

Review Article

Applied Surveillance Technologies for Mosquito Identification Across the Life Cycle: A Comparative Review

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Abstract

Reliable mosquito identification is essential for surveillance systems that support vector monitoring, risk assessment, and targeted intervention. However, conventional morphology-based identification remains labor-intensive, expertise-dependent, and difficult to scale for large monitoring programs. Advances in molecular diagnostics, imaging technologies, and artificial intelligence have enabled faster and more objective alternatives across the mosquito life cycle. This review presents a stage-aware comparative synthesis of mosquito identification methods for eggs, larvae, pupae, and adults, covering classical morphology, molecular and proteomic assays, geometric morphometrics, deep learning-based image analysis, acoustic sensing, and IoT-enabled smart traps. Structured as a narrative comparative review, the article evaluates these approaches in terms of diagnostic role, scalability, cost, infrastructure requirements, and field deployability. The analysis shows that each life stage supports a distinct surveillance function and that no single method is optimal across the full mosquito life cycle. Effective surveillance, therefore, requires tiered workflows that combine low-cost collection, automated screening, and selective confirmatory analysis according to operational needs.

Keywords: Deep learning, Geometric morphometrics, Molecular diagnostics, Multi-stage mosquito identification, Smart traps, Vector surveillance

1 Introduction

Accurate identification of mosquito species is essential for surveillance systems that support vector monitoring, risk assessment, and targeted intervention. This requirement extends across medically important vector genera, including *Aedes*, *Anopheles*, and *Culex*, which are associated with arboviral, malarial, filarial, and encephalitic diseases [1]. In practice, reliable identification remains technically challenging because mosquito specimens vary across developmental stages, collection environments, and sensing conditions. Conventional morphology-based taxonomy is widely used, but it is labor-intensive, expertise-dependent, and difficult to scale for large monitoring programs [2]. Molecular approaches, such as polymerase chain reaction (PCR),

nucleic acid sequencing, DNA barcoding, and nanopore-based assays, provide higher taxonomic certainty, particularly for cryptic, damaged, or morphologically ambiguous specimens [3]. Automated image-based classification using deep learning, particularly convolutional neural networks (CNNs), has also emerged as a scalable alternative for high-throughput mosquito identification [4].

The practical importance of this problem is reinforced by the medical significance of several mosquito taxa. *Aedes aegypti*, the principal vector of dengue, also transmits chikungunya, Zika virus, yellow fever, and the emerging Mayaro virus [5], [6]. *Aedes albopictus* contributes to the transmission of several of these viruses, although generally with lower efficiency. Other medically important vectors include *Anopheles cracens*, associated with zoonotic

malaria caused by *Plasmodium knowlesi* in Southeast Asia [7]-[9], and *Culex quinquefasciatus*, an important vector of lymphatic filariasis, West Nile virus, and Japanese encephalitis virus, with reported involvement in Rift Valley fever virus transmission. These examples illustrate why mosquito identification must be not only taxonomically reliable, but also operationally practical for surveillance and control.

This review focuses on the identification of mosquito species rather than epidemiological modeling or vector control policy [10]. It is presented as a comprehensive narrative review with a stage-aware comparative framework spanning eggs, larvae, pupae, and adults. Rather than promoting a single dominant technique, the review compares morphological, molecular, biochemical, imaging-based, acoustic, and AI-driven approaches. The comparison considers diagnostic role, scalability, cost, infrastructure requirements, validation practices, and field deployability. It also highlights how biological accessibility and operational constraints shape method selection and support tiered surveillance workflows for practical mosquito monitoring systems.

As shown in Figure 1, the mosquito life cycle includes egg, larval, pupal, and adult stages. Each stage presents distinct morphological and ecological characteristics that influence sensing, sampling, and identification strategies. Larvae are frequently monitored because their confined aquatic habitats facilitate collection, although their transparency and interspecies similarity can complicate automated recognition. Eggs and pupae, while relevant to early intervention and population forecasting, remain comparatively understudied in automated identification workflows. Adults provide the most direct epidemiological signal, but they also present the greatest environmental variability during field surveillance.

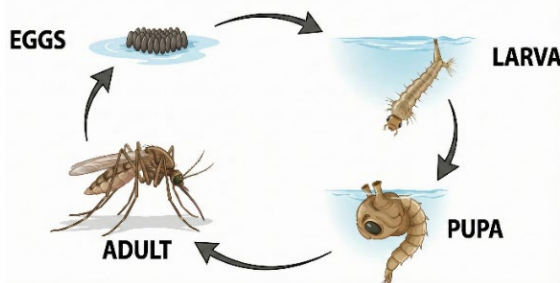


Figure 1: Mosquito life cycle stages.

Accordingly, this review provides a stage-aware comparison of mosquito identification methods across the full life cycle, tracing the progression from classical taxonomic keys to molecular diagnostics and AI-based analysis. It emphasizes that each developmental stage supports a different surveillance objective and that no single method is universally optimal. Instead, effective mosquito surveillance depends on matching the identification approach to stage-specific biological characteristics, operational requirements, and deployment constraints.

2 Overview of identification methodologies

Mosquito species identification is a core component of vector surveillance, ecological assessment, and targeted control. Existing approaches differ in diagnostic certainty, infrastructure requirements, scalability, and suitability for routine deployment. Broadly, current methodologies can be grouped into three main categories: molecular and biochemical techniques, morphological and morphometric analysis, and automated image-based classification using machine learning and deep neural networks.

2.1 Molecular and biochemical techniques

Molecular identification based on DNA, RNA, and proteomic profiling is widely regarded as the reference standard because of its high sensitivity and taxonomic precision. These methods are especially useful for confirming cryptic taxa, damaged specimens, or ambiguous samples. Cytochrome c oxidase subunit (COI) barcoding and PCR are commonly used to establish reliable ground-truth labels for curated datasets and to support downstream computational analysis [11], [12]. Molecular assays are also particularly valuable in early developmental stages, where morphological characters may be incomplete or difficult to interpret [13], [14].

In proteomic workflows, protein spectra obtained from mosquito tissues are compared with validated reference libraries, allowing rapid discrimination among species when spectral databases and sample preparation protocols are standardized. Unlike DNA-based assays, these biochemical and proteomic methods do not directly amplify genetic markers. Instead, they use reproducible protein mass profiles as diagnostic fingerprints, making them useful for rapid laboratory-based confirmation and batch processing [15]-[17]. Despite their diagnostic strength, molecular and biochemical methods require laboratory infrastructure, specialized equipment, and

trained personnel. These requirements limit their routine use in large-scale field surveillance.

2.2 Morphological and morphometric approaches

Morphological examination remains the most accessible and widely used form of mosquito identification. It relies on visual assessment of anatomical characteristics and requires relatively simple equipment, making it suitable for routine field and laboratory practice. To assess structures such as wing venation, scale patterns, leg banding, and segmentation, conventional identification uses light microscopy and standardized taxonomic keys. Although practical and interpretable, its accuracy depends strongly on operator expertise and specimen integrity. During collection or handling, traits may be damaged, increasing inter-observer variability and the risk of misclassification.

Morphometric approaches extend conventional morphology by converting visible anatomical variation into quantitative descriptors. Geometric morphometrics, particularly wing-based analysis, improves reproducibility and supports the discrimination of closely related or morphologically similar taxa [18],[19]. Nevertheless, morphology-based methods remain labor-intensive and less scalable than automated systems.

2.3 Automated classification and deep learning

Automated mosquito identification increasingly relies on machine learning and deep neural networks, which enable feature extraction directly from raw images and support scalable classification across multiple developmental stages. To improve efficiency and field deployment potential, recent studies have applied

transfer learning, transformer-based models, and real-time detection frameworks such as YOLO [20]-[23]. These approaches reduce dependence on manual expertise and support rapid, high-throughput analysis. However, their performance remains closely tied to dataset diversity, acquisition quality, and environmental conditions. Table 1 summarizes the principal identification paradigms and highlights their operational trade-offs. Molecular methods provide the highest diagnostic certainty. Morphology remains accessible and interpretable. Proteomic methods support rapid confirmation. Deep learning offers the strongest pathway toward scalable automated surveillance workflows.

2.4 Summary of methodological roles

As outlined above, the methodological groups should be viewed as complementary components of surveillance workflows rather than as isolated alternatives. Morphological and molecular approaches remain important reference methods for taxonomic confirmation and dataset validation. Automated image-based systems increasingly support scalable and near real-time analysis. The practical value of each approach depends not only on diagnostic performance but also on cost, throughput, infrastructure, and deployment requirements [24].

3 Classification of mosquito eggs

For early surveillance, the egg stage offers important opportunities. At this stage, practical identification remains challenging because mosquito eggs are small, visually indistinct, and often collected under heterogeneous field conditions. For outbreak

Table 1: Comparison of major mosquito identification paradigms.

Approach	Identification Principle	Equipment / Infrastructure	Cost	Scalability	Practical Advantages	Key Limitations
Morphological microscopy	Visual inspection of anatomical traits	Light microscope, taxonomic keys	Low	Low-Medium	Simple, interpretable, field-ready, minimal setup	Expert-dependent, slow, specimen damage sensitive
Molecular assays (PCR/COI)	DNA amplification and sequencing	Laboratory instruments, reagents	High	Medium	Gold-standard, resolves cryptic species	Expensive, lab-based, not real-time
Proteomic profiling (MALDI-TOF MS)	Protein spectral fingerprint matching	MALDI-TOF spectrometer	Medium-High	High	Rapid batch processing, faster than PCR, high reproducibility	Specialized equipment, database dependent
Deep learning (CNN/DNN)	Automated image feature learning	Camera + GPU/edge device	Medium	Very High	Fast, scalable, real-time, minimal expert input	Requires large datasets, sensitive to domain shift



prediction, oviposition surveillance, and early source-reduction programs, egg-stage monitoring is nevertheless valuable, particularly when linked to scalable collection and counting workflows. Within this stage, identification methods range from conventional microscopy and ovitrap inspection to confirmatory laboratory assays and automated image-based analysis.

3.1 Morphological and ovitrap-based approaches

Morphological inspection remains one of the earliest and most widely used approaches for mosquito egg identification. It relies on examination of chorionic structure under light or electron microscopy to support genus-level and, in some cases, species-level discrimination without rearing or molecular testing. Diagnostic cues include oviposition patterns, such as single eggs in *Aedes*, rafts in *Culex*, and lateral floats in *Anopheles*. They also include micromorphological features such as size, surface sculpturing, and exochorionic ornamentation. Quantitative morphometrics and high-resolution imaging, including SEM and microtomography, improve discrimination. These methods also support reference library development and validation of automated systems [25]-[28].

When higher taxonomic certainty is required, egg-stage identification often depends on confirmatory laboratory methods. SEM, for instance, reveals fine chorionic features that are often difficult to resolve under light microscopy, including exochorionic ridges, tubercles, and pore patterns, which may aid in distinguishing species such as *Anopheles subpictus* [20] and *Psorophora cyaneescens* [22]. For differentiation of closely related aedine species, high-resolution stereomicroscopy provides a more field-applicable approach [29]. However, SEM requires specialized instrumentation, specimen preparation, and low-throughput laboratory workflows. Consequently, it is more suitable for taxonomic reference development and validation than for routine surveillance. Despite the low cost and interpretability of morphology, it remains labor-intensive, highly dependent on expertise, and sensitive to specimen damage and subtle interspecies variation.

For egg-stage surveillance, ovitraps provide a simple and scalable complementary strategy. By attracting gravid females to standardized substrates, they facilitate the estimation of vector presence, seasonal trends, and infestation risk across

institutional and community monitoring programs. Their effectiveness depends on trap design, placement, and attractant optimization. Large-scale deployment can also support early detection of invasive species and targeted source reduction [30], [31]. Population levels are commonly summarized using standard indices, such as the mosquito ovitrap index (MOI), Breteau index (BI), and area density index (ADI) [32]. Recent systems have also integrated automated imaging and deep learning to replace manual counting, directly detecting and classifying eggs from trap images and achieving operational F1-scores above 90% [33]. Although ovitrap-based surveillance is operationally attractive, its performance remains sensitive to environmental conditions, imaging quality, and deployment practices.

3.2 Molecular and biochemical confirmation

When morphology is ambiguous or when mixed samples must be resolved, molecular and biochemical methods provide more definitive identification. DNA-based approaches, including COI barcoding, multiplex or targeted PCR, sequencing, and environmental DNA assays, enable reliable detection of single or multiple species directly from ovitrap samples or breeding water [34]-[37]. These methods are most useful when species-level certainty is required, particularly for damaged, early-stage, mixed, or morphologically similar samples. Proteomic profiling using MALDI-TOF MS further supports identification through species-specific protein fingerprints and can provide rapid laboratory-based confirmation when validated reference spectra are available [15]-[17]. Despite their diagnostic value, these approaches require laboratory infrastructure, specialized equipment, trained personnel, and reference databases. These requirements limit their routine use in high-volume field surveillance.

The selection of egg-stage methods depends on the surveillance objective. Routine monitoring is best supported by ovitrap collection, microscopy, and automated counting, as these approaches are low-cost and scalable. For detailed morphological validation and taxonomic reference work, SEM is most appropriate. When confirmatory species-level identification is required, molecular assays are preferred. Proteomic methods such as MALDI-TOF MS are useful for rapid laboratory confirmation when reference spectra are available.

3.3 Automated egg detection and counting

In egg-stage surveillance, automated image-based analysis has become increasingly important. Manual ovitrap counting is labor-intensive and prone to observer variation. Early semi-automated image-processing systems have shown good agreement with manual counts. Recently, deep learning models have enabled fully automated detection and segmentation, with several studies reporting precision and recall above 95% in both laboratory and field settings [38]-[42]. These systems reduce observer dependence, improve throughput, and support more standardized surveillance pipelines. Embedded and edge platforms further strengthen their practical value by allowing portable and near-real-time operation in decentralized monitoring contexts.

In addition to imaging-based systems, alternative batch-estimation approaches such as bulk weight or volume measurement also correlate strongly with true egg counts and can provide rapid, low-cost proxies when image acquisition is impractical [43], [44]. Table 2 summarizes the principal egg-stage identification approaches across accuracy, scalability, and field suitability.

3.4 Stage-specific limitations and operational role

In mosquito monitoring, the egg stage is valuable because it represents the earliest intervention point for source reduction, targeted larviciding, and oviposition-based risk assessment. Ovitrap-based surveillance studies demonstrate that egg monitoring can be used to detect the presence of *Aedes*, estimate population abundance, and support dengue risk assessment in operational settings [45]. At the same time, this stage presents substantial practical limitations. Eggs are small, often morphologically similar, and sensitive to imaging quality, which makes manual inspection expertise-dependent and constrains automated analysis under uncontrolled conditions. Nevertheless, despite reducing processing time and improving reproducibility, the reliability of automated

egg-counting algorithms still depends on image quality, acquisition consistency, and field validation [46]. SEM, PCR, and proteomic workflows improve taxonomic certainty but remain laboratory-bound. AI-based systems depend heavily on representative training data, standardized acquisition, and stable deployment conditions.

Taken together, these characteristics indicate that egg-stage methods differ mainly in operational demand rather than in diagnostic relevance. For routine large-scale monitoring, ovitrap collection and automated image-based counting are the most practical options. In contrast, SEM, molecular assays, and proteomic methods are better suited to selective confirmation, validation, and reference labeling. A tiered workflow should combine scalable ovitrap-based surveillance and automated analysis for routine monitoring. Targeted laboratory confirmation should then be used when higher taxonomic resolution is required.

4 Classification of mosquito larvae

For mosquito surveillance and control, the larval stage is one of the most important targets. Intervention at this stage can prevent adult emergence within localized aquatic habitats. Restricted mobility and concentrated breeding sites make larvae easier to sample than adults and more operationally useful than eggs for repeated monitoring. As a result, larval identification remains central to routine surveillance programs. Conventional taxonomy still relies on light microscopy and standardized keys. At the same time, automated imaging, computer vision, and deep neural networks increasingly support scalable image-based classification under both laboratory and field-oriented conditions.

4.1 Traditional morphological identification

Traditionally, larval identification relies on microscopic examination of external anatomical features using

Table 2: Comparison of mosquito egg identification and surveillance methodologies.

Approach	Principle	Strengths	Limitations	Typical Use
Morphology	Microscopy of chorion/shape	Low cost, field ready	Expert-dependent, low throughput	Field screening
Ovitrap	Passive egg collection	Scalable, inexpensive	Manual counting	Community monitoring
SEM	Ultrastructure imaging	High precision	Expensive, lab only	Taxonomic/validation
Molecular (PCR/COI)	DNA barcoding	Gold-standard accuracy	Cost, infrastructure	Ground truth labeling
Deep Learning	Automated detection/counting	Fast, scalable, objective	Needs datasets & imaging control	Large-scale programs

dichotomous or pictorial keys. It is usually performed at the fourth instar, when diagnostic traits are fully developed. Distinguishing features include cephalic and thoracic setae, respiratory siphon length and shape, pecten teeth, and abdominal comb scales. These morphological traits support genus-level and often species-level discrimination (Figure 2). Typical distinctions include the short siphon of *Aedes*, the longer tufted siphon of *Culex*, and the absence of a siphon in *Anopheles* [47]–[49].



Figure 2: Close-up microscopic view of the respiratory siphon and comb-like pecten teeth of a fourth-instar *Aedes aegypti* larva, illustrating key morphological traits used for larval taxonomic identification.

Morphological identification requires only basic optical equipment. However, it is labor-intensive and highly dependent on taxonomic expertise. Trait visibility may also be influenced by developmental and environmental factors, including temperature, humidity, and local adaptation, which affect larval growth and morphology [50]. Life-cycle timing can assist in the interpretation of mixed collections, although it provides only supplementary evidence. For these reasons, morphological identification continues to function mainly as a taxonomic reference method for species confirmation, dataset annotation, and validation of automated systems.

When morphological traits are unclear or species-level confirmation is required, molecular and biochemical methods provide important support for larval identification. DNA-based methods, including PCR, COI barcoding, sequencing, and rDNA-based assays, can resolve ambiguous or closely related larvae. MALDI-TOF MS can further provide rapid confirmation through species-specific protein fingerprints when validated reference spectra are available [14], [17]. However, these approaches are more suitable for confirmatory analysis and data validation than for routine field screening.

4.2 Deep learning and automated larval classification

By reducing reliance on manual microscopy and supporting scalable image-based recognition, deep learning has substantially advanced larval identification. CNN-based methods, including transfer learning and ensemble frameworks, often report high accuracy under controlled conditions, frequently exceeding 90%, while remaining computationally efficient [51]. Approaches that incorporate entomological priors, such as region-focused detection, can improve interpretability. Temporal frameworks that combine CNNs with sequential analysis can exploit motion cues from short video clips to improve robustness [52], [53]. Recently, robustness-oriented work has also shown that modified YOLO-based classification frameworks can enhance larval recognition under degraded imaging conditions, such as blur, on the MosquitoLarvae-7400 dataset [54].

Beyond standard classification models, automated larval analysis is increasingly being adapted for practical deployment. Low-cost consumer imaging devices combined with efficient architectures such as MobileNet and EfficientNet can achieve competitive performance, often in the 90–98% range, using smartphone- or camera-based datasets supported by augmentation [55], [56]. Edge and mobile platforms further extend these capabilities to on-device inference. Without requiring specialized hardware, motion-based and video-driven systems enable automated counting and abundance estimation, in some cases exceeding 95% accuracy [40], [57]–[59]. These developments indicate that larval-stage AI systems are moving toward accessible, low-cost, and decentralized monitoring pipelines.

4.3 Dataset and acquisition considerations

Despite strong performance, larval-stage classification is highly sensitive to dataset composition and image acquisition conditions. Larvae are small, translucent, and typically imaged in aquatic environments. Consequently, consistent image acquisition remains challenging, and classification accuracy may be affected by lighting variation, turbidity, blur, occlusion, and background clutter. Therefore, models trained and evaluated on curated laboratory datasets may not transfer reliably to operational environments.

Under controlled conditions, deep neural networks can achieve near-perfect accuracy using preprocessing, transfer learning, and ensemble strategies [51]. In less controlled settings, accuracy often declines substantially because of dataset homogeneity, small sample sizes, class imbalance, and acquisition artifacts. In some real-world scenarios, the performance of larval-stage classification can fall below 70% [60]–[62]. Augmentation and synthetic data generation can partially improve robustness [63]. However, reliable deployment depends more on large, diverse, and standardized datasets than on increasing architectural complexity alone. Table 3 summarizes the principal larval identification approaches and compares them in terms of operational principle, strengths, limitations, and typical use.

4.4 Stage-specific limitations and operational role

Larval-stage identification is important in mosquito surveillance because larvae are accessible for repeated sampling and are directly relevant to control interventions. At this stage, effective control can prevent later vector emergence. For this reason, larval surveillance is especially well suited to routine monitoring workflows that combine microscopy, image-based classification, and mobile or edge-assisted tools.

For reference annotation, microscopy remains biologically interpretable and essential, although it scales poorly to large collections. Neural networks enable faster and more automated processing. However, their reliability is governed chiefly by acquisition conditions and dataset variability rather than nominal model accuracy. Mobile and edge-based systems improve field deployability, but they often rely on simplified models and constrained hardware, which can limit discrimination of closely related taxa. In practice, routine screening should use automated image-based detection and classification. Periodic morphological confirmation should support taxonomic validation.

5 Classification of pupae

The pupal stage is the final aquatic phase before adult emergence and therefore has direct relevance to near-term vector abundance, operational forecasting, and mass-rearing workflows. Compared with eggs, larvae, and adults, pupal identification is less studied as a stand-alone taxonomic task. Pupae are non-feeding, mobile, and physiologically distinct from larvae, and their short developmental duration imposes different surveillance and handling constraints. Pupal-stage methods are used less for routine image-based classification and more for confirmation, sorting, and operational surveillance support.

Pupal identification or processing is especially useful in three operational scenarios. First, in sterile insect technique/incompatible insect technique (SIT/IIT) sex sorting, male pupae must be separated for release programs. Second, in mass-rearing quality control, pupal viability and emergence readiness must be monitored. Third, in adult-emergence forecasting, pupal density provides a near-term indication of expected adult abundance.

5.1 Morphological and rearing-based identification

Pupal identification primarily relies on external morphology and chaetotaxy. Species discrimination is based on respiratory trumpet and paddle shape, segmentation, and setal arrangement, which are assessed using microscopy and taxonomic keys. When pupal traits are insufficient for reliable identification, specimens may be reared to adults for confirmatory taxonomic assessment. High-resolution imaging, including SEM, can further resolve fine structural features and improve separation of closely related taxa [64], [65]. However, diagnostic reliability may be affected by environmental and physiological factors that alter morphology, including hypoxic stress and insect growth regulators that produce atypical forms [66]. This approach is morphologically grounded and taxonomically interpretable. Nevertheless, it is labor-intensive and

Table 3: Comparative summary of mosquito larvae identification approaches.

Approach	Principle	Strengths	Limitations	Typical Use
Morphology	Microscopic anatomy	Interpretable, low cost	Slow, expert required	Taxonomic labeling
CNN/DNN	Image classification	High accuracy, automated	Domain shift sensitive	Field AI screening
Mobile/Edge	Smartphone inference	Portable, Low-cost	Hardware limits	Community surveillance
Video counting	Temporal motion analysis	Non-invasive, abundance data	Overlap errors	Density estimation
Data augmentation	Synthetic expansion	Improves robustness	Risk of bias	Training support

constrained by the short pupal duration, which limits its scalability in large surveillance programs.

In operational practice, pupae are often collected alongside larvae and identified indirectly by rearing them to adulthood. Adult morphological traits allow more reliable species confirmation. This practice makes rearing an important bridge between aquatic-stage sampling and adult-stage taxonomy, especially when direct pupal traits are insufficiently distinctive. Pupal monitoring can also provide a useful indication of imminent adult emergence. Pupal densities may correlate more closely with subsequent adult abundance than larval counts, supporting predictive assessment and operational planning. At the same time, the short duration of the pupal stage, typically 24–48 h, narrows the sampling window and limits the practicality of detailed stand-alone taxonomic analysis.

5.2 Molecular, biochemical, and integrated support methods

When greater certainty is required, molecular diagnostics can provide objective identification of cryptic taxa. Methods such as PCR and sequencing are commonly integrated with morphological assessment [67]. Additional transcriptomic, genetic, and biochemical approaches extend the role of pupal analysis beyond taxonomy to applications such as sex separation, resistance monitoring, and population-level characterization [68]–[70]. These methods are especially valuable for species verification and specialized tasks in research, biosecurity, and release-program pipelines. Their laboratory dependence makes them better suited to confirmatory support than to routine high-throughput field deployment.

5.3 Mechanical and automated pupal processing

Compared with egg- and larval-stage systems, pupal automation is oriented less toward image-based taxonomy. Instead, it focuses more on mechanical handling, particularly in SIT/IIT programs. Sexual size dimorphism and the greater physical robustness of pupae make them well suited to automated sorting,

counting, and transport workflows. Size-based separators support rapid stage and sex differentiation, thereby preserving specimen integrity during large-scale processing [71].

Semi-automated and robotic systems improve consistency and reduce operator bias [72]. Controlled parameters such as pupal density and water volume influence the performance of sorting pipelines [73]. Electronic recirculating counters enable fast, low-mortality enumeration, while optimized packaging and transport procedures can maintain viability for downstream assessment [74]. Mechanical systems remain more practical than purely image-based classification in most operational settings because pupae have limited visual distinctiveness and are often processed in bulk.

5.4 Stage-specific limitations and operational role

Pupal-stage identification is constrained more by biological and operational factors than by a lack of analytical methods. The short duration of the pupal stage, specimen fragility, and reliance on fine chaetotaxic features restrict detailed taxonomic assessment. Accurate diagnosis often requires specialized expertise and careful handling. Pupae also show physiological resilience that can complicate intervention assessment. For example, agents causing more than 90% larval mortality may yield only 13–16% pupal mortality, reducing the usefulness of this stage for evaluating some control effects [75]. In addition, the scarcity of standardized datasets, annotated repositories, and stage-specific imaging resources continues to limit reproducibility.

Table 4 summarizes the principal pupal identification approaches and their operational trade-offs. Chaetotaxy provides interpretable taxonomic assessment but remains labor-intensive and sensitive to specimen conditions. Rearing offers highly reliable confirmation but is time-consuming. Molecular and biochemical methods provide precise identification but require higher laboratory costs. Mechanical systems

Table 4: Comparison of pupal-stage mosquito identification approaches discussed in section 5.

Approach	Principle	Strengths	Limitations	Typical Use
Chaetotaxy	Setal patterns inspection	Species resolution	Slow, fragile specimen	Lab taxonomy
Rearing	Adult emergence	Very reliable	Time consuming	Surveillance confirmation
PCR/Sequencing	DNA confirmation	Objective, precise	Cost, lab setup	Research/biosecurity
MALDI-TOF	Protein fingerprinting	Rapid, reproducible	Specialized equipment	Advanced labs
Mechanical sorting	Size-based automation	Very fast, scalable	Not taxonomic	SIT mass-rearing

prioritize rapid, scalable processing in SIT/IIT and related workflows.

Pupal surveillance is mainly useful for predictive and operational support rather than detailed taxonomy. For species-level certainty, device-assisted counting can be supplemented with rearing, morphology, or molecular confirmation. Purely image-based pupal classification remains comparatively limited because pupae are often processed in bulk and have fewer distinctive visual features.

6 Classification of adult mosquitoes

To achieve genus- and species-level classification, adult identification traditionally relies on stereomicroscopic examination of external morphology using dichotomous keys. Although taxonomically reliable, manual inspection depends on specialist expertise and becomes impractical for large trap collections. To automate feature extraction while retaining biological interpretability, contemporary systems increasingly integrate morphology with digital imaging, machine learning, and embedded sensing. Compared with earlier life stages, adults provide the most direct epidemiological signal because they represent the disease-transmitting phase. Nevertheless, they also face the greatest environmental variability during field surveillance.

6.1 Traditional and hybrid identification methods

Classical adult identification relies on external morphological characters and dichotomous keys to separate taxa [76]. This method remains taxonomically grounded and interpretable. Despite these strengths, it is slow, labor-intensive, and dependent on specialized expertise, especially when applied to large trap collections. These limitations have motivated the development of semi-automated and image-based alternatives. Such approaches retain morphological cues and reduce dependence on manual inspection.

For adult mosquito identification, early hybrid systems used handcrafted image descriptors rather than deep neural networks. To localize diagnostic regions and perform portable recognition, embedded platforms combined feature matching, texture operators, and shallow classifiers [77,] [78]. These methods are computationally lightweight and suitable for on-device inference. However, they are less adaptable than learned models and remain sensitive to variation in illumination, pose, and specimen

condition. Subsequent approaches have focused more explicitly on diagnostically informative regions instead of full-body imagery. Region-specific preprocessing has improved discrimination of closely related taxa and reduced sensitivity to background noise [79]. Lightweight CNNs such as MobileNetV2 have further enabled edge deployment. Under unconstrained field conditions, performance has remained moderate, with reports near 80% [80]. When specimens are damaged, cryptic species are suspected, or confirmation is required, molecular and biochemical methods can support adult identification. DNA-based assays, including PCR, COI barcoding, sequencing, and nanopore-based methods, provide species-level confirmation. MALDI-TOF MS enables rapid identification through protein fingerprints when reference spectra are available [3], [16]. Collectively, these methods represent a transitional stage between classical morphology and fully learned adult recognition systems.

6.2 Deep learning for adult classification

Modern convolutional and deep neural networks replace handcrafted descriptors with automatically learned hierarchical features. As a result, they have become dominant in image-based adult mosquito classification. When fine-tuned on curated mosquito datasets, standard CNN backbones such as VGG, ResNet, DenseNet, EfficientNet, and MobileNet achieve high accuracy. Across species- and sex-classification tasks, these models typically report performance above 90%, with some studies approaching 99% [81]-[88]. Interpretability analyses such as Grad-CAM further indicate that these models often focus on biologically meaningful regions rather than irrelevant image content. Differences in performance across architectures are influenced less by model choice alone than by dataset quality, acquisition consistency, and evaluation design.

To improve robustness under more heterogeneous conditions, ensemble and hybrid frameworks combine deep features with classical classifiers, detection-first pipelines, or multi-stage decision strategies. Across studies, these methods generally report high performance, commonly in the 95-99% range. They also demonstrate improved stability across variable imaging scenarios [89]-[92]. Even so, gains over well-trained single-model architectures are usually modest. Practical effectiveness remains strongly tied to dataset diversity

and domain alignment rather than to additional model complexity alone.

6.3 Wing morphology and acoustic sensing

When specimen pose, image quality, or operational constraints limit full-body visual classification, adult identification can also exploit anatomical and behavioral cues beyond full-body images. In such settings, wing morphology and flight acoustics are especially useful because they provide alternative sensing modalities with different strengths and constraints [18], [93].

Mosquito wings exhibit species-specific venation patterns and landmark configurations that serve as stable taxonomic markers. Geometric morphometrics converts these features into quantitative descriptors capable of separating medically important genera and species. Combined with machine learning or lightweight CNNs, wing imagery supports real-time recognition on embedded platforms [92]. MobileNetV2 and EfficientNet-B0, for example, have been used for portable discrimination of *Aedes aegypti* and *Aedes albopictus*. Geometric features alone have achieved near-perfect separation of closely related taxa such as *Wyeomyia* sp. and *Limatus durhamii*. Wing-based systems provide a compact and computationally efficient alternative to full-body classification, particularly for resource-constrained devices [4].

For adult mosquito identification, flight-acoustic sensing provides a non-contact method. It analyzes species-specific wingbeat frequencies and harmonic signatures captured through microphones or optical sensors. In flight-acoustic identification, recent advances in signal processing and deep learning include convolutional, attention-based, and lightweight temporal models. These models have delivered reliable performance, typically exceeding 88-90%, while maintaining computational requirements compatible with edge and IoT deployment [93]-[97]. Acoustic sensing complements vision-based systems. It is especially valuable under poor imaging conditions or when non-contact monitoring is preferred.

6.4 Smart traps and automated field surveillance

Adult mosquito surveillance is moving from manual or offline analysis toward autonomous smart traps that detect, count, and classify mosquitoes directly in field environments. These systems integrate optical or

imaging sensors, embedded processors, and onboard inference capabilities to provide continuous, time-stamped monitoring with minimal manual handling. Field deployments, including beam-break, camera-based, and IoT-enabled platforms, have reported automated detection accuracies above 90% [98]-[100]. These systems also support temporal activity tracking and large-scale population assessment. Hybrid configurations that combine automated trapping with molecular confirmation can further improve taxonomic reliability when needed [101].

This shift toward real-time surveillance significantly enhances scalability. In practice, deployment remains dependent on hardware durability, maintenance, power availability, and environmental stability. As a result, smart traps should be viewed not merely as classification tools but as integrated surveillance systems that combine sensing, inference, and continuous monitoring in operational settings.

6.5 Stage-specific limitations and operational role

Adult-stage identification has the greatest direct epidemiological relevance because adult mosquitoes represent the disease-transmitting stage. Data from adult mosquitoes provide immediate information for risk assessment, dispersal monitoring, and host-seeking behavior. At the same time, this stage is the most affected by environmental variability. Vision-based systems can degrade under specimen damage, unstable lighting, pose variation, occlusion, debris, and heterogeneous backgrounds. Acoustic approaches are sensitive to wind, ambient noise, and sensor placement and calibration. In addition, many adult-stage studies rely on geographically narrow, non-standardized datasets, leading to domain shifts that limit transferability and reproducibility across deployment settings [102].

Table 5 summarizes the principal adult identification approaches and their operational trade-offs. Morphology remains important for taxonomic confirmation but lacks scalability. CNN-based and ensemble-assisted AI methods provide automated, high-accuracy classification under controlled conditions. Wing morphometrics, acoustic sensing, and IoT-enabled traps offer complementary modalities when full-body imaging is insufficient. Reliable adult surveillance depends less on any single model than on the combined use of appropriate sensing modalities, diverse datasets, acquisition consistency, and standardized validation. The most dependable adult-monitoring workflows combine automated screening

Table 5: Comparative summary of adult mosquito classification approaches.

Approach	Principle	Strengths	Limitations	Typical Use
Morphology	Visual keys	Interpretable, cheap	Labor-intensive	Field labs
CNNs and ensemble AI methods	Automated image-based classification and model fusion	High accuracy, scalable, improved stability under controlled conditions	Requires diverse datasets: ensemble models increase computational and validation complexity	Automated surveillance and advanced AI-based screening
Wing morphometrics	Shape features	Lighting robust	Requires intact wings	Embedded devices
Acoustics	Wingbeat sound	Non-contact, passive	Noise sensitive	Smart traps
IoT traps	Sensors + AI systems	Continuous monitoring	Hardware cost	City-scale program

with selective morphological or molecular confirmation under standardized deployment conditions.

7. Cross-stage analysis, challenges, and future directions

Across the life cycle, mosquito identification is shaped less by algorithmic sophistication alone than by stage-specific biological accessibility, specimen characteristics, and operational surveillance requirements. Each stage of development supports a distinct monitoring role, favoring different sensing, validation, and deployment strategies. For early warning, oviposition monitoring, and source-reduction programs, egg-stage surveillance is most useful. It typically relies on ovitrap collection, microscopy, and increasingly automated counting or image-based analysis. When species-level certainty is required, molecular confirmation is used.

Larvae provide the strongest balance among detectability, repeated sampling feasibility, and direct intervention value. This balance makes larvae especially suitable for routine microscopy, image-based classification, and mobile or edge-assisted screening. Pupae are less suited to stand-alone image-based taxonomy and are instead more closely associated with predictive monitoring, mass-rearing, and SIT/IIT workflows. For pupal-stage workflows, rearing, molecular confirmation, and mechanical sorting are often more practical than visual classification alone. Adults provide the most direct epidemiological signal and support real-time surveillance through optical imaging, wing analysis, acoustic sensing, and smart traps. They are also the most affected by field variability, including occlusion, specimen damage, unstable lighting, and environmental noise [85].

Across stages, no single identification modality is universally optimal. Morphological methods remain important because they are interpretable, inexpensive, and widely accessible. Despite these advantages,

morphology remains labor-intensive and strongly dependent on specimen integrity and taxonomic expertise. Molecular and biochemical approaches provide the highest diagnostic certainty, particularly for cryptic, damaged, or early-stage specimens. High cost, infrastructure requirements, and laboratory dependence limit routine large-scale deployment of these methods. Automated imaging and deep learning represent the clearest route toward scalable surveillance, especially for eggs, larvae, and adults. Model performance depends heavily on dataset composition, acquisition control, and environmental consistency. In summary, effective mosquito surveillance systems are tiered, combining low-cost collection and automated screening with selective morphological, molecular, or biochemical confirmation according to operational needs.

The lack of consistent benchmarking remains a major challenge in the literature. Direct comparison of performance across studies is often difficult. This difficulty arises from differences in species coverage, developmental stages, image quality, acquisition devices, preprocessing pipelines, class balance, annotation quality, and evaluation protocols. Accuracy reported under controlled laboratory conditions may not transfer directly to field deployment [62]. This limitation is especially evident in egg- and larval-stage studies, where datasets are often small, geographically narrow, and insufficiently diverse. A similar issue is also apparent in adult-stage studies, where curated images and controlled recordings often fail to capture the variability of real surveillance environments. Occlusion, debris, pose variation, specimen damage, heterogeneous backgrounds, acoustic interference, and hardware differences continue to reduce generalizability across sensing conditions and collection sites.

These limitations indicate that future progress will depend less on marginal architectural refinement and more on data quality, validation rigor, and deployment-oriented system design. To improve reproducibility and



practical relevance, public multi-stage benchmark datasets are needed. These datasets should be supported by harmonized imaging and annotation protocols, along with evaluation procedures that include cross-site and cross-device testing. Lightweight, edge-deployable models and robust field-ready hardware will be important for decentralized monitoring, particularly in low-resource settings. At the system level, multimodal surveillance frameworks that integrate optical, acoustic, and molecular cues offer a promising path toward improved reliability when a single sensing modality is insufficient [97]. Domain adaptation, transfer learning across regions, and federated or distributed learning may further strengthen robustness. Such methods can reduce dependence on narrowly curated datasets. Together, these directions support the transition from isolated proof-of-concept models toward integrated, scalable, and operationally reliable mosquito surveillance systems.

8 Conclusion

This review provides a stage-aware synthesis of mosquito identification methods across eggs, larvae, pupae, and adults. It highlights the progression from manual morphology-based taxonomy to more automated, scalable, and technology-enabled surveillance approaches. Across the mosquito life cycle, each developmental stage serves a distinct surveillance function: eggs are most useful for early warning and source reduction, larvae for routine habitat surveillance, pupae for predictive assessment and mass-rearing operations, and adults for direct epidemiological monitoring. The synthesis shows that no single identification method is optimal across all life stages. Instead, practical mosquito surveillance depends on tiered workflows that align identification techniques with stage-specific biological characteristics, operational constraints, and deployment requirements. Morphological and molecular methods remain important for taxonomic confirmation and reference validation. Meanwhile, AI-based imaging, acoustic sensing, and smart surveillance platforms increasingly support scalable and near-real-time surveillance operations. Future progress will depend on standardized multi-stage datasets, stronger benchmarking practices, lightweight edge-deployable models, robust field-ready hardware, multimodal systems that integrate optical, acoustic, and molecular information, and comprehensive cost-effectiveness studies that compare implementation cost, throughput, maintenance, and field performance.

Advancing these directions can support more reliable, scalable, and operationally effective mosquito surveillance systems for vector management and targeted intervention.

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Author Contributions

M.U.R.: conceptualization, writing an original draft, investigation, data curation; H.I.: writing-reviewing editing, validation; W.P.: investigation, methodology, writing-reviewing editing, funding acquisition, project administration.

Conflicts of Interest

The authors declare no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors utilized the ChatGPT tool to enhance the language and readability of the manuscript.

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