

DEVELOPMENT AND TESTING OF A SMARTPHONEBASED SOLID ORAL DOSAGE FORM IMAGE RECOGNITION SYSTEM BY MACHINE LEARNING TO SUPPORT THE IDENTIFICATION OF DISPENSING ERRORS

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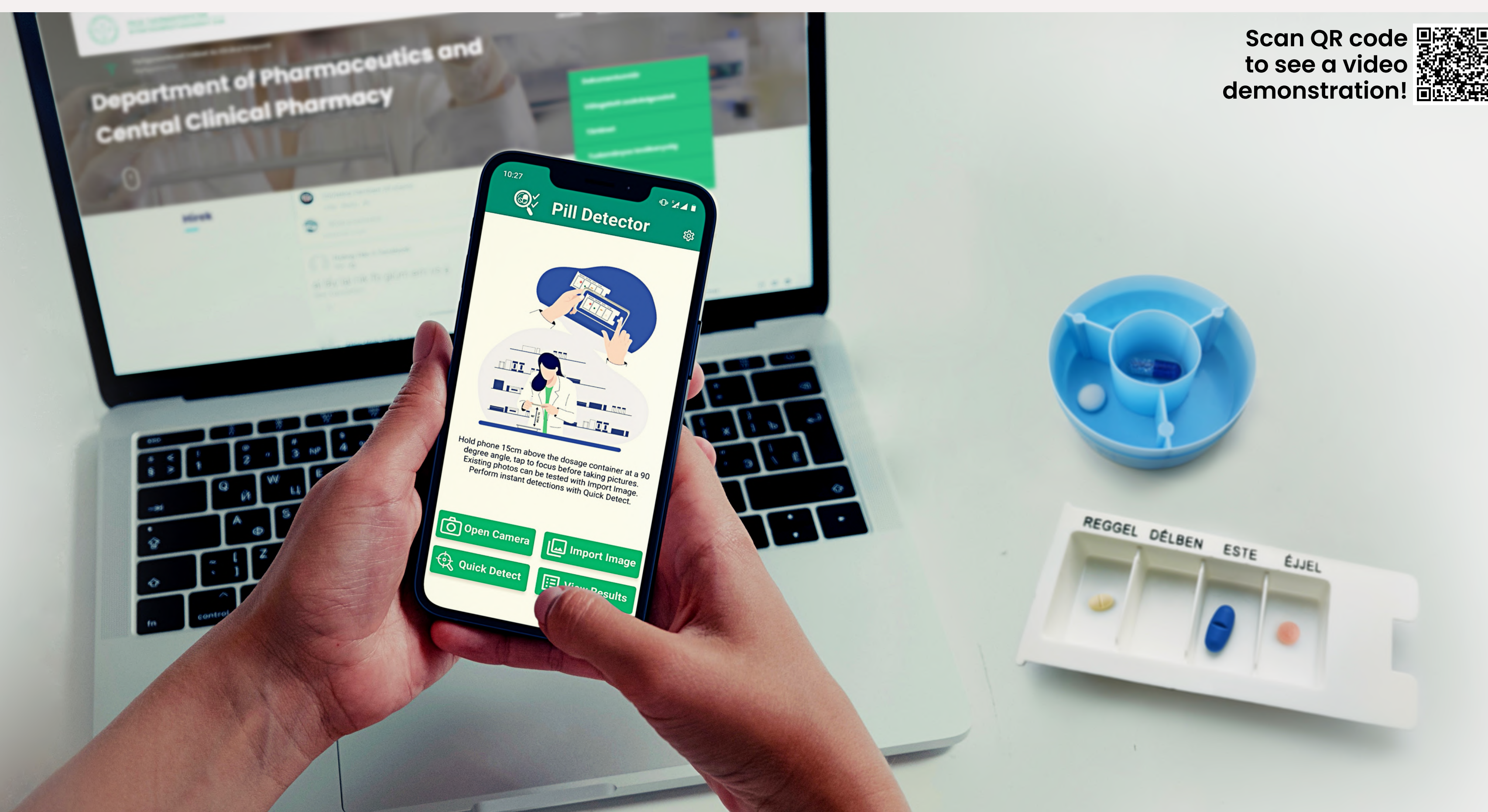
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BACKGROUND AND IMPORTANCE

Misidentification of oral dosage forms contribute to medication errors and compromise patient safety. Especially in manual dose dispensing, identification, and verification of medicinal products can be a challenge.

Machine learning is a powerful tool for object detection and image classification.

As smartphones have developed exponentially in terms of computing power and camera systems, they could serve as convenient tools and cost-effective solutions for supporting the identification and verification of dispensed oral dosage forms in real time at point-of-care settings.



AIM AND OBJECTIVES

We aimed to develop and test the real-world point-of-care applicability of a smartphone based pill recognition system using machine learning.

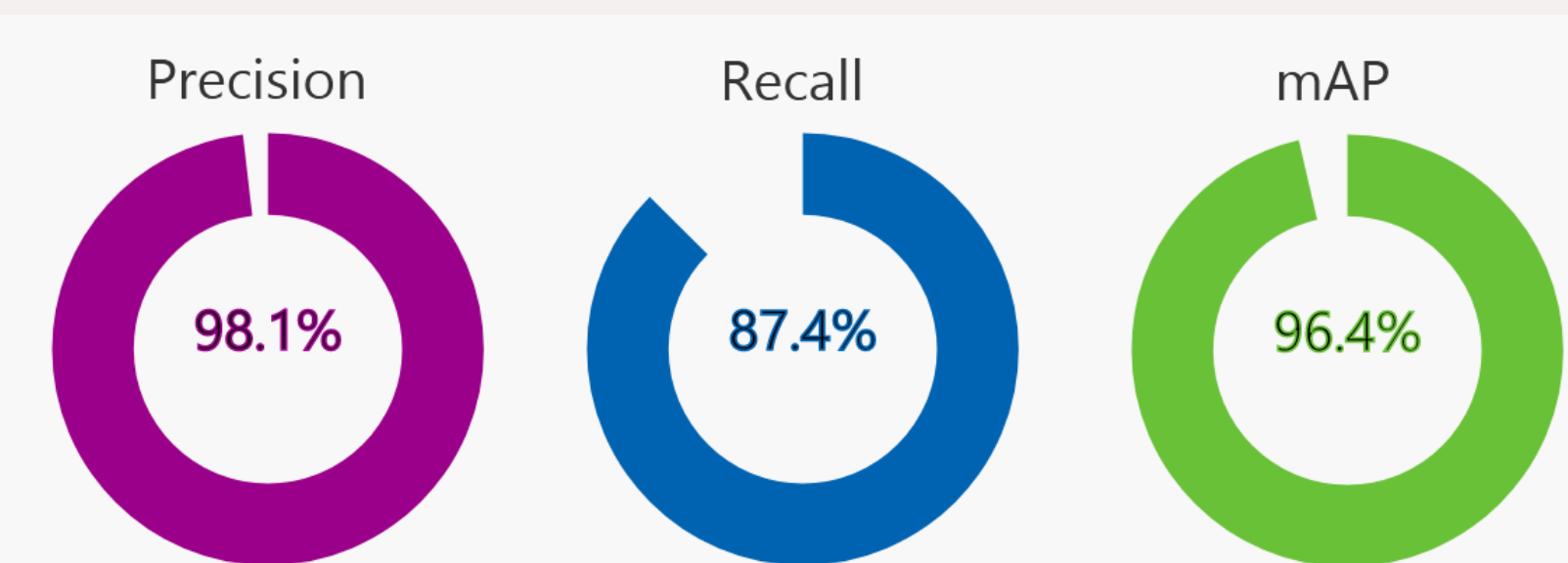
MATERIAL AND METHODS

Formularies of three Hungarian hospitals were evaluated to select ten most commonly prescribed and dispensed oral dosage forms. A total of 8960 images were taken with a Sony IMX363 camera sensor with resolution of 12 megapixels under various conditions (lighting, distance, angle, dose container) and were used without augmentation to train the model.

Microsoft Azure Custom Vision platform was utilized to develop our object detection and image classification model. An application was built using Android Developer Studio, the model was exported in TensorFlow lite format and integrated in the application. A validation dataset of 200 test images were captured by two pharmacists at the Central Clinical Pharmacy, precision, recall, mean average precision (mAP) and F1 score evaluation metrics were calculated.

RESULTS

Our model reached **98.1% precision, 87.4% recall and 96.4% mAP** after training, with probability and overlap thresholds set to 50% and 30% respectively under the reference condition.



Precision: Measures how accurate are the predictions. It's calculated as the ratio between the number of *True Positive* objects correctly identified, to the *total number of objects classified as Positive*. Unidentified objects are not included in this metric.
Recall: Measures the model's ability to detect *True Positive* objects out of *total number of positive objects* present. This metric includes unidentified objects, but false positives are excluded in the calculation.
mAP: Overall object detector performance across all object classes.

Confusion matrix of 200 real-world test images showed a lower overall **mAP (73.04%), recall (72.35%) and F1 score (70.6%)**. Per-class (medication) precision and recall ranges were between 50-100% and 20-100% respectively.

HOW OUR APP WORKS

- Photos can be captured within the application, or imported from the phone's gallery.
- A bounding box is drawn around each recognized medication, labeled with a corresponding tag and confidence value, using a unique color.
- Precision level threshold, maximum number of objects labeled in each image, and storage directory to save results can be changed in the app settings.
- To ensure results are always fully legible, they are printed at the bottom of each image.
- Users can save each processed image, providing a convenient solution for documentation of results and real-world testing of the system at point-of-care.
- Detection result is affected by light, distance, angle and background. Results may vary after slight changes in environmental conditions. (Figures 1-4)

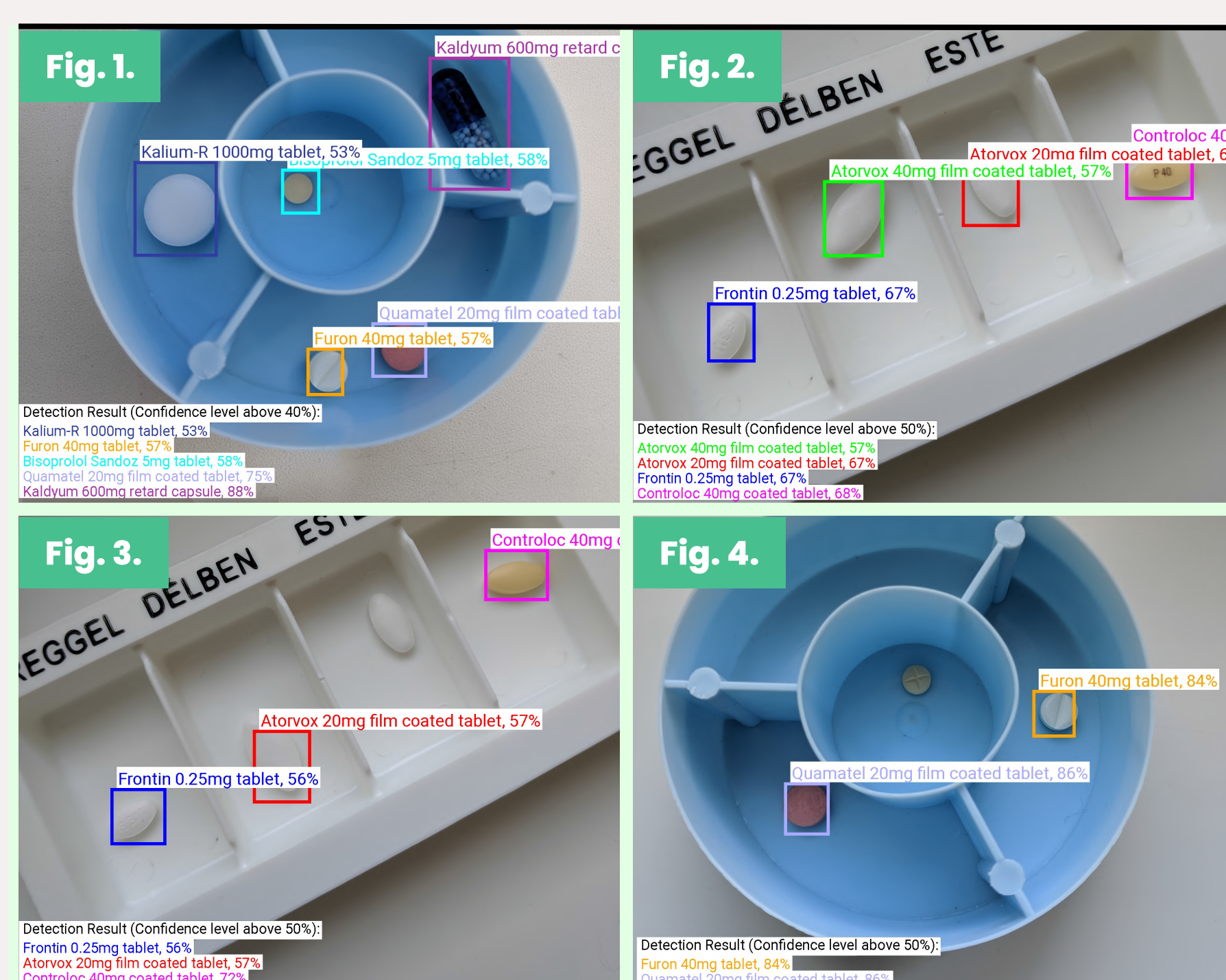


Figure 1: Every medication present in the image is correctly identified.
Figure 2: Correct identification of all pills with similar shape and color.
Figure 3: One detection failure and one misidentification (Atorvax 40mg as 20mg) Controloc 40mg and Frontin 0.25mg correctly identified.
Figure 4: One detection failure and correct identification of other two pills.

CONCLUSION AND RELEVANCE

Our model's performance indicates promising potential for application of smartphone based identification and verification of dispensed medications at point-of-care. We plan to extend our

dataset and train our model with additional images, to recognize the most commonly used medications in the hospitals participating in our project. Eventually, robustness of AI medication recognition models must be improved before such systems can be utilized in healthcare settings. These novel technologies can be

valuable tools to optimize hospital pharmacist human resources and further improve patient safety by supporting remote online and back-office clinical pharmacy services (e.g. medication reconciliation, drug-interaction screening), however can not replace highly trained individuals.