Demo video showing the project in action:

https://www.youtube.com/watch?v=kaymrFW9rgo

PalAST: A Cross-Platform Mobile Application for Automated Disk Diffusion Antimicrobial Susceptibility Testing

Ayah ElShawa, Ghadeer Alhayek, Malak Ghabayen, Raghad Alkhattib

Faculty of Information Technology, The Islamic University of Gaza, Palestine, P.O. Box 108

Abstract

Antibiotic resistance is the ability of bacteria to resist the effects of antibiotics, making infections more difficult to treat and increasing the risk of complications and death. One way to fight antibiotic resistance is by identifying the most effective antibiotics for treating bacterial infections. This can be done through a laboratory test called AST , which is used to determine the susceptibility of bacteria to antibiotics. However, manual AST has several limitations that include time delay, limited accuracy, limited testing capacity, and subjective interpretation of results. Therefore, there is an emergent need for a more reliable and efficient alternative to manual AST.

Recently, few works have tried to automate disk diffusion AST through AI-based solutions and mobile applications. However, these works do not support advanced analysis and interpretation of results, do not present evaluation of detection performance, or are not publicly available to download and use.

This work proposes PalAST, a cross-platform mobile application that supports automated disk diffusion AST. The application enables biologists to take AST photos and analyze them in real time with minimal human intervention. It uses image processing and a pre-trained machine learning model to detect antibiotic disks in the agar plate and predict bounding circles for inhibition zones. Then, it provides an interpretation of results including the diameters of the

inhibition zones, the labels on the antibiotic disks, and the rating of the bacteria as susceptible, intermediate, or resistant to each antibiotic. PalAST also stores the results of tests, allowing users to access and review past test results.

PalAST was tested using a number of real AST photos, and the detection performance was evaluated by using common metrics, i.e. precision, recall, and Intersection over Union. We also used expert evaluation through a questionnaire to assess the PalAST usability and ease of use.

Keywords: AST (Antimicrobial Susceptibility Testing), disk diffusion, antibiotic resistance, inhibition zone, mobile application, cross platform, machine learning

1 Introduction

Antibiotic resistance is a growing problem worldwide. It occurs when bacteria develop mechanisms to resist the effects of antibiotics, rendering these drugs ineffective in treating bacterial infections. This can lead to longer hospital stays, more expensive treatments, and even death in severe cases.

One way to combat antibiotic resistance is through antibiotic susceptibility testing (AST). AST is a laboratory technique used to determine the most effective antibiotic for treating a specific infection[16]. It involves growing bacteria in the presence of different antibiotics to see which drugs are most effective in killing bacteria. By using AST to guide antibiotic treatment, healthcare providers can avoid prescribing antibiotics that are unlikely to work, reducing the likelihood of antibiotic resistance. This approach can also help to ensure that patients receive the most effective treatment for their infection, leading to better outcomes and reduced healthcare costs.

One of the most common methods for performing AST is the disk diffusion method [5], which involves placing small disks containing different antibiotics on a culture plate inoculated with a bacterial isolate. The plate is then incubated, and the resulting growth or inhibition of bacteria around the disks is measured to determine the susceptibility of the organism to antibiotics. Figure 1. Illustrates the AST test. It shows the antibiotic disks with the resulting inhibition zones in an agar plate. The inhibition zone refers to the area of bacterial growth inhibition around an antibiotic disk. This zone is measured to determine the susceptibility

or resistance of the bacterial isolate to the antimicrobial agent being tested. Based on comparisons of inhibition zones on the plate and standard values, the bacteria tested were determined to be resistant, intermediate, and susceptible to different antibiotics present.

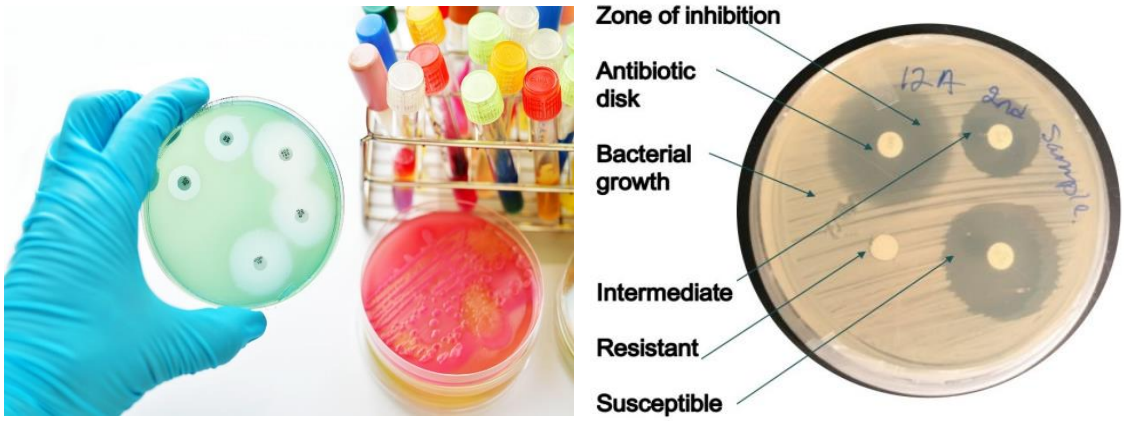

Figure 1. Antimicrobial Susceptibility Testing [11]

AST can be done manually or automatically, depending on the laboratory's resources and capabilities. Manual AST methods involve the use of agar plates such as the one shown in Figure 1. Plates are inoculated with bacterial samples and incubated overnight. The plates are then examined to determine the minimum inhibitory concentration (MIC)[13] of antibiotics required to inhibit bacterial growth. The results are interpreted by measuring the diameter of the zone of inhibition around each antibiotic disk. However, manual methods are often less expensive and can be performed in resource-limited settings, but are more time-consuming and prone to human error [8].

On the other hand, automated AST methods involve the use of specialized equipment that uses predefined protocols to perform the testing process [15, 20]. The equipment can process a large number of samples quickly and accurately, and the results can be interpreted automatically or with minimal human intervention. Automated methods are faster and more accurate, but they require specialized equipment and can be more expensive to set up and maintain.

In the Gaza Strip, the AST test is often performed manually in medical laboratories and hospitals, due to the lack and high cost of the equipment needed for automated tests. In light of increasing antimicrobial resistance around the world, there is an emerging need for an alternative solution to improve the speed, accuracy, and standardization of AST, while also reducing costs.

Driven by the aforementioned needs, this work proposes PalAST, a mobile application that enables to perform disk diffusion AST automatically. PalAST uses image processing and ML techniques to analyze the photo of the agar plate captured by the mobile camera. Then it provides measurements and interpretations that include the diameters of the inhibition zones, the antibiotic labels, and the rating of the bacteria as susceptible, intermediate, or resistant to each antibiotic.

The following sections are organized as follows: The next section discusses related works and compares them with PalAST. Then, the PalAST usage scenario is presented along with snapshots to highlight its key features and capabilities. Afterwards, the architecture and implementation of PalAST are described, focusing on the system components and the role of each component in the analysis process. The evaluation of PalAST using both quantitative and qualitative approaches is then presented, and the evaluation results are discussed. Finally, the conclusions and future works are presented.

2 Related Works

In recent years, increasing interest has been shown to the use of AI and image processing to support medical diagnosis. These technologies have been shown to improve diagnostic accuracy and speed and reduce healthcare costs. Recently, many mobile applications have used AI and image processing techniques to support a variety of medical tests, such as the detection of dermatological diseases [12, 14, 17] and breast cancer [1, 7]. However, a few works have been proposed to aid in antibiotic resistance and AST. In what follows, we give an overview of these works and highlight the differences between them and PalAST.

Kadlec, et al. [10] proposed a mobile application that offers an automated approach to AST by using a method called gas-permeable microwell arrays, a colorimetric cell viability reagent. Although it uses image processing to analyze bacterial growth, this approach is less common when compared to the disk diffusion method, which is currently the most common, less expensive and most accurate approach for AST.

AntibiogramJ [2] is a desktop Java-based application that takes antibiogram images as input, then identifies and measures inhibition zones as output. However, it has not been produced as a mobile application. In addition, it does not recognize antibiotic labels from captured image, and does not provide interpretations of measurements as we do PalAST.

Baltekin, et al. [3] developed a point-of-care susceptibility test for urinary tract infection. Bacterial cells are directly captured from samples using a custom designed microfluidic chip. This test requires loading samples to the chip and then diagnostic readout, which is done in 30 minutes. This work is restricted to AST for urinary tract infection. In addition, the production of the microfluidic chip needed for this test could be a costly solution, especially in areas with limited resources.

Burg, et al. [4] proposed an automated platform that identifies urinary tract infection pathogens in 45 min and provides phenotypic AST results in less than 5 hours from urine specimens without colony isolation. Again, this work is limited to AST for urinary infections, and requires special equipment. PalAST does not require any hardware other than the mobile application.

Panpradist, et al. [18] proposed OLA (oligonucleotide ligation assay), which is a kit developed for detection of HIVDR (HIV Drug Resistance) against non-nucleoside/nucleoside reverse transcriptase inhibitors. However, this work does not consider disk diffusion AST.

Pascucci, et al. [19] presented an AI-based mobile app for antimicrobial analysis. To the best of our knowledge, this is the most recent and only work that offers an automatic approach for AST by using the disk diffusion method. They also offered an image processing library to analyze images of plates. However, their mobile application works only on Android devices. They also do not provide their mobile application for public use. This has motivated us to build a similar application that performs similar functionality, but is freely available for public use. In fact, we employed the pre-trained ML model from their library to analyze the captured images of plates in PalAST. PalAST offers additional services, such as local storage of test results and user authentication. Furthermore, our app is developed to be cross-platform, and thus can work on both Android and iOS devices. Our work also evaluates the usability of the mobile application and the accuracy of the underlying detection methods.

Croxatto, et al. [6] presented a mobile application designed specifically for interpreting AST results from urine cultures. It provides guidance on which antibiotics are likely to be effective for treating urinary tract infections caused by specific bacteria. However, this application is used particularly for automated inoculation of urine samples to generate isolated colonies. It is not tailored for disk diffusion AST.

Antibiogram[1] is a mobile application that allows users to create custom antibiograms based on local susceptibility data. It also includes tools for tracking resistance patterns over time and comparing data across different healthcare facilities. However, this app does not employ image processing or AI. The laboratory technician still needs to perform AST manually, and then input the measures to Antibiogram in numeric format. Then, it interprets the input measurements to categorize the susceptibility of the bacteria.

Antibiotic Guide[2] is an application that offers a comprehensive database of antibiotics and their indications, dosages, and adverse effects. It also includes information on resistance patterns and susceptibility testing methods. However, this app offers information and guidance, but does not perform AST or offer any AI-based functionalities.

It can be concluded from the above review is that many works that tackled AST have focused on specific diseases, such as HIV or urinary infections, but a few of them have targeted disk diffusion AST. Some of them required special equipment or devices that are difficult to secure in areas with limited resources. Works that support disk diffusion AST through mobile applications either do not support advanced analysis and interpretation of results, or are not publicly available to download and use. Table 1 summarizes the differences between the aforementioned works and PalAST.

Table 1. Comparison between works that tackle automated AST

Work	Measurement of inhibition zones	Identification of antibiotic labels	Interpretation of measurements	Mobile app
Kadlec, et al. [10]	✓ (using gas-permeable microwell arrays)			✓
AntibiogramJ [2]	✓			
Baltekin, et al. [3]	✓ (for urinary tract infection only, requires custom-designed chip)	✓	✓	
Burg, et al. [4]	✓ (for urinary tract infection only, requires	✓	✓	

[1] https://play.google.com/store/apps/details?id=co.inergia.antiBiograma2&hl=en&gl=US
[2] https://play.google.com/store/apps/details?id=com.emra.AntibioticGuide

	special devices)			
Panpradist, et al. [18]	✓ (a kit for detection of HIV Drug Resistance)	✓	✓	
Pascucci, et al. [19]	✓	✓	✓	✓ (Not available for public use, only for Android device)
Croxatto, et al. [6]	✓ (from urine cultures only)	✓		✓
Antibiotic Guide[3]				✓
Antibiogram[4]			✓ (Measurements should be performed manually and inputted by the user)	
PalAST	✓	✓	✓	✓ (cross-platform)

3 PalAST in action

This section demonstrates the PalAST usage scenario. PalAST can be used by laboratory technicians to perform disk diffusion AST in real time as the following:

First, the user needs to register for the app. User registration is necessary to create a profile for each user, where all his/her conducted tests and results can be saved so that they can be retrieved and accessed at a later time from anywhere.

The user then creates a new AST test by specifying its settings that include the nutrition medium and the type of bacteria as shown in Figure 2.A, and then taking a high-quality photo of the plate. For the analysis to give good results, the captured photo should fulfil the following requirements: 1) the plate should be entirely

[3] https://play.google.com/store/apps/details?id=com.emra.AntibioticGuide
[4] https://play.google.com/store/apps/details?id=co.inergia.antiBiograma2&hl=en&gl=US

included in the photo with no perspective distortion, and should not touch the borders of the photo. 2) the photo is not blurred. 2) There are no shadows or light reflection on the plate.

After taking the photo, PalAST will send it to the server side for analysis. The server side analyzes the photo to detect the antibiotic disks, identify the antibiotic labels, and measure the diameters of inhibition zone. The entire analysis takes a few seconds to complete, and the results are returned to the client to be presented and interpreted on the mobile device.

After the analysis completes, the photo of each antibiotic disk with the surrounding inhibition zone is cropped out and displayed to the user one by one, as shown in Figure 2.A. Each cropped photo will be augmented with annotations showing the detected antibiotic label and the bounding circle of inhibition zone. Although the underlying ML model used in PalAST has high prediction accuracy as will be revealed from the evaluation results, some bounding circles may not match the boundaries of the inhibition zones perfectly. Therefore, PalAST gives the user the ability to manually adjust the size of the predicted bounding circle or choose a different antibiotic label from a predefined list of labels as shown in Figure 2.B. This feature enables the user to correct any potential prediction errors. After verifying the measurements related to one antibiotic disk, the user clicks on the next button to view the photo of the next antibiotic.

The above process continues until the user verifies all results. At this point, the application will display the entire photo of the plate annotated with the predicted/adjusted bounding circles and antibiotic labels (see Figure 2.C). It also shows a final report summarizing the susceptibility categories of the bacteria isolate as resistant (R), intermediate (I), or susceptible (S) to each antibiotic used in the plate. These categories are determined based on the comparison between the diameters of detected bounding circles and establish standards such as those developed by the Clinical and Laboratory Standards Institute (CLSI)[5].These standards define what so called breakpoints, which are the diameters of the zone that that separates susceptible, intermediate, and resistant categories for each bacteria type. For example, a bacterial isolate is considered susceptible if the size of the inhibition zone is larger than the established breakpoint for susceptibility. The final results report can be exported in PDF format and shared via email or social networks. In addition, test results are stored in the user's profile so that the user can access and view past tests at any time.

[5] https://clsi.org/ (Clinical and Laboratory Standards Institute)

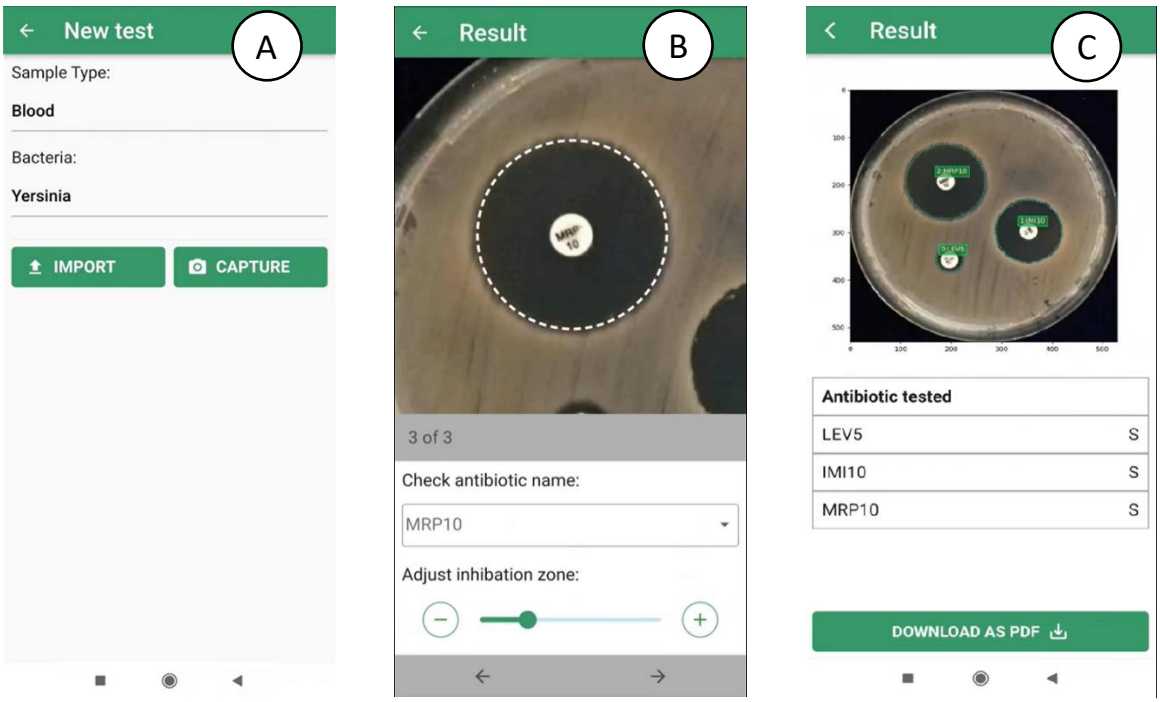

Figure 2. Screenshots of sample screens from PalAST: A) The user creates a new AST and specifies its settings. B) Detected zones are presented one by one in sequence to the user for verification and correction. C) Final results showing the entire plate with annotations, the susceptibility categories of the bacteria.

4 PalAST Architecture and Implementation

The architecture of PalAST consists of two components: the server side, where all the AI and image processing functionalities are performed, and the client side, where results are interpreted and displayed to the user. The two parts of PalAST communicate through a RESTful web service. The codes of both server and client sides are freely available for download[6] [7]. These components are explained in what follows.

4.1 The Server Side of PalAST

The image analysis is carried out on the server side and goes through the steps shown in Figure 3 as follows:

1. Image cropping: The image of the plate that was captured and sent by the client side is first pre-processed to detect and crop the plate. An edge detection algorithm from OpenCV is used to detect the edges of the plate and then crop it to remove the surrounding empty spaces.

[6] Client side code (PalAST Flutter App) can be downloaded from https://github.com/malak271/AST
[7] Server side code can be downloaded from https://github.com/GhadeerHayek/AST-Flask

2. Detection of inhibition zones: The cropped image is then passed as input to a pre-trained ML model from the AST library [19]. The model is pre-trained to automatically recognize inhibition zones and predict bounding circles around these zones, as shown in Figure 3. For each inhibition zone, the model returns the diameter in pixels, the center coordinates, and a confidence score that represents how confident the model is about the zone measurements. Note that the library measures the diameter in pixels. The scale in pixels cannot be directly converted to real length in millimeters because the image can be captured from different perspectives or zoom ratios. To determine the real diameter from the image of the plate, it is necessary to have a reference to scale the zone in the image. Therefore, we chose the antibiotic disk as a reference object because it typically has a fixed size of 6 mm [9]. We then calculated the scaling factor by dividing the diameter of the antibiotic disk by its diameter in pixels as in Equation 1. This will give a scaling factor, expressed in millimeters per pixel.

$$Scaling\ factor\ (mm/pixel) = \frac{Diameter\ of\ antibiotic\ disk\ (6\ mm)}{Measured\ diameter\ of\ antibiotic\ disk\ in\ pixels} \quad (1)$$

3. Finally, we multiply the diameter of the inhibition zone in pixels by the scaling factor to obtain the real diameter in millimeters as in Equation 2.

$$Diameter\ of\ inhibition\ zone\ (mm) = Diameter\ of\ inhibition\ zone\ in\ pixels\ *\ Scaling\ facto \quad (2)$$

4. Detection of antibiotic labels: The AST library also offers an optical character recognition (OCR) function that enables recognizing and reading the label written on the antibiotic disk.
5. Cropping the inhibition zones: After detecting the antibiotic disks and the associated zones, the next step is to crop out each zone in a separate image. Therefore, the plate image is divided into multiple images, each of which shows a single antibiotic disk with the surrounding inhibition zone. These images are stored on the server and will be retrieved later by the client side to be presented to the user on the mobile for verification, as explained in Section 3.
6. Creating JSON representation of analysis results: At this point, the analysis process should have been completed, and the analysis results are grouped together and presented in JSON format, which will be sent

back to the client side. The JSON output contains a sequence of JSON objects, each of which corresponds to an antibiotic disk and its cropped image. The Information of each detected antibiotic includes:

- The detected antibiotic label.
- Center coordinates (position of the disk)
- Diameter of the inhibition zone.
- ID of the corresponding cropped image (to be accessed from the mobile device).

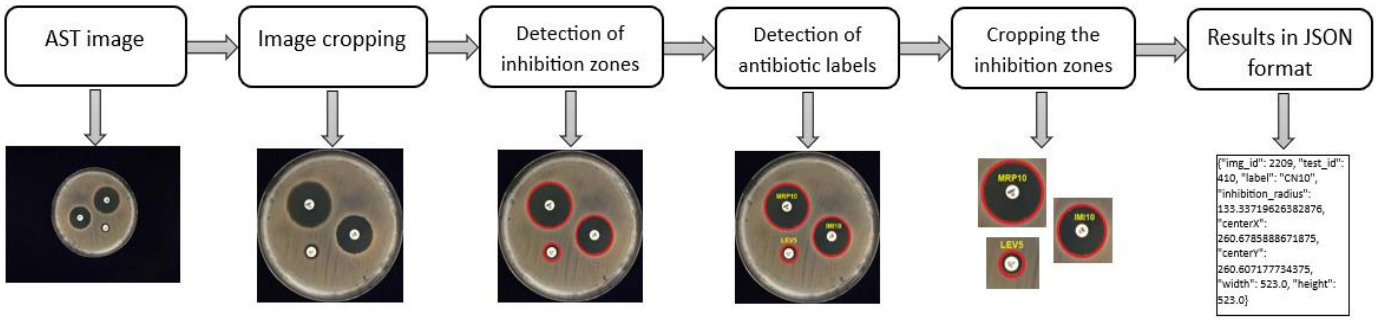

Figure 3. Image analysis in PalAST

4.2 The Client Side of PalAST

The client side of PalAST is a mobile application that enables the user to initiate the AST test and get results in real time through a user-friendly interface. The application was developed using Flutter, which allows it to run on both the Android and iOS platforms. The application has five main modules:

- The connector: This module is responsible for submitting the captured image of the agar plate to the server side, and then receiving the analysis results in JSON format. Then it extracts information from JSON and sends it to the annotator module.
- The annotator: It creates and displays annotations over the image of the plate. These annotations include textual labels showing the antibiotic label and the diameter of the inhibition zone. It also draws a bounding circle around the inhibition zone.
- The verifier: The verifier is a UI module that displays the cropped inhibition zones of detected antibiotic disks one by one in sequence. It enables the user to correct potential errors by adjusting the bounding circle and the detected label of the antibiotic as illustrated in Section 3.

- The storage manager: This module is responsible for storing results of all AST tests performed by the user; and enabling access to these results at any time.
- The interpreter: Using the measured diameters of detected inhibition zones and the establish standards for breakpoints in AST, this module provides an interpretation of the results. It categorizes the tested bacteria as susceptible, intermediate, or resistant to each antibiotic disk on the plate.

5 Evaluation

The objectives of our evaluation are to:

- assess the ability of PalAST to accurately create bounding circles that capture the full extent of the inhibition zones.
- assess the ability of PalAST to recognize antibiotic labels written on disks.
- assess the usability and ease of use of PalAST.

We used two evaluation methods:

- Evaluation of the detection performance by using common metrics used to evaluate object detection.
- Expert evaluation of usability and ease of use through a user-centered questionnaire.

In the following subsections, we explain each evaluation method in detail.

5.1 Evaluation of the detection performance

5.1.1 Data Collection

To evaluate the object detection performance, we need to experiment with a number of AST images using disk diffusion method, and then use common metrics for evaluating object detection. However, we could not find any freely available dataset of AST images that we could use for evaluation. Therefore, we contacted biologists from our local university to provide us with real photos of disk diffusion AST. We asked them to take photos of agar plates that use various types of bacteria and antibiotics using their mobile phones. We gave them instructions on how to capture good quality photos. In addition, we collected several photos of AST plates from the Internet. In total, we collected 14 photos of agar plates. These plates contain 138 antibiotic disks in total, around which zones of inhibition are present. The number of unique antibiotics in these photos is 12. AST plates were selected to have different shapes, i.e. circular and square, and colors of nutrition

medium so that the detection results can be assessed under different conditions. Figure 4 shows sample photos. The dataset can be accessed from[8].

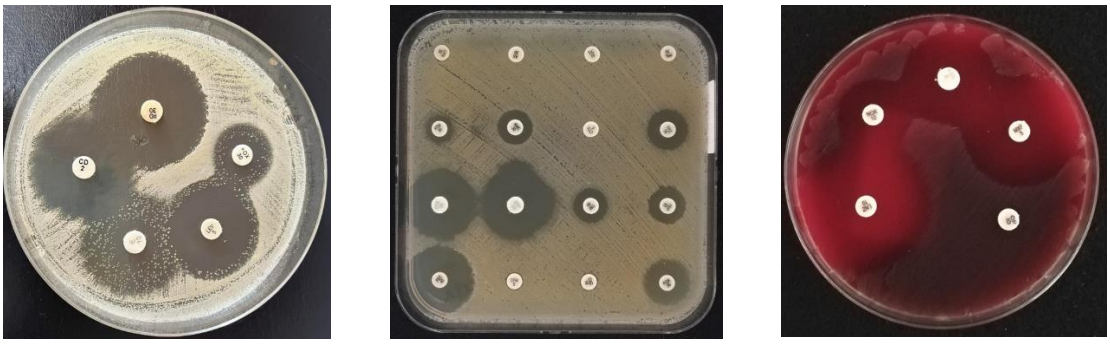

Figure 4. Photos from the testing dataset

5.1.2 Evaluation Metrics

We use several metrics to evaluate the detection performance. In the following, we present these metrics and explain how we adapt them to our evaluation.

Precision: Precision measures the percentage of true positive detections in relation to the total number of detections. It is calculated as TP / (TP + FP), where TP in our case denotes the number of truly detected antibiotic labels or bounding circles. FP is the number of false positives. In our case, false positives refer to antibiotic disks that are detected, but are mistakenly identified as of another type, or are localized with misaligned bounding circles that are too small or large.

Recall: Recall measures the percentage of true positive detections in relation to the total number of ground-truth objects. It is calculated as TP / (TP + FN). FN refers to the number of undetected antibiotic labels or inhibition zones.

Intersection over Union (IoU): IoU measures the overlap between the predicted bounding circle and the actual boundaries of the zone. It is calculated as the area of intersection between the two circles divided by the area of their union.

Since PalAST performs two different detection tasks: the detection of inhibition zones and the detection of antibiotic labels, we calculated the precision and recall values for each detection method separately. The IoU is calculated only for the zone detection task

[8] AST dataset https://github.com/GhadeerHayek/AST-Flask/tree/main/dataset

5.1.3 Results and Discussion

Plate images were processed by PalAST to obtain new images annotated with predicted bounding circles and antibiotic labels similar to the image in Figure 2.C. The annotated images were then presented to a human expert (me) to evaluate the predict bounding circles and antibiotic labels with reference to actual values. Tables 2 and 3 present the evaluation results of the zone detection task. In total, 97 of 138 zones were accurately detected and localized accurately, and the predicted bounding circles matched the zones as indicated by the evaluator. In general, PalAST achieved 0.858 precision and 0.795 recall.

Note that some inhibition zones are not perfectly circular. In such a case, the bounding circles may not fully include the zones of inhibition as in Figures 5.A and 5.B. These bounding circles may have different diameters in different directions. For these zones, the detection algorithm automatically picks the inner diameter that makes a full circle, excluding areas beyond this radius.

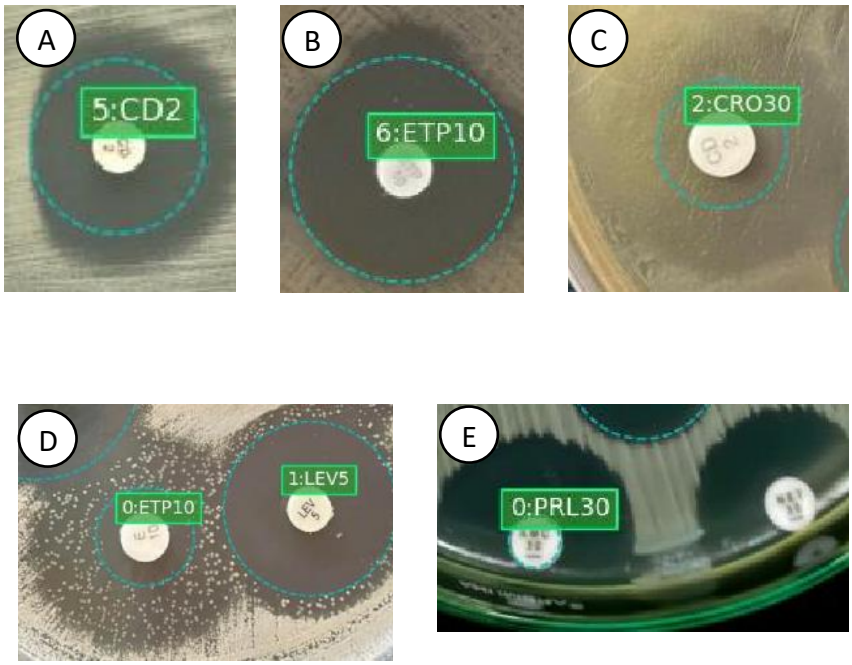

Figure 5. Examples of inaccurate detections of inhibition zones: A,B) Inhibition zones with non-circular shape. C) The zone is obscure due to poor lighting. D) Zones of partial inhibitions. E) Zones that collide with the edge of the plate

The number of zones that were detected but with misaligned bounding circles were 16 out of 138. When inspected, we found that the diameters of these zones were incorrectly measured due to factors such as poor lighting and light reflection that made the inhibition area imperceptible and hard to distinguish, as in Figure 5.C. In addition, some detection errors resulted from inhibition zones that are not completely empty and may

show some bacterial growth such as the one shown in Figure 5.D. Experts identified these as zones of partial inhibition, and indicated that such cases occurred due to factors related to the concentration of the antibiotic and the incubation conditions. These cases can be resolved by repeating the test with different settings. Other detection errors were due to antibiotic disks placed close to the edges of the plate, and thus their zones grew as strips rather than complete circles (see Figure 5.E). In general, many of the detection errors can be resolved by capturing high-quality images with no blurring or light reflection, or by allowing enough space between the antibiotic disks and the plate borders.

The average IoU value is 0.706. This indicates about 70% overlap between the actual zones and the predicted bounding circles. For the true positive cases only (accurately bounded zones), the average IoU is 0.901. For the false-positive cases (zones bounded with misaligned circles), the average IoU is 0.702. The IoU is considered to be 0 for false negative cases (undetected zones).

Tables 4 and 5 show the result of the label detection task. PalAST achieved 0.733 precision and 0.81 recall for this task. When the false predictions were inspected, we found that most of them resulted from issues related to blurred images and poor lighting that made it impossible to read labels. By comparing the results of Tables 5 and 6, it can be concluded that PalAST performed slightly better with the zone detection task than with the label detection task.

Note that in both detection tasks, TN (true-negative) represents the number of locations in an image that are correctly classified as not containing inhibition zones or antibiotic disks. Therefore, the TN value is considered to be zero.

Table 2. Confusion matrix of the zone detection process

		Actual	
		Positive	Negative
Prediction	Positive	97	16
	Negative	25	0

Table 3. Results of the zone detection process

Precision	0.858
Recall	0.795
F-measure	0.825
IoU	0.706

Table 4. Confusion matrix of the antibiotic label detection process

		Actual	
		Positive	Negative
Prediction	Positive	85	31
	Negative	20	0

Table 5. Results of the antibiotic label detection process

Precision	0.733
Recall	0.810
F-measure	0.77

5.2 Expert evaluation of PalAST usability and ease of use

We prepared the questionnaire shown in Table 6, which includes questions covering key aspects of usability, such as ease of use, efficiency, and user satisfaction. Each question should be answered using a 5-point Likert scale, where 1 denotes “Very weak” and 5 denotes “Very good”. The questionnaire also includes an open question about any further comments or suggestions for improvement. We presented PalAST to two experts from our university and asked them to fill out the questionnaire. Both experts are medical professionals with expertise in microbiology and infectious diseases.

Table 6 also shows the feedback received from the two experts. In general, both experts provided a very positive feedback, giving “Good” or “Very good” ratings for all the functions of PalAST. Both experts highly agreed that the application automates that AST in a way that saves time and efforts. When asked about the

functions that they liked most, they both mentioned the fast detection of zones and the automatic rating of bacteria. They also indicated that the ability to adjust the detected bounding circles is extremely helpful. Even in manual measurement, experts may measure or interpret results differently due to incomplete inhibition or the overlapping between zones.

When asked about suggestions for improvement, they both suggested the need to add new types of antibiotics and bacteria species, as well as update the interpretive criteria of AST which is likely to change over time. They also highlighted the need to run the application offline because the internet connection may not be available in some areas.

Table 6. Questionnaire used to assess PalAST with expert responses

Question	Expert 1 responses	Expert 2 responses
PalAST saves time and effort by automating the AST	Very good	Very good
PalAST enables me to easily start a new AST test and capture AST photo	Very good	Good
Inhibition zones are accurately detected and measured by PalAST	Good	Good
Antibiotic names are accurately detected and recognized by PalAST	Good	Good
PalAST responds quickly to AST requests and presents results without incurring significant delay	Very good	Very good
PalAST enables me to easily verify the analysis results and correct any wrong detections or measurements.	Good	Good
PalAST correctly rates bacteria as susceptible, intermediate, or resistant to each antibiotic	Good	Good
PalAST enables me to access and review past test results	Very good	Very good
PalAST is easy to use and navigate	Very good	Very good

6 Conclusion and Future Work

This work proposes PalAST, a cross-platform mobile application that supports automated AST by using disk diffusion method. The application enables biologists to take AST images and analyze them in real time and with minimal human intervention. PalAST also provides an interpretation of the results including the measured diameters of the inhibition zones, the recognized antibiotic labels, and the categorization of the bacteria isolate as susceptible, intermediate, or resistant to each antibiotic.

PalAST was tested using a number of real AST images, and the detection performance was evaluated by using common metrics, i.e. precision, recall and IoU. We also used expert evaluation through a questionnaire to assess the usability and ease of use of PalAST.

We believe that PalAST can have important implications for patient care and public health in Palestine and other less advantaged areas in the world. More importantly, we think that PalAST contributes to the global efforts and priorities of the World Health Organization, which has recognized the antibiotic resistance as of the most health threats facing the world in the coming years. However, it should be noted that mobile applications should not be used as a substitute for professional medical advice or laboratory tests. They can be a useful tool to supplement clinical decision making, but should be used in conjunction with other sources of information and guidance from healthcare professionals.

In the future, we aim to upgrade PalAST to work offline, as it currently works online only. This is particularly important in areas that have limited or interrupted access to the Internet. Second, we aim to conduct a large-scale evaluation of PalAST by testing it with a larger number of AST images and getting feedback from a larger number of users and experts. This will help us to better identify potential defects or additional functionalities.

References

[1] M. A. S. Al Husaini, M. Hadi Habaebi, T. S. Gunawan, and M. R. J. E. Islam, "Self-detection of early breast cancer application with infrared camera and deep learning," vol. 10, no. 20, p. 2538, 2021.

[2] C. Alonso *et al.*, "Antibiogramj: A tool for analysing images from disk diffusion tests," vol. 143, pp. 159-169, 2017.

[3] Ö. Baltekin, A. Boucharin, E. Tano, D. I. Andersson, and J. J. P. o. t. N. A. o. S. Elf, "Antibiotic susceptibility testing in less than 30 min using direct single-cell imaging," vol. 114, no. 34, pp. 9170-9175, 2017.

[4] L. Burg *et al.*, "Rapid pathogen identification and phenotypic antimicrobial susceptibility directly from urine specimens," vol. 12, no. 1, p. 18315, 2022.

[5] L. Coorevits, J. Boelens, G. J. E. J. o. C. M. Claeys, and I. Diseases, "Direct susceptibility testing by disk diffusion on clinical samples: a rapid and accurate tool for antibiotic stewardship," vol. 34, pp. 1207-1212, 2015.

[6] A. Croxatto, K. Dijkstra, G. Prod'hom, and G. J. J. o. c. m. Greub, "Comparison of inoculation with the InoqulA and WASP automated systems with manual inoculation," vol. 53, no. 7, pp. 2298-2307, 2015.

[7] C. Hou *et al.*, "Predicting breast cancer in Chinese women using machine learning techniques: algorithm development," *JMIR medical informatics*, vol. 8, no. 6, p. e17364, 2020.

[8] R. M. Humphries *et al.*, "The continued value of disk diffusion for assessing antimicrobial susceptibility in clinical laboratories: report from the clinical and laboratory standards institute methods development and standardization working group," vol. 56, no. 8, pp. e00437-18, 2018.

[9] B. E. Igere, A. I. Okoh, U. U. J. I. j. o. e. r. Nwodo, and p. health, "Antibiotic susceptibility testing (AST) reports: A basis for environmental/epidemiological surveillance and infection control amongst environmental vibrio cholerae," vol. 17, no. 16, p. 5685, 2020.

[10] M. W. Kadlec, D. You, J. C. Liao, and P. K. J. S. T. Wong, "A cell phone–based microphotometric system for rapid antimicrobial susceptibility testing," vol. 19, no. 3, pp. 258-266, 2014.

[11] A. Kohli, "Antimicrobial Sensitivity Testing: The Search for Antibiotics," 2021.

[12] I. Kousis, I. Perikos, I. Hatzilygeroudis, and M. Virvou, "Deep learning methods for accurate skin cancer recognition and mobile application," *J Electronics*, vol. 11, no. 9, p. 1294, 2022.

[13] B. Kowalska-Krochmal and R. J. P. Dudek-Wicher, "The minimum inhibitory concentration of antibiotics: Methods, interpretation, clinical relevance," vol. 10, no. 2, p. 165, 2021.

[14] V. B. Kumar, S. S. Kumar, and V. Saboo, "Dermatological disease detection using image processing and machine learning," in *2016 Third International Conference on Artificial Intelligence and Pattern Recognition (AIPR)*, 2016, pp. 1-6: IEEE.

[15] Y. Li, X. Yang, and W. Zhao, "Emerging microtechnologies and automated systems for rapid bacterial identification and antibiotic susceptibility testing," *SLAS TECHNOLOGY: Translating Life Sciences Innovation*, vol. 22, no. 6, pp. 585-608, 2017.

[16] M. Luc, "A comparison of disc diffusion and microbroth dilution methods for the detection of antibiotic resistant subpopulations in Gram negative bacilli," 2015.

[17] R. Pangti *et al.*, "A machine learning-based, decision support, mobile phone application for diagnosis of common dermatological diseases," vol. 35, no. 2, pp. 536-545, 2021.

[18] N. Panpradist *et al.*, "OLA-Simple: a software-guided HIV-1 drug resistance test for low-resource laboratories," vol. 50, pp. 34-44, 2019.

[19] M. Pascucci *et al.*, "AI-based mobile application to fight antibiotic resistance," vol. 12, no. 1, p. 1173, 2021.

[20] S. Puttaswamy, S. K. Gupta, H. Regunath, L. P. Smith, and S. J. A. C. M. Sengupta, "A comprehensive review of the present and future antibiotic susceptibility testing (AST) systems," vol. 9, no. 3, 2018.