y., Rollins, A. M., Levenson, R. M., Fereidouni, F., & Jenkins, M. W. (2021). Pocket MUSE: an affordable, versatile and high-performance fluorescence microscope using a smartphone. *Communications biology*, 4(1), 334. [DOI]

Mandeel, Q. A. (2005). Fungal contamination of some imported spices. Mycopathologia, 159, 291–298. [DOI]

Martins, M. L., Martins, H. M., & Bernardo, F. (2001). Aflatoxins in spices marketed in Portugal. *Food Additives & Contaminants*, *18*(4), 315–319.

McKay, G. N., Mohan, N., Butterworth, I., Bourquard, A., Sánchez-Ferro, Á., Castro-González, C., & Durr, N. J. (2020). Visualization of blood cell contrast in nailfold capillaries with high-speed reverse lens mobile phone microscopy. Biomedical optics express, 11(4), 2268–2276. [DOI]

Meiburger, K. M., Savoia, P., Molinari, F., Veronese, F., Tarantino, V., Salvi, M., Fadda, M., Seoni, S., Zavattaro, E., Santi, B., & Michielli, N. (2019). *Automatic Extraction of Dermatological Parameters from Nevi Using an Inexpensive Smartphone Microscope: A Proof of Concept*. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference, 2019, 399–402. [DOI]

Mir, M. A., Ashraf, M. W., & Andrews, K. (2024). Assessment of heavy metals and fungi contamination of spices available in Saudi Arabian food cuisines. *Food Chemistry Advances*, 4, 100694. [DOI]

Naz, N., Kashif, A., Kanwal, K., Khan, A. M., & Abbas, M. (2016). Quantitative Scrutinization of Aflatoxins in Different Spices from Pakistan. *International journal of analytical chemistry*, 2016, 4907425. [DOI]

Nordin, S., Samsudin, N. A., Mohd Esah, E., Zakaria, L., Selamat, J., Rahman, M. A. H., & Mahror, N. (2022). Prevalence, identification and mycotoxigenic potential of fungi in common spices used in local Malaysian cuisines. *Foods*, 11, 2548. [DOI]

Ogur, S. (2022). Microbiological quality and safety of some dried spices obtained from markets, spice shops and homes. *Brazilian Archives of Biology and Technology*, 65, e22220315. [DOI]

Onal, E. G., & Tekgul, H. (2022). Assessing kidney stone composition using smartphone microscopy and deep neural networks. *BJUI compass*, 3(4), 310–315. [DOI]

Ormachea, O., Villazón, A., Rodriguez, P., & Zimic, M. (2022). A Smartphone-Based Low-Cost Inverted Laser Fluorescence Microscope for Disease Diagnosis. *Biosensors*, 12(11), 960. [DOI]

Orth, A., Wilson, E. R., Thompson, J. G., & Gibson, B. C. (2018). A dual-mode mobile phone microscope using the onboard camera flash and ambient light. *Scientific reports*, 8(1), 3298. [DOI]

Özbey, F., & Kabak, B. (2012). Natural co-occurrence of aflatoxins and ochratoxin A in spices. *Food Control,* 28(2), 354–361. [DOI]

Pham, D. N., Prokisch, L., Meyer, B., & Thumbs, J. (2026). *MobileMold: A smartphone-based microscopy dataset for food mold detection*. Proceedings of the ACM Multimedia Systems Conference, 402-408. [DOI]

Phillips, Z. F., D'Ambrosio, M. V., Tian, L., Rulison, J. J., Patel, H. S., Sadras, N., Gande, A. V., Switz, N. A., Fletcher, D. A., & Waller, L. (2015). Multi-contrast imaging and digital refocusing on a mobile microscope with a domed LED array. *PLOS ONE,* 10(5), e0124938. [DOI]

Picek, L., Šulc, M., Matas, J., Heilmann-Clausen, J., Jeppesen, T. S., & Lind, E. (2022). Automatic fungi recognition: Deep learning meets mycology. *Sensors,* 22, 633. [DOI]

Pirnstill, C. W., & Coté, G. L. (2015). Malaria diagnosis using a mobile phone polarized microscope. *Scientific Reports,* 5, 13368. [DOI]

Pongpom, M., Sookkhee, S., Chongkae, S., Wattanasombat, S., Pikulkaew, K., Lawan, N., Upaphong, P., & Wangsanut, T. (2026). Fungal recognition in vaginal discharge using deep learning analysis of mobile device-acquired microscopic images. *Frontiers in cellular and infection microbiology,* 16, 1787545. [DOI]

Prelle, A., Spadaro, D., Garibaldi, A., & Gullino, M. L. (2014). Co-occurrence of aflatoxins and ochratoxin A in spices commercialized in Italy. *Food Control,* 39, 192–197. [DOI]

Rahman, M. A., Clinch, M., Reynolds, J., Dangott, B., Meza Villegas, D. M., Nassar, A., Hata, D. J., & Akkus, Z. (2023). Classification of fungal genera from microscopic images using artificial intelligence. *Journal of pathology informatics,* 14, 100314. [DOI]

Rivenson, Y., Ceylan Koydemir, H., Wang, H., Wei, Z., Ren, Z., Günaydin, H., Zhang, Y., Göröcs, Z., Liang, K., Tseng, D., & Ozcan, A. (2018). Deep learning enhanced mobile-phone microscopy. ACS Photonics, 5(6), 2354–2364. [DOI]

Riya, K., & Jose, C. J. (2025). *CBAM-enhanced EfficientNet for interpretable microscopic fungal classification*. In 2025 11th International Conference on Smart Computing and Communications. IEEE. [DOI]

Safavizadeh, V., de Oliveira, C. A. F., Nekoukar, Z., Aman Mohammadi, M., Tognon, G., & Moore, M. D. (2022). Aflatoxin B1 in imported cinnamon consumed in the Yazd province of Iran. Food Additives & Contaminants: Part B, 15(1), 52–55. [DOI]

Schwab, A. H., Harpestad, A. D., Swartzentruber, A., Lanier, J. M., Wentz, B. A., Duran, A. P., Barnard, R. J., & Read, R. B., Jr (1982). Microbiological quality of some spices and herbs in retail markets. *Applied and environmental microbiology,* 44(3), 627–630. [DOI]

Shah, M. I., Mishra, S., Sarkar, M., & Sudarshan, S. K. (2016). *Automatic detection and classification of tuberculosis bacilli from camera-enabled smartphone microscopic images*. In 2016 Fourth International Conference on Parallel, Distributed and Grid Computing (pp. 287–290). IEEE. [DOI]

Shanmugam, A., Usmani, M., Mayberry, A., Perkins, D. L., & Holcomb, D. E. (2018). Imaging systems and algorithms to analyze biological samples in real-time using mobile phone microscopy. *PloS one,* 13(3), e0193797. [DOI]

Shrestha, R., Duwal, R., Wagle, S., Pokhrel, S., Giri, B., & Neupane, B. B. (2020). A smartphone microscopic method for simultaneous detection of (oo)cysts of Cryptosporidium and Giardia. *PLoS neglected tropical diseases,* 14(9), e0008560. [DOI]

Singla, S., Kumar, N. S., Bhandari, N., Sharma, K., Anjali, & Shukla, A. (2026). *An Xception-based deep learning framework for microscopic fungi image classification*. In 2026 5th OPJU International Technology Conference (pp. 1–6). IEEE. [DOI]

Sirithanaphol, W., Incharoen, N., Rompsaithong, U., Kiatsopit, P., Lumbiganon, S., & Chindaprasirt, J. (2021). Improvement of allograft kidney biopsy yield by using a handheld smartphone microscope as an on-site evaluation device. *Heliyon,* 7(6), e07189. [DOI]

Skandarajah, A., Reber, C. D., Switz, N. A., & Fletcher, D. A. (2014). Quantitative imaging with a mobile phone microscope. *PLOS ONE,* 9(5), e96906. [DOI]

Smith, Z. J., Chu, K., Espenson, A. R., Rahimzadeh, M., Gryshuk, A., Molinaro, M., Dwyre, D. M., Lane, S., Matthews, D., & Wachsmann-Hogiu, S. (2011). Cell-phone-based platform for biomedical device development and education applications. *PLOS ONE,* 6(3), e17150. [DOI]

Soltani Nezhad, F., Rahnama, K., Javidan, S. M., & Asefpour Vakilian, K. (2024). Application of microscopic image processing and artificial intelligence detecting and classifying the spores of three novel species of Trichoderma. *Discover Applied Sciences,* 6, 669. [DOI]

Sowerby, S. J., Crump, J. A., Johnstone, M. C., Krause, K. L., & Hill, P. C. (2016). Smartphone Microscopy of Parasite Eggs Accumulated into a Single Field of View. *The American journal of tropical medicine and hygiene,* 94(1), 227–230. [DOI]

Sun, K., Wang, Z., Tu, K., Wang, S., & Pan, L. (2016). Recognition of mould colony on unhulled paddy based on computer vision using conventional machine-learning and deep learning techniques. *Scientific Reports,* 6, 37994. [DOI]

Sung, Y., Campa, F., & Shih, W. C. (2017). Open-source do-it-yourself multi-color fluorescence smartphone microscopy. *Biomedical optics express,* 8(11), 5075–5086. [DOI]

Switz, N. A., D'Ambrosio, M. V., & Fletcher, D. A. (2014). Low-cost mobile phone microscopy with a reversed mobile phone camera lens. *PLOS ONE,* 9(5), e95330. [DOI]

Tahir, M. W., Zaidi, N. A., Rao, A. A., Blank, R., Vellekoop, M. J., & Lang, W. (2018). A Fungus Spores Dataset and a Convolutional Neural Network Based Approach for Fungus Detection. *IEEE transactions on nanobioscience,* 17(3), 281–290. [DOI]

Tapley, A., Switz, N., Reber, C., Davis, J. L., Miller, C., Matovu, J. B., Worodria, W., Huang, L., Fletcher, D. A., & Cattamanchi, A. (2013). Mobile digital fluorescence microscopy for diagnosis of tuberculosis. *Journal of Clinical Microbiology,* 51(6), 1774–1778. [DOI]

Tosun, H., & Arslan, R. (2013). Determination of aflatoxin B1 levels in organic spices and herbs. *The Scientific World Journal,* 2013, 874093. [DOI]

Treepong, P., & Theera-Ampornpunt, N. (2023). Early bread mold detection through microscopic images using convolutional neural network. *Current Research in Food Science,* 7, 100574. [DOI]

Tricco, A. C., Lillie, E., Zarin, W., O'Brien, K. K., Colquhoun, H., Levac, D., Moher, D., Peters, M. D. J., Horsley, T., Weeks, L., Hempel, S., Akl, E. A., Chang, C., McGowan, J., Stewart, L., Hartling, L., Aldcroft, A., Wilson, M. G., Garritty, C., Lewin, S., Godfrey, C. M., Macdonald, M. T., Langlois, E. V., Soares-Weiser, K., Moriarty, J., Clifford, T., Tunçalp, Ö., & Straus, S. E. (2018). PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation. *Annals of Internal Medicine,* 169(7), 467-473. [DOI]

Wakhungu, C., Okoth, S., Amimo, N., Wachira, P., Amakhobe, T., Owiti, A., & Wachira, P. (2024). Screening of mycoflora and ochratoxin A on common culinary herbs and spices in Kenya. *Food Additives & Contaminants: Part A,* 41(8), 1003–1017. [DOI]

Yang, A., Bakhtari, N., Langdon-Embry, L., Redwood, E., Grandjean Lapierre, S., Rakotomanga, P., Rafalimanantsoa, A., De Dios Santos, J., Vigan-Womas, I., Knoblauch, A. M., & Marcos, L. A. (2019). Kankanet: An artificial neural network-based object detection smartphone application and mobile microscope as a point-of-care diagnostic aid for soil-transmitted helminthiases. *PLoS neglected tropical diseases,* 13(8), e0007577. [DOI]

Zhang, D., Tao, W., Cheng, T., Zhou, X., Hu, G., Qiao, H., Guo, W., Wang, Z., & Gu, C. (2024). GSD-YOLO: A lightweight decoupled wheat scab spore detection network based on YOLOv7-Tiny. *Agriculture,* 14, 2278. [DOI]

Zhang, Y., Wu, Y., Zhang, Y., & Ozcan, A. (2016). Color calibration and fusion of lens-free and mobile-phone microscopy images for high-resolution and accurate color reproduction. *Scientific reports,* 6, 27811. [DOI]

Zhao, E., Zhao, H., Liu, G., Jiang, J., Zhang, F., & Zhang, J. (2024). Automated recognition of conidia of nematode-trapping fungi based on improved YOLOv8. *IEEE Access,* 12, 81314–81328. [DOI]

Zhou, H., Lai, Q., Huang, Q., Cai, D., Huang, D., & Wu, B. (2024). Automatic detection of rice blast fungus spores by deep learning-based object detection: Models, benchmarks and quantitative analysis. *Agriculture,* 14, 290. [DOI]

Zhu, H., Yaglidere, O., Su, T.-W., Tseng, D., & Ozcan, A. (2011). Cost-effective and compact wide-field fluorescent imaging on a cell-phone. *Lab on a Chip,* 11(2), 315–322. [DOI]

Zieliński, B., Sroka-Oleksiak, A., Rymarczyk, D., Piekarczyk, A., & Brzychczy-Włoch, M. (2020). Deep learning approach to describe and classify fungi microscopic images. *PLOS ONE,* 15(6), e0234806. [DOI]