

RESEARCH ARTICLE

Entomoscope: An Open-Source Photomicroscope for Biodiversity Discovery

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ABSTRACT Understanding and slowing down biodiversity loss are critical tasks for the survival of our planet. They are difficult because much of the earth's biodiversity is concentrated in abundant and species-rich groups of invertebrates like insects. Traditionally, bulk samples of insects had to be analyzed manually by experts using morphology. Not only did this require much taxonomic expertise, but it was also error-prone, time-consuming, and almost always involved commercially available microscopes that are too expensive for many biodiverse, tropical countries with limited science funding. An alternative to sorting bulk samples by experts using morphology is the use of DNA barcoding. However, this requires a well-equipped molecular laboratory and a different skill set. We present an alternative solution - the Entomoscope, a low-cost, open-source photomicroscope for taking high-resolution, focus-stacked images that can be used for insect classification. We describe two different versions of the Entomoscope, a standalone version that can be operated without additional hardware and an even simpler version, that is operated via a computer. We show that the optics are of sufficiently high quality to classify specimens with >95% accuracy into 15 different types of insects (mostly 'families' according to the Linnaean classification). The classifier can be successively extended or individually trained for specific classification tasks. We provide the building instructions, 3D files, and a list of commercially available parts so that everyone can build their own Entomoscope. We predict that open-source DIY hardware like the Entomoscope will facilitate cutting-edge biodiversity research by entomologists around the planet.

INDEX TERMS Biodiversity, classification, DIY hardware, entomology, invertebrates, low-cost, open-source, smart microscopy, taxonomy, automation.

I. INTRODUCTION

Insects and other invertebrates provide many key ecosystem services like pollination, decomposition, and predation, while also being an important food resource for other species [1], [2]. Unfortunately, the global biodiversity decline also affects invertebrates and the population sizes of many insect species are decreasing while others are in the process of going extinct [3], [4], [5]. Despite the importance of insects, the

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study of insect diversity is often restricted to charismatic taxa such as butterflies [6] and bees [7]. However, these groups comprise only a small proportion of the overall species diversity. New methods are needed to monitor whole insect communities, including (and especially) the abundant and species-rich groups that are often ignored. These methods must yield species diversity and abundance information because extinction is often preceded by a decline in abundance [7]. Especially important are new techniques for the discovery and monitoring of undescribed species in so-called 'dark taxa' [8] given the World Economic Forum

considers biodiversity loss to be one of the most severe threats to the world [9]. At this point, insects and other arthropods are already routinely collected for biodiversity monitoring using standardized traps like Malaise Traps that use ethanol as preservative [10], [11]. However, samples typically contain several thousand specimens, so that manual evaluation of species composition and abundance is too slow and labor-intensive. In addition, it requires highly skilled personnel and expensive microscopes. In particular, classification into species requires one or more experienced taxonomists per family-level taxon. An alternative is characterizing an entire sample based on DNA ('metabarcoding') [12], [13], but this technique provides at best approximate abundance information. In addition, the sample is often destroyed during DNA extraction and cannot be used for follow-up research. DNA barcoding of individual specimens overcomes these disadvantages as it provides accurate abundance information if whole samples are examined while keeping the specimens intact, albeit with the drawback of being also labor intensive [14], [15]. In addition, all three techniques (manual examination by experienced taxonomists, 'metabarcoding', and DNA barcoding of individual specimens) struggle with determining biomass. Usually, only the total mass of an insect sample is measured and the distribution among species remains unknown.

Due to the varying sizes of insects and other variables, we currently lack an affordable standard photomicrography solution for tackling the imaging, classification, and biomass of insect samples. Commercially available imaging solutions are often so expensive, that they are unsuitable for widespread biodiversity research. For example, a popular microscope for imaging invertebrates is the VHX-7000 digital microscope by Keyence. Priced in the upper five-digit dollar range, this solution is primarily viable for well-established research institutions with substantial financial resources. An alternative are digital cameras with mounted macro lenses and flashes in custom setups [16], [17], [18], or cheaper microscopes that are equipped with cameras. There are also some low-cost, open-source, Do It Yourself (DIY) microscopes [19], [20], [21], [22], [23], but they are often designed for specific purposes. Examples are a DIY microscope for the detection of *C. elegans* nematodes - a widely used model organism in developmental biology [20], a fluorescence microscope for 3D imaging of cell cultures [21], or open-source microscopes for the automated observation of bacterial cultures [22], [23]. These DIY microscopes are mostly compound microscopes while dissecting microscopes are needed for insects. Unfortunately, they have received very little attention to date [24], [25], [26]. Therefore, high-quality imaging of insects preserved in ethanol remains a major challenge, and expensive laboratory microscopes or high-quality camera systems are typically used [27], [28], [29], [30]. This is unfortunate because several algorithms for identifying insects via images have been published. Accurate classification results based on neural networks have been achieved for insect taxa ranked as families [31], [32], [33]

and even at the species level [34], [35]. Additionally, the images also proved useful for estimating biomass [31], [35] and provide information about abundance when complete collections are imaged and evaluated. Furthermore, the digitized data allows subsequent studies on other aspects that might be of interest to other researchers. Thus, it is desirable to develop a DIY microscope for standardized and high-quality imaging of insects, so the images could be assigned to a species using automatic classification. This would allow for a biodiversity sample to be evaluated both rapidly, and without the help of taxonomic experts. In addition, if expensive microscopes, special cameras, and the necessary software could be replaced by a DIY approach with low-cost components, this solution would facilitate biodiversity research in countries and institutions where resources are limited [19].

II. CONCEPT AND METHODS

We developed two low-cost open-source photomicroscopy systems that take images and automatically classify specimens belonging to insect families with a high abundance in Malaise trap samples. The systems differ in their setup. The first is a compact, standalone device that includes all hardware components. The second works as a plug-in device and is operated via a computer with Microsoft's Windows operating system. In designing, we emphasized the need for the systems to be easily produced at low cost. Expensive manufacturing processes such as milling and turning are therefore avoided and all housing parts and connecting elements are 3D printable. To achieve high-quality imaging, we selected low-cost but high-performance components. Previous publications have shown that single-board computers combined with matching cameras are a low-cost solution for biological microscopy [22], [36], [37]. For this reason, both versions, the standalone and the plug-in versions use Raspberry Pi 4k cameras. However, since different lenses are needed for insects of various sizes, the systems should also be adaptive and feature a c/cs-mount lens adapter. To develop an autonomous system with an input unit, an inexpensive touchscreen with HD resolution is added to the standalone version, while the display of the connected computer serves as an input unit for the plug-in version. In comparison to other DIY microscopes, special emphasis is paid to high resolution and image stacking, so that even small morphological features can be used for classification. We use Python for the control software, given that this language has a large selection of libraries. Due to the comparatively low costs, even researchers with limited funds can afford the system and participate in automated biodiversity research [19].

To classify the insects, we use a Convolutional Neural Network (CNN) for which we have already obtained accurate results [31]. The data set is available at <https://doi.org/10.7479/4tbx-qm72>. It contains 5083 images that can be assigned to 15 groups and will be referred to as 'classes' hereafter: 14 classes (mainly at the family level

in the Linnaean hierarchy) and one ‘other’ class, including images of other invertebrates, as well as debris and broken off insect parts (e.g. legs). The ‘other’ class is used to distinguish the known classes from anything else that can be found in a Malaise trap sample. An exact representation of the data set can be found in the publication by Wühl et al. [31]. To perform the classification of known object classes and the detection of unknown specimens or other objects, a cascaded CNN architecture with two ResNet-50 encoders is used (see Figure 1). One encoder predicts the respective class index $c \in \{1, \dots, n\}$ for n known classes. The second encoder outputs an outlier probability score $0.0 \leq p \leq 1.0, p \in \mathbb{R}$. If p is bigger than the threshold θ , the outlier class $\mathcal{O} = n + 1$ is output. Otherwise the predicted known class c . In this work, θ is always 0.5. The samples of the data set are normalized to be

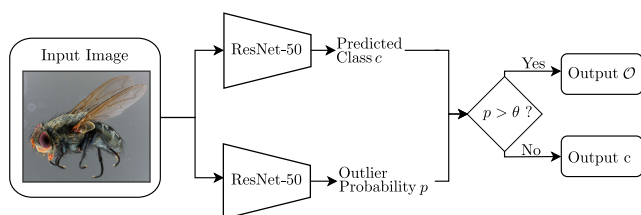


FIGURE 1. The CNN architecture. Two ResNet-50 encoders are employed to detect the class c and the outlier probability p . If p is greater than the threshold θ , the outlier class \mathcal{O} is predicted. Otherwise the determined class c .

in the range $[0, 1]$ and are divided into an 80% / 20% split of training and validation. Various augmentation techniques are applied to enhance the model’s robustness and generalization. Specifically, the images undergo horizontal flipping with a probability of 50%, random adjustments to brightness and contrast (up to 10% of the initial values), rotation by a maximum of 25%, and the application of Gaussian blur with sigma values ranging from 0.0 to 1.0. To train the classification task with our architecture (Figure 1), the c classes are set to be the 14 known classes, and the outlier detection is conducted with the ‘other’ class. To evaluate the performance of the classification, we provide the accuracy for each class as well as the overall accuracy, together with the recall and F1 score.

To evaluate the image quality and thus the imaging hardware, we have decided to use visual inspection of the images by experts as the decisive criterion.

III. RESULTS

We here describe both setups, the standalone Entomoscope (Figure 2) and the plug-in version (Figure 3). They are designed for different work environments. The standalone version is ideal for cramped spaces with a limited number of power supplies. The plug-in version, on the other hand, is easier, faster, and cheaper to build due to the significantly reduced number of components. It is suitable for environments where a computer is available and space or power supply is not a major concern.



FIGURE 2. The standalone Entomoscope, with (1) base, (2) USB and network hub, (3) lighting, (4) 12 MP camera with (5) telecentric lens, (6) 10" HD touchscreen, (7) Graphical User Interface, and (8) manual focus wheel.

A. MECHANICAL SETUP

1) STANDALONE

The standalone Entomoscope has three main parts: The base, the upper main frame, and the focus stacking unit. The base houses the electronics and lighting and serves as a platform for a 60 mm Petri dish for preserved insects. Its dimensions are 200 mm x 200 mm x 80 mm. The custom-made lighting illuminates from the circumference of the Petri dish with white Light Emitting Diodes (LEDs). The upper main frame is mounted to the base with two 20 mm x 20 mm aluminum strut profiles (Bosch Rexroth, Germany) that are covered with 3D-printed parts to allow the cables to be guided to the upper main frame. The standalone Entomoscope can be adapted to almost any lens with a c-/cs-mount connector by selecting a suitable length of the aluminum strut profiles to match the object distance of the lens. We have developed three variants



FIGURE 3. The plug-in Entomoscope, with (1) base, (2) lighting, (3) 12 MP Camera with (4) telecentric lens, (5) linear stage.

with different lenses as examples. The upper main frame carries a 10" touchscreen (10BS7 Beetrionics, Duesseldorf, Germany) and the focus stacking unit with the camera and lens setup. A 3D view of the focus stacking unit of the standalone Entomoscope is given in Figure 4 (a). The camera can be moved in the z-axis for 45 mm by a motorized linear stage, consisting of a standard stepper motor (NEMA 17-02 by Joy-It, SIMAC Electronics GmbH, Neukirchen-Vluyn, Germany) and a precision linear stage (VT 45N by Owis GmbH, Staufen im Breisgau, Germany) that are connected by a flexible aluminum coupling adapter. This allows the object

distance of the 12.3-megapixel camera with Sony IMX477 sensor (Raspberry Pi HQ camera, Raspberry Pi Foundation) with the lens (e.g. Lensagon TC10M0565i by Lensation, Karlsruhe, Germany) to be changed for focusing and focus stacking. A focusing wheel is fitted to the upper end of the drive shaft to enable manual focusing.

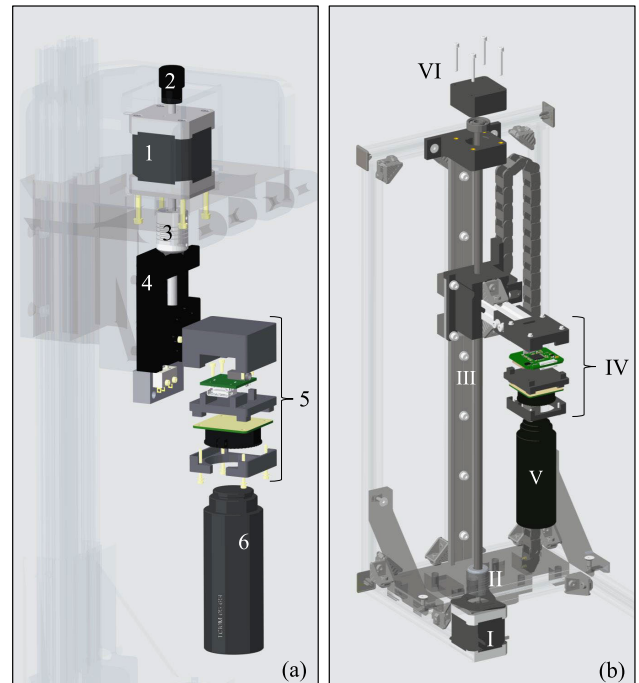


FIGURE 4. 3D view of the focus stacking unit for the (a) standalone and (b) plug-in version of the Entomoscope, with (1) stepper motor, (2) manual focus wheel, (3) coupling adapter, (4) linear table, (5) camera unit with Raspberry Pi HQ camera and HDMI-adaptor shield, (6) lens and (I) stepper motor, (II) coupling adapter, (III) linear rail and threaded rod, (IV) camera assembly with Raspberry Pi HQ-camera and USB-adaptor shield, (V) lens, (VI) upper bearing for threaded rod.

2) PLUG-IN

The basic mechanical setup of the plug-in version of the Entomoscope is the same as for the standalone version. However, the upper main frame can be omitted and the stepper motor (NEMA 17-01 by Joy-It, SIMAC Electronics GmbH, Neukirchen-Vluyn, Germany) is moved to the base. Therefore, the base is minimally larger and measures 200 mm x 205 mm x 95 mm. The lighting in both versions is the same. Due to the higher base, the lighting unit does not protrude in the plug-in version. Due to the motor being in the base, a longer linear stage is installed. A 3D view of the focus stacking unit of the plug-in version of the Entomoscope can be seen in Figure 4 (b). The design differences have the advantage that the plug-in Entomoscope is suitable for many different lenses, as the distance of the camera to the base of the lighting can be automatically adjusted in a range from 25 mm to 365 mm. The linear stage is mounted to the base with three 20 mm x 20 mm x 410 mm aluminum strut profiles (Bosch Rexroth, Germany).

All CAD files for both systems are available for download in the *.stl* file format so that they can be 3D-printed directly. For printing the parts, any FDM 3D printer with a minimum printing area of 205 mm x 205 mm x 150 mm is suitable. Currently, the files for 3D printing are available for different standalone Entomoscopes as well as for the plug-in Entomoscope.

B. ELECTRICAL SETUP

1) STANDALONE

The standalone Entomoscope is equipped with a Raspberry Pi 4 Model B 8 GB single-board computer as the central control unit (see Figure 5). The power supply is a 12 V DC power adapter (EA10731J1201 by EDAC Power Electronics, New Taipei City, Taiwan). This voltage is required for the stepper motor and the touch screen. Additionally, the 12 V DC is converted to 5 V DC for the Raspberry Pi with a DC-DC converter (SD-30G-5 by MeanWell, New Taipei City, Taiwan). A stepper driver board

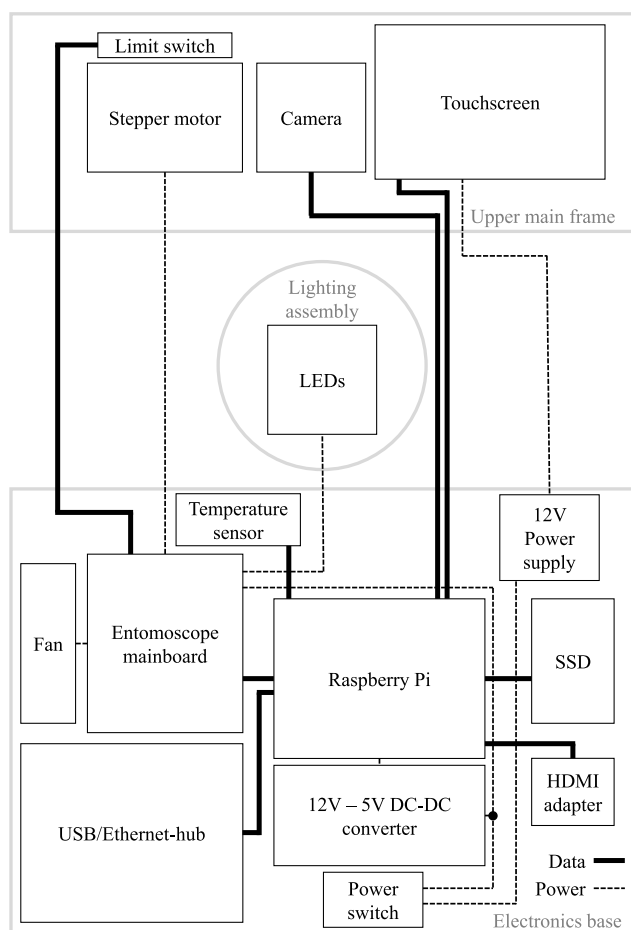


FIGURE 5. Schematic view of the electronics used in the standalone Entomoscope. The main components for controlling are housed in the *Electronics base*. The touch screen as well as the camera with the focus stacking unit including a stepper motor with limit switch are mounted to the *Upper main frame*. The *Lighting assembly* is mounted to the *Electronics base* and can be interchanged for different Petri dish sizes. Data transmission lines are shown as solid lines, power lines are dotted.

(SilentStepStick TMC2209 V2 Watterott electronic GmbH, Leinefelde-Worbis, Germany) is used for controlling the stepper motor and a mainboard is designed to connect the motor driver with the Raspberry Pi. Additionally, two Metal Oxide Semiconductor Field-Effect Transistors (MOSFETs; FQP20N06L) are used to switch both the lighting and the cooling fan. For data transfer from the Entomoscope and network connection, a USB hub with an Ethernet adapter is installed and made accessible from the outside. Data can either be stored on an internal solid state drive (SSD) or on external storage via a USB interface.

2) PLUG-IN

For the plug-in Entomoscope, the electrical setup can be simplified as the connected computer serves as the main control unit, also replacing the need for a touchscreen. This computer is linked to the Entomoscope through a USB connector. To control the stepper motor for the stacking mechanism, an Arduino Uno is employed. It is equipped with a CNC stepper motor shield (Joy-It, SIMAC Electronics GmbH, Neukirchen-Vluyn, Germany) and a stepper motor driver board (SilentStepStick TMC2209 V2 from Watterott electronic GmbH, Leinefelde-Worbis, Germany). The camera (Raspberry Pi HQ camera, Raspberry Pi Foundation) is connected to a USB adapter shield (Arducam USB 3.0 Camera Shield Plus, Arducam, Nanjing, China) and plugged into the USB hub. The brightness of the LEDs used for object lighting can be adjusted using an analog LED dimmer. For a visual representation of the electrical setup, refer to Figure 6.

C. CONTROL SOFTWARE

A graphical user interface (GUI) is provided for both versions of the Entomoscope. The Entomoscope Imaging Software (ENIMAS) is written in Python 3. The GUI is created, using the Python package *Qt*. As the requirements for the standalone and plug-in Entomoscope differ in some points the software for both systems has minor differences. However, the operation is very similar.

1) STANDALONE

The Raspberry Pi boots directly to the GUI. It has two main tabs, the *Imaging* tab, which can be seen in Figure 7, and the *Viewer* tab, which can be used to examine the images and to transfer them to a USB data drive. The *Viewer* tab allows the user to examine both individual and stacked images. In addition, the images can be opened in full-screen mode and zoomed in and out.

The standalone Entomoscope can either be used in a manual focus mode or with automated focusing by enabling the stepper motor in the GUI ((i) in Figure 7). The linear actuator is then referenced by moving until a limit switch is reached. Having enabled the lighting (ii), the autofocus can be started (iii), and a single image (iv) or multiple images at different focal planes (to capture all parts of the specimen in focus), can be taken. Both the stack step size (v) and the number of images per stack (vi) can be selected in ENIMAS. To test whether the parameters are correct, the

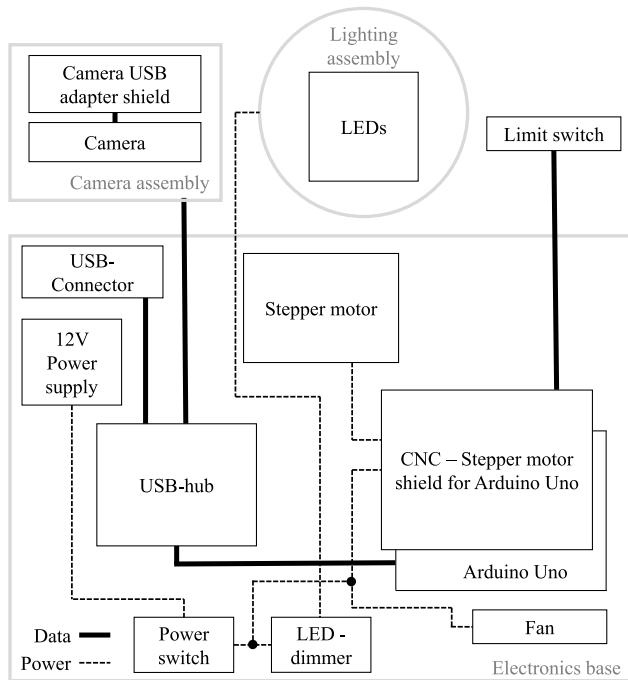


FIGURE 6. Schematic view of the electronics used in the plug-in version of the Entomoscope. A USB hub connects the camera and an Arduino Uno to the computer. The Arduino Uno controls the stepper motor, and the object lighting brightness can be manually regulated using an LED dimmer. Data transmission lines are represented as solid lines, while power lines are depicted as dotted.

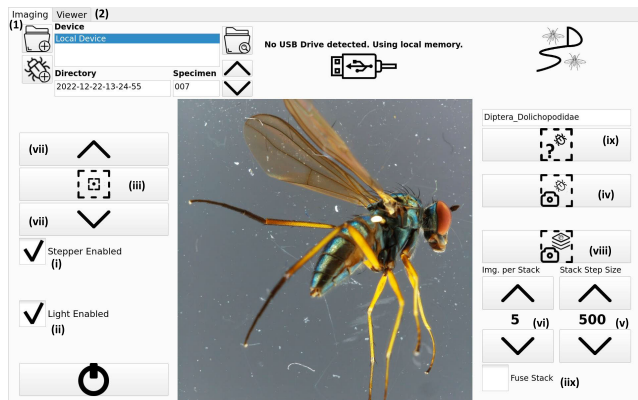


FIGURE 7. Screenshot of the GUI (*Imaging* tab selected) of the standalone Entomoscope with two main Tabs: (1) *Imaging* and (2) *Viewer* and the main functions: (i) enable stepper, (ii) enable light, (iii) autofocus, (iv) take a single image, (v) set stack size, (vi) set number of images per stack, (vii) focus in/out, (viii) take stack, (iix) fuse stack (ix) classify.

focus in/out (vii) buttons can be used, as the distance that the stacking unit moves by clicking once is set to the value that is chosen for the stack step size. Finally, the selected number of images with predefined distances between the images can be automatically taken by starting the stack-taking process (viii). The stack can then be automatically fused to a single image by activating *Fuse Stack* (iix). For specimen classification, the GUI includes a designated button (ix). When this button is clicked, the Entomoscope captures an image of the specimen

and subsequently presents the classification result in the text box located above the button.

2) PLUG-IN

The GUI of the plug-in Entomoscope is very similar. Since the plug-in version does not have the manual focus mode, the stepper motor does not need to be explicitly enabled. Upon launching the program, it is still necessary to reference the axis, which can be achieved by clicking on the *Reference Axis* button. Given that there are many image viewers for Windows, that cater to diverse user needs, the *Viewer* tab has not been implemented in the Windows version of ENIMAS. Instead, images can be opened directly in the user's default image viewer. The stacking of the images can be done either by a stacking algorithm implemented in Python (the same as in the standalone version) or by Helicon Focus (HeliconSoft, Charkiw, Ukraine). The user can choose which method to use after capturing the first stack. As the plug-in version can handle different types of lenses, without any hardware adaptations, the GUI provides options to handle different lenses. One crucial parameter to specify is their length, which must be provided and saved in the software. This ensures that the lens does not collide with the Petri dish for holding the insect during autofocus.

D. IMAGING

We recommend a lens magnification of 0.3x for insects from 12-25 mm, 0.5x magnification for 6-12 mm, and 1x for insects ranging between 3-6 mm. In particular, telecentric lenses with a working distance between 40 mm and 110 mm are well-suited for the Entomoscopes. The following lenses were tested with the standalone Entomoscope (all by Lensation GmbH, Karlsruhe, Germany):

- 1) Lensagon TC5M-10-65: 1x magnification
- 2) Lensagon TC10M-05-65: 0.5x magnification
- 3) Lensagon TC5M-03-110: 0.3x magnification

But other cheaper telecentric lenses (by GetCameras, Eindhoven, Netherlands) with comparable imaging parameters also show very good results:

- 1) LCM-TELECENTRIC-1X-WD65-1.5-NI
- 2) LCM-TELECENTRIC-0.5X-WD65-1.5-NI
- 3) LCM-TELECENTRIC-0.3X-WD65-1.5-NI2

Figure 8 shows the stacking procedure for four focal planes (z-stacks) taken with the standalone Entomoscope with a lens for large-sized specimens (12-25 mm). As can be seen in Figure 8 (i)-(iv), the focus moves from the lowest point to the highest point of the specimen. Figure 8 (v) shows the final result of the fusing procedure. All areas are in focus. The fusing of the focal planes was performed using the integrated Python stacking function of ENIMAS.

E. SPECIMEN CLASSIFICATION

Figure 9 displays the confusion matrix with the classification accuracy for each class individually. The confusion matrix presents the actual classes in the rows, with the predicted classes listed in the columns. Accuracy for each class



FIGURE 8. Single focal planes (i-iv) taken with the standalone Entomoscope for large-sized specimens (12 mm - 25 mm) and the fused image (v).

can be derived from the diagonal elements, where correct classifications align. Values off the diagonal indicate misclassifications. The overall accuracy for all classes calculates to 95.1%. For calculating the precision, recall, and F1 score, macro averaging is performed. The total values for the classifier are determined by calculating the values for each class and then averaging them. That way, precision calculates to 92.43%, the recall is 91.94% and the F1 score results in 91.91%. The CNN network is saved as two lightweight ONNX files, which are used for execution on the Entomoscope. These files are executed on the machines using the CPU, but can also be employed on GPUs for faster execution. Classifying a specimen on a PC with a GPU takes less than one second per image. On a modern GPU (NVIDIA RTX 3090) for example, the classification takes 0.06 s. Classifying the images on the standalone Entomoscope with the CPU of the Raspberry Pi takes a bit longer. Results can be obtained in about five seconds. Therefore, the classification results can be displayed after imaging and a short processing time. On a powerful PC with a modern GPU, the results are almost real-time. The memory consumption is minimal, as even the Raspberry Pi with 8 GB memory can handle the classification. For the Entomoscope plug-in, ENIMAS can be run on any modern PC or notebook. No internet connection is required to run the classification or ENIMAS. However, an Internet connection is required to install or update ENIMAS.

IV. SUMMARY AND DISCUSSION

The Entomoscope is a DIY photomicroscope designed for imaging and classifying samples of invertebrates obtained with Malaise traps (or other mass collection methods) and preserved in ethanol. Thousands of such samples are acquired every month, as Malaise traps are the most widely used

biomonitoring tool for flying insects [10], [38], [39]. The control software (ENIMAS), the construction plans, and the necessary files for 3D printing are available for download at the Center for Open Science:

- Standalone Entomoscope: <https://osf.io/h5qmv>
- Plug-in Entomoscope: <https://osf.io/3vmrg/>

This enables others to build their own Entomoscope or modify it for their specific requirements. Two different designs are provided: the standalone Entomoscope and the plug-in Entomoscope. The first is developed as a standalone device, which is recommended to users, who have limited space and use the Entomoscope at different locations because the use of a Raspberry Pi and an HD touchscreen makes it a standalone and portable device. The total material cost of building a standalone Entomoscope depends mainly on the lens that is used. Without the lens, the system can be built for approximately \$1.100. However, the limited computing power of the Raspberry Pi can be a bottleneck during image processing. Merging large numbers of images takes comparatively long, therefore we recommend that the stacking of many images should be carried out on a separate computer using available focus stacking software such as [Helicon Focus](#) (HeliconSoft, Kharkiv, Ukraine) to batch process the images after they were taken. Another consideration is that the number of high-quality images stackable with the Raspberry Pi is limited to five, due to its limited RAM of 8 GB. In practice, however, five focal planes are sufficient when the spacing of the images is adjusted to the size of the insect. More focal planes can be imaged, but merging must be done on a more powerful computer. The plug-in version of the Entomoscope requires an additional Windows computer, but the reduced number of parts, compared to the standalone version makes it cheaper to build (approximately \$750). ENIMAS is developed for Windows 10/11. The computer used should have at least a USB 3.0 port, otherwise, the image transfer will be too slow. Since, to the best of our knowledge, there are no inexpensive telecentric zoom lenses available for the desired working distance, we used telecentric lenses with fixed focal lengths. For the standalone Entomoscope, therefore, one must first decide on a size class of insects that will be the focus, or assemble multiple standalone Entomoscopes for insects of the different size classes. Here, the plug-in version of the Entomoscope offers the advantage that it can accommodate different lenses without the need for hardware adjustments.

The design and evaluation of the device were carried out in close collaboration with several experienced entomologists. The feedback provided was and will be in the future implemented in the design of the Entomoscopes. We would like to emphasize the dynamic nature of the Entomoscope, which is an open-source initiative. User feedback from various institutions in Germany and Italy has been instrumental in the ongoing enhancements of our hardware components. Furthermore, the functionality of ENIMAS continues to evolve based on user input.

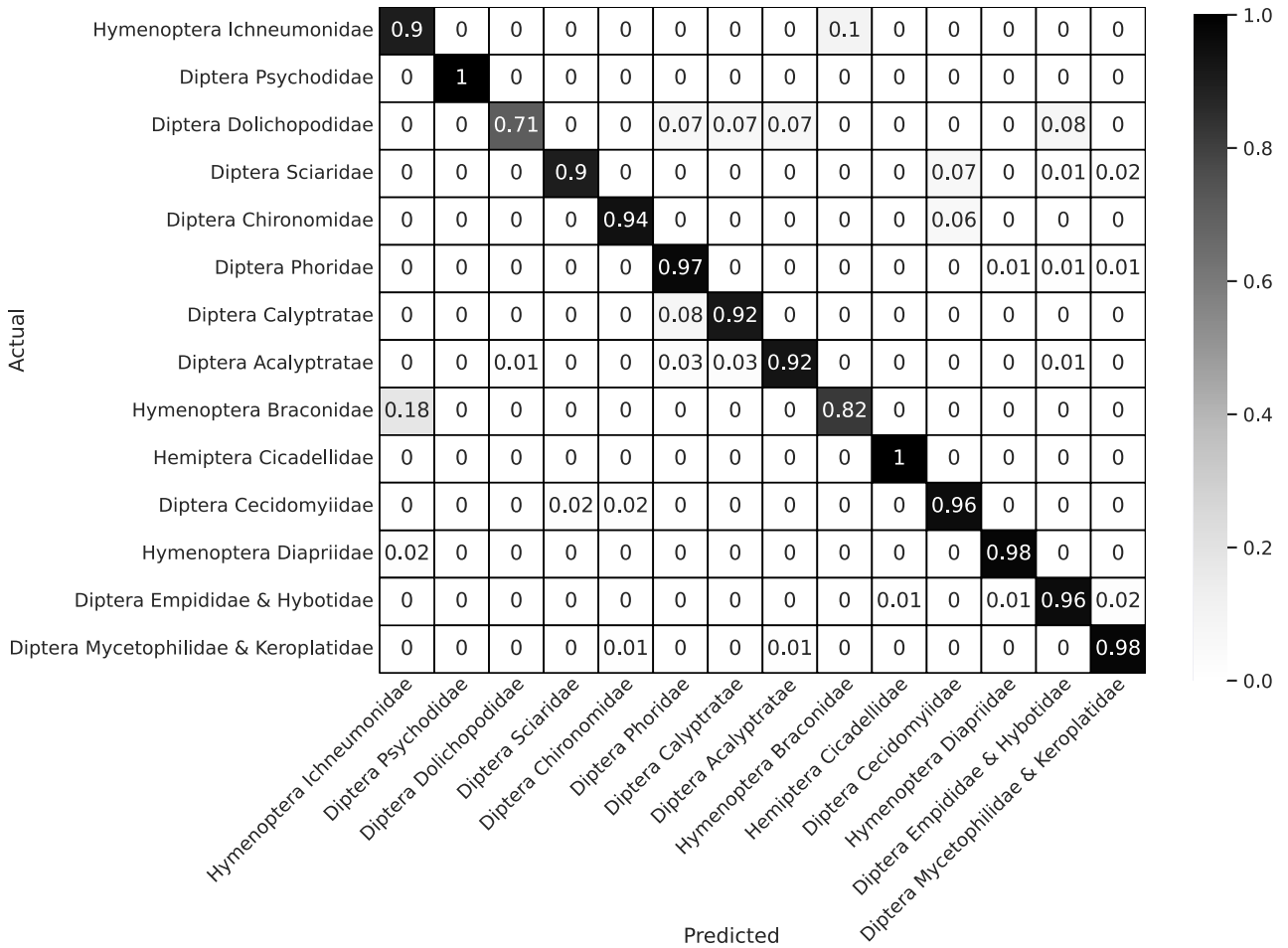


FIGURE 9. The confusion matrix for the 14 classes. Since the “Other” class is categorized by the outlier detection, it is not listed here. In the matrix, every row corresponds to a predicted value for a specific instance, and each column signifies the actual value associated with those predictions. The values are percentages in the range [0,1], normalized with the actual labels (rows).

Both Versions of the Entomoscope can be used to image species and families not covered by the trained CNN, so it is important that new CNNs can be trained by researchers to create an expert system for biodiversity research for any desired insect taxon. If the insects are also to be sorted, for example in preparation for DNA barcoding, we recommend using a sorting robot such as the DiversityScanner [31]. Fortunately, the images acquired with the Entomoscope are compatible with those from the Diversity Scanner, allowing neural networks to be trained that work on both systems. The available CNN described above provides high (95%) accuracy, with nearly all classes above 90% accuracy. It is notable that the class “Dolichopodidae, a family of Diptera” does not perform as well as the other classes. This is due to the morphological similarity of the phenotype of insects belonging to different classes in the dataset. An example is provided in Figure 10 (a)-(c) that combines images for Dolichopodidae, Acalypratae, and Calyptratae. Currently, the trained CNN only covers 14 classes. This already allows automated pre-sorting of bulk samples. However, we are currently expanding the number of taxa to enable classification from family to subfamily to genus level. The

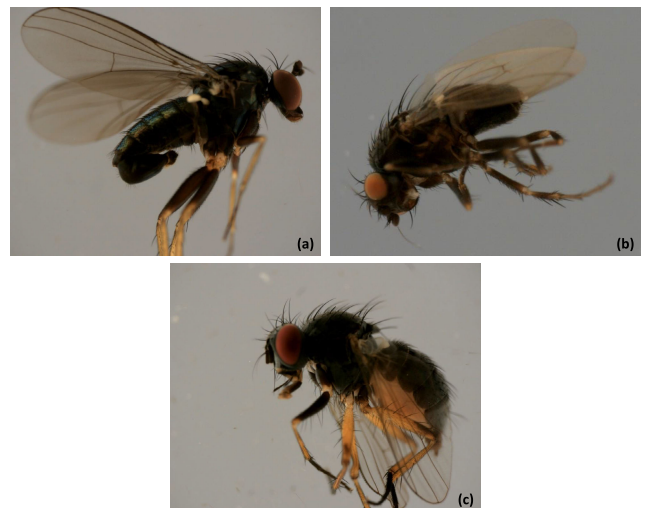


FIGURE 10. Example images of the classes (a) Diptera (Dolichopodidae), (b) Diptera (Acalypratae), and (c) Diptera (Calyptratae) illustrating the highly similar phenotypes of these classes.

Entomoscope is a tool that can be used to image and classify large numbers of insects quickly. Due to the different

versions, the simple design, and low cost, Entomoscopes can significantly accelerate the study of insect biodiversity.

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