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Mosquito tracking, classification, and identification: A glance at the technologies available

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Abstract
Malaria and dengue fever infect over one million people every year, according to the World Health Organization. A disease's vector mosquitoes are specific to that illness. The disease is propagated throughout a region by the majority of carrier mosquitoes living in it. The species of mosquitoes in a given area may now be simply and quickly identified using recordings of their wing movements thanks to advances in Machine Learning and Computer Vision technology. Because each mosquito species' wingbeats are distinct, this is a solid approach for identifying them. The Zika virus is carried by this mosquito species, which is well-known. The detection of mosquito-borne diseases in the investigated area can also be aided by identifying such carrier species. In this research, we look at several strategies that have shown to be effective in identifying mosquito species. Several mosquito-borne diseases have emerged, demanding rapid and effective responses. The behavior of mosquitoes must be fully understood to develop and effectively implement mosquito control strategies, with a detailed examination of mosquito flight being an essential component. A review of recent advances in automated tracking approaches allowing a thorough understanding of mosquito movement is presented. Tracking techniques can improve or replace existing monitoring tools, as well as provide knowledge into mosquito behavior that can lead to more inventive and effective vector-control measures. Wingbeat frequency is the most widely used and most accurate method of mosquito identification.
The latest IoT technology can also be used to track mosquitos. Image-based mosquito identification is becoming more common as a result of high-resolution cameras.

Keywords: Wingbeat, sensor, mosquito, Zika, malaria, dengue, chikungunya, IoT, remote sensing

Introduction

Mosquitoes play a significant role in disease transmission.
Mosquito-borne infections afflict around 700 million people each year, with over 700,000 people leading to death.
There are at least 3500 mosquito species, with about 200 species consisting solely of females. Only 200 of them are responsible for human diseases. Various mosquito species transmit different diseases. Detecting the presence of disease-carrying mosquitos in humans is important in ways to tackle illnesses including Zika, malaria, Dengue fever, and Chikungunya, among others. Microcephaly and other congenital abnormalities in the developing fetus and newborn are caused by Zika virus infection during pregnancy. Pregnancy problems such as fetal loss, miscarriage, and premature delivery can all result from Zika infection during pregnancy. Zika virus is primarily transmitted by the bite of an infected mosquito from the *Aedes* genus, mainly *Aedes aegypti*, in tropical and subtropical regions [1].

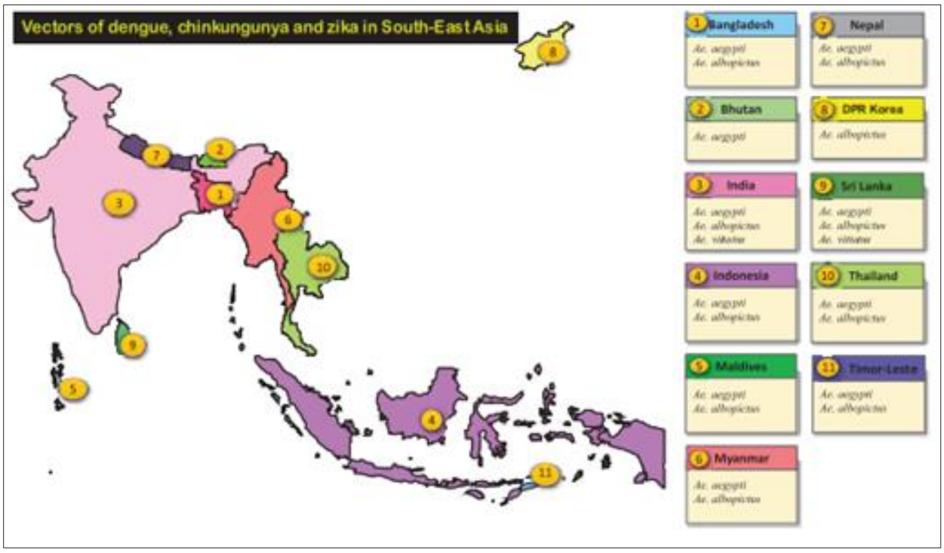

Image source: (Asia, 2020)

Fig 1: Mosquito-produced diseases image

Need & significance of the research

Mosquito-produced diseases pose a huge threat to the wellness of living beings as per the statistics close to seven hundred million individuals annually, which causes more than one million demises in humans. It not only affects to human lives but also degrades the quality and quantity of domestic and wild animals. This in turn, directly and indirectly, affects the economy of our country, therefore these threats trigger the motivation of this study to curb, prevent lives and strengthen the economy.

To develop eco-epidemiologic models' fact full insights into the growing number and dispersal of affecting types of insects is of utmost importance [3].

In May 2015, the Pan American Health Organization issued an alert regarding the first confirmed Zika virus infections in Brazil. Since this identification, the virus has spread rapidly throughout America. The illness is sometimes mild with symptoms lasting for several days to per week after being bitten by an infected mosquito. However, Zika infection during pregnancy can cause a significant congenital anomaly called microcephaly, furthermore as other severe fetal brain defects. Dengue is the most vital vector-borne viral disease of humans and certainly more important than malaria globally in terms of morbidity and economic impact Studies estimate that 3.6 billion people live in areas of risk, with 390 million [4].

Mosquito is a dangerous vector

Mosquito (*Culicidae*) taxonomy

Culex is a genus of mosquitoes in which several species act as vectors for the transmission of one or more important human diseases. The family Culicidae is derived from *culex*. The family Culicidae includes about 3200 recognized species [5].

Mosquito classification

Mosquito belongs to the kingdom Animalia its Phylum is Arthropoda and Subphylum Hexapoda. It belongs to the class of insect and its order is Diptera [6].

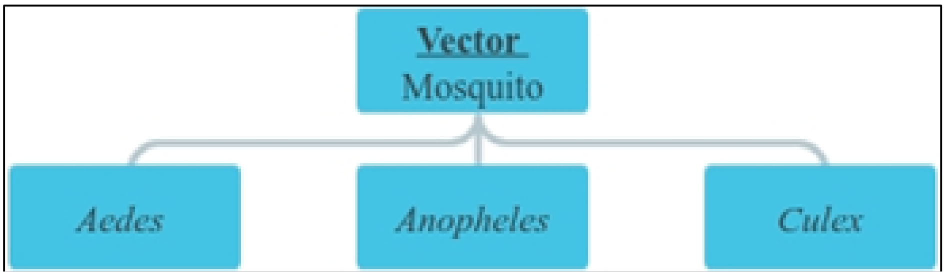

Fig 2: Mosquito-Borne Diseases and Species

Diseases transmitted by Mosquitos Species

- ***Aedes****:* Chikungunya, Dengue, Lymphatic filariasis, Rift Valley fever, Yellow Fever, Zika
- ***Anopheles****:* Lymphatic filariasis, Malaria
- ***Culex****:* Japanese encephalitis, Lymphatic filariasis, West Nile fever [7].

Burden of Mosquito-Borne Diseases

Malaria Global burden

According to a WHO report released in December 2013, there were approximately 207 million cases of malaria and 627 000 mortality in 2012. Malaria death rates have decreased by 45 percent globally and 49 percent in the WHO African Region since 2000.

Dengue Global burden

Dengue fever, a mosquito-borne disease, now threatens more than 2.5 billion people or over 40% of the global population. Dengue fever is estimated to affect 50-100 million people worldwide each year, according to the World Health Organization.

Chikungunya Global burden

The disease has spread over Africa, Asia, and the Indian subcontinent. In recent decades, Chikungunya mosquito vectors have spread across Europe and America. In the Indian Ocean islands of Comoros, Mayotte, Mauritius, Seychelles, and especially Reunion Island, a significant chikungunya outbreak occurred in 2005-2006, infecting 35 percent of the 770 000 residents in six months [8]. (Fact sheets on vector-borne diseases in India, 2014)

Mosquito-Borne Dieses Burden in India in 2021

Disease	No of Cases	No. of Death Cases
Malaria	99239	80
Dengue	123106	90
Chikungunya	8806	0

Source: (NCVBDC) [35]

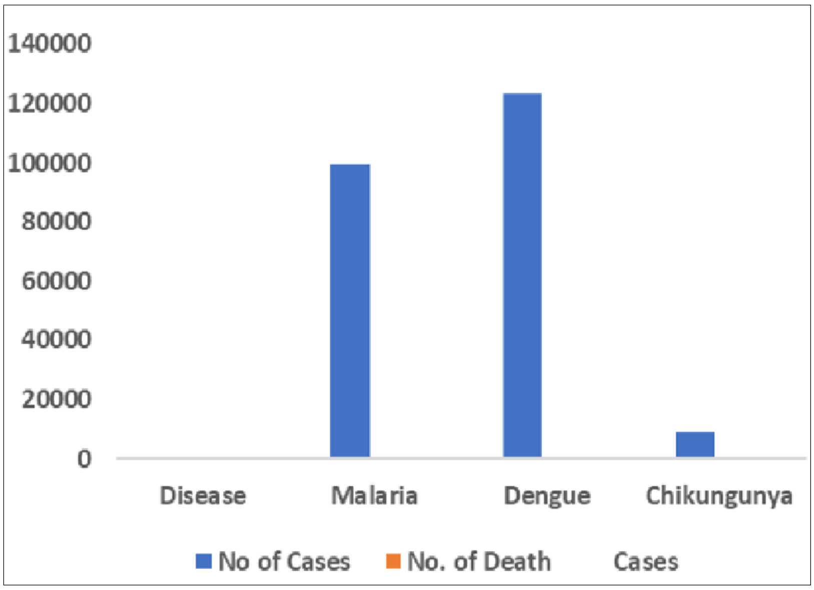

Fig 2: Mosquito Borne Dieses Burden in India in 2021

Mosquito Identification

Mosquito identification and classification is the utmost important aspect to control and prevent mosquito-borne diseases which are the biggest threat to livestock. There are different electronic techniques for the identification and classification of mosquitos.

- Mosquito-Detection Through the Wing-beat Frequency
- Mosquito-Detection Through the Images of mosquito
- Real-time mosquito identification

Table 1: Electronic mosquito identification

Sr. No	Mosquito Identification	Techniques
1	Wingbeat	Optical, acoustic, optoelectronic sensor
2	Image	High-speed photography, digital photographs, videos
3	Remote sensing	Optical remote sensing
4	IoT	Embedded System

Table 2: Mosquito identification techniques at a glance

Sr. No	Author	Methods	Year	Detection Techniques	Instrument /Device
1	Wheatstone	Wingbeat based wing motion optical method	1827	optical method	Kymograph
2	Marey	High-speed photography	1868	High-speed photography	stroboscope
3	L. E. Chadwick	Wingbeat	1939	cyclic move	stroboscope
4	W. H. Offenhauser Jr and M. C. Kahn	Wingbeat	1949	a sound-baited trap	Microphones
5	O. Sotavalta	Wingbeat based Acoustic methods	1952	Signal processing frequency of wing stroke by flight	Oscillographs, stroboscopes
5	I. Richards	Insect flight Sound	1955	photoelectric cell	photocell
6	A. Moore	optical signal analysis	1986	Optoelectronic sensor	Optoelectronic sensor photocell
7	R. Mankin	acoustic method	1990s	Acoustic	Acoustical device
8	D. R. Raman, R. R. Gerhardt	Flight tune	2004	acoustic method	Acoustic detector
9	L. J. Cator, B. J. Arthur	Flight sound	2011	acoustic method	optical system that uses laser beam
10	G. E. Batista, Y. Hao	WBFs	2011	Optical method	optical device with a laser beam

12	Ayan Kumar Biswas, Nahian Alam Siddique	Wingbeat	2013	Sensor trap, Machine learning techniques	fiber-optic sensor
13	Y. Chen, A. Why, G. Batista	Wingbeat	2014	Optical method	sensor
14	D. F. Silva, V. M. Souza	Wingbeat	2015	Optical method	Lasor sensor
13	I. Potamitis and I. Rigakis	Wingbeat	2015	Optical method	laser and LEDs
14	Kiskin, I. (2017)	Wingbeat	2017	Optical method, CNNs	Sensor
15	M. D. Keller	Wingbeat	2016	Laser	Phonec Fence
16	Mona Minakshi	Images	2020	CNN model for Inception-ResNet	cell phones
17	Clinton Haarlem	photos of mosquito wings	2018	SURF algorithm	cell phones
18	Reyes,	Image	2016	SVM	smartphone
19	Mukundarajan,	wingbeat sounds	2017	Acoustic	cell phones
20	Minakshi	Images	2018	SVM	smartphone
21	Simões,	Wing Images	2020	CVA	CDC Trap
22	Motta,	Images	2019	CNN	Digital camera
23	Park,	Images	2020	Deep learning	Digital camera
24	Zhong,	Images	2018	SVM,YOLO	Digital camera
25	Huang,	IoT	2018	Edge Computing, image processing	camera
26	Adrien P. Genoud,	Optical remote sensing	2018	Signal processing wing beat frequency	long-range lidars

Mosquito-Detection Through the Wing-beat Frequency

Marey (1868) investigated wing motion using Wheatstone's (1827) optical method. Marey (1868) invented the use of the kymograph in the study of wing motion. High-speed photography is a third technique proposed by Marey, and his followers have contributed to its development. The stroboscopic concept has been used in most endeavors at high-speed photography. Cyclic movements can be made to appear to stop using a stroboscope, irrespective of their accurate frequency. An innovative arrangement that allowed air currents to be generated allowed frequency to be automatically coordinated with the wings. To access a very light key in the main circuit by the wing at a particular phase in each beat. The movement of an insect's wings is primarily a cyclical concept, a cyclic phenomenon [9]. In 1949, microphones were used as the primary tool in research on the classification of flying insects. At this point, the low amplitude sensitivity of the signals received by the microphones available at the time, as well as the requirement to design filters capable of removing external noise, were already a source of concern [10].

Acoustic methods, such as oscillographs, are used to determine the frequency of wing strokes based on the flight tone emitted by the wing hum of a flying insect. By 1952, researchers were using kymographs and chronophotographic systems, as well as stroboscopes and oscilloscopes, to classify flying insects [11]. In 1955, it was discovered that when a flying insect crosses the sensor field of a photoelectric cell, the cell can detect some sunlight modulation [12]. The optical signal analysis theory in the identification of flying insects is based on the belief that an insect in free flight can modulate the sunlight experienced by a photocell. However, there is an absence of instrumentation for the automated acquisition and measurement of biological data. Until 1986, the lack of information made it difficult to invest in technology that could take advantage of this concept [13]. In the 1990s, the acoustic method was widely adopted in studies to detect mosquito swarms. A sequence of recordings was conducted both in the open and in an airtight cabinet in a laboratory-controlled environment in studies undertaken at the US Department of Agriculture's Insect Attractants, Behavior, and Basic Biology Research Laboratory. A microcomputer scanned, filtered, and evaluated the recordings. The results reveal that, under the technological conditions of the time, mosquito swarms could be detected at a distance of 10 to 50 meters in a silent environment [14]. Since about the 1990s, acoustic techniques had limited accuracy when it came to identifying flying insect species. To address this issue, a 2004 study proposed the construction of an acoustic detector. A prototype field-deployable acoustic insect flight detector was built using a noise-canceling microphone and an off-the-shelf optical sound recorder capable of 10 h tracks. A variety of approaches were developed to track insect flight tone. Simple approaches, such as detecting the fundamental frequency (1st harmonic) and 2nd harmonics, were capable of detecting insects; however, other ambient sounds, such as human voices, birds, frogs, cars, helicopters, sirens, and trains, resulted in a significant number of false positives. It investigates the viability of employing this method to detect mosquito activity with low-cost sensors [15]. In a study conducted in Thailand in 2011, the fundamental Wing Beat Frequency and related harmonics of Aedes aegypti mosquitoes were evaluated using an array of microphones. The trials used a total of eight microphones set at equal distances to record 3.5 hours of mosquito sound waves. The fundamental frequency of the female Aedes aegypti mosquito was discovered to be 664.3 Hz at 32.6°F ambient temperature [16]. Each mosquito that entered the trap was detected and counted by the fiber-optic sensor. With this data, machine learning techniques were utilized to develop parallel processing techniques that allow the sensor to distinguish sex, age, and species at all times. Males had a higher basic frequency than females, and Aedes mosquitos had a higher basic frequency than Culex mosquitos [17]. (Ayan Kumar Biswas, 2013) One of these studies, published in 2015, proposes the use of laser and LEDs as light sources for sensor design (Light Emitting Diodes) [18]. A recent study used an optical device with a laser beam to identify three distinct insect species based on WBFs: *Aedes aegypti, Culex quinquefasciatus, and Anopheles stephensi* [19]. A unique context of this study is that hardware deployment costs were considered, resulting in the acquisition of a low-cost sensor. The study also looked into using a simple algorithm to improve insect classification accuracy. To study the spatial and temporal dynamics of mosquito behavior, enough data was collected. Then it was shown that optical sensors had already solved most of the challenges in insect sensing [20]. Millions of recordings have been made possible by such sensors, providing enough data to speed up research and enable device deployment in a real-world situation. The use of Machine Learning to offer an accurate classification system is the culmination of the research process [21]. A mosquito's presence from its acoustic signature is detected using deep convolutional neural networks (CNNs). They compare artificial deep feature learning to standard classifiers based on both hand-tuned and generic features to demonstrate the power of artificial deep feature learning (Kiskin, 2017) [22]. Two distinct varieties of insects were used to test the device's classification ability.

Using a sophisticated combination of optical sources, sensors, and algorithms, this system identifies and classifies flying insects in real-time. In addition, the technique can use a lethal laser beam to destroy insects. The device employs a PF (Photonic Fence) for increased mid-range monitoring. Further researchers focus on laser-based mosquito-eradication technologies [23]. The authors demonstrate that commercially available mobile phones can be used to acoustically map the location of mosquito species around the world. The authors show that even very basic, low-cost cell phones can collect acoustic data on genus mosquito wingbeat noises while concurrently recording the time and location of a human mosquito contact. The primary goal of acoustic surveillance is to correctly identify a mosquito species using the sound characteristic wingbeat (Mukundarajan, 2017) [24].

Mosquito-Detection Through the Images of mosquito

The research is based on mosquito images. The study employs an external camera that is similar to the one used to photograph caught mosquitoes on cell phones. These methods also recommended using photos to automatically classify the kind of genus and species. The V22-based CNN model for Inception-ResNet [25] (Mona Minakshi, 2005) The author investigates how images of mosquito wings taken with standard mobile phone cameras and clip-on lenses can be employed to differentiate mosquito species when fed into image attribute extraction algorithms. The findings suggest that traits acquired using the SURF algorithm can be used to distinguish genera (Clinton Haarlem, 2018) [26]. The paper employs digital image processing and a support vector machine (SVM) to detect Aedes aegypti mosquitoes. The study proposed a method for determining whether a mosquito is an Aedes aegypti. Matlab and the support vector machine algorithm were employed by the author (Reyes, 2016) [27].

In this study, the authors developed a smartphone-based system that allows anyone to take photographs of a still mosquito that is either living or dead and automatically classifies the species.

The model integrates image processing, feature selection, unsupervised clustering, and a classification machine learning method based on SVM [28]. 2018 (Minakshi)Wing geometric morphometrics (WGM) has been used to classify mosquito species in addition to traditional identification approaches.

Adult mosquitoes were captured using CDC (Centers for Disease Control) traps and morphologically classed and evaluated by WGM. To show the patterns of species separation, a canonical variate analysis (CVA) was performed and a Neighbor-joining (NJ) tree was constructed (Simões, 2020) [29]. The authors developed a computer system based on a convolutional neural network (CNN) to extract features from mosquito visuals to classify adult mosquitoes of the species *Aedes aegypti, Aedes albopictus, and Culex quinquefasciatus*. To teach CNN how to distinguish mosquitos morphologically autonomously. CNN has been designed to conduct automated mosquito morphological classification (Motta, 2019) [30].

Mosquito-Detection Through IoT

The authors of this study investigated the ability of deep learning models to detect mosquito species with high inter-similarity and intra-species differences. Furthermore, they investigated if this high classification accuracy can be accomplished by modifying the discriminative areas used by deep learning models. Deep learning models utilize morphological features similar to those employed by human experts, according to research findings (Park, 2020) [31]. In this study, a vision-based counting and classification system for flying insects is being developed and tested. The system is constructed as follows: initially, a yellow sticky trap is created to capture flying insects in the monitoring area, and a camera is installed to collect real-time pictures. Then, using a feature map, a detection and coarse counting approach based on You Just Look Once (YOLO) object detection is built, followed by classification and fine counting method based on Support Vector Machines (SVM). Finally, the insect counting and identification technique is followed on the Raspberry Pi.

The bee, ant, mosquito, moth, chafer, and fruit fly are among the six flying insect species chosen (Zhong, 2018) [32].

The authors have developed a mosquito classification approach that can automatically differentiate between Aedes and Culex mosquitos. To promote the deployment of an Internet of Things (IoT)-based system, they first develop a trap device with a stable region for photographing mosquitoes. The next evaluate video frames to decrease the video size for transmission. Deep learning is also used by the authors to construct a model for classifying different types of mosquitoes. They perfect the edge computing on the trap computer later to enhance machine performance. When experiments are performed in rural regions, the results demonstrate a large effect. The authors achieve a validation accuracy of 98 percent and a data testing accuracy of 90.5 percent (Huang, 2018) [33].

Mosquito-Detection Through Remote Sensing

This research is focused on the remote characterization of flying mosquitoes utilizing a continuous-wave infrared optical remote sensing device. Mosquitoes are free to fly at a distance of 4 m from the collection optics in a controlled environment where the device is set up to resemble long-range lidars. The backscattered light from mosquitoes moving through the laser beam is used to calculate the frequency of the wing beat. The author analyses the use of wingbeat frequency as the primary predictor for two Bayesian classifications: gender alone and species and gender. The gender of each mosquito is identified with 96.5 percent accuracy, whereas the species and gender is identified with 62.3 percent accuracy (Adrien P. Genoud, 2018) [34].

Conclusion

Vector intervention methods are being adopted as part of the WHO's Global Vector Control Action plan.

As a result of the most recent advancements in flying insect control technology, new technology trends have emerged.

Various mosquito detection and monitoring approaches have been suggested in numerous studies.

1. The use of optoelectronic sensors to identify and classify mosquito species based on the fundamental wingbeat frequency found in the literature.
2. Acoustic approaches involving laser and LED are also being investigated.
3. Computer vision technology has advanced, and automated mosquito tracking is now largely owing to developments in digital performance and the invention of high-resolution cameras.
4. A sticky trap is set up in the monitoring area to catch flying insects, and a camera is set up to collect photos in real-time.
5. A mosquito classification research study based on remote sensing was also investigated. A remote classification of flying mosquitoes was achieved using a continuous-wave infrared optical remote sensing system.
6. Wingbeat frequency is an extensively used and highly accurate method of mosquito identification. The latest IoT technology can also be used to track mosquitos. Image-based mosquito identification is becoming more popular as a result of the high-resolution camera.

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