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OnePetri: accelerating common bacteriophage Petri dish assays with computer vision

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Abstract

Introduction: Bacteriophage plaque enumeration is a critical step in a wide array of protocols. The current gold standard for plaque enumeration on Petri dishes is through manual counting. However, this approach is not only time consuming and prone to human error, but also limited to Petri dishes with countable number of plaques resulting in low throughput.

Methods: We present OnePetri, a collection of trained machine learning models and open-source mobile application for the rapid enumeration of bacteriophage plaques on circular Petri dishes.

Results: When compared against the current gold standard of manual counting, OnePetri was approximately 30x faster. Compared against other similar tools, OnePetri had lower relative error (~13%) than Plaque Size Tool (~86%) and CFU.AI (~19%), while also having significantly reduced detection times over Plaque Size Tool (1.7x faster).

Conclusions: The OnePetri application is a user-friendly platform that can rapidly enumerate phage plaques on circular Petri dishes with high precision and recall.

Introduction

Bacteriophage (phage) enumeration is central to many assays and experiments, including the production of phage-based products and therapies, detection of bacterial infections, and biocontrol of food-borne pathogens[1]. Many methods to quantify phage particles exist and include transmission electron microscopy (time-intensive, costly), flow cytometry (specialized equipment and high titres required), qPCR (rapid, requires prior knowledge of phage genomic sequence), and epifluorescence microscopy (low throughput, high experimental variability, commonly used with environmental samples), among others[1–3]. Despite the diverse repertoire of quantification techniques, the classical double agar overlay plaque assay protocol has long been the gold standard for phage enumeration, yielding visible phage plaques on a solid lawn of susceptible host bacteria [4], and where plaque formation is usually a direct result of phage infection and bacterial death [5]. However, in addition to being time-intensive, this method is often limited to plates with a countable number of plaques, typically less than 300, and results may be inconsistent upon recount by different individuals [4]. To this end, several image processing techniques for automating plaque counts have been created in recent years, many of which rely on contour or edge detection to identify plaques [6–9]. Some of these tools require specific types of images, such as those obtained through fluorescence microscopy, to obtain plaque counts, increasing experimental complexity for the benefit of automation. Despite being designed to automate plaque counts, these tools often require user intervention and fine-tuning of image processing parameters to improve detection results and avoid false positives. Furthermore, most tools created for this purpose are designed to run on a desktop computer, breaking the workflow where counts would be followed by calculations and immediate experimental continuation. We thus developed OnePetri, a mobile application using a collection of trained machine learning object detection models for the rapid enumeration of phage

plaques on circular Petri dishes. Using images provided by the Howard Hughes Medical Institute's (HHMI) Science Education Alliance-Phage Hunters Advancing Genomics and Evolutionary Science (SEA-PHAGES) program [10], we successfully trained Petri dish and phage plaque object detection models which have high recall and precision. Using machine learning and computer vision, we were able to build a flexible solution which can detect diverse plaque morphologies on different types of agar media, regardless of lighting conditions, without requiring any special image capture devices or fluorescent labeling. When benchmarked against two other similar tools, CFU.AI (Apple App Store) and Plaque Size Tool [8], OnePetri was significantly faster and more accurate, reproducibly detecting hundreds of overlapping and non-overlapping phage plaques within a few seconds.

Methods

Image dataset description

Over 12,000 image files were generously provided by the HHMI SEA-PHAGES program from the PhagesDB database [10] for use in training machine learning models, most of which were of plaque assays in circular Petri dishes. Files which were not images (such as Microsoft Word documents, text files, and PDF files) were excluded from our dataset. Some images were not Petri dish images, but rather transmission electron micrographs of phage isolates – these were excluded from our dataset. Information on the size of the Petri dishes, growth media, bacterial host, and phage in each image was not provided. No other inclusion or exclusion criteria were applied.

Image dataset curation, annotation, and preprocessing

After manual curation to remove images smaller than 1,024 x 1,024 pixels in size, as the plaques in these images would be too low resolution for model training, 10,261 images remained. A random subset of 98 images (75 training + 23 validation) and 38 images (29 training + 9 validation) were manually selected and used in preparing the Petri dish detection and plaque detection models, respectively. Most Petri dish images in the training and validation datasets had more than one Petri dish, while most plaque assay images had at least 100 plaques. Images were manually annotated (bounding boxes drawn around each Petri dish or plaque to train the model with) using the Roboflow online platform (Roboflow Inc., Des Moines, IA, USA). Prior to export for training, annotated images for the Petri dish detection model were preprocessed to fit within 1,024 x 1,024 pixels (maintaining aspect ratio). Annotated images for the plaque detection model were automatically preprocessed on the Roboflow platform as follows: tiled into 5 rows and 5 columns, tiles resized to fit within 416 x 416 pixels (maintaining aspect ratio). Tiling can help with detection of small objects (such as phage plaques) while decreasing training times by fragmenting a large image into multiple smaller tiles, resulting in each small object taking up a larger proportion of the tiled image than it did pre-tiling. The following augmentations were applied to the plaque detection training dataset, with a total of 3 outputs being produced per training example (tile): grayscale applied to 35% of images, hue shift between -45° and +45°, blur up to 2 pixels, mosaic. Image augmentations can increase the performance of object detection models by artificially increasing the diversity of images in a given training dataset. After augmentations (training set only) and tiling (training + validation sets), the total number of tiles used for training and validating the plaque detection model were 2,175 and 225, respectively.

93 **Machine learning model training and validation**

94 The trained PyTorch models were generated using the annotated, preprocessed, and augmented
95 dataset and the Ultralytics YOLOv5 training script ("You Only Look Once" version 5, Ultralytics,
96 Los Angeles, CA, USA) [11, 12]. The YOLO family of models were designed to rapidly detect
97 and identify objects in images by drawing boxes (bounding boxes) around those which resemble
98 objects the model was trained on [13]. The YOLOv5 models use a modified Cross-Stage Partial
99 Networks (CSPNet) backbone which extracts useful features from images for downstream
100 machine learning or inference [14]. When working with object detection machine learning models,
101 the training and inference processes are generally faster and uses less video random access memory
102 (VRAM) on the graphics processing unit (GPU) when the training images are of lower resolution.
103 While it would be ideal to train a model using images with their native multi-megapixel resolution,
104 this is not usually feasible given the VRAM limits on many GPUs. The following parameters were
105 used to train the Petri dish detection model: 320 x 320 pixel image resolution (scale to fit each
106 Petri dish image), 500 epochs, batch size of 16, YOLOv5s model (yolov5s.pt weights file), cache
107 images enabled, default hyperparameters (hyp.scratch.yaml file). The following parameters were
108 used to train the plaque detection model: 416 x 416 pixel image resolution (scale to fit each tile),
109 500 epochs, batch size of 128, YOLOv5s model (yolov5s.pt weights file), cache images enabled,
110 default hyperparameters (hyp.scratch.yaml file).

111 The generated "best.pt" weights files for the trained YOLOv5 models were converted to the Apple
112 Core ML "mlmodel" file format using the coremltools Python package (version 4.1,
113 https://github.com/apple/coremltools) in conjunction with a custom script provided by Hendrik
114 Kueck (Pocket Pixels Inc., Vancouver, BC, Canada) which is available at the following GitHub

repository link: https://github.com/pocketpixels/yolov5/blob/better_coreml_export/models/coreml_export.py .

iOS mobile application development and benchmarking

The mobile application for iOS was developed with the Swift programming language (version 5) using the Xcode 12.5.1 (build 12E507) integrated development environment (Apple Inc., Cupertino, CA, USA) with a target SDK of iOS 13. Benchmarking of the application was carried out on the iPhone 12 mini simulator available within Xcode 12 (iOS 14.5, build 18E182), as well as on a physical iPhone 12 Pro running the same operating system build as the simulator. The iOS development simulator was running on a 2020 MacBook Air with M1 chip (8 CPU cores and 8 GPU cores variant) and 16GB RAM, and which was connected to the power adapter.

Benchmarking OnePetri

Fifty images were randomly selected from the original unprocessed dataset provided by the SEA-PHAGES team to be used in the benchmarking analysis. These images were not included in any of the model training or validation datasets for either the petri dish or plaque YOLOv5 models, meaning this is the first time the models encounter these images for inference. Images were processed sequentially in OnePetri (version 1.0.1-8) and compared to the manual counting gold standard and to two other software programs. These include CFU.AI (version 1.4), a free mobile application on iOS and Android originally developed in 2019 to count bacterial colony forming units (CFU), as well as Plaque Size Tool (PST), a recently published Python tool for desktop computers which detects plaques and measures their size [8]. Various methods were employed to determine the speed at which the final output is obtained, depending on the tool. OnePetri uses

code embedded within the compiled application to report runtime statistics to the debug console when running in debug mode on-device and in simulator. PST runtime was measured using the "time" command from the command line. CFU.AI runtime was approximated with a stopwatch, as the source code is not publicly available and there is no way to natively measure application runtime on iOS. All statistical analyses and data visualizations were performed using R (version 4.1.0, 2021-05-18, aarch64) [15], ggplot2 (version 3.3.5) and ggpubr (version 0.4.0) [16], ggsignif (version 0.6.2) [17], reshape2 (version 1.4.4) [18], and tidyverse (version 1.3.1) [19].

Code and data availability

The Swift source code and Xcode project for OnePetri for iOS is available under the GNU General Public License v3.0 (GPL-3.0) at the following link: https://github.com/mshamash/OnePetri. The trained machine learning models (PyTorch and Apple MLModel formats) are available at the following link: https://github.com/mshamash/onepetri-models. The training data used for the initial versions of the Petri dish and plaque detection models are available under the Attribution-NonCommercial-ShareAlike 4.0 International (CC BY-NC-SA 4.0) license on the Roboflow Universe platform: https://universe.roboflow.com/onepetri/onepetri. The benchmarking dataset, analysis scripts, and raw data are available at the following link: https://github.com/mshamash/onepetri-benchmark.

Results

Trained Petri dish and bacteriophage plaque object detection models are accurate and precise

Due to a lack of publicly available trained object detection models able to identify Petri dishes and phage plaques, we first set out to train two such models. Using the YOLOv5 training scripts, we developed a model to detect common circular Petri dishes in a lab environment. The training and validation datasets were comprised of 75 and 23 images, respectively. The models trained using these images performed well and as such no additional images were added to the training datasets. After 500 epochs, the model achieved 96% precision (**Figure 1A**) and 100% recall (**Figure 1B**). In computer vision, the intersection over union (IoU), also known as the Jaccard index, is a measure to evaluate how well the detected object boundaries (obtained from testing the trained model) overlap with the actual object boundaries specified prior to training [20]. The mAP@[0.5:0.95] (range of IoUs from 0.50 to 0.95, step size 0.05) and mAP@0.5 metrics are a measure of the model's mean average precision (mAP) at the indicated IoU threshold (or range of thresholds), where detections below the threshold are not counted. Models with high mAP@[0.5:0.95] values (typically greater than 50%) are thus preferred, as this would suggest the models' precision remains high despite increasingly stringent cutoff values for what can be considered a true positive detection. The mAP at an IoU of 0.50 (mAP@0.5) was 99.5% (**Figure 1C**), while the mAP@[0.5:0.95], was 95.7% (**Figure 1D**).

Next, to be able to detect a wide variety of plaque morphologies on diverse agar colors, we developed a model to detect phage plaques using our tiled and augmented initial dataset. The training and validation datasets were comprised of 2,175 and 225 tiles, respectively. After 500

183 epochs, the model achieved 93.6% precision (**Figure 1A**) and 85.6% recall (**Figure 1B**). The
184 mAP@0.5 was 89.5% (**Figure 1C**), while the mAP@[0.5:0.95] was 59.9% (**Figure 1D**).
185 All performance metrics for both models plateaued after around 300 epochs, indicating that it may
186 have been sufficient to stop training at this point.
187

188 **An image processing pipeline for rapid Petri dish detection and bacteriophage plaque**
189 **enumeration**

190 We then set out to create a mobile application wrapper for the trained models above, to allow for
191 rapid phage plaque enumeration and assay calculations with a user-friendly interface while in the
192 laboratory environment, without having to transfer images from a mobile phone or camera to a
193 computer. The OnePetri mobile application was developed to fulfill this purpose and is currently
194 available for download on the Apple App Store for free. Briefly, upon launching OnePetri, the user
195 is first prompted to select an image for analysis (from photo library or to be taken with camera).
196 The Petri dishes are then identified, and the user selects the Petri dish of interest to proceed with
197 plaque enumeration analysis. This approach allows users to serially analyze multiple Petri dishes
198 from a single image, increasing throughput. The image is cropped to the Petri dish boundaries and
199 tiled into overlapping tiles of 416 x 416 pixels in size, where plaques are then identified serially
200 on each tile. Finally, plaque deduplication occurs to account for plaques which may have been
201 identified twice on overlapping tiles, and the final counts are returned to the user (**Figure 2**).
202 Additionally, OnePetri for iOS can automatically perform the necessary calculations to obtain
203 phage titre from Petri dishes of multiple phage dilutions as needed by the user.
204
205

206 **OnePetri rapidly and precisely enumerates bacteriophage plaques on a mobile device**

207 In order to compare OnePetri's accuracy to other currently available tools with a similar purpose,
208 we benchmarked OnePetri against manual counts, as well as Plaque Size Tool, and CFU.AI, using
209 a collection of 50 test images which the trained models would be seeing for the first time. One
210 image had too many plaques to count manually (> 1,000) and was excluded from further analysis,
211 despite OnePetri returning a value of 1,641 plaques, a seemingly accurate value.

212 OnePetri was benchmarked directly on-device and using the iOS development simulator included
213 with the Xcode IDE on macOS. The time to result was significantly shorter when using OnePetri
214 on-device versus Plaque Size Tool (p=0.0029, nonparametric one-way ANOVA with Wilcoxon
215 rank sum test and Benjamini-Hochberg correction for multiple comparisons), manual counts
216 (p<0.001), and OnePetri in the iOS simulator (p=0.0041) (**Figure 3A**). No significant difference
217 in time to result was seen when comparing OnePetri (on-device) to CFU.AI (p=0.4833). The mean
218 time to result for OnePetri on-device was 1.91 seconds, OnePetri in simulator was 3.76 seconds,
219 CFU.AI was 1.80 seconds, Plaque Size Tool was 3.21 seconds, and manual counts was 57.98
220 seconds (**Figure 3A**). OnePetri on-device was approximately 2x faster than the iOS development
221 simulator, 1.7x faster than Plaque Size Tool, and 30x faster than manual counts, on average.

222 We compared the relative percent error of each approach to manual counts to get a sense of the
223 overall accuracy of each tool. This value was calculated by taking the absolute value of the
224 difference between actual and expected plaque counts, dividing by the expected plaque count, and
225 multiplying by 100%. OnePetri on-device had the lowest median relative error of 12.90%, with a
226 rate of 12.26% in the simulator, while CFU.AI and Plaque Size Tool had median relative errors of
227 19.23% and 85.71%, respectively, with these differences remaining significant after correcting for

228 multiple comparisons (**Figure 3B**, nonparametric one-way ANOVA with Wilcoxon rank sum test
229 and Benjamini-Hochberg correction for multiple comparisons).
230 Finally, we investigated whether the relative error rates of each tool correlated with the true plaque
231 counts of the images (**Figure 3C**). All 4 of the calculated Pearson correlations were very weak,
232 indicating no strong relationship between any tool's error rate and the number of plaques on the
233 Petri dish: OnePetri on-device (ρ=-0.07, R^2=0.01), OnePetri in iOS simulator (ρ=-0.08, R^2=0.01),
234 CFU.AI (ρ=-0.11, R^2=0.01), Plaque Size Tool (ρ= 0.04, R^2=0.001).
235

236 **Discussion**

237 Phage enumeration through manual plaque counting has long been the gold standard in the field,
238 despite the time-intensive nature of this approach. Over the years, several tools have been
239 developed to help automate this approach, with varying levels of user intuitiveness and accuracy.
240 However, most tools have been developed for desktop computers, requiring Petri dish images to
241 be uploaded to the computer for analysis, removing the user from their workflow in the laboratory.
242 To this end, we developed OnePetri, a set of object detection models and a mobile application
243 which can perform rapid plaque counting in a high-throughput fashion, directly in a laboratory
244 environment, and which will improve regularly with ongoing model updates.
245 Using a diverse training dataset of Petri dish and plaque assay images from the HHMI SEA-
246 PHAGES program, we were able to train YOLOv5s object detection models which could detect
247 Petri dishes and phages plaques with high precision and recall (**Figure 1**). When benchmarked on
248 a set of 50 images which the models have not been previously exposed to, OnePetri running on a
249 physical iOS device was significantly faster for plaque counting than Plaque Size Tool and manual
250 counting (**Figure 3A**). Using mean values for comparison, OnePetri on-device was approximately

251 30x faster than manual counts, representing significant time savings for the user, especially when
252 analyzing multiple Petri dishes. Notably, OnePetri on-device was also significantly faster than
253 using the iOS simulator included in the Xcode development suite, highlighting the need to
254 benchmark iOS applications on-device rather than in simulators for accurate real-world values. No
255 significant difference was seen in inference times between OnePetri on-device and CFU.AI.
256 Despite having quicker detection times, OnePetri significantly outperformed CFU.AI and Plaque
257 Size Tool in terms of relative error rates when comparing plaque counts from each tool to the true
258 manual counts using the benchmarking image dataset (**Figure 3B**). The median error rate for
259 OnePetri on-device (12.90%) was approximately 1.5x and 6.6x lower than CFU.AI (19.23%) and
260 Plaque Size Tool (85.71%), respectively. No significant difference was observed between
261 OnePetri error rates on-device versus in the iOS simulator. While a median error rate of 12.90%
262 is quite low relative to the other tools, there remains room for improvement. Given the current
263 error rate, we recommend that this version of OnePetri be used only when this level of error is
264 acceptable for the assay at hand, and users should first evaluate how OnePetri performs with their
265 phage-host pairings before considering replacing manual counts entirely. There was essentially no
266 correlation between the relative error rates of each tool and the number of plaques per Petri dish
267 (**Figure 3C**).
268 During benchmarking, we remarked that the Petri dish's background surface (for example, on a
269 dark lab bench, or held up against room light) can affect results, with more accurate counts being
270 obtained when the Petri dish was against a dark surface. Furthermore, certain plaque morphologies,
271 such as the "bull's eye", were sometimes incorrectly detected with the current version of
272 OnePetri's plaque detection model. CFU.AI also often struggled with this plaque morphology,
273 while Plaque Size Tool was able to detect about half of the "bull's eye" plaques on the images

274 tested. OnePetri does require that images be of sufficient resolution for individual plaques to be
275 distinguishable by the machine learning models, though we did not test this directly. However, all
276 supported devices (modern smartphones from past 5-7 years) have camera resolutions which are
277 well beyond what would likely be the minimum image size for reliable results.

278 The user-friendly approach we developed for image analysis on a mobile device allows users to
279 serially analyze multiple Petri dishes within a single image, increasing throughput and reducing
280 the time to results (**Figure 2**). Multiple detection parameters (object detection confidence
281 thresholds and plaque deduplication overlap thresholds) can be easily changed within the
282 application itself, allowing users to fine-tune the application's performance to their unique setup,
283 should the default values not be ideal. The recently released Plaque Size Tool also allows for fine-
284 tuning of detection parameters; however, it is not as user-friendly, and requires the user to be
285 comfortable with installing and running applications from the command line on a computer, and
286 is only able to process only one Petri dish per image. Our unique machine learning approach for
287 Petri dish and plaque detection allows for improved accuracy over traditional image processing
288 approaches, such as those used in Plaque Size Tool. Additionally, the object detection models we
289 developed can be improved upon further using user-submitted data due to the inherent trained
290 nature of machine learning model.

291 The phage titration assay is the only assay currently supported within the mobile application. Upon
292 entering the volume of sample plated and corresponding plate dilutions, the initial phage titre is
293 calculated based on the number of plaques present on serially diluted plates. Support for additional
294 phage and bacterial assays is planned for late-2021/early-2022. OnePetri does not currently support
295 spot assays for approximating phage titre and requires that each Petri dish contain phage of a single
296 dilution, as all plaques on a given dish are counted assuming they are from the same diluted sample.

Unlike Plaque Size Tool, OnePetri does not currently directly measure or infer individual plaque size. This may be added in a future version of OnePetri, along with support for exporting a summary report of all Petri dishes analyzed in a given session. A version of the OnePetri mobile application which supports Android devices is currently under development and should be released early-2022.

Conclusion

We present a pair of trained object detection machine learning models for the identification of Petri dishes and phage plaques, as well as OnePetri, a mobile application for iOS which leverages these models for the rapid and reproducible enumeration of phage plaques. OnePetri is now freely available to download from the Apple App Store on iOS. The application source code, trained models, training data, and benchmarking dataset and analysis scripts are all available for download under open-source licenses. When compared to the manual counting gold standard, as well as CFU.AI and Plaque Size Tool, OnePetri had minimal relative error with significantly lower time to results.

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376 **Figure Legends**

377

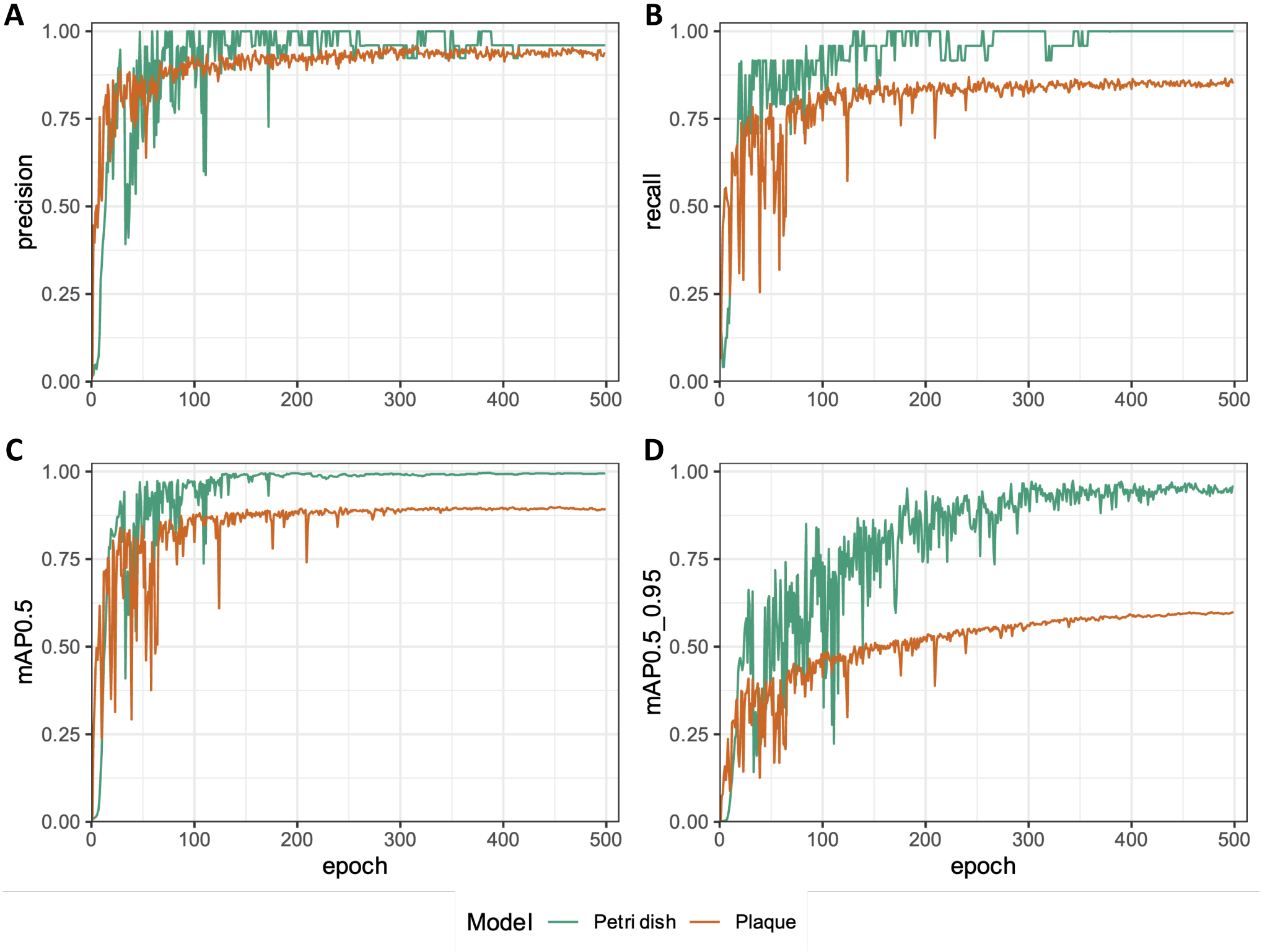
378 **Figure 1. The trained Petri dish and plaque object detection models have high recall and**
379 **precision after 500 training epochs.**

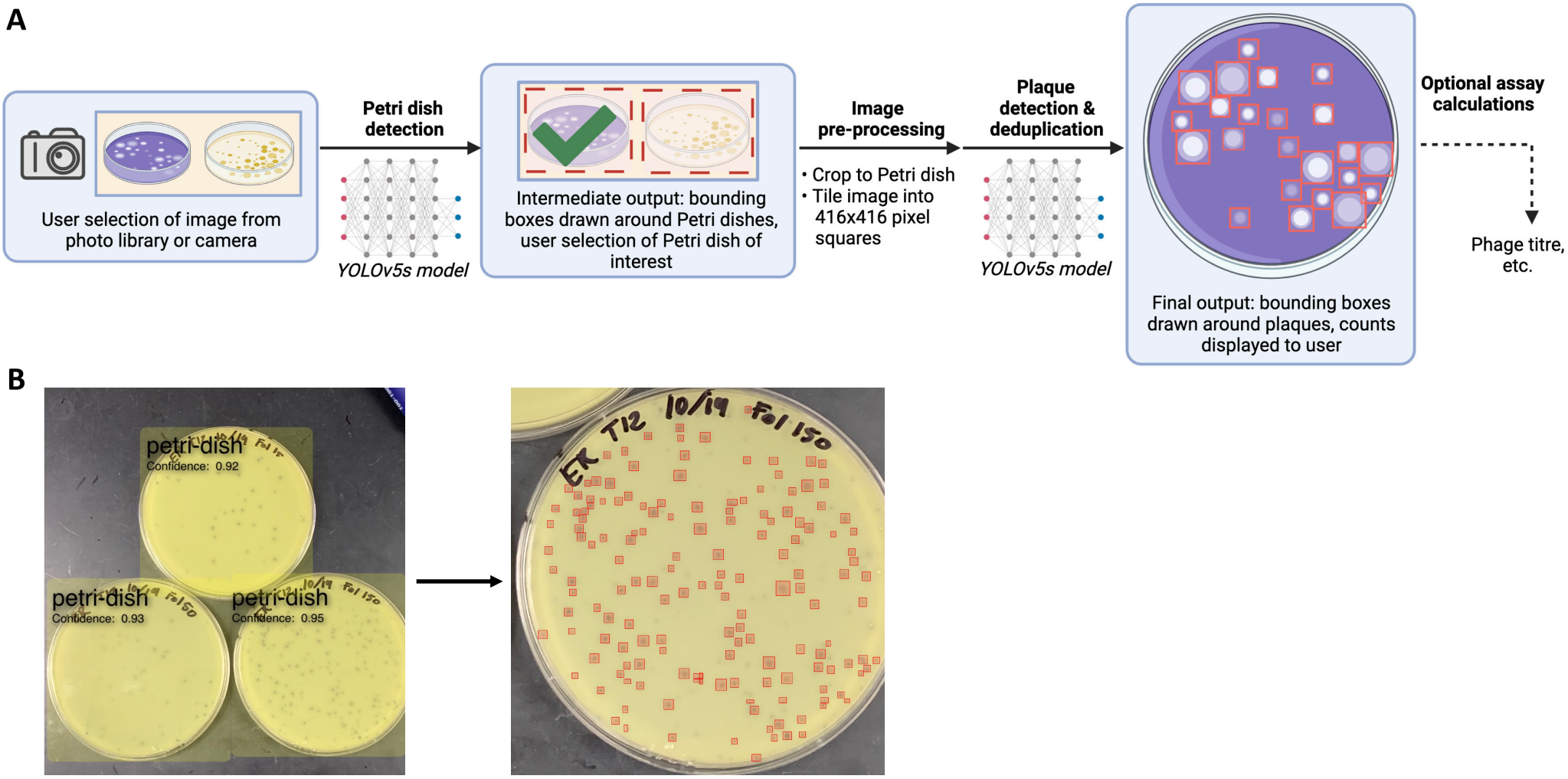
380 Petri dish and plaque object detection model performance metrics were recorded throughout model
381 training using the validation datasets to test the models after each round of training, over the 500
382 training epochs. The following metrics were recorded and included in the figure above: **(a)**
383 precision, **(b)** recall, **(c)** mean average precision for an intersection over union of 0.50 (mAP0.5),
384 and **(d)** mean average precision for intersection over union ranging from 0.50 to 0.95 (step size
385 0.05; mAP0.5_0.95).

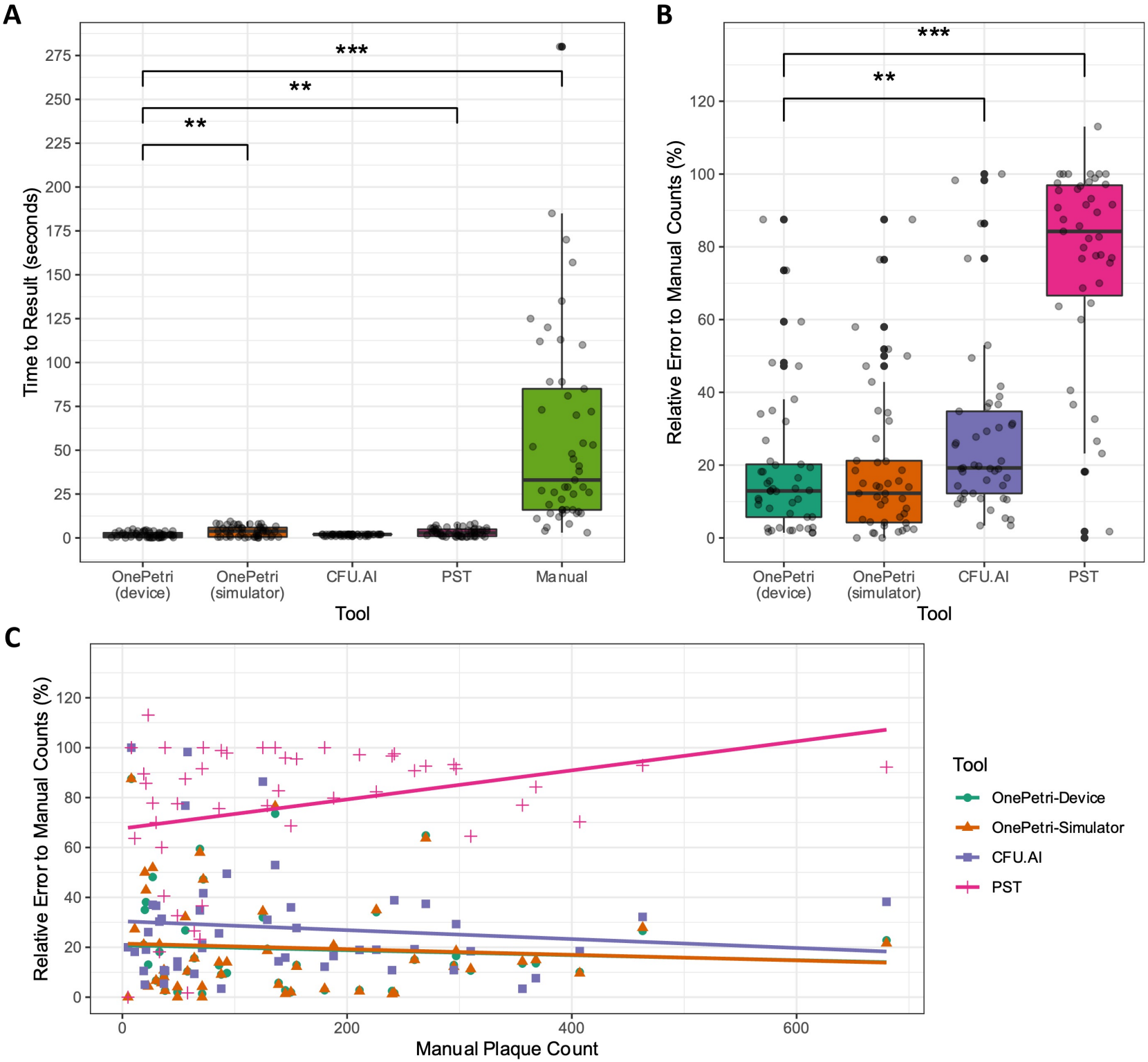
386

387 **Figure 2. Overview of the OnePetri mobile application image processing pipeline for Petri**
388 **dish detection and plaque enumeration.**
389 **(a)** Upon selecting an image for analysis, all circular Petri dishes are detected using the trained
390 Petri dish detection model. The user selects the Petri dish they wish to analyze, and the image is
391 cropped to fit that Petri dish of interest, tiled into overlapping 416 x 416 pixel squares, and resulting
392 tiles are fed serially to the trained plaque detection model. The detected plaques are deduplicated
393 to account for the overlapping tiles which may have resulted in some plaques being detected twice,
394 and the final annotated image is presented to the user. Optionally, the user may proceed with assay
395 calculations within the application directly (for example, to determine phage titre) using the
396 obtained plaque counts and dilution volumes. Figure created with BioRender. **(b)** Example image
397 processed in the OnePetri mobile application. Three Petri dishes are detected with high confidence
398 scores. Upon selecting a Petri dish, 155 phage plaques are enumerated and highlighted with a red
399 box. Image provided by the Howard Hughes Medical Institute's Science Education Alliance-Phage
400 Hunters Advancing Genomics and Evolutionary Science (SEA-PHAGES) program.
401

402 **Figure 3. The OnePetri mobile application rapidly detects plaques with minimal error**
403 **compared to other tools.**
404 OnePetri (on-device and in the iOS simulator) was benchmarked against CFU.AI, Plaque Size
405 Tool (PST), and manual counts. The **(a)** total time to obtain plaque counts (in seconds), and **(b)**
406 relative error rate of each tool (%), comparing counts from the tool to gold standard manual counts,
407 were calculated and compared. (n = 49 images in the benchmarking dataset analyzed using each
408 tool, * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$, nonparametric one-way ANOVA using Wilcoxon rank
409 sum test with Benjamini-Hochberg correction for multiple comparisons) **(c)** The relative error rate
410 of each tool (%) was compared to the manual plaque count value. The resulting correlations are
411 overlaid. Note that the OnePetri-Device (green circle) and OnePetri-Simulator (orange triangle)
412 correlation lines mostly overlap.
413


A
B
C
D
precision
recall
mAP0.5
mAP0.5_0.95
epoch
epoch
1.00
0.75
0.50
0.25
0.00
0
100
200
300
400
500
Model
Petri dish
Plaque


A
User selection of image from photo library or camera
Petri dish detection
YOLOv5s model
Intermediate output: bounding boxes drawn around Petri dishes, user selection of Petri dish of interest
Image pre-processing
• Crop to Petri dish
• Tile image into 416x416 pixel squares
Plaque detection & deduplication
YOLOv5s model
Final output: bounding boxes drawn around plaques, counts displayed to user
Optional assay calculations
Phage titre, etc.
B
petri-dish
Confidence: 0.92
petri-dish
Confidence: 0.93
petri-dish
Confidence: 0.95


A
Time to Result (seconds)
275
250
225
200
175
150
125
100
75
50
25
0
***
**
**
OnePetri (device)
OnePetri (simulator)
CFU.AI
PST
Manual
Tool
B
Relative Error to Manual Counts (%)
120
100
80
60
40
20
0
***
**
OnePetri (device)
OnePetri (simulator)
CFU.AI
PST
Tool
C
Relative Error to Manual Counts (%)
120
100
80
60
40
20
0
0
200
400
600
Manual Plaque Count
Tool
OnePetri-Device
OnePetri-Simulator
CFU.AI
PST