A Cost-effective and Reliable Method to detect Prohibited items for Improving Transportation Security

Team Leander, 2021-22 Season

According to the Transportation Security Administration (TSA), nearly 2 Million passengers, 5.5 Million Carry-on items and 1.4 Million checked items are screened daily. The number of Firearms detected at security checkpoints per million passengers traveled annually has been consistently increasing. In 2015, a study conducted revealed that 95% of security trials failed to detect firearms at dozens of the nation's busiest airports. While the TSA continues to invest Billions of US dollars in improving security checks, according to Times, in 2021, nearly 70,000 passengers, including some of our team members, missed flights due to long security lines. We have built a Smart-See-Thru solution using Artificial Intelligence and Machine Learning to detect prohibited items reliably and cost-effectively for less than $250, which can be integrated with existing security scanners at the airport. Our solution augments the TSA professionals and accelerates the security lines, while also improving the overall transportation security.

We are affiliated with

http://www.stem4girls.org/roborink/

Special thanks to our team advisor, mentors and to our parents for their support throughout the season

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Abstract

According to the Transportation Security Administration (TSA), nearly 2 Million passengers, 5.5 Million Carry-on items and 1.4 Million checked items are screened daily. The number of firearms detected at security checkpoints per million passengers traveled annually has been consistently increasing year over year. In 2015, a study conducted revealed that 95% of security trials failed to detect firearms at dozens of the nation's busiest airports. While the TSA continues to invest Billions of US dollars in improving security checks, according to Times, in 2021, nearly 70,000 passengers (including some of our team members) missed flights due to long security lines. Existing solutions require TSA professionals to manually audit each X-Ray image of luggage to detect any prohibited item, such as guns, scissors, knives, hammer etc. This process takes time and during the busy travel season. Human fatigue may cause TSA professionals to miss a few prohibited objects. We asked ourselves, "how can we cost-effectively and reliably detect prohibited items during security X-Ray scanning at the airports?", and have built a **Smart-See-Thru** solution for less than $250 to augment TSA professionals for detecting prohibited items automatically, and reduce security lines at the airports. We used freely available Artificial Intelligence and Machine Learning software to build our solution and plan to make our software and tools freely available to integrate with existing security scanners at the airports. We have received positive feedback from both security and technology experts on the viability of our solution. In the future, we hope to expand the Smart-See-Thru solution to detect all prohibited items and also expand to all security checkpoints nationwide.

Resources: IRB Form

eCYBERMISSION Survey Approval Form**

eCYBERMISSION team name: Team Leander

Team Advisor name: Ananth Sankaranarayanan

Team Advisor email: ananth.sankaranarayanan@gmail.com

Team Advisor phone: 503-780-5874

Student usernames: shreyas, vortex, ptekym, bobbyjean

School name: Neighborhood Team

School address: 1909 Western Justice, Leander, TX 78641

Describe the survey your team will conduct:

We will conduct a survey of X-ray images collected from airport security checkpoints to develop an automatic, reliable and cost-effective method to detect prohibited items.

Describe the participants you plan to distribute your survey to:

Transportation Security professionals, Machine Learning technology experts

Project approved by school administration?

☒ Yes ☐ No

Approved by: Ananth Sankaranarayanan

Title: Team Advisor

Date approved: 11/02/2022

Signature, School Administrator:

*Please have form completed, signed and dated BEFORE surveys are administered.

**As of August 2017, an IRB approval form (below) must be completed for all surveys as well as the information requested above.

INSTITUTIONAL REVIEW BOARD

APPROVAL FORM

Student(s) User Name(s): shreyas, vortex, ptekym, bobbyjean

Grade: 9 **Team Advisor:** Ananth Sankaranarayanan

Team Name: Team Leander

Brief Description of Project:

According to the Transportation Security Administration (TSA), the number of Firearms detected at security checkpoints has been increasing yearly. We have built a Smart-See-Thru solution using Artificial Intelligence and Machine Learning technology to detect multiple prohibited items reliably and cost-effectively for less than $250

Team Advisor: Please sign here if the project proposed is a viable eCYBERMISSION Project in which neither animals nor humans will be harmed.

Team Advisor Approval Signature: ____________________ **Date:** 11/02/2021

IRB Waiver of Written Informed Consent for Human or Animal Participation

The IRB may waive the requirement for documentation of written informed consent/assent/parental permission if the research involves **only minimal risk *and* anonymous data collection *and* if it is one of the following**: (NOTE: This statement only applies to providing the written certification mentioned in 1a or 2a above).

- Research involving normal educational practices.
- Research on individual or group behavior or characteristics of individuals where the researcher does not manipulate the subjects' behavior and the study does not involve more than minimal risk.
- Surveys, questionnaires, or activities that are determined by the IRB to involve perception, cognition, or game theory and do NOT involve gathering personal information, invasion of privacy or potential for emotional distress.
- Studies involving physical activity where the IRB determines that no more than minimal risk (Daily Activity) exists and where the probability and magnitude of harm or discomfort anticipated in the research are not greater than those ordinarily encountered in DAILY LIFE or during performance of routine physical activities.

If there is any uncertainty regarding the appropriateness of waiving written informed consent/assent/parental permission, it is strongly recommended that documentation of written informed consent/assent/parental permission be obtained.

HUMAN or ANIMAL SUBJECTS
Permission Slips needed? (see above to determine) Yes ☐ No ☑ **(Scan and attach slips to Mission Folder)**
Check-up of Human or Animal Subjects required by Doctor, school nurse or Veterinarian? (see above to determine) Yes ☐ No ☑ **If yes, Doctor's, Nurse's or Veterinarian's (before and after experimentation) current evaluation report must be attached to Mission Folder.**

APPROVALS –

Principal / Administrator Signature ____________ Date Reviewed ____________

Doctor or Medical Professional Signature ____________ Date Reviewed ____________

Science Fair Coordinator or other Science Teacher Signature ____________ Date Reviewed ____________

Resources: Risk Assessment Form

ARMY EDUCATIONAL OUTREACH PROGRAM

eCYBERMISSION ACCEPT THE CHALLENGE

U.S. ARMY

Risk Assessment Form

For a print version click here.

Must be completed BEFORE any TESTING begins.

Team Name: Team Leander

Student Usernames: shreyas vortex ptekym BobbyJean

To be completed by the team in collaboration with Team Advisor: (All questions must be answered; additional page(s) should be attached.)

1. Will any hazardous chemicals, activities, or devices be used? (see Hazardous Chemicals, Activities, Devices document).

- [ ] YES
- [x] NO (if no, skip to 4)

2. List all hazardous chemicals, activities, or devices that will be used.

3. Explain how all hazardous chemicals, activities, or devices will be handled based on the requirements explained on the Hazardous Chemical, Activities & Devices document.

4. Will any Potentially Hazardous Biological Agents be used? (see Potentially Hazardous Biological Agents document).

- [ ] YES
- [x] NO (if no, skip to 7)

5. List all Potentially Hazardous Biological Agents that will be used AND their biosafety level (BSL).

(continued)

6. Explain how all Potentially Hazardous Biological Agents will be handled based on the requirements explained on the [Potentially Hazardous Biological Agents document](#).

7. Identify and assess the risks and hazards involved in this project.

None

8. Describe the safety precautions and procedures that will be used to reduce the risks.

N/A - Our solution is software based

9. Describe the disposal procedures that will be used (when applicable).

N/A - Our solution is software based

10. List the source(s) of safety information.

N/A - Our solution is software based

To be completed and signed by the Team Advisor:

I agree with the risk assessment and safety precautions and procedures described. I certify that I, or another responsible adult, will provide direct supervision when required.

Ananth Sankaranarayanan

Team Advisor Printed Name

Team Advisor Signature

08/20/2021

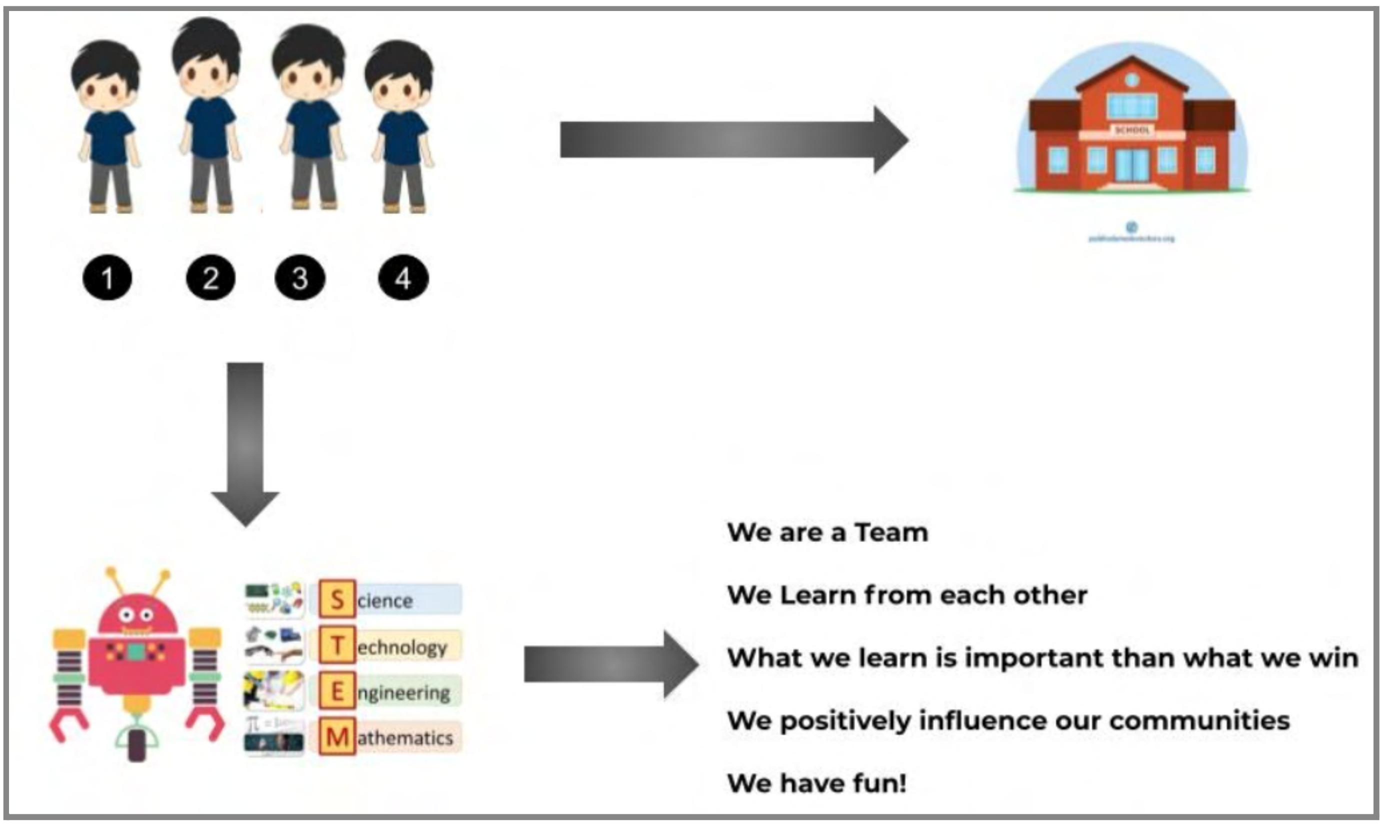
Date

Team Collaboration

How was your team formed? Was your team assigned or did you choose to work with each other?:

Team Formation

We are Team Leander, a group of 9th graders from Leander, Texas, participating in this year's 2021-22 eCYBERMISSION season. Part of our team have participated in previous eCybermission challenges. We go to the same school, Leander High, which makes communication and cooperation a lot easier. We've known each other for a while, participating in competitions like Science Olympiad, Speech and Debate and FLL (First Lego League Robotics). We also all hold similar interests like programming, robotics, research and STEM that make working together so much more enjoyable.



Provide a detailed description of each team member's responsibilities and jobs during your work on the Mission Folder:

Roles & Responsibilities

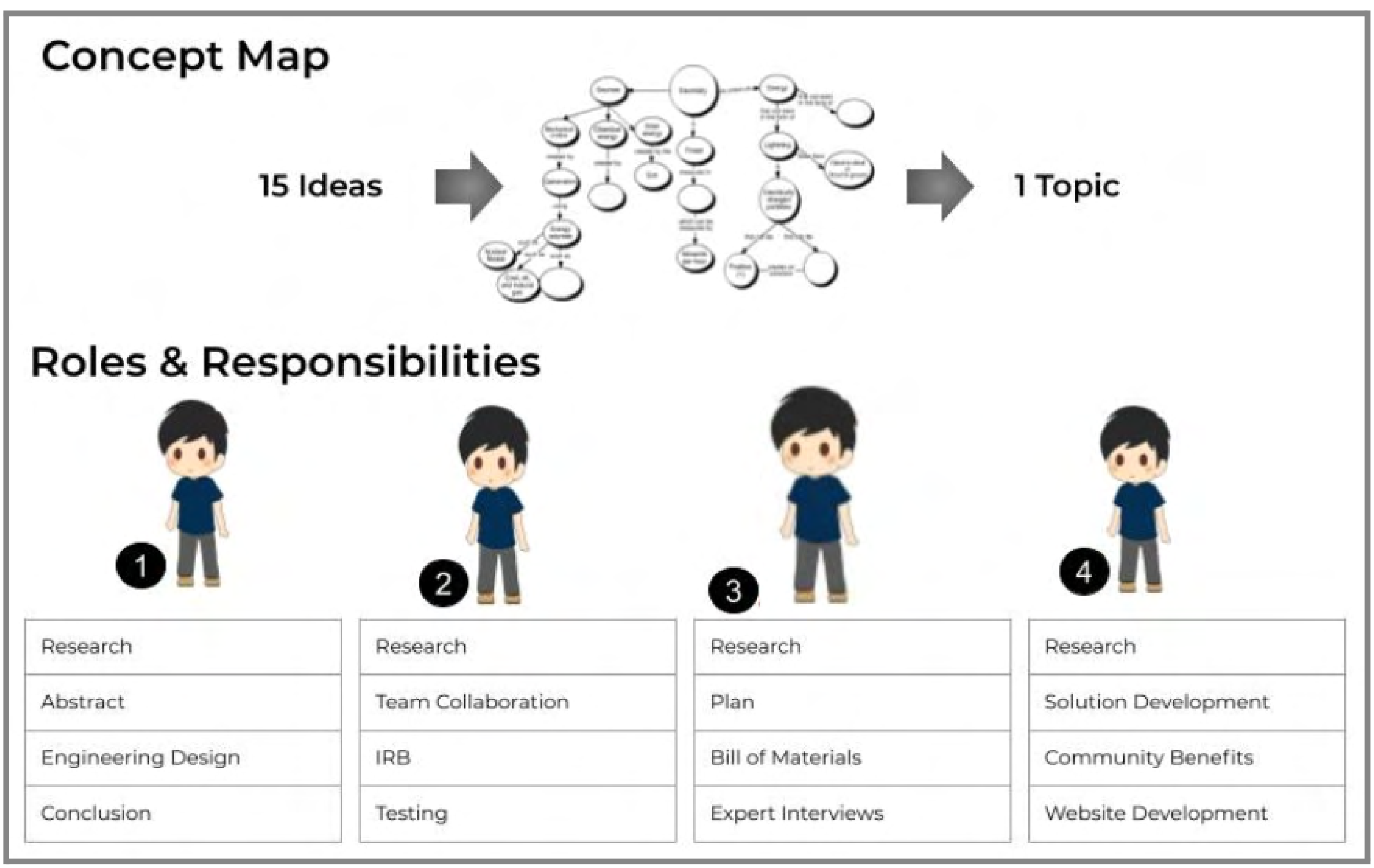
We explored over 40 different topics and arranged them into several different concept maps. We took some of those ideas and narrowed it down to 20 topics, 5 for each team member Each meeting, we would present a new topic and receive feedback from the others with the Rose, Bud, and Thorn analogy. A Rose is an idea that will work well, a Bud is an idea to improve on, and a Thorn is an idea that we didn't think would work. After we decided on the issue we would solve, we broke our mission folder responsibilities into 4 roles based on each of our interest areas:

Team Member # 1: Research, Abstract, Engineering and Design, Conclusion

Team Member # 2: Research, Team Collaboration, IRB Form, Testing

Team Member # 3: Research, Plan, Bill of Materials, References

Team Member # 4: Research, Engineering, and Design, Community Benefits

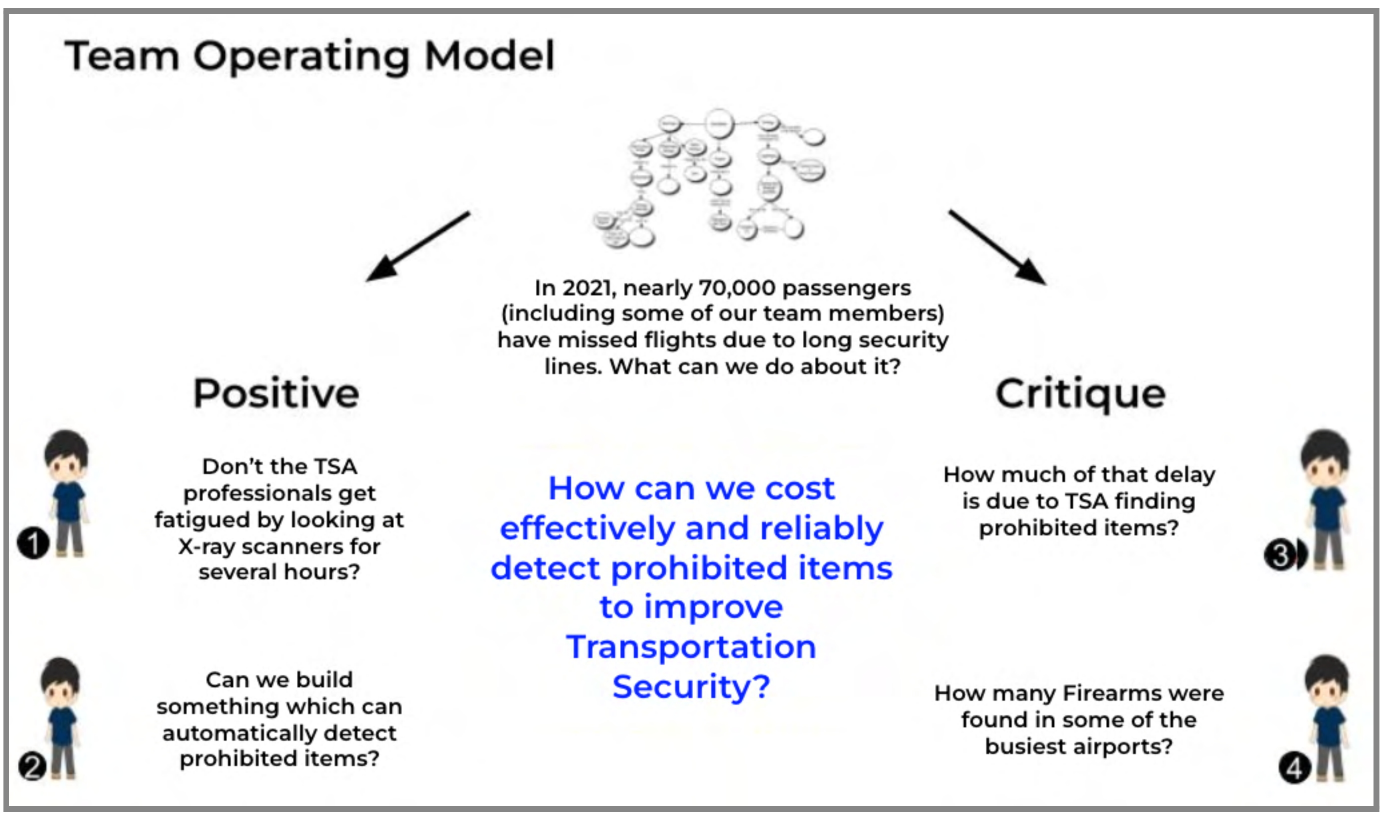


Did your team face any problems working together? If so, how did you solve them? If not, why do you think you were able to work together so well?:

Operating Model

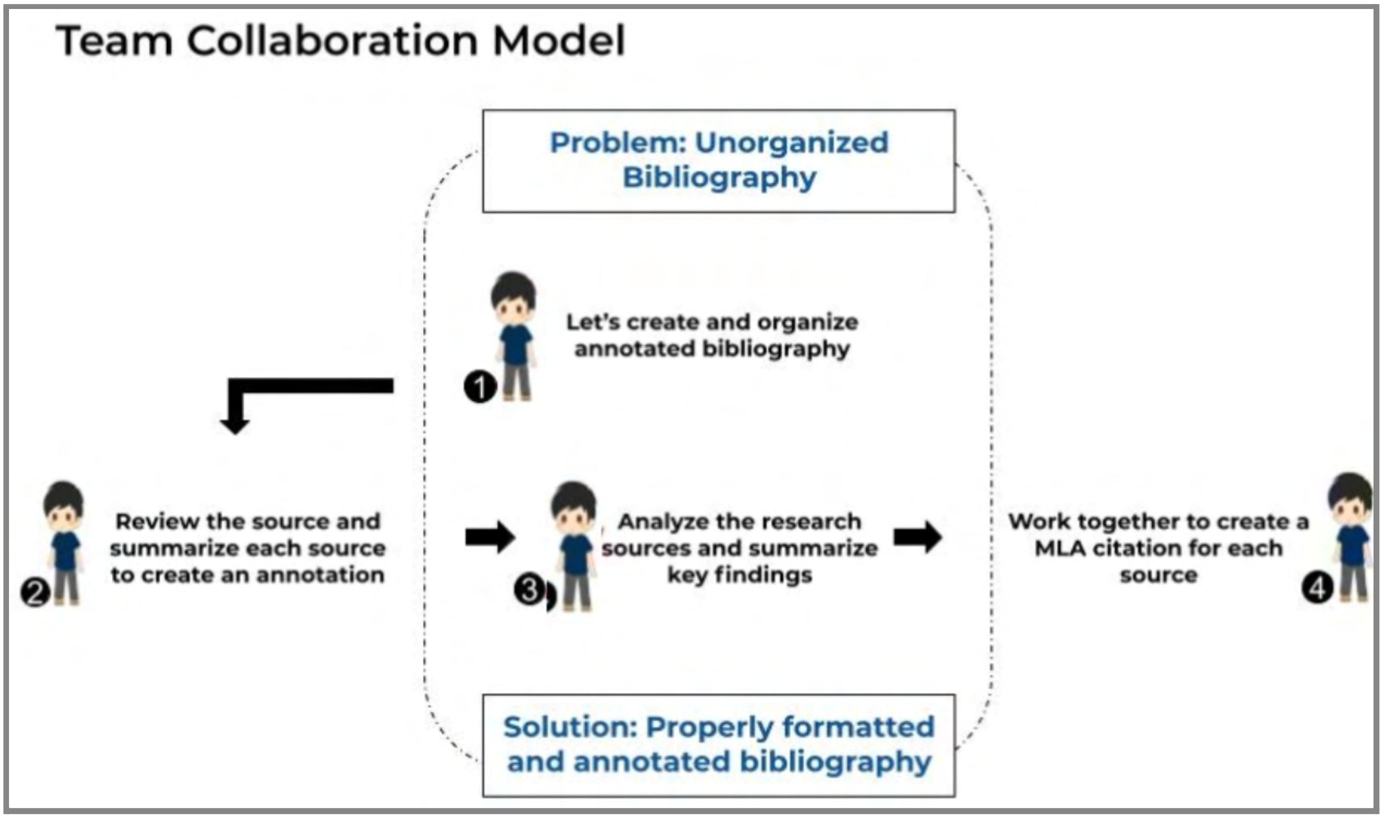
This season due to COVID-19, we were not able to travel outside our homes and schools for most part of the season. Therefore, when we brainstormed various ideas, we intentionally focused on ideas that can be explored and solved completely virtually with expert and team meetings that can be done online via zoom or google Meet. Observing several people who are now able to travel to meet with their families in person, we wanted to explore ideas on how to creatively and most-efficiently address travel security related problems.

When we formed the team, we originally faced challenges in keeping track of our progress and updating each other with our research. We adopted a shared drive to keep track of each other’s work and stay organized throughout the season. By constructively critiquing each other's ideas, we were able to work together as one team to achieve our goals.



We shared our research work with each other between our meetings and its benefits to the community. We would collect as many resources as possible and we would decide if that source was usable. Most of the time we would scrap it for two main reasons. One, because the source was unreliable and two was because it was not something that helped the community.

While each of us had specific focus areas for the mission folder mapped to our areas of interest, we learned from each other based on our research work and challenged each other to perform at our very best. For example, for every source that we used in our research, we had to follow the MLA format for the reference section in the mission folder. Team Member #1 took the responsibility of holding all of us accountable for following the MLA standard, so overall as a team we met our objectives.



What were some possible advantages to working together as a team on this project? How would working as individuals have made this project more difficult?:

Importance of Teamwork

Our coach taught us, “teamwork is the ability to work together toward a common vision”. We observed several advantages of working together as a team. As a team, we were able to learn a lot more new topics than as individuals. We shared what we learned with each other in team meetings, and while each of us had specific roles and responsibilities, we also helped each other when we were not able to make progress. Working as individuals, each of us would have had to do at least three times more work in conducting research, building and testing our prototype, meeting with experts to gather feedback and in completing mission folder requirements.

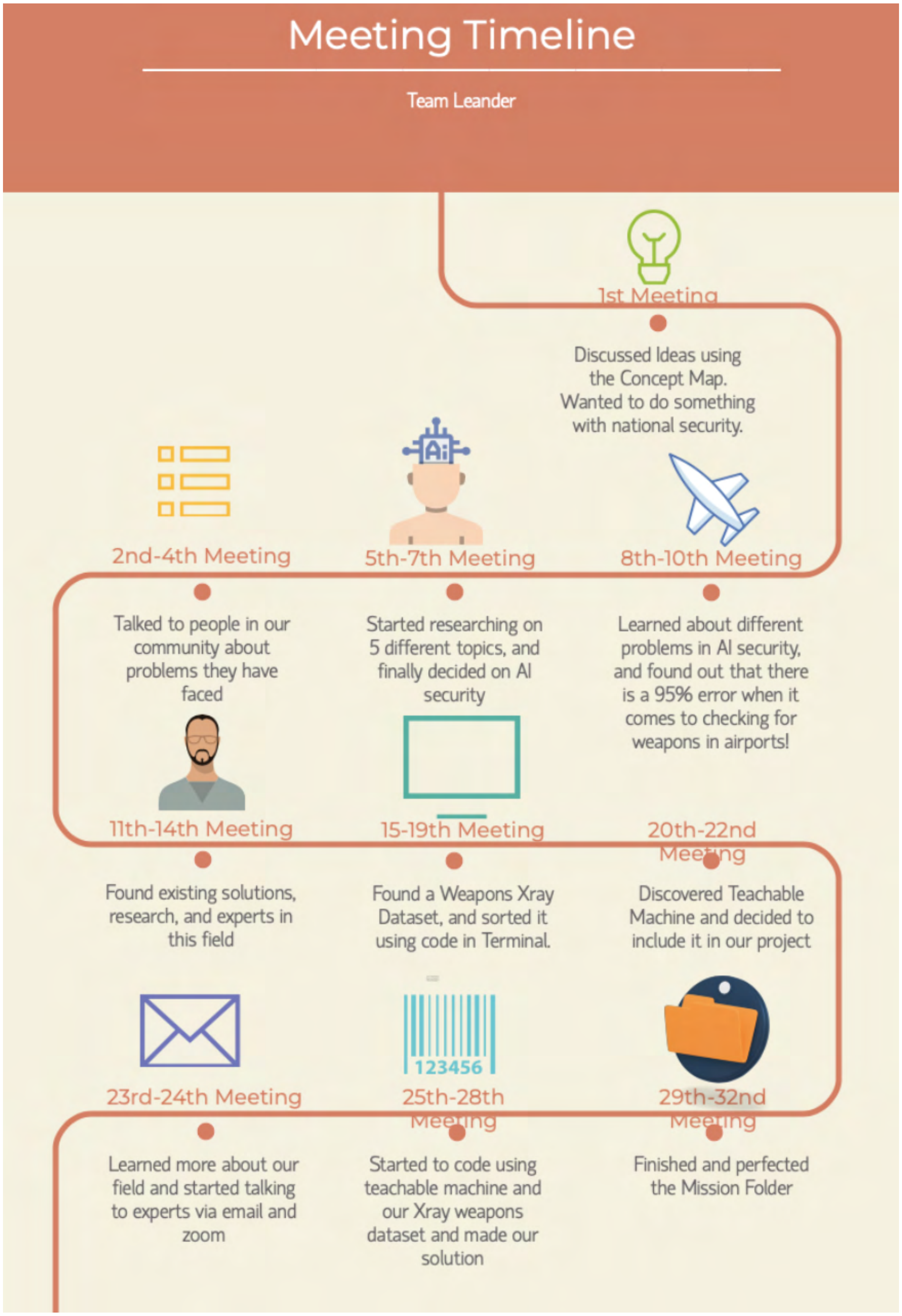
Our teamwork was very effective in many ways. We gave each other a lot of feedback, learned from each other, finished all the work by the due dates we set for ourselves and had fun. For example, our brainstorming process involved the use of a whiteboard to produce concept maps and write ideas that we thought affected our community. We all split the twenty total relevant ideas and did an extensive amount of research on our topics.

At our next meeting, we went over what we learned from the topic and any feedback or related queries we had with the topic. We used the provided resources to develop team-building skills which we used to conduct research, solve arguments and make important decisions. We also worked together to edit and review the others' work which provided a more polished final product.

After working out the details of our problem statement and coming up with a rough idea for our solution, we decided to split up the work. Although our research and designing were handled individually, we worked as a team to assist each other throughout the way, for e.g. taking on creating test criteria and plan for two datasets as team-member1 was stuck in that area as it was not their core expertise.

Plan

Timeline

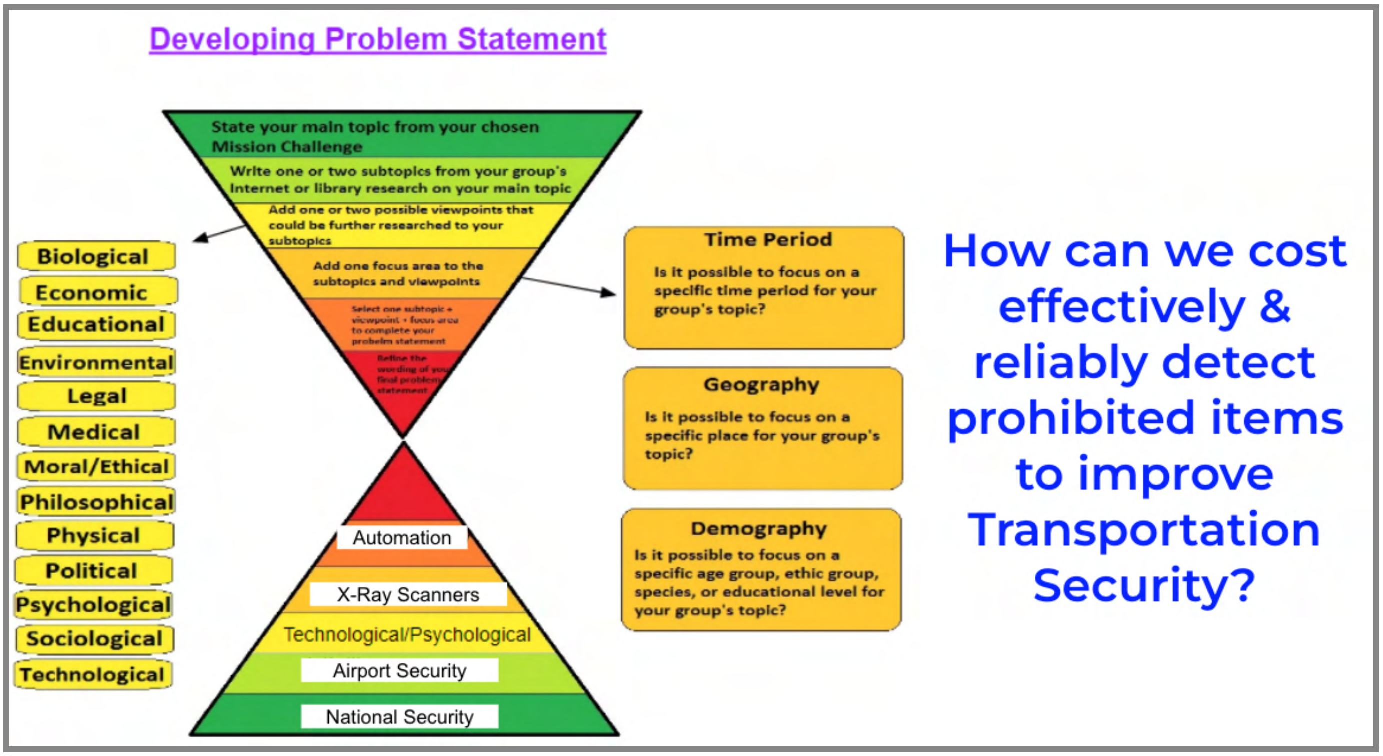


Meeting Logs

Meeting #	Goal	Accomplishment
1(Aug)	Team Kick-Off	Created Concept Map and Generated more than 20 ideas!
2(Aug)	Narrow down our Ideas	Narrowed down to focus on Distance Learning
3(Aug)	Reach out to students and teachers to hear their opinions on distance learning	Created a Google Form Survey, and sent it out on Facebook
4(Aug)	Review Survey	Got back 30 answered surveys
5(Sep)	Research	Decided that Distance learning was a short-term problem
6(Sep)	Research	Discovered community based problems in Texas and nation-wide
7(Sep)	Research and Pick a topic	Researched the different problems based on the previous meeting and chose TSA security
8(Sep)	Research	Researched about Transportation Security
9(Oct)	Research	Researched about existing solutions
10(Oct)	Research	Discovered Computer Vision technology
11(Oct)	Research	Learned about different machine learning techniques
12(Oct)	Research	Learned about different machine learning techniques
13(Nov)	Research	Learned about different ML models
14(Nov)	Research	Learned about Teachable Machines
15(Nov)	Research	Explored more about AI ML
16(Nov)	Research	Explored more about building Apps
17(Dec)	Research	Learned how to program Machine

		Learning Model
18(Dec)	Research	Learned how to program Machine Learning Model
19(Dec)	Research	Learned how to program Machine Learning Model
20(Dec)	Research about different VR controllers	Learned how to program Machine Learning Model
21(Dec)	Research	Learned how to program Machine Learning Model
22(Dec)	Research	Learned how to program Machine Learning Model
23(Jan)	Expert Meeting	Learned more about the experiences of analyzing X-ray images
24(Jan)	Expert Meeting	Learned more about applying deep learning on X-ray images
25(Jan)	Prototype	Started collecting annotated X-ray images from various expert sources
26(Jan)	Prototype	Trained our first machine learning model with sample data
27(Jan)	Prototype	Optimized our machine learning model to improve prediction accuracy
28(Jan)	Prototype	Optimized our machine learning model to improve prediction accuracy
29(Feb)	Mission Folder	Worked on the Mission Folder
1(March)	Mission Folder	Worked on the Mission Folder
2(March)	Mission Folder	Worked on the Mission Folder
3(March)	Mission Folder	Finished the Mission Folder

Concept Map Creation



Expert Discussions

As some of the offices were closed during the global pandemic, many of our expert interviews had to be done via email and phone meetings. Below we summarize the experts we interacted with and information we gathered from those interactions.

Team-Member Airport Visits

- Team members visited IAH, MIA, PHX, AUS airports
- Each airport has one or more security checkpoints
- Each security checkpoint has two to three X-ray scanners for carry-on luggages

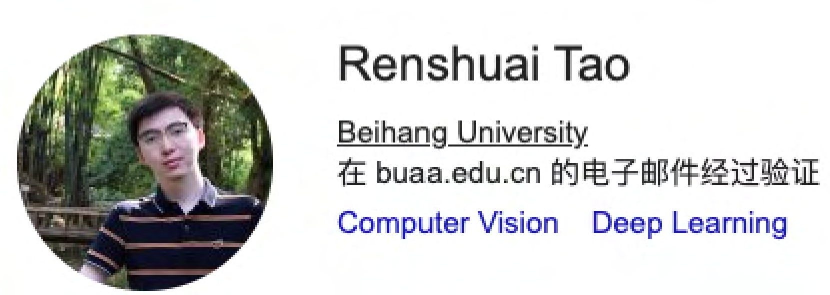
Transportation Security Administration Experts

- TSA invests Billions of US Dollars to improve security checks
- TSA professionals work in shifts to manually analyze X-ray images for objects
- Both carry-on and checked baggage go through X-ray security checks
- X-Ray images are color coded based on their properties (plastic, metal, liquid, electronics etc)
- Manually auditing X-ray image requires expertise
- TSA job applicants are tested to analyze the X-ray images for prohibited objects

AI/ML Deep Learning Expert - Joe Spisak

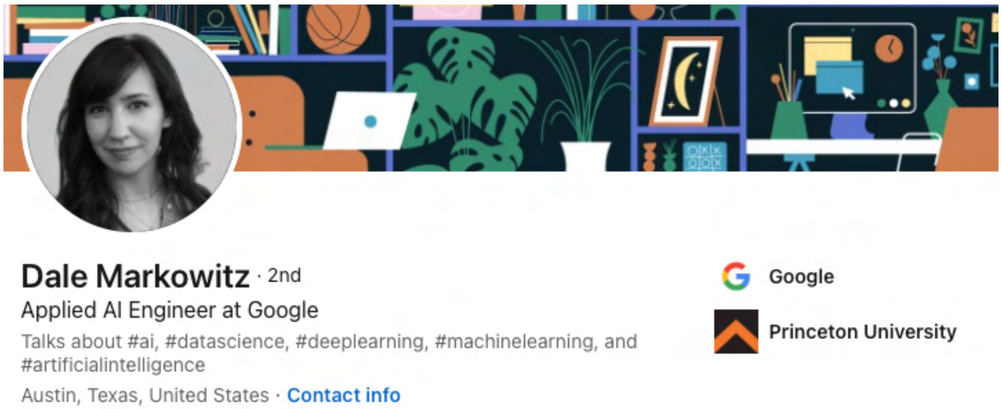
- Machines can be trained to perform better than humans, especially for security checks
- Artificial Intelligence has many techniques, including Deep Learning
- Computers can be programmed to learn and think like humans
- Field of Computer Vision in Machine Learning has many latest advancements
- Machine Learning models can be trained with annotated data for prohibited objects
- Trained model can be deployed on any device to detect and alert

AI/ML Deep Learning Expert - Renshuai Tao



- Annotated Airport security X-Ray images are available under DOAM OPIXray dataset
- Each X-ray image has to be annotated for objects in them
- Existing dataset includes knives, scissors, utility knives, multi-tool knives etc
- Machine Learning models need to be trained for 5 epochs for better prediction accuracy

Dale Markowitz, Google Creative Lab



- Teachable Machines allows one to build machine learning models
- Object detection model can be trained using teachable machines
- Trained model can be downloaded onto personal computing device
- Javascript can be used to call trained model to detect objects in new images

Engineering Design

Problem Statement

What problem in your community will your team attempt to solve using the engineering design process?:

Problem Statement

According to the Transportation Security Administration (TSA), nearly 2 Million passengers, 5.5 Million Carry-on items and 1.4 Million checked items are screened daily. The number of Firearms detected at security checkpoints per million passengers traveled annually has been consistently increasing year over year. In 2015, a study conducted revealed that 95% of security trials failed to detect firearms at dozens of the nation's busiest airports. While the TSA continues to invest Billions of US dollars in improving security checks, according to Times, in 2021, nearly 70,000 passengers (including some of our team members) missed flights due to security lines. We have built a Smart-See-Thru technology using Artificial Intelligence and Machine Learning to detect prohibited items reliably and cost-effectively for less than $250, which can be integrated with existing security scanners at the airports, to augment TSA professionals and accelerate security lines.

How can we cost effectively and reliably detect prohibited items automatically to improve Transportation Security?

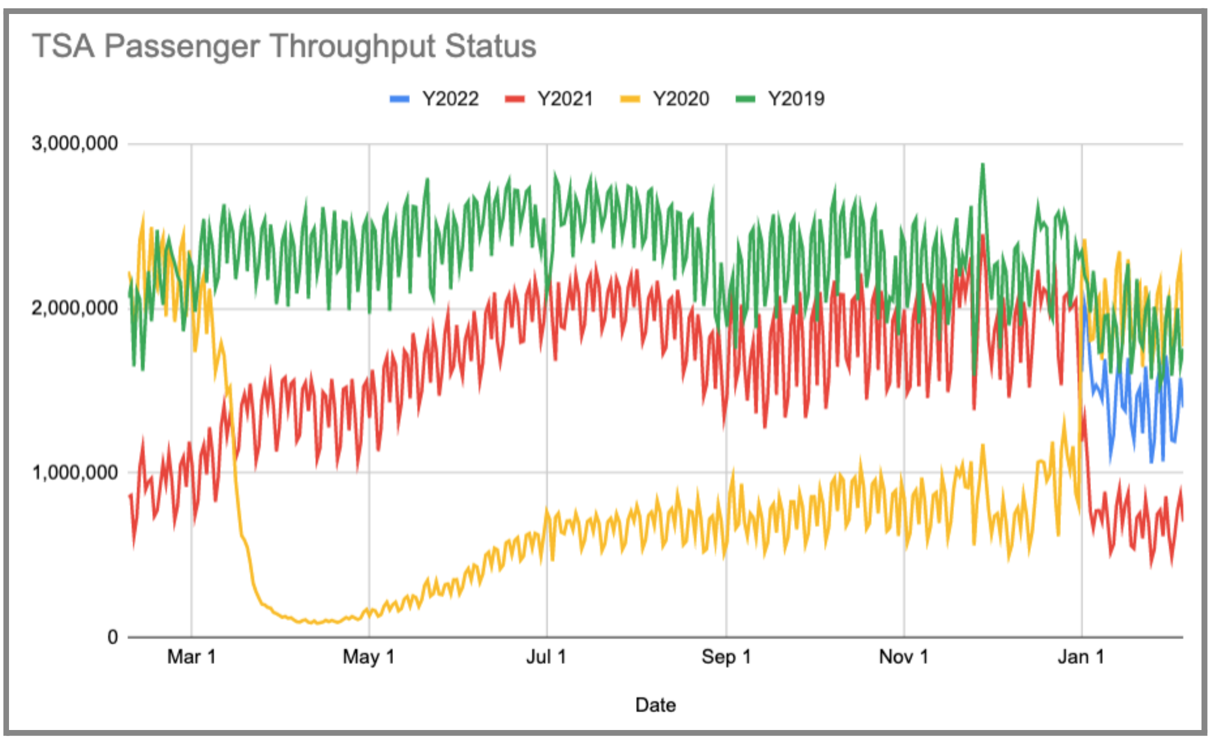
Research

Explain what you learned from your research. What did you find out about your problem that you didn't know before? What kinds of possible solutions already exist? Be sure to put this in your OWN words, do not just copy and paste information. Also, be sure to cite your sources:

According to the Transportation Security Administration (TSA), nearly 2 Million passengers, 5.5 Million Carry-on items and 1.4 Million checked items are screened daily. The number of Firearms detected at security checkpoints per million passengers traveled annually has been consistently increasing year over year. [30]

In 2015, a study conducted revealed that 95% of security trials failed to detect firearms at dozens of the nation's busiest airports. While the TSA continues to invest Billions of US dollars in improving security checks, according to Times, in 2021, nearly 70,000 passengers (including some of our team members) missed flights due to security lines [7].

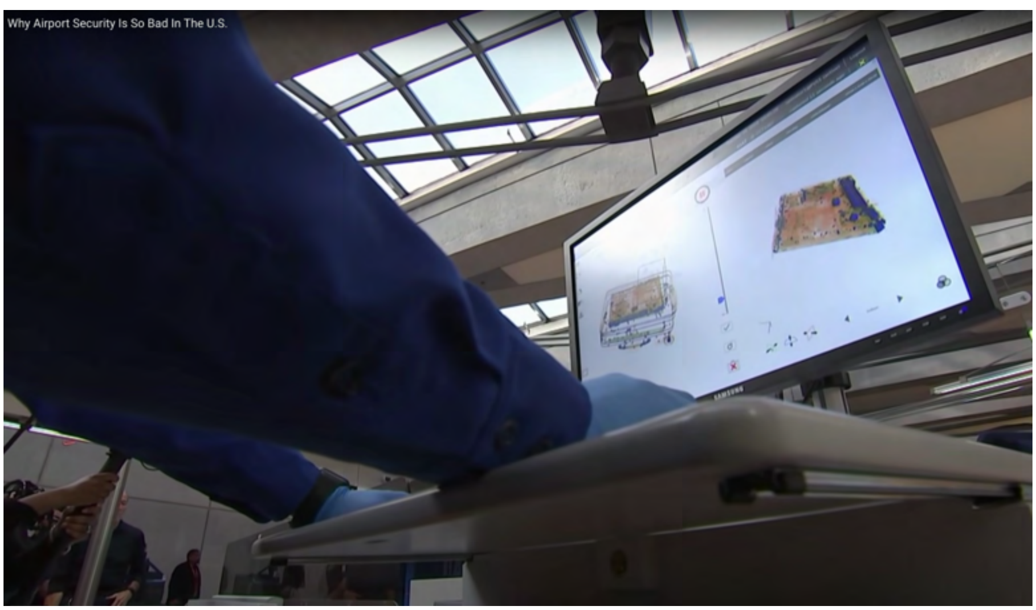
To further complicate this, overall change in Air passengers pre-pandemic has been growing faster while at the same time the investments in TSA agents has been going down as shown in the chart above [3]. When the global pandemic hit us in March 2020, the daily average of airport passengers dropped from over 2 million to less than half a million. TSA agents to Passenger ratio changed substantially due this, and there's evidence that the TSA agents were able to identify prohibited items more accurately than before [7].



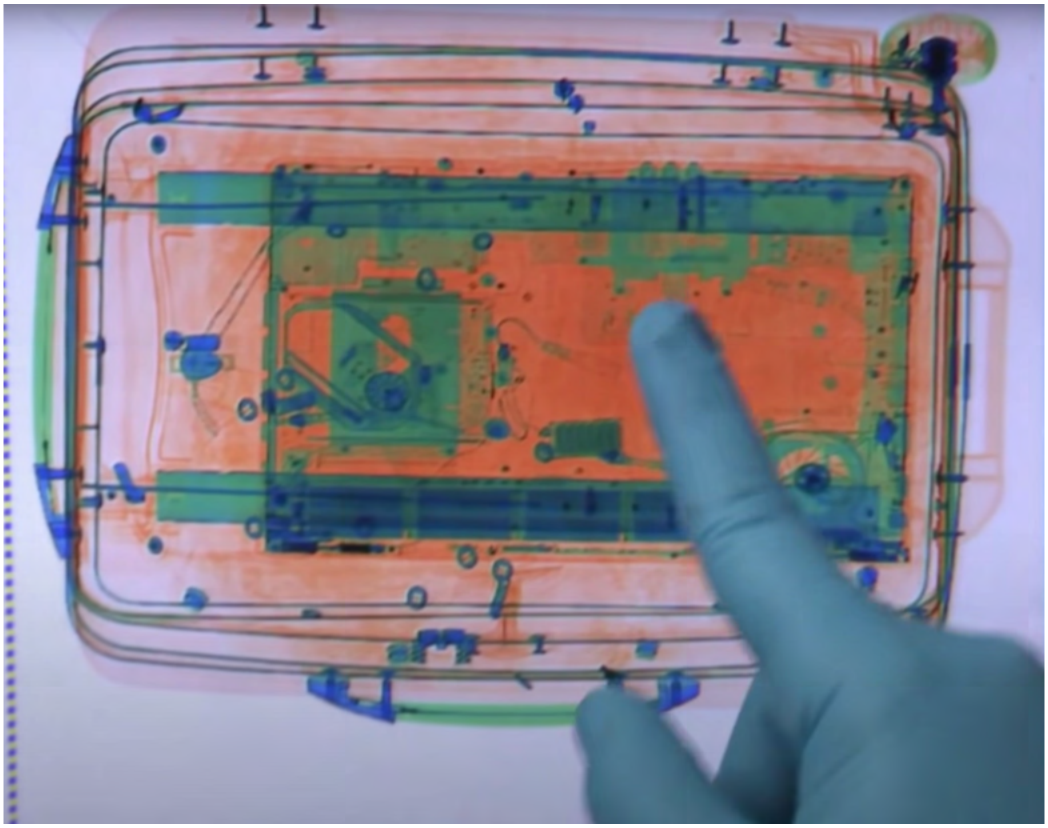
Existing Solutions

Existing solutions require TSA professionals to manually audit each X-Ray image of luggage to detect any prohibited item, such as guns, scissors, knives, hammer etc. This process takes time and during the busy travel season, human fatigue may cause TSA professionals to miss a few prohibited objects [9].

Trained TSA agents audit each X-ray image manually to detect prohibited items. X-Ray images are generally color coded [9].



Current airport X-ray scanners produce images in orange, blue and green. Each color corresponds to a material category—orange means organic material (food, paper, marijuana), green is for medium-dense non-organic materials like plastic soda bottles, and blue means metals or hard plastics. Each of these objects are carefully evaluated manually for any violation, and manually checked by opening the bags for additional scrutiny [9].



After this research, we asked ourselves,

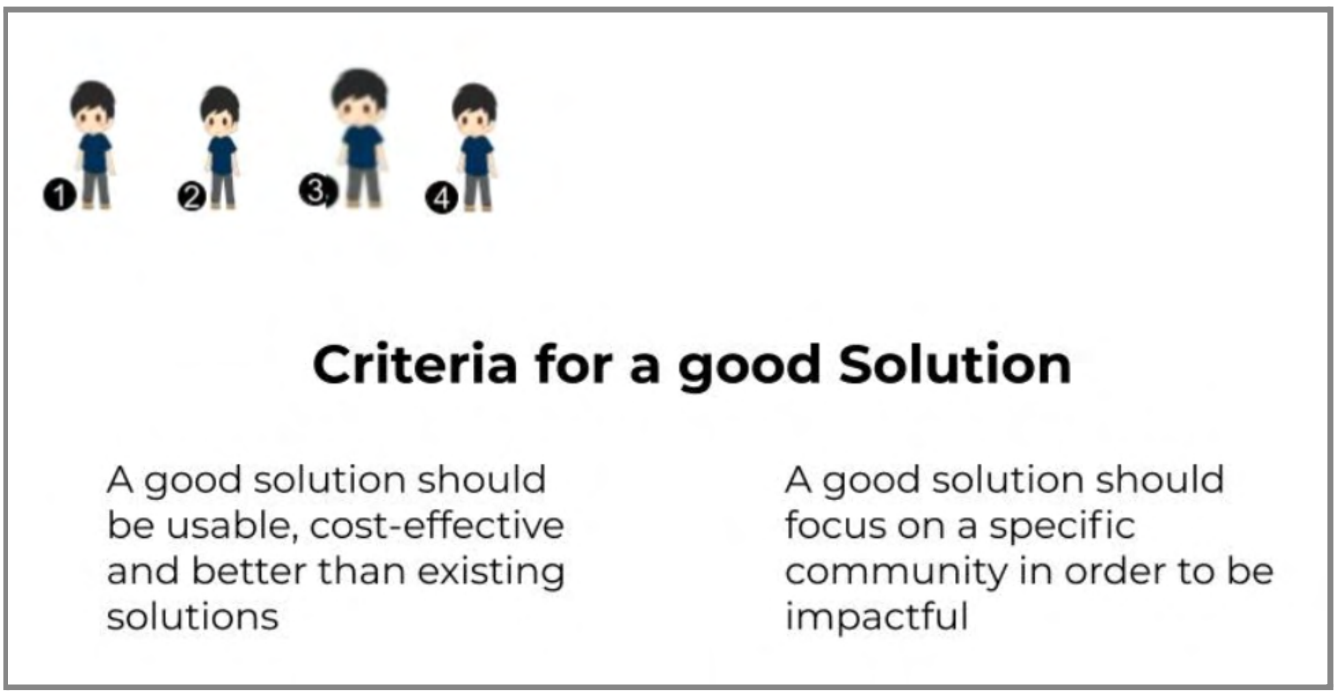
How can we cost effectively and reliably detect prohibited items automatically to improve Transportation Security?

Design Development

What MUST be a part of your solution? This is called the criteria. What does your solution need to have in order to solve the problem? (NOTE: Don't discuss a specific solution here, just the characteristics of a good solution):

Criteria Statement

- Our solution should focus on solving problem in a specific community
- Our solution should be usable by all age groups of people
- Our solution should offer equal or better experience than existing solutions
- Our solution should be cheaper than existing solutions
- Our solution should not introduce any side-effects to people who are using it
- Our solution should not require recurring maintenance costs or service fees

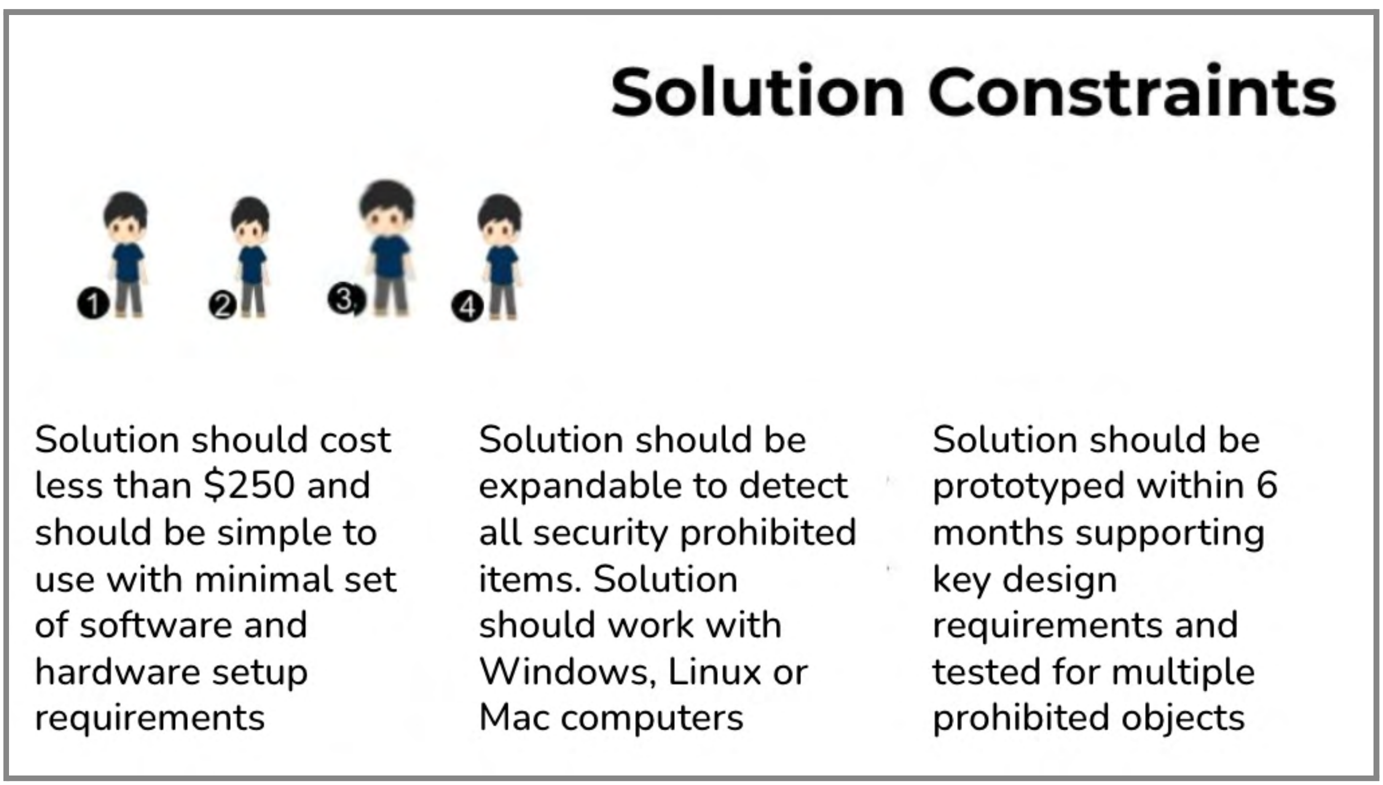


Constraints

What limits are there on your solution? These are called constraints. Does it need to be a certain size? A certain weight? Is the cost a factor? Write down all of the limits on your solution:

There were a few constraints placed on our solution that restricted us:

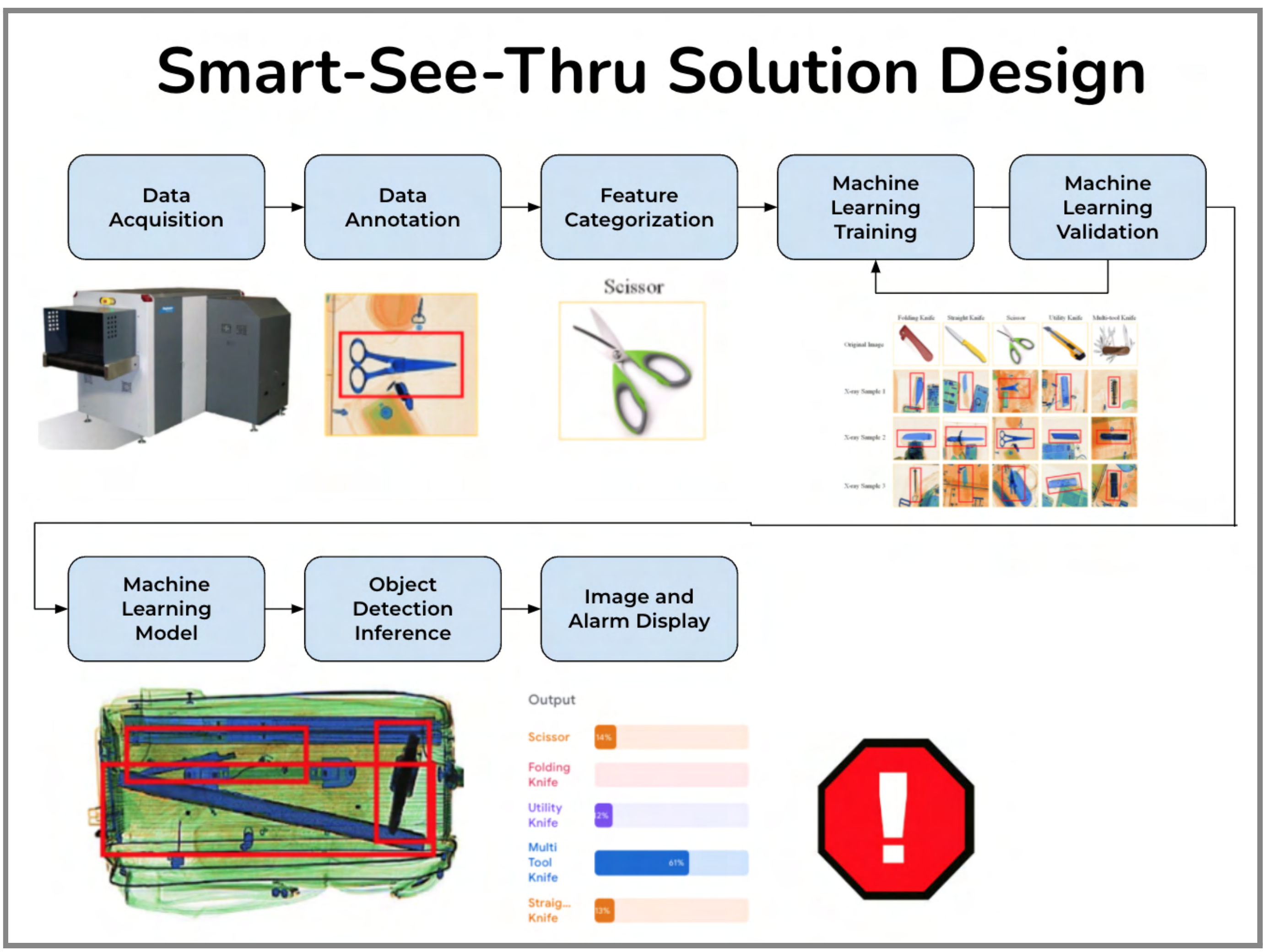
- We had to keep our solution under $250. This restricted us because we had to make our solution as simple as possible while sufficiently solving the problem. We managed to do this by trying to find the cheapest and most-effective parts
- We also only had 8 months to fully complete our project, which heavily limited us because we weren’t able to fully test all the possible security prohibited items
- Due to the COVID-19 global pandemic, our state was in lockdown mode for several months during this season. Therefore, we set an additional constraint for our solution to be remotely developed and tested in various locations without us having to get together as a team
- Our solution also had to be usable and efficient. Another major constraint was that the solution has to be easy to set up with minimal instructions to follow
- Our solution has to be based on open-source software and can be integrated with existing airport security software systems



Based on your criteria and constraints, what is your proposed solution to the problem you chose? Explain what it will look like and how it will work. If you can, include a detailed, labeled drawing:

Our Solution

Our solution's main purpose was to train computers to think and operate like humans using existing intelligence from the experts. The field of Artificial Intelligence offers many techniques including machine and deep learning that support this process. We collected airport security images of prohibited objects and built a machine learning model which can be exported to any device (computer, phone or tablet) and used to scan and detect prohibited objects in the new image automatically. We took on an additional goal to also expand our model for additional object categories. We graded each object detected by the computer against expert reviews to verify the accuracy. Based on our research and expert interviews no other similar solution is available on the market, especially at below $250 price point.



Smart-See-Thru Solution Steps

Step-1: Data Acquisition
We collected thousands of security scanned X-ray images from various sources, including Google, Kaggle dataset and several research papers.

Step-2: Data Annotation
We worked with the experts to identify prohibited objects, such as scissors, knives, guns, multi-tool knives etc, and drew bounding boxes to tag each object within the image and recorded the X and Y coordinates of the bounding box.

Step-3: Feature Categorization
We categorized each identified prohibited object within the image by type. We had a total of 6 prohibited objects: Gun, Scissor, Utility Knife, Multi-Tool knife, Straight Knife and Folding Knife.

Step-4: Machine Learning Training and Validation
We used https://teachablemachine.withgoogle.com/ to develop and test our machine learning model for prohibited object detection.

Step-5: Model Export
We exported the model from teachable machines to a Javascript program and ran that program to detect any prohibited objects on new images, which were not used to train the machine learning model, and verified the accuracy to be at acceptable levels.

Step-6: Object Detection and Alerting
We built and ran an application using the trained Smart-See-Thru model, and provided a new X-ray image as input to our application. We were able to detect the object with acceptable level of accuracy and also trigger the alarm for the TSA professional to pay attention to.

Step-1: Data Acquisition

We collected the X-Ray image data of prohibited objects from DOAM, Kaggle and Through Google image searches and organized them by categories.

Image Category	**Number of Images (Training)**
Folding Knife	1589
Multi Tool Knife	1612
Utility Knife	1635
Straight Knife	809
Scissor	1494
Gun	102

```
cd xray/OPIXray/train/train_annotation

grep Folding_Knife * > Folding_Knife.txt
grep Scissor * > Scissor.txt
grep Utility_Knife * > Utility_Knife.txt
grep Multi * > Multi-Tool_Knife.txt
grep Straight_Knife * > Straight_Knife.txt

cat Utility_Knife.txt| cut -d ":" -f2 | cut -d " " -f1 > 1-UK
cat Straight_Knife.txt| cut -d ":" -f2 | cut -d " " -f1 > 1-SK
cat Scissor.txt| cut -d ":" -f2 | cut -d " " -f1 > 1-SC
cat Folding_Knife.txt| cut -d ":" -f2 | cut -d " " -f1 > 1-FK
cat Multi-tool_Knife.txt| cut -d ":" -f2 | cut -d " " -f1 > 1-MTK

mkdir SCS SK MTK UK FK


for file in `cat 1-SC`; do cp ../test_image/$file ./SCS/; done
for file in `cat 1-SK`; do cp ../test_image/$file ./SK/; done
for file in `cat 1-MTK`; do cp ../test_image/$file ./MTK/; done
for file in `cat 1-UK`; do cp ../test_image/$file ./UK/; done
for file in `cat 1-FK`; do cp ../test_image/$file ./FK/; done

To Separate Files into different amounts for testing


COUNT=0;for file in `cat 1-MTK`; do cp MTK/$file ./MTK_test/; COUNT=$(( COUNT+1
));echo $COUNT; if [ $COUNT -ge 5 ]; then break; fi;done
```

```
COUNT=0;for file in `cat 1-MTK`; do cp MTK/$file ./MTK_test/; COUNT=$(( COUNT+1 ));echo $COUNT; if [ $COUNT -ge 5 ]; then break; fi;done
```

Create list of directories

```
for d in "FK" "UK" "MTK" "SK" "SCS"; do for n in 10 100 250 500 1000; do mkdir $d$n; done; done
```

Remove Folders

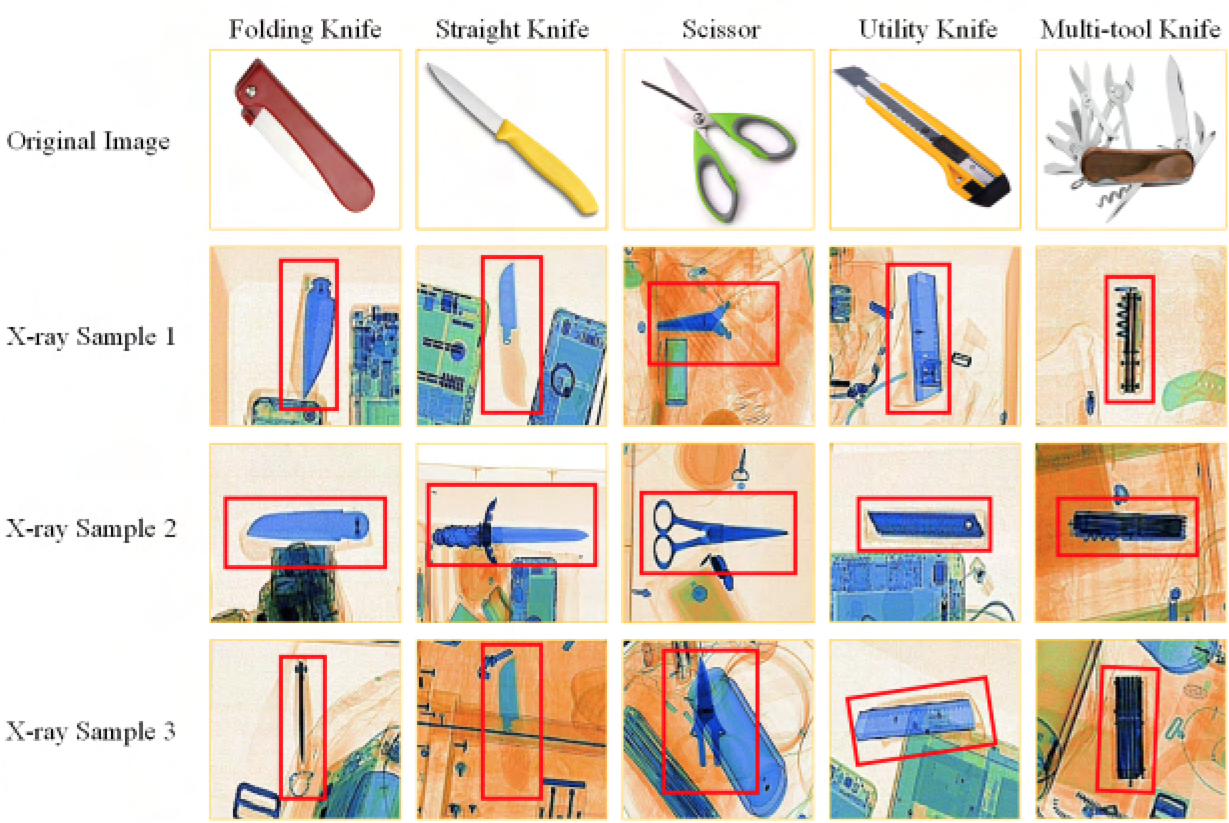
```
for d in "FK" "UK" "MTK" "SK" "SCS"; do for n in 10 100 250 500 1000; do echo $d$n; rmdir $d$n; done; done
```

Full

```
for d in "FK" "UK" "MTK" "SK" "SCS"; do for n in 10 100 250 500 1000; do mkdir $d$n;COUNT=0;for file in `cat 1-$d`; do cp $d/$file ./$d$n/; COUNT=$(( COUNT+1 ));echo -n $COUNT;echo "copying $d$file to $d$n"; if [ $COUNT -ge $n ]; then break; fi;done; done; done
```

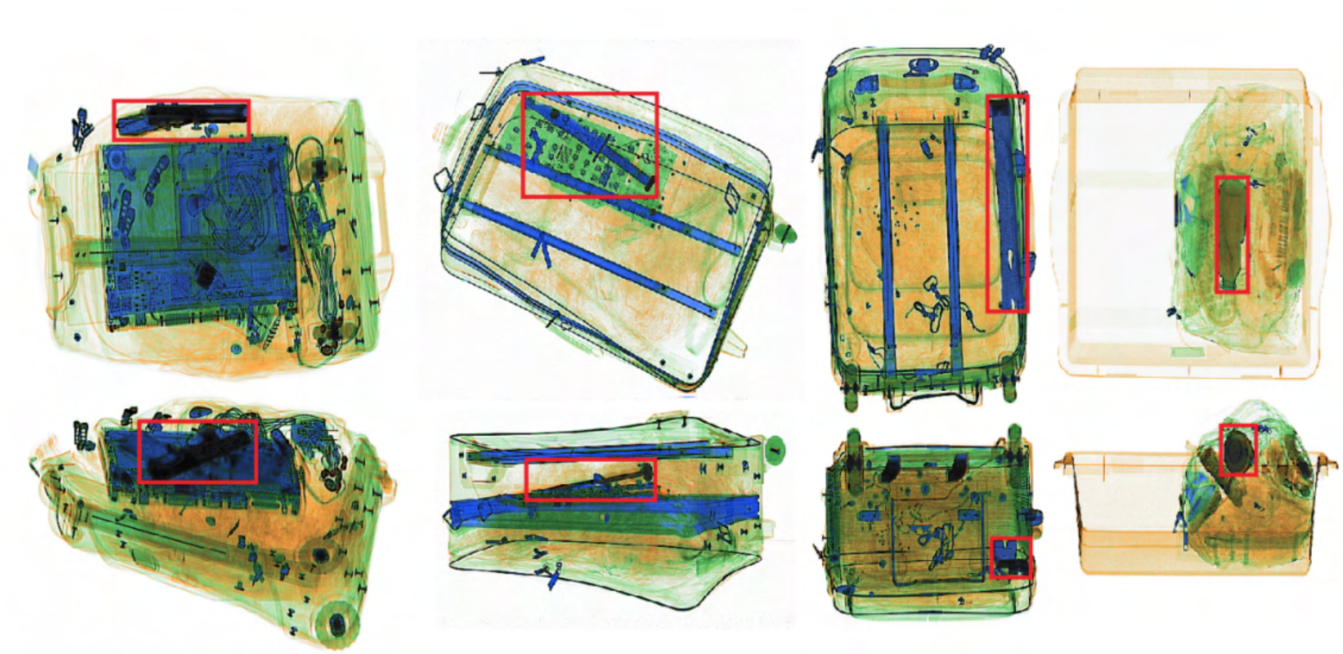
Step-2: Data Annotation

We worked with the experts to identify prohibited objects, such as scissors, knives, guns, multi-tool knives etc, and drew bounding boxes to tag each object within the image and recorded the X and Y coordinates of the bounding box.



Step-3: Feature Categorization

We categorized each identified prohibited object within the image by type. We had a total of 6 prohibited objects: Gun, Scissor, Utility Knife, Multi-Tool knife, Straight Knife and Folding Knife. Each prohibited object's coordinates within each image is recorded. Please see the examples below:



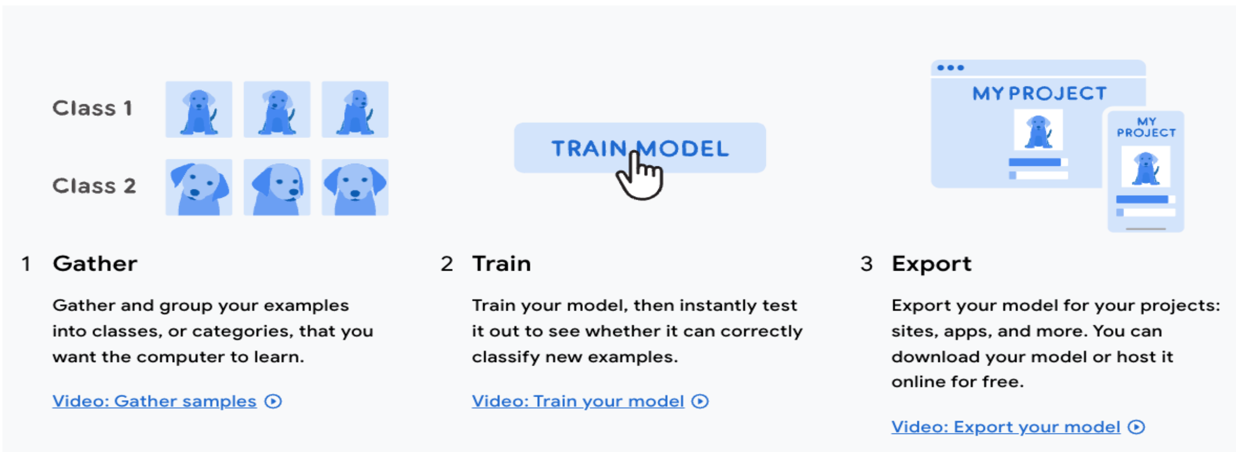
Examples

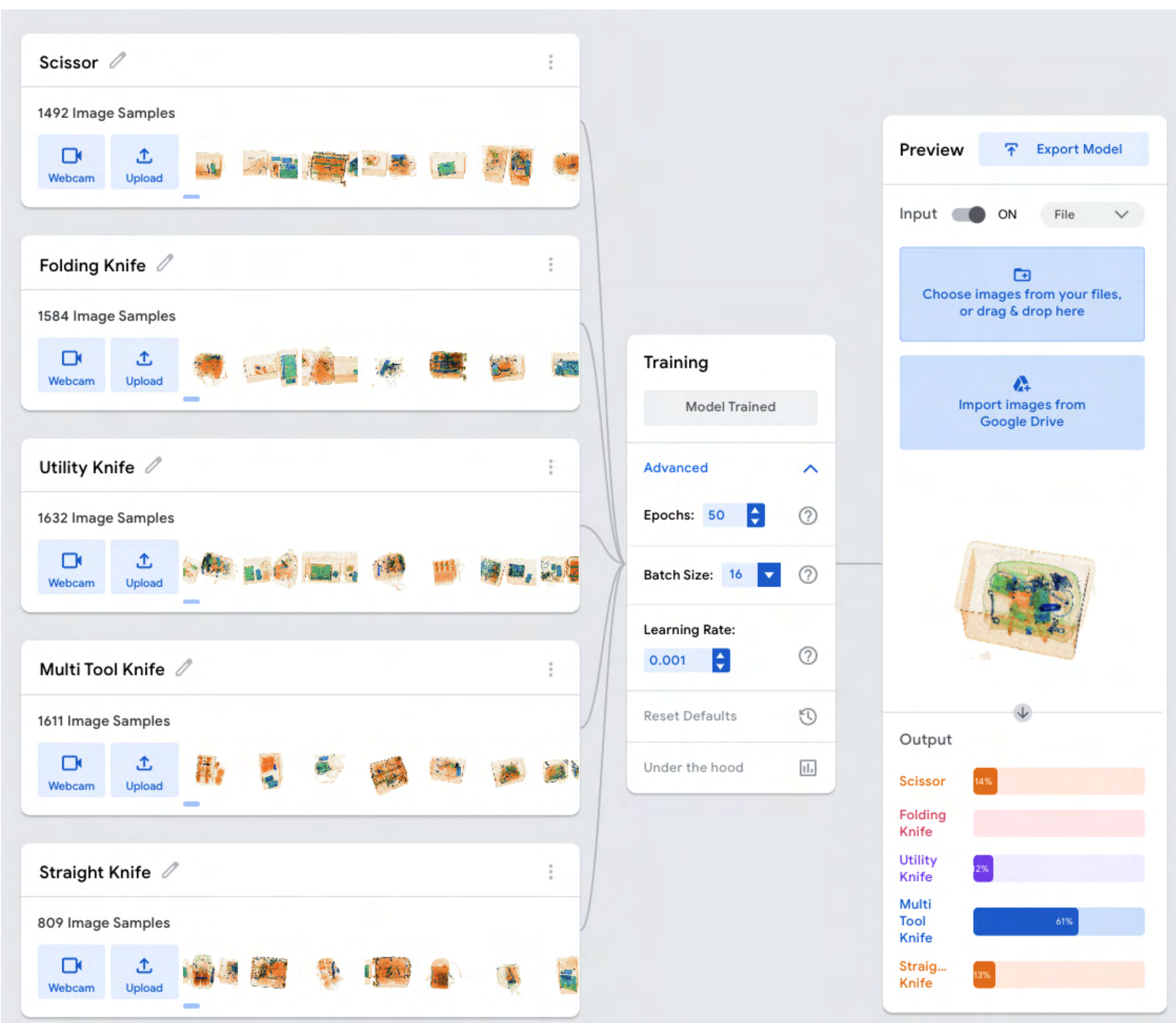
<image name> <image category> <top-left-x> <top-left-y> <bottom-right-x> <bottom-right-y>

```
026822.jpg Folding_Knife 606 331 696 429
026823.jpg Utility_Knife 753 389 809 559
026824.jpg Multi-tool_Knife 73 449 143 598
026825.jpg Folding_Knife 234 358 385 435
026830.jpg Folding_Knife 663 468 717 558
026834.jpg Multi-tool_Knife 1050 556 1131 690
026835.jpg Utility_Knife 540 314 604 493
026838.jpg Folding_Knife 701 417 789 554
026839.jpg Multi-tool_Knife 924 412 958 522
026840.jpg Multi-tool_Knife 720 267 859 313
026842.jpg Folding_Knife 829 486 947 594
026844.jpg Utility_Knife 609 333 669 506
026849.jpg Multi-tool_Knife 602 455 743 531
026853.jpg Utility_Knife 187 464 249 565
026854.jpg Folding_Knife 741 395 810 449
026856.jpg Utility_Knife 472 462 578 568
026861.jpg Utility_Knife 579 413 649 595
026867.jpg Folding_Knife 629 451 689 605
```

Step-4: Machine Learning Training & Validation

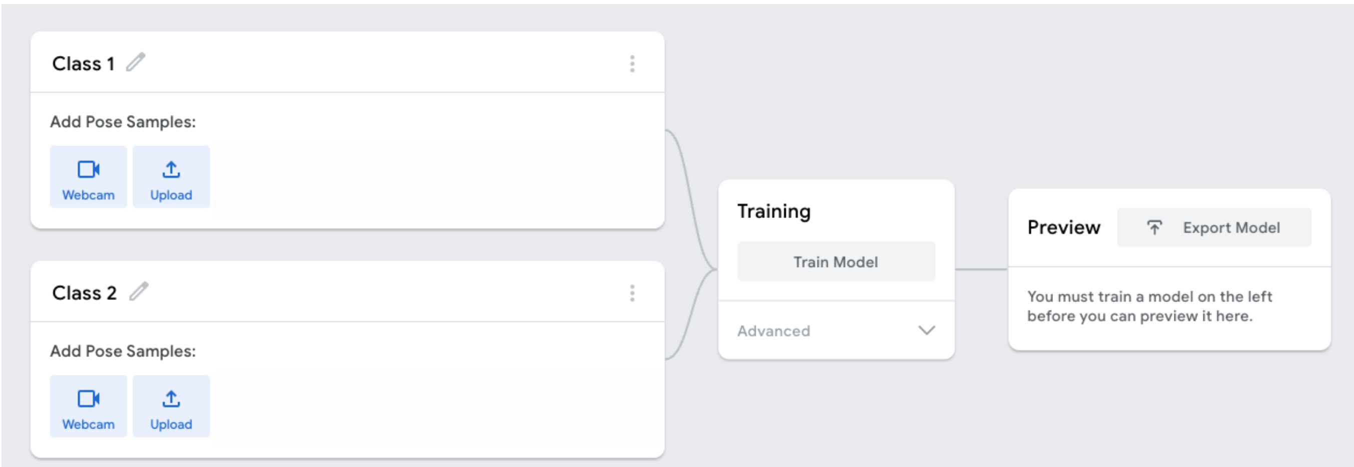
We used https://teachablemachine.withgoogle.com/ to develop and test our machine learning model for prohibited object detection.





Step-5: Model Export

We exported the model from teachable machines to a Javascript program and ran that program to detect any prohibited objects on new images, which were not used to train the machine learning model, and verified the accuracy to be at acceptable levels.



Step-6: Object Detection and Alerting

We built and ran an application using the trained Smart-See-Thru model, and provided a new X-ray image as input to our application. We were able to detect the object with acceptable level of accuracy and also trigger the alarm for the TSA professional to pay attention to.

```
<div>Teachable Machine Pose Model</div>
<button type="button" onclick="init()">Start</button>
<div><canvas id="canvas"></canvas></div>
<div id="label-container"></div>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@1.3.1/dist/tf.min.js"></script>
<script
src="https://cdn.jsdelivr.net/npm/@teachablemachine/pose@0.8/dist/teachablemachine-pose.min.js
"></script>
<script type="text/javascript">
    // More API functions here:
                                                                                            //
https://github.com/googlecreativelab/teachablemachine-community/tree/master/libraries/pose

    // the link to your model provided by Teachable Machine export panel
    const URL = "https://teachablemachine.withgoogle.com/models/C5aws4tys/";
    let model, webcam, ctx, labelContainer, maxPredictions;

    async function init() {
        const modelURL = URL + "model.json";
        const metadataURL = URL + "metadata.json";

        // load the model and metadata
        // Refer to tmImage.loadFromFiles() in the API to support files from a file picker
        // Note: the pose library adds a tmPose object to your window (window.tmPose)
```

```
        model = await tmPose.load(modelURL, metadataURL);
        maxPredictions = model.getTotalClasses();

        // Convenience function to setup a webcam
        const size = 200;
        const flip = true; // whether to flip the webcam
        webcam = new tmPose.Webcam(size, size, flip); // width, height, flip
        await webcam.setup(); // request access to the webcam
        await webcam.play();
        window.requestAnimationFrame(loop);

        // append/get elements to the DOM
        const canvas = document.getElementById("canvas");
        canvas.width = size; canvas.height = size;
        ctx = canvas.getContext("2d");
        labelContainer = document.getElementById("label-container");
        for (let i = 0; i < maxPredictions; i++) { // and class labels
            labelContainer.appendChild(document.createElement("div"));
        }
    }

    async function loop(timestamp) {
        webcam.update(); // update the webcam frame
        await predict();
        window.requestAnimationFrame(loop);
    }
    async function predict() {
        // Prediction #1: run input through posenet
        // estimatePose can take in an image, video or canvas html element
        const { pose, posenetOutput } = await model.estimatePose(webcam.canvas);
        // Prediction 2: run input through teachable machine classification model
        const prediction = await model.predict(posenetOutput);

        for (let i = 0; i < maxPredictions; i++) {
            const classPrediction =
                prediction[i].className + ": " + prediction[i].probability.toFixed(2);
            labelContainer.childNodes[i].innerHTML = classPrediction;
        }

        // finally draw the poses
        drawPose(pose);
    }
    function drawPose(pose) {
        if (webcam.canvas) {
            ctx.drawImage(webcam.canvas, 0, 0);
            // draw the keypoints and skeleton
            if (pose) {
                const minPartConfidence = 0.5;
                tmPose.drawKeypoints(pose.keypoints, minPartConfidence, ctx);
                tmPose.drawSkeleton(pose.keypoints, minPartConfidence, ctx);
            }
        }
    }
</script>
```

High-Level Test plan

Number of prohibited objects = 6

Average number of X-ray images per category = ~1000

- Build 5 machine learning models (t.10, t.100, t.250, t.500, t.1000) by varying number of training images per each category
- Export the machine learning model for each category (model.10, model.100, model.250, model.500, model.1000)
- Identify 5 images from the validation set for each prohibited object category (image-1, image-2, image-3, image-4, image-5)
- Use those 5 images to measure the accuracy of each of the 5 models, for the 5 prohibited object categories to measure the accuracy
- Prove/Disprove the hypothesis that the object detection accuracy of prohibited objects improves based on the number of images used for machine learning training
- In other words, the prohibited object detection accuracy of model.1000 should be better than model.100 for the same image category (ex: Scissor)

Test-Plan-Details

Test #	Gun	Straight Knife	Utility Knife	Multi Tool Knife	Scissor	Folding Knife
t.10	10	10	10	10	10	10
t.100	100	100	100	100	100	100
t.250	250	250	250	250	250	250
t.500	500	500	500	500	500	500
t.1000	1000	1000	1000	1000	1000	1000

Validation Plan

Model Name	Gun	Straight Knife	Utility Knife	Multi Tool Knife	Scissor	Folding Knife
model.10	image-1	image-1	image-1	image-1	image-1	image-1
model.100	image-2	image-2	image-2	image-2	image-2	image-2
model.250	image-3	image-3	image-3	image-3	image-3	image-3

model.500	image-4	image-4	image-4	image-4	image-4	image-4
model.1000	image-5	image-5	image-5	image-5	image-5	image-5

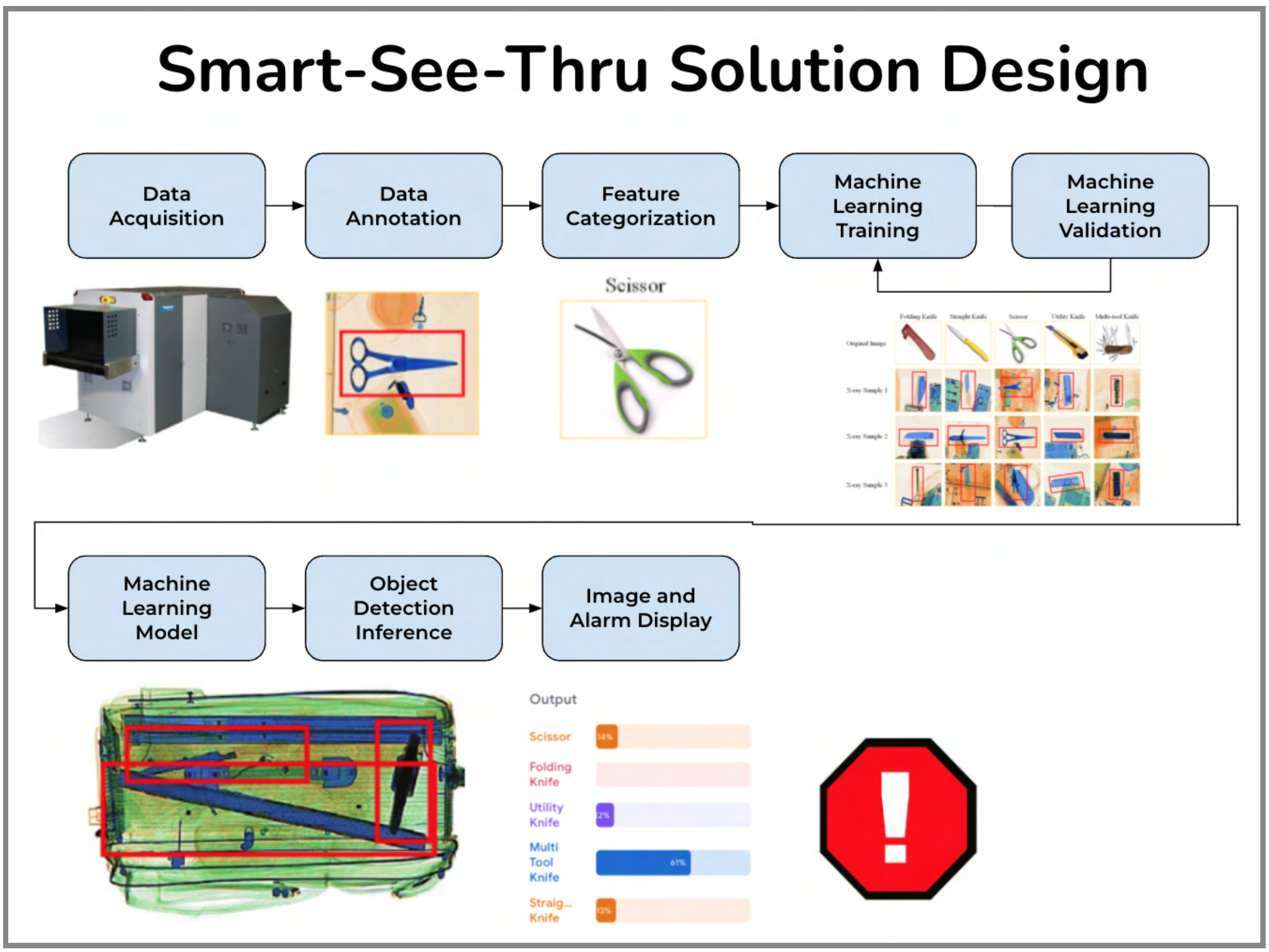
Model Accuracy Testing

Model Name	Gun	Straight Knife	Utility Knife	Multi Tool Knife	Scissor	Folding Knife
model.10	accuracy-1	accuracy-1	accuracy-1	accuracy-1	accuracy-1	accuracy-1
model.100	accuracy-2	accuracy-2	accuracy-2	accuracy-2	accuracy-2	accuracy-2
model.250	accuracy-3	accuracy-3	accuracy-3	accuracy-3	accuracy-3	accuracy-3
model.500	accuracy-4	accuracy-4	accuracy-4	accuracy-4	accuracy-4	accuracy-4
model.1000	accuracy-5	accuracy-5	accuracy-5	accuracy-5	accuracy-5	accuracy-5

Prototype

To demonstrate the benefits of Smart-See-Thru solution, we have built a prototype with the components listed under Bill of materials.

1) We collected nearly 8000 sample security X-ray images from various sources on the internet
2) We categorized those 8000 images by prohibited object type
3) We used Teachable Machines to train our machine learning model with those images
4) We exported the trained model using the scripts provided by Teachable Machines
5) We copied the script to our Google Drive
6) We used the drv.tw [Drive to Web] API to make the HTML/Javascript file executable
7) We positioned an external web camera inside a box for better lighting conditions
8) We printed a few security images
9) We inserted images one at a time into the box
10) We launched the Smart-See-Thru executable via Chrome browser
11) With the model.max which was trained with maximum number of images, we prove that we can detect the security prohibited objects with the highest accuracy, close to human expert level



We decided to use the following two datasets to train our models. We varied the number of epochs (which determines the total number images in the training) for each test to get the object detection accuracy as close as to 1.0

Dataset: XraySet

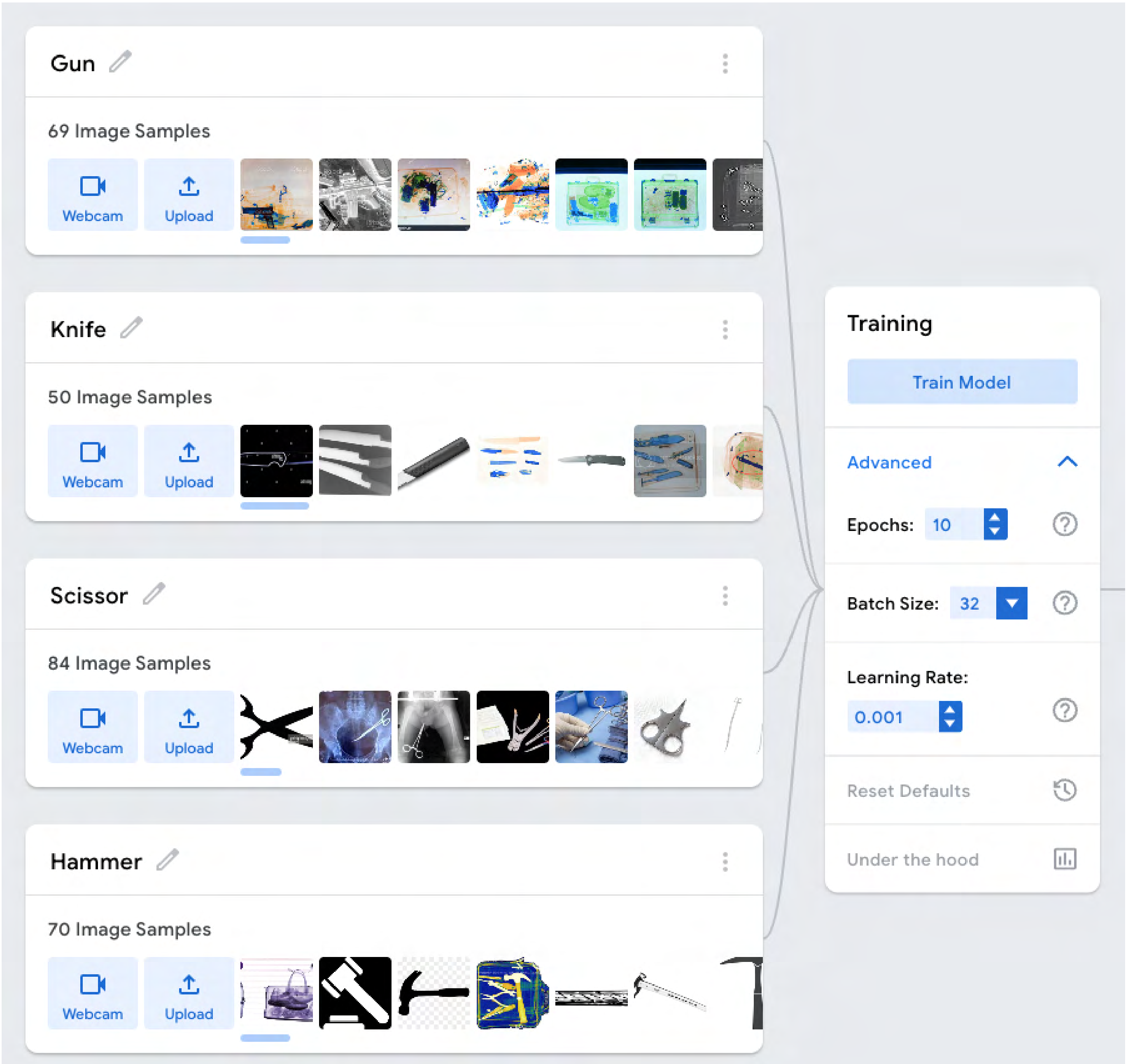
Object Category	Number of Images
Gun	69
Hammer	70
Scissor	84
Knife	50

Dataset: OPIXRaySet

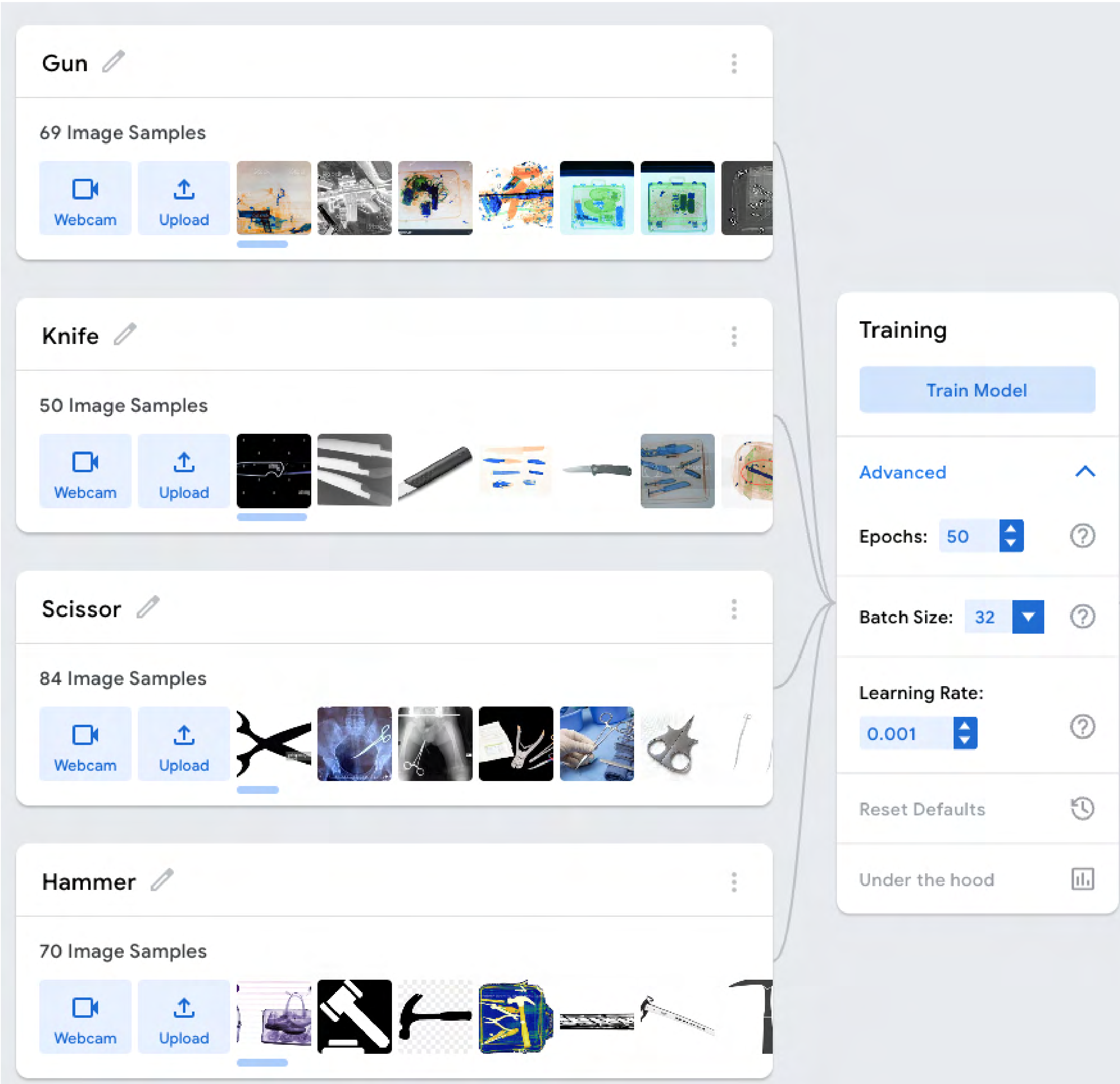
Object Category	Total Number of Images	Images used for Model Training
Scissor	1494	10
Folding Knife	1589	10
Straight Knife	809	10
Multi-Tool Knife	1612	10
Utility Knife	1635	10

Dataset: XraySet - Model Training

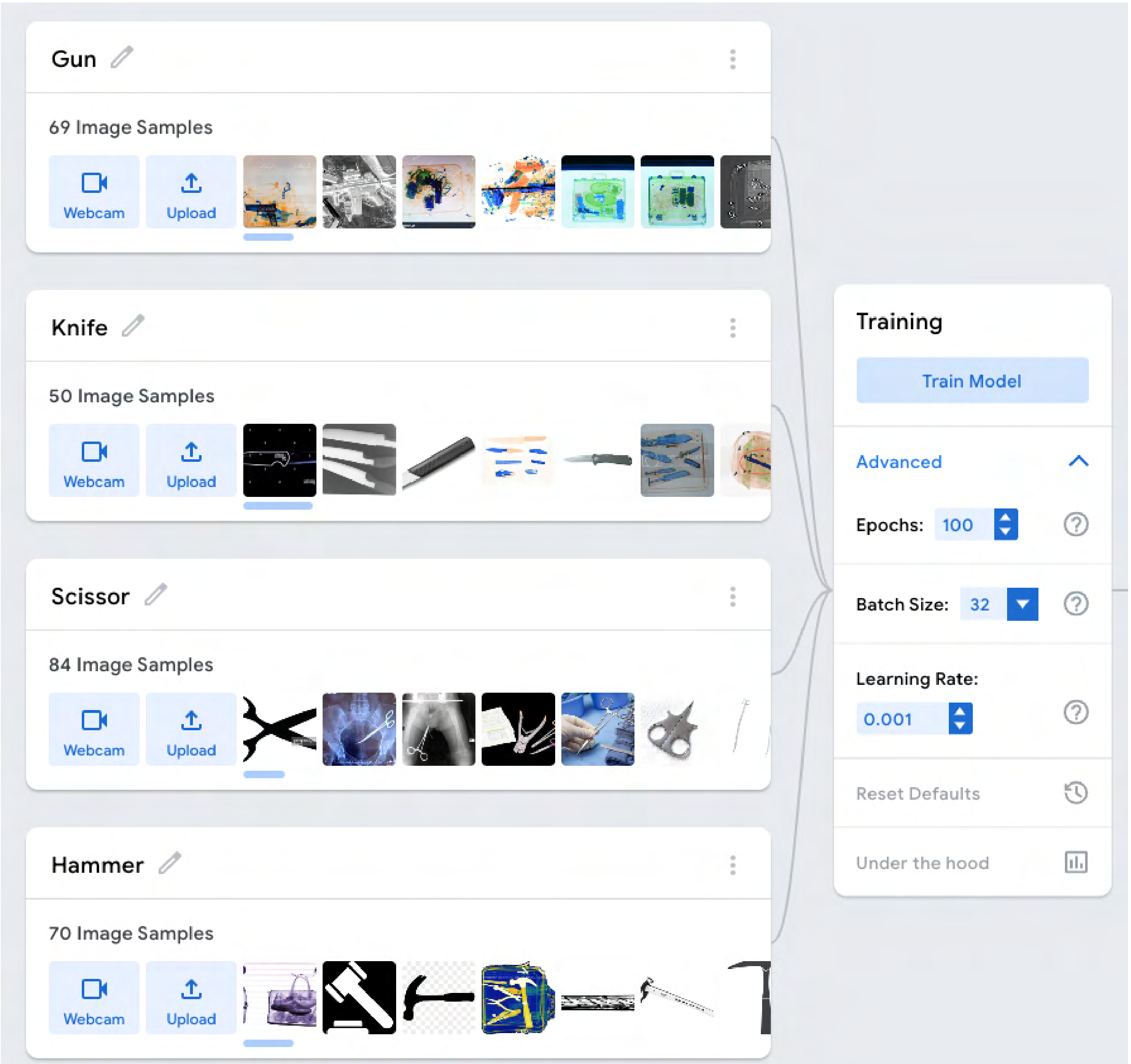
Model.10



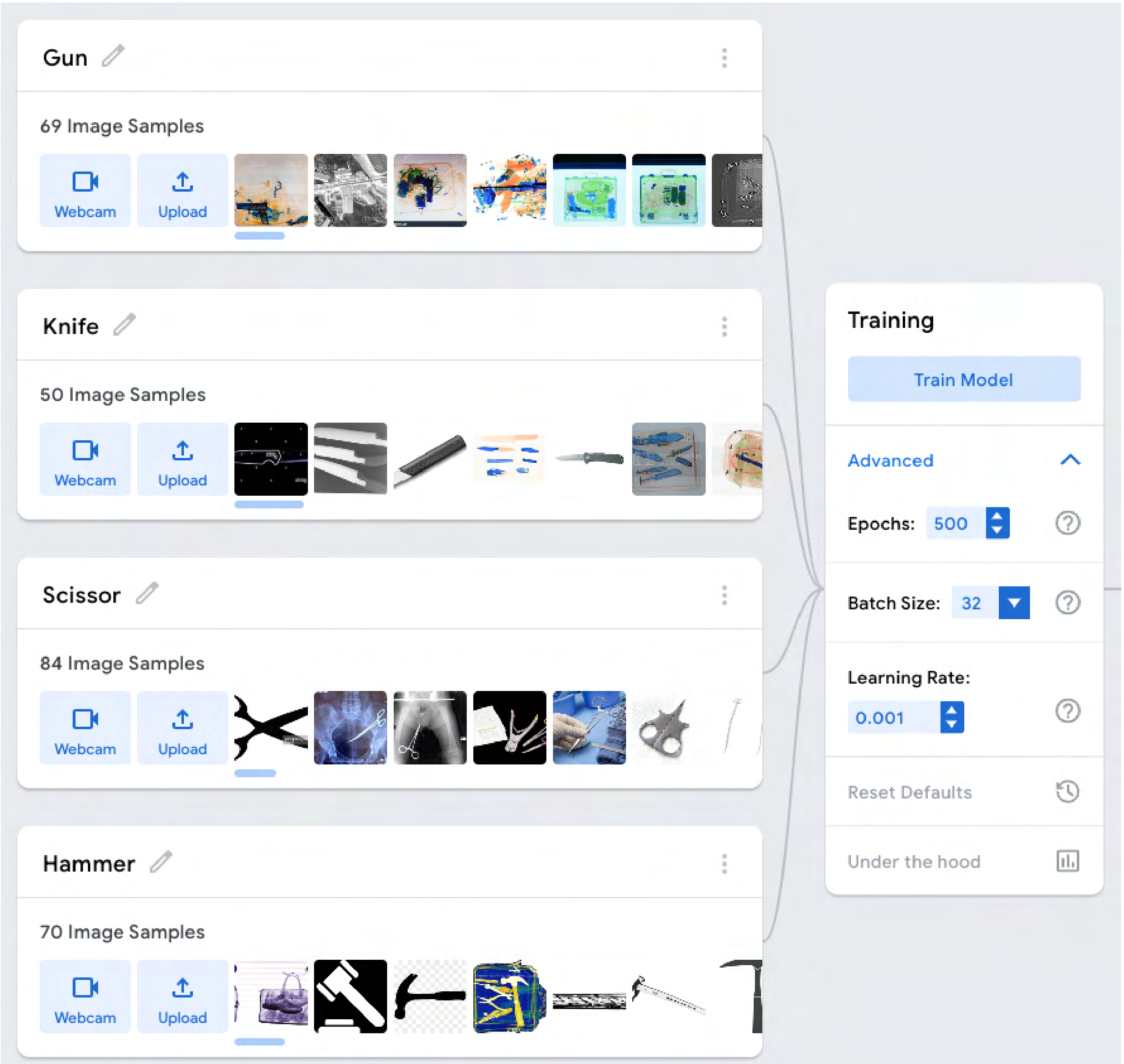
Model.50


Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Train Model
Advanced
Epochs: 50
Batch Size: 32
Learning Rate:
0.001
Reset Defaults
Under the hood

Model.100

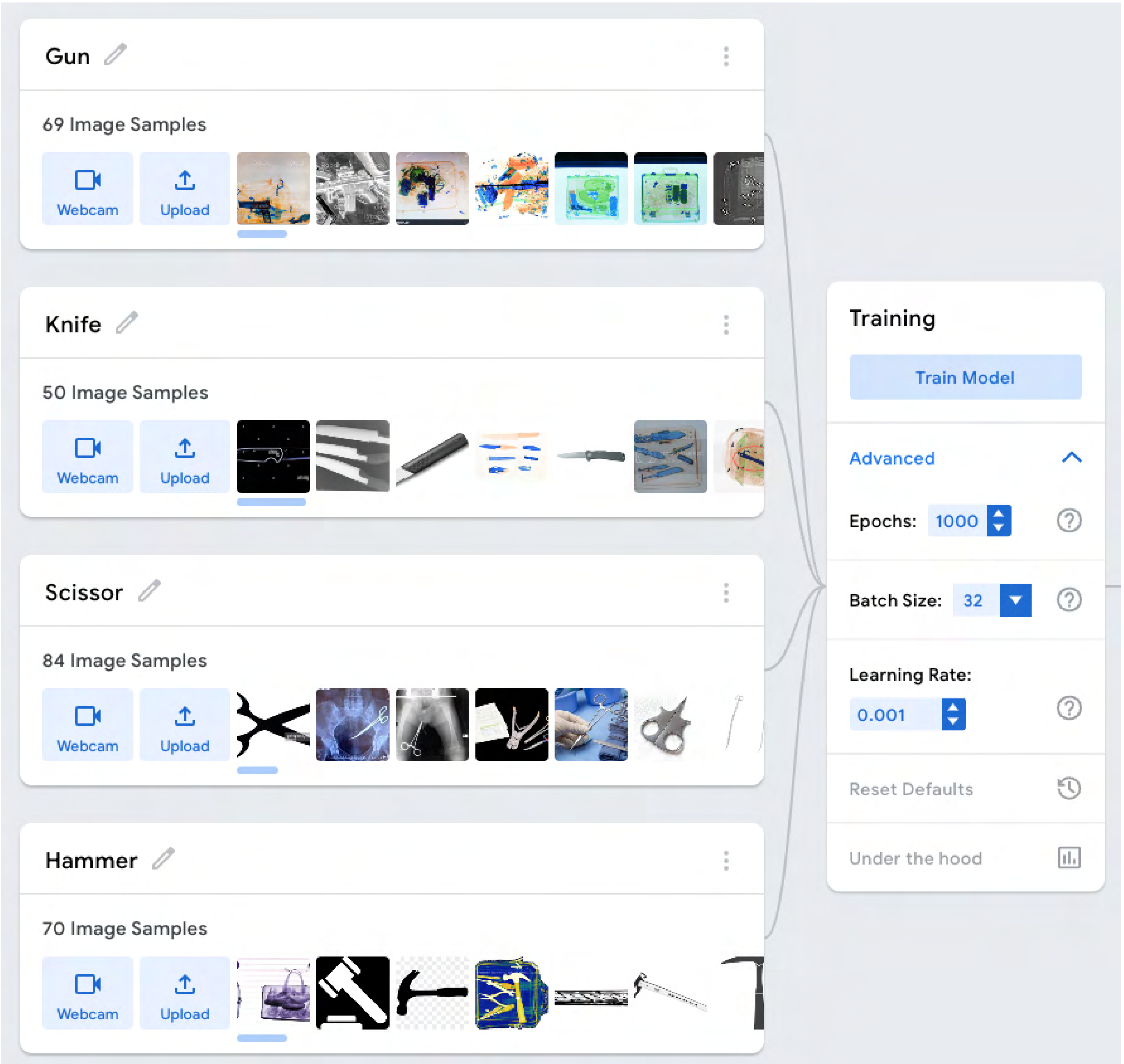

Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Train Model
Advanced
Epochs: 100
Batch Size: 32
Learning Rate:
0.001
Reset Defaults
Under the hood

Model.500



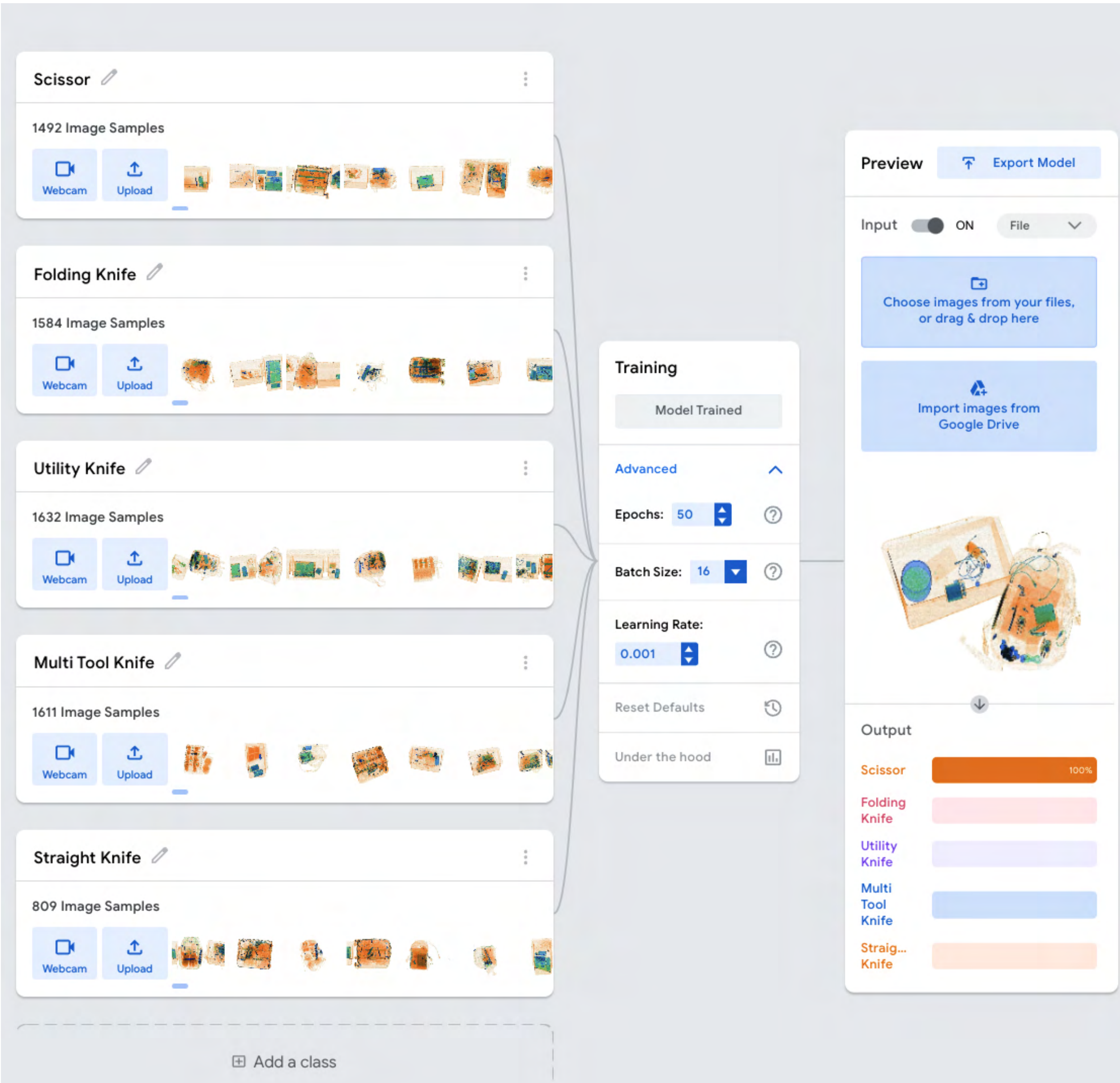
Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Train Model
Advanced
Epochs: 500
Batch Size: 32
Learning Rate:
0.001
Reset Defaults
Under the hood

Model.1000

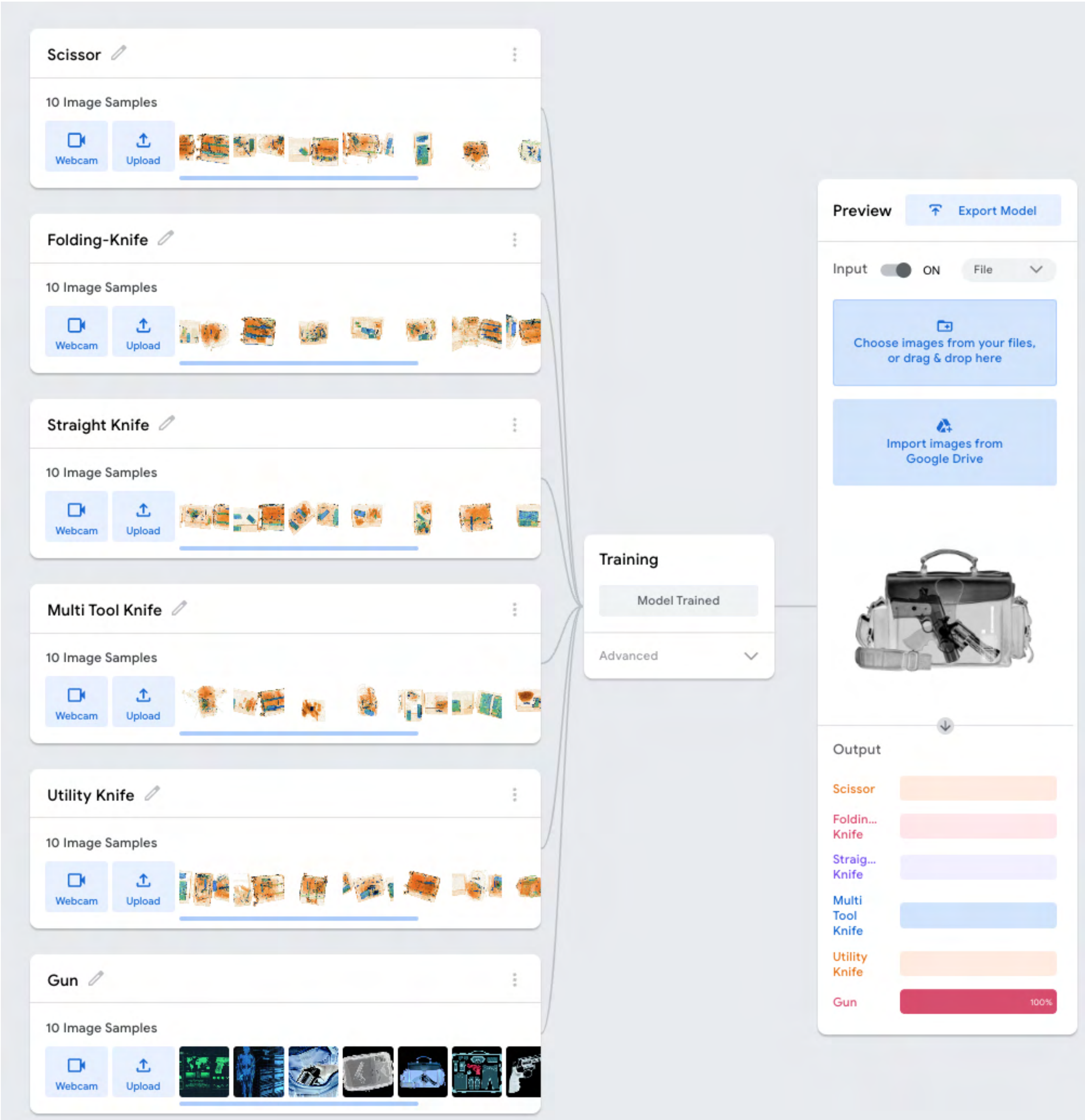

Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Train Model
Advanced
Epochs: 1000
Batch Size: 32
Learning Rate:
0.001
Reset Defaults
Under the hood

Dataset: XraySet - Model Training

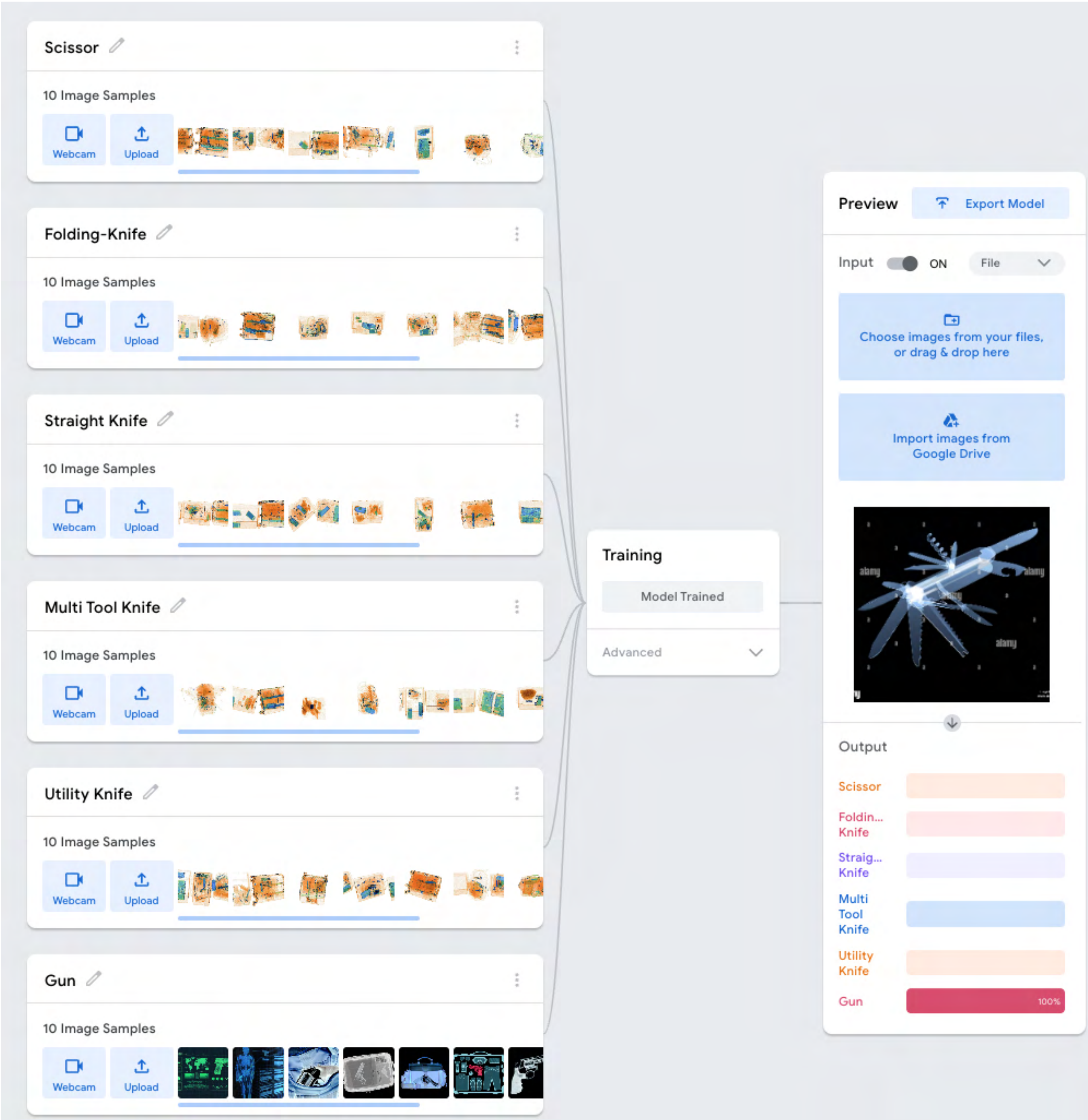
Model-1



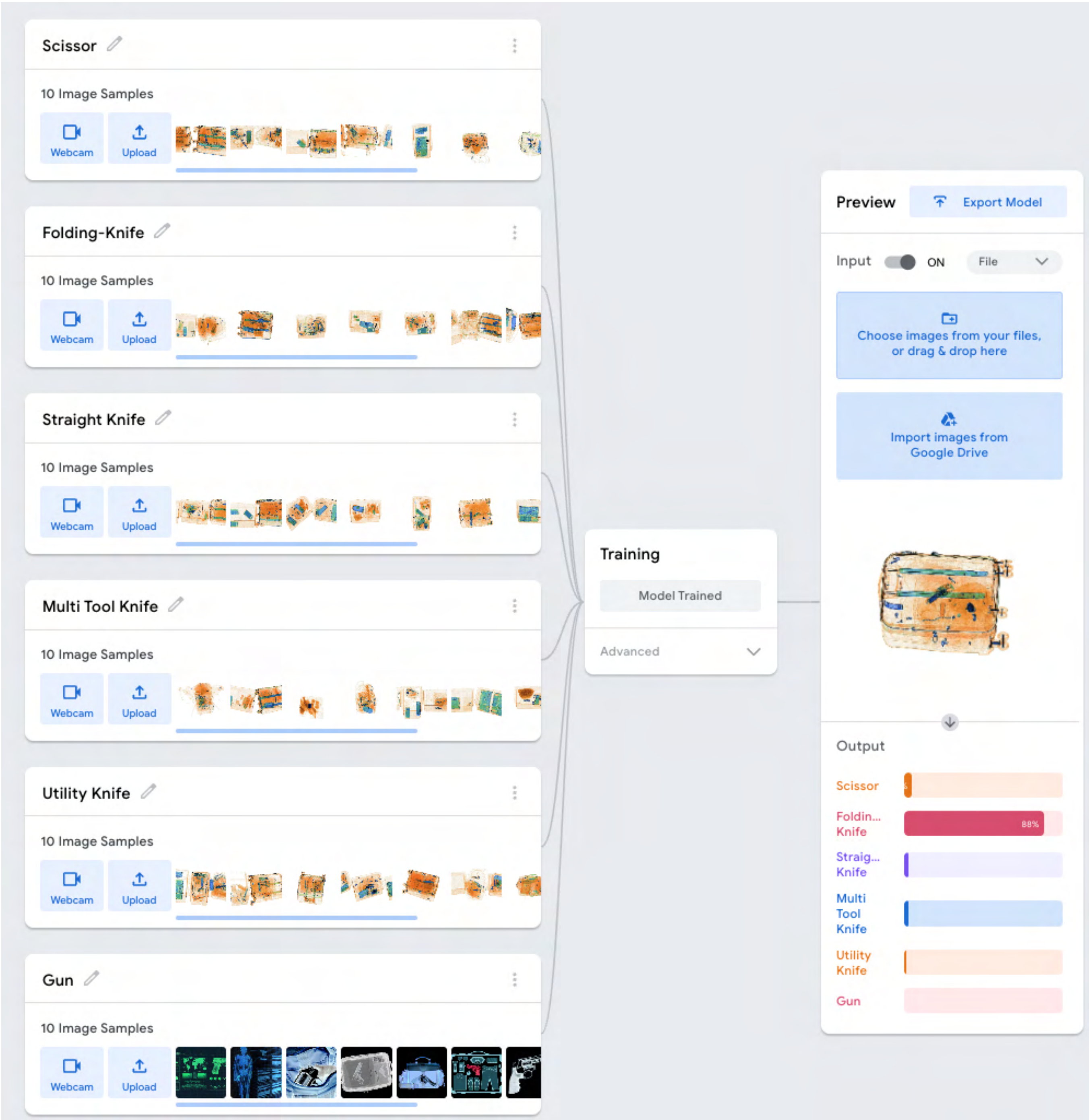
Model.10


Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
Utility Knife
Gun
100%

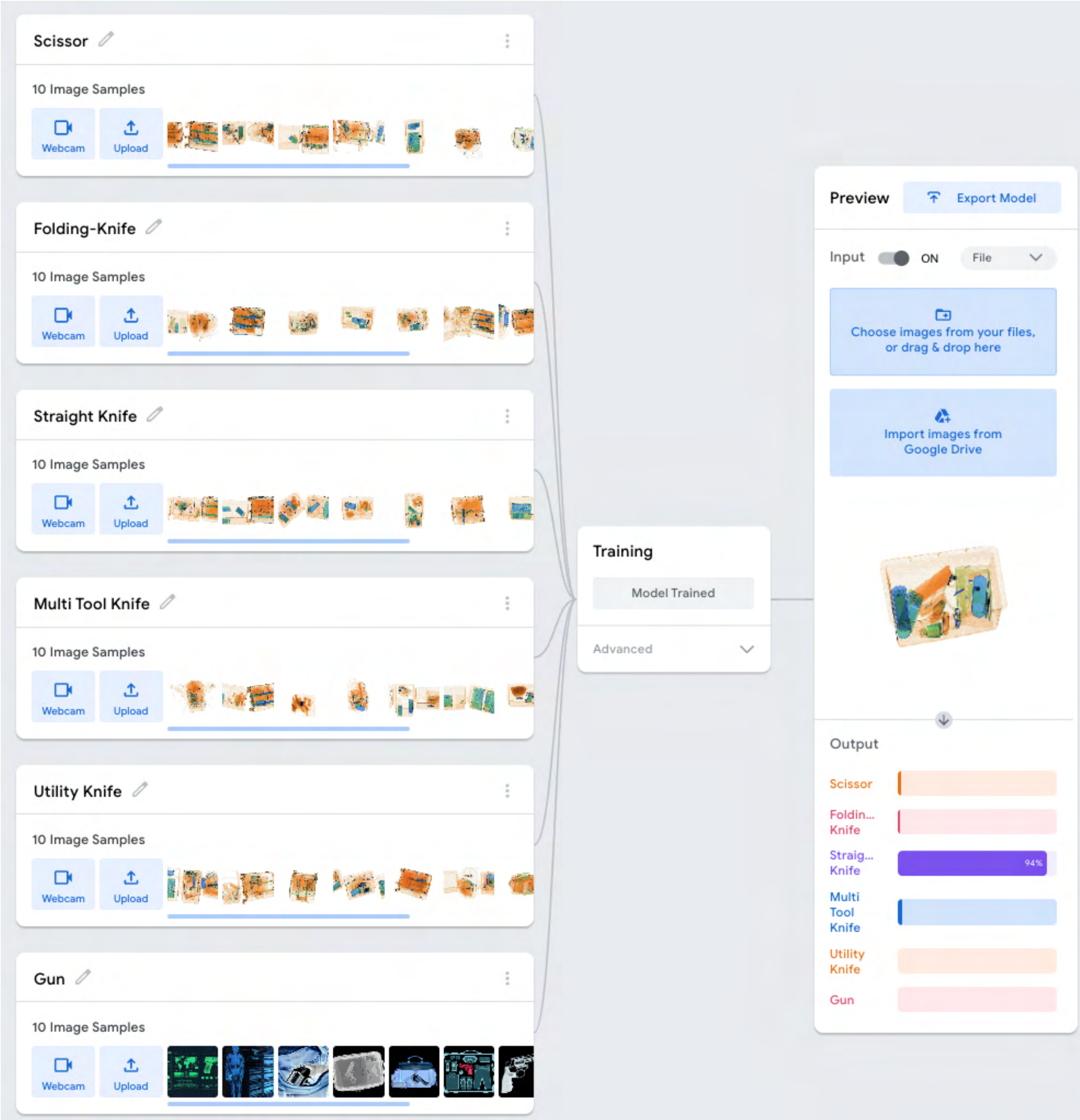
Model.100

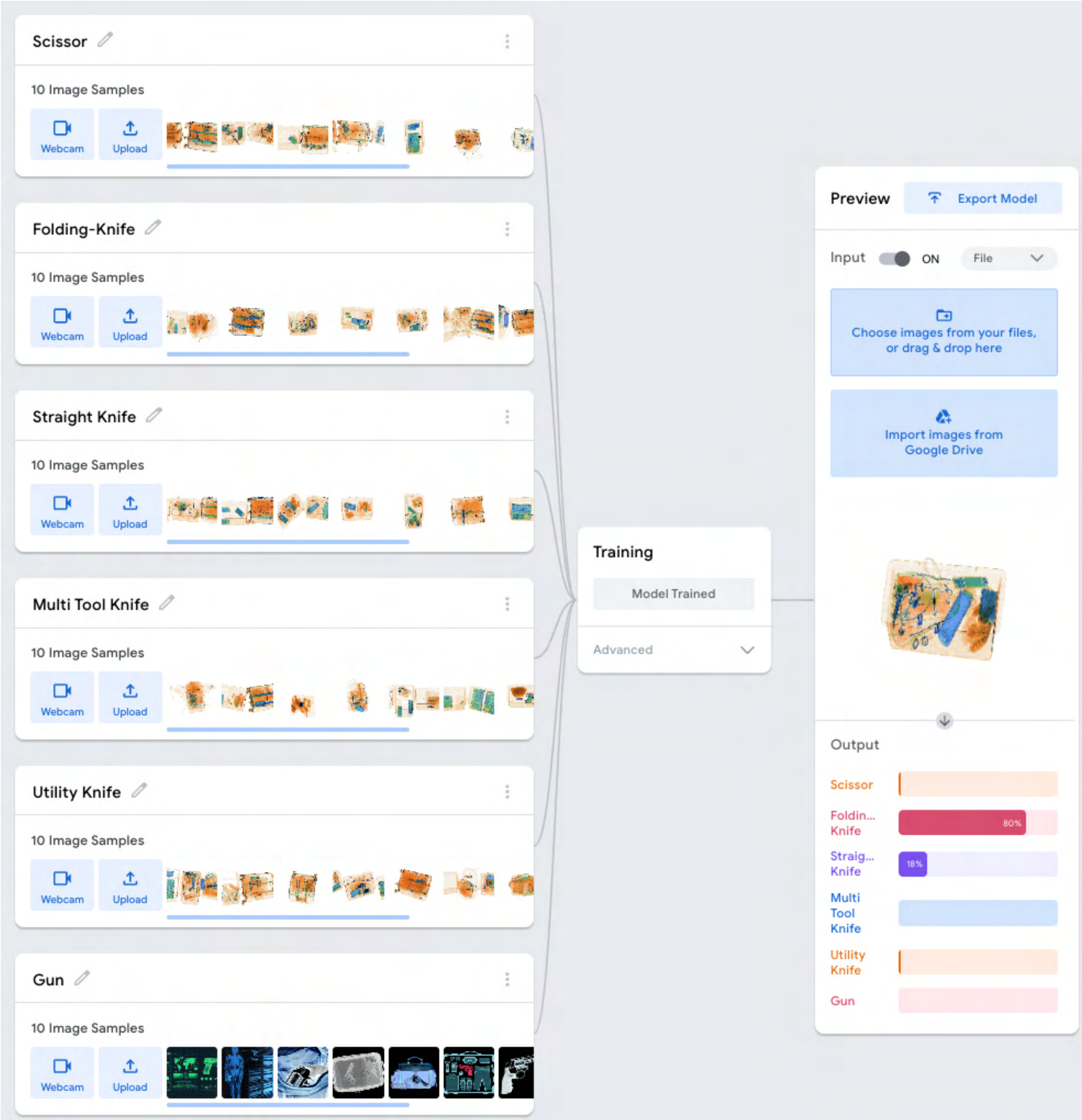

Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
Utility Knife
Gun
100%

Model.500

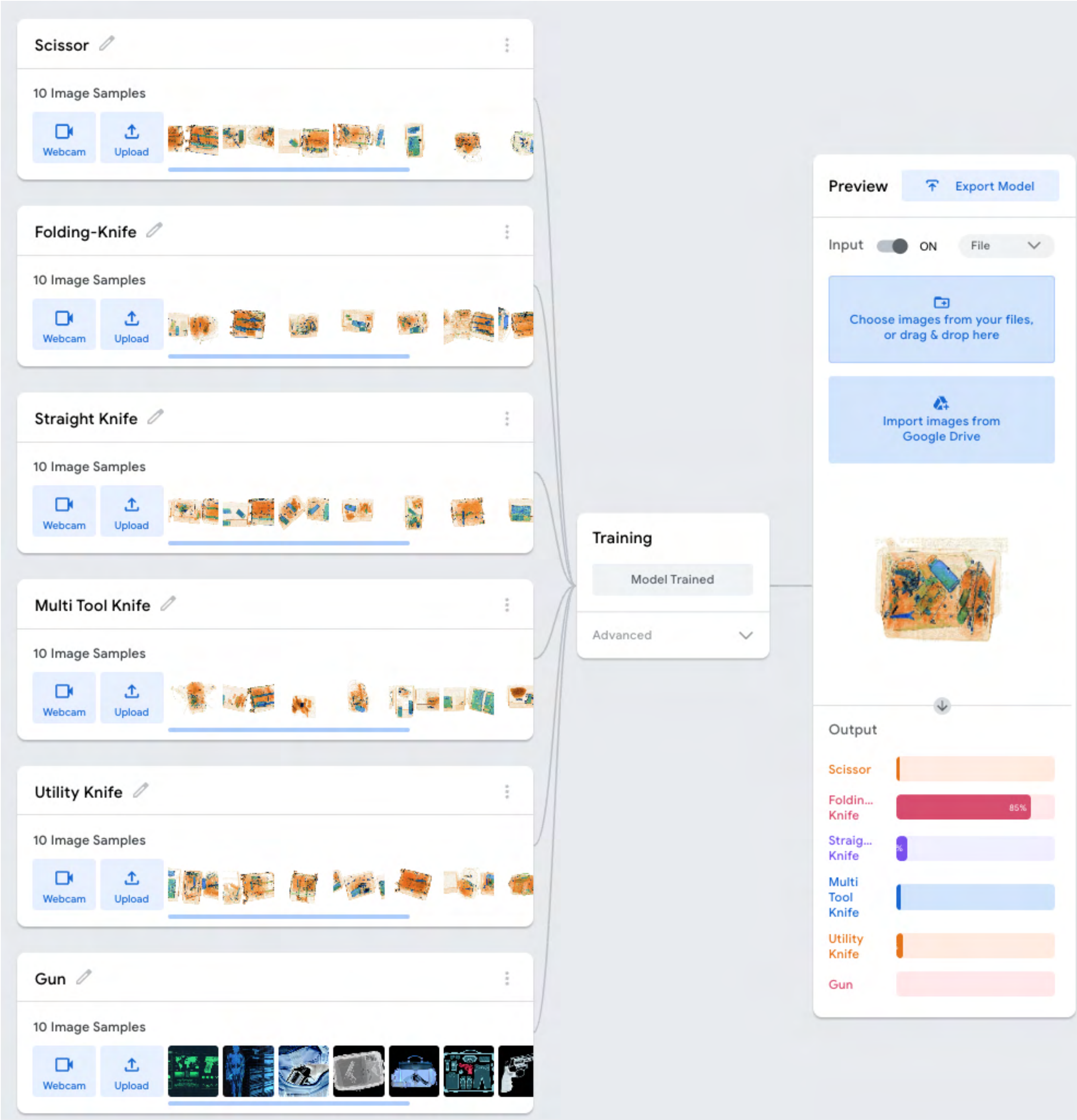


Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
88%
Straig... Knife
Multi Tool Knife
Utility Knife
Gun

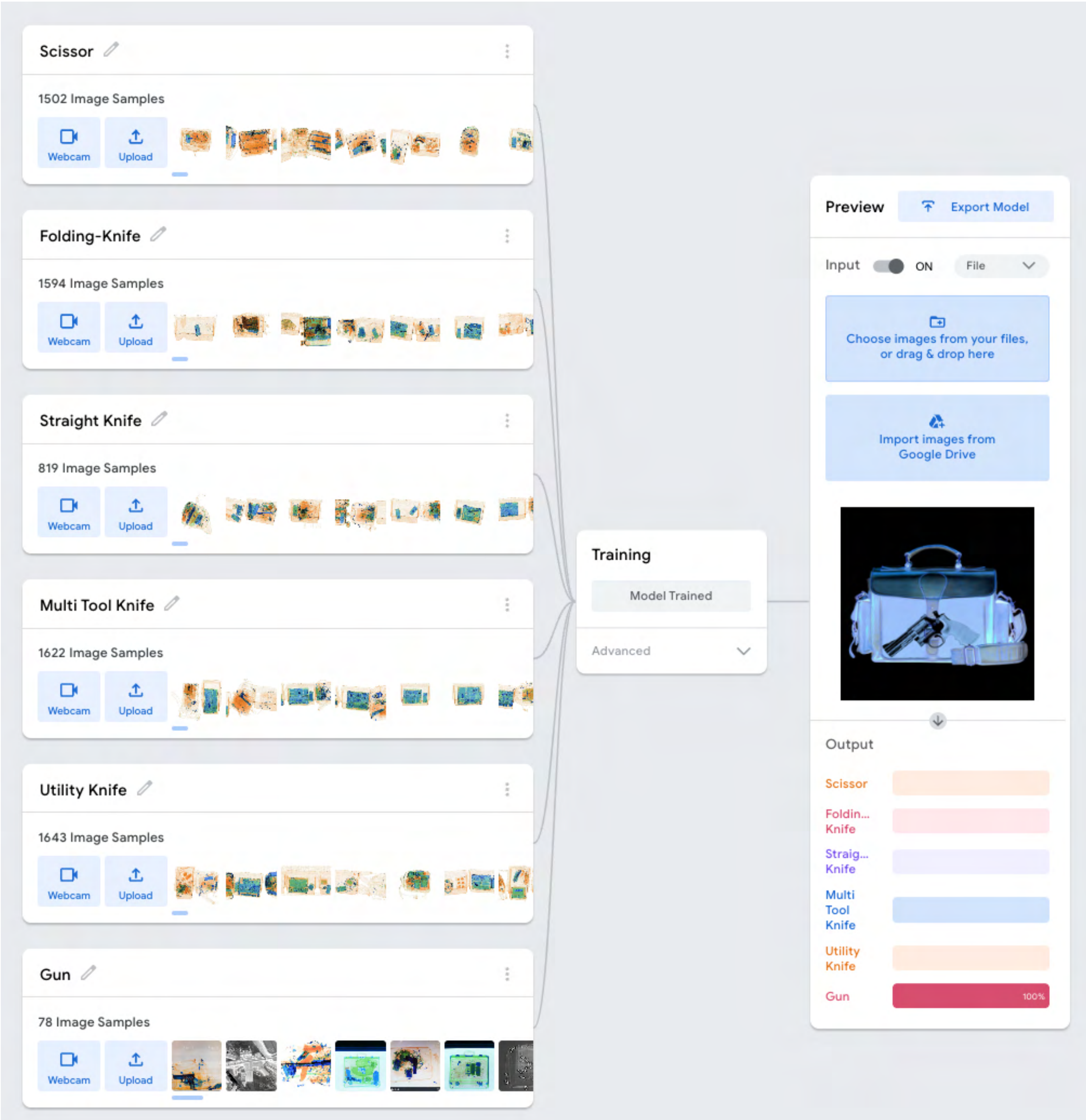

Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
94%
Multi Tool Knife
Utility Knife
Gun

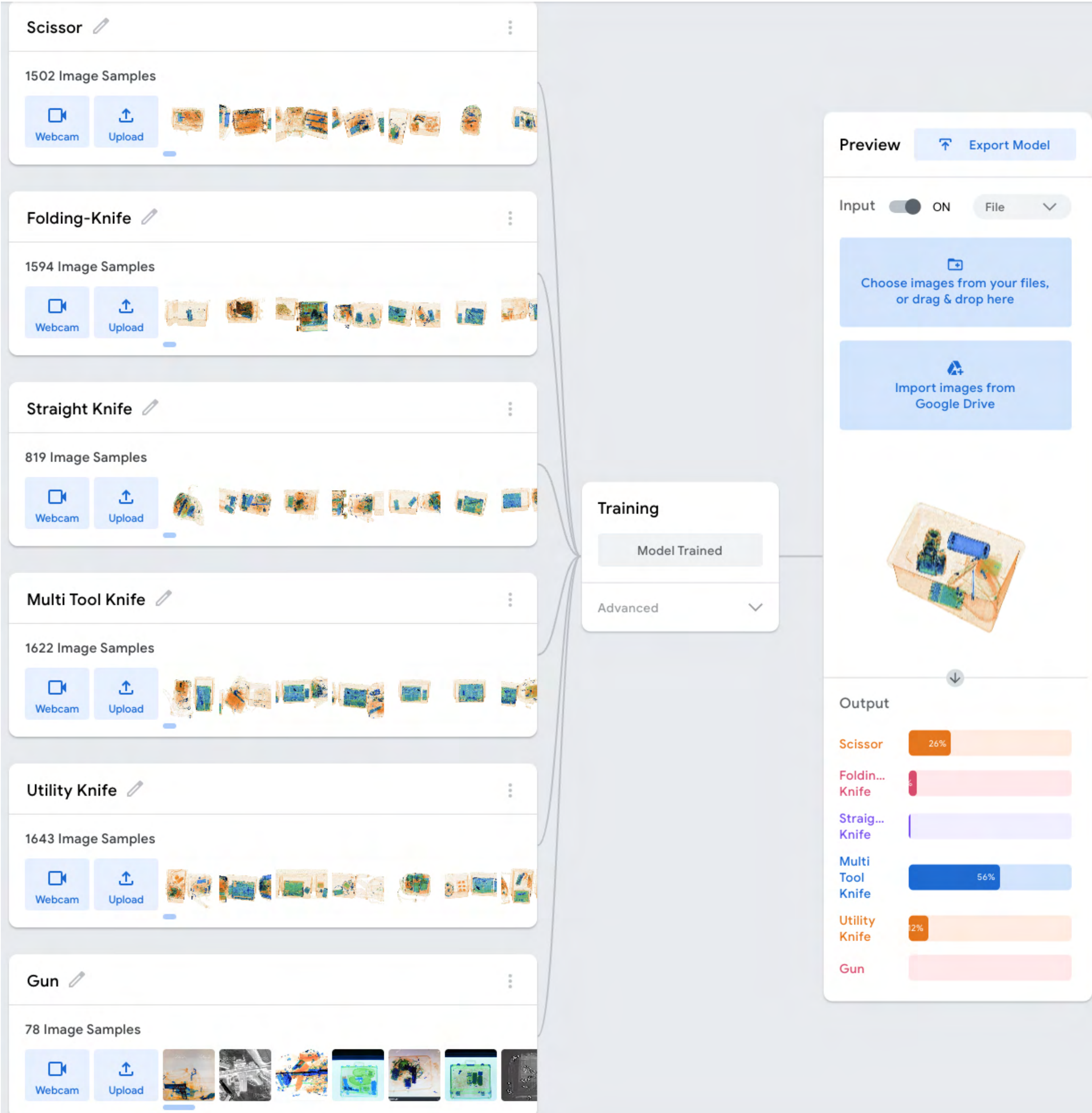


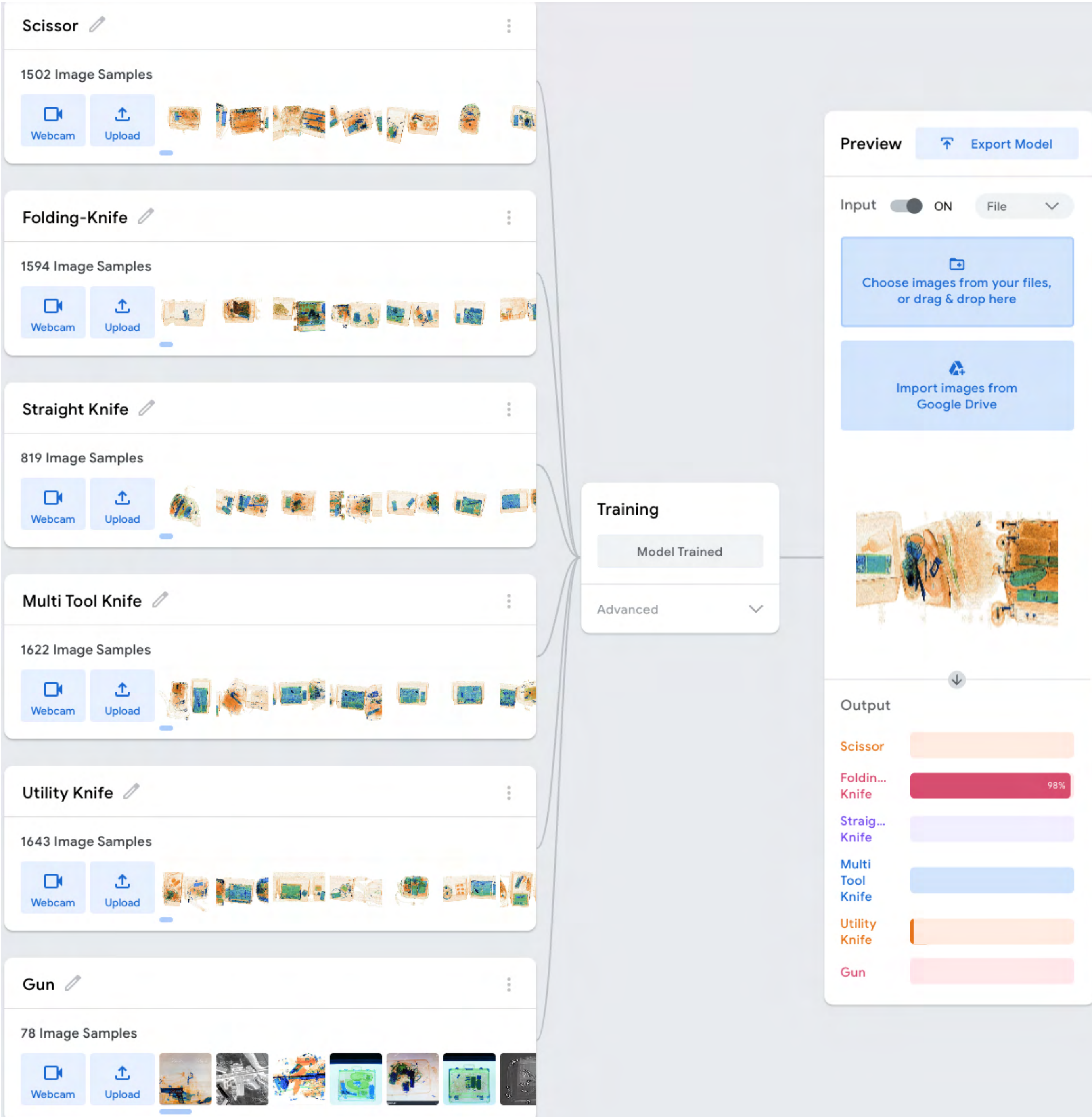
Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
80%
Straig... Knife
18%
Multi Tool Knife
Utility Knife
Gun


Scissor
10 Image Samples
Webcam
Upload
Folding-Knife
10 Image Samples
Webcam
Upload
Straight Knife
10 Image Samples
Webcam
Upload
Multi Tool Knife
10 Image Samples
Webcam
Upload
Utility Knife
10 Image Samples
Webcam
Upload
Gun
10 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
85%
Straig... Knife
Multi Tool Knife
Utility Knife
Gun

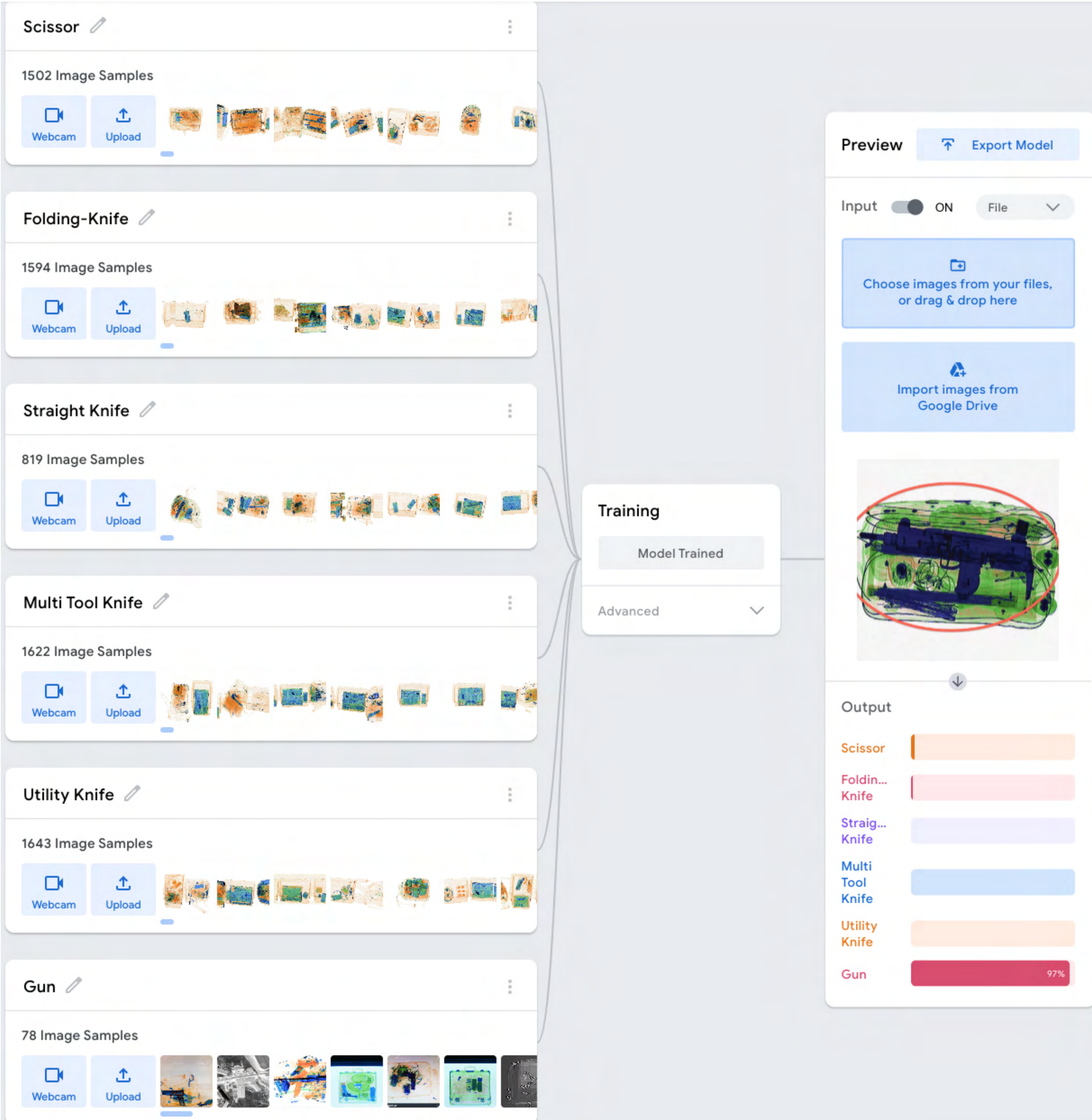
Model.1000

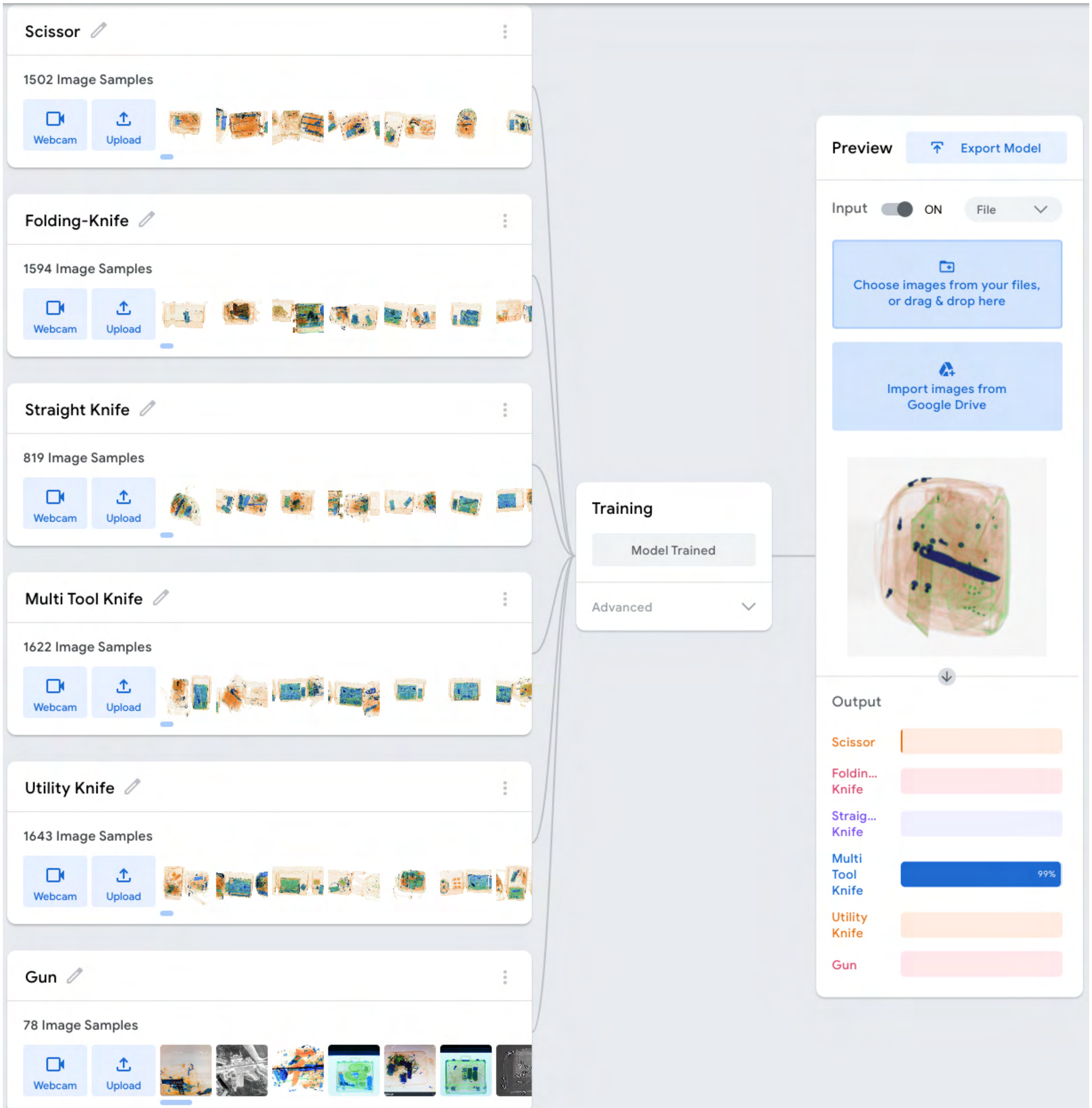

Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
Utility Knife
Gun
100%

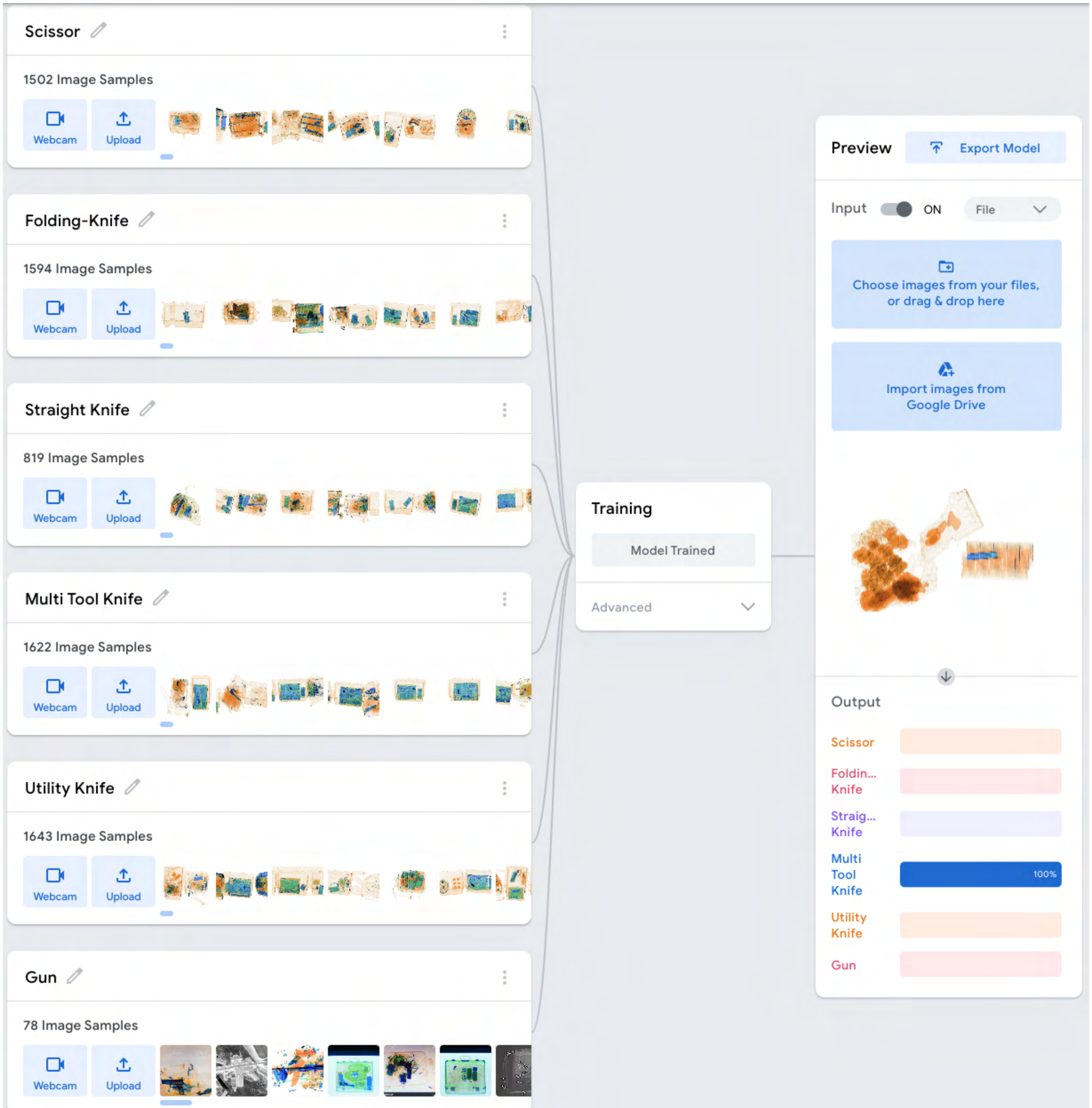

Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
26%
Foldin... Knife
Straig... Knife
Multi Tool Knife
56%
Utility Knife
Gun

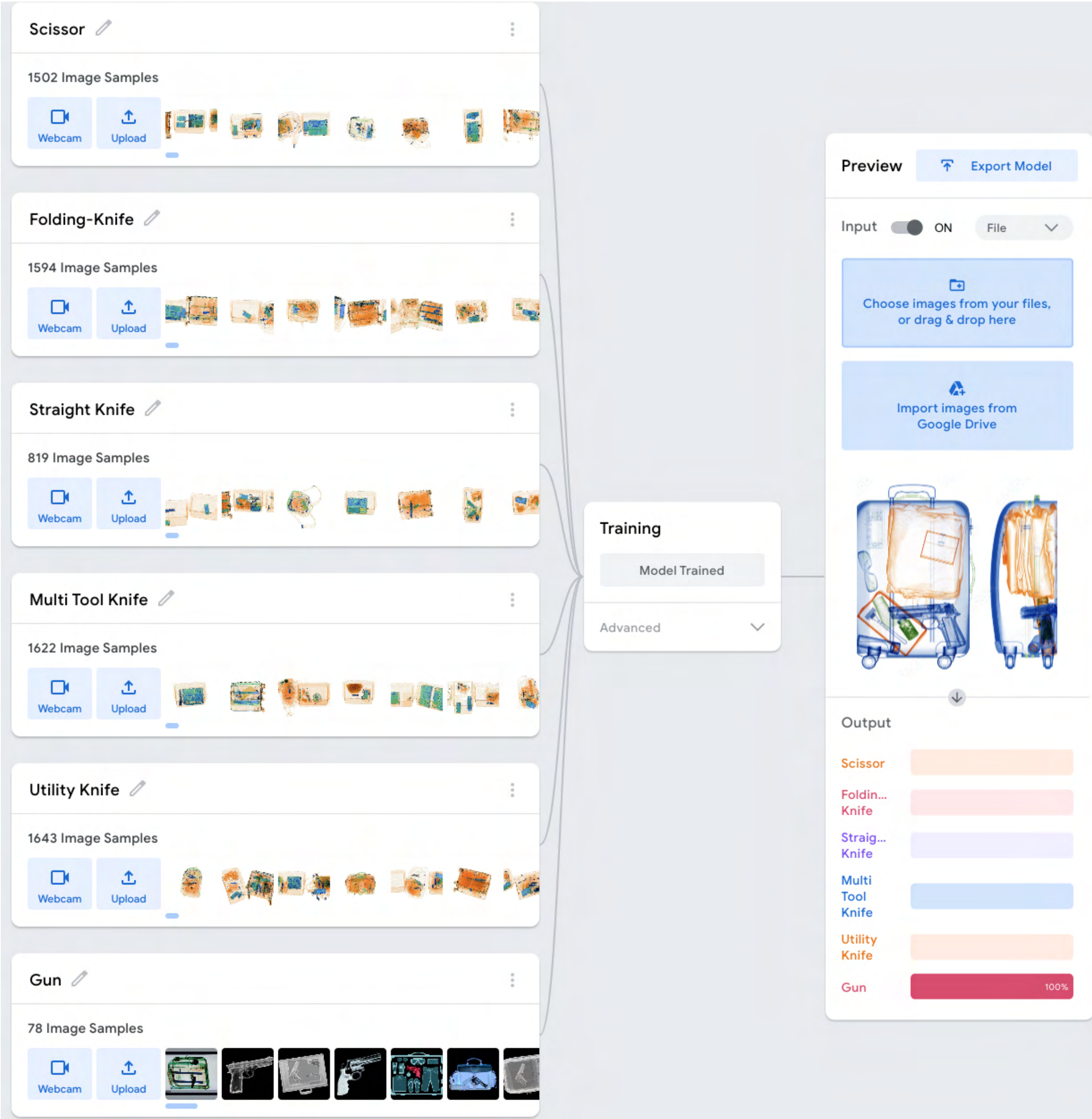


Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Straight Knife
819 Image Samples
Multi Tool Knife
1622 Image Samples
Utility Knife
1643 Image Samples
Gun
78 Image Samples
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
98%
Straig... Knife
Multi Tool Knife
Utility Knife
Gun


Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
Utility Knife
Gun
97%


Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
99%
Utility Knife
Gun


Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
100%
Utility Knife
Gun


Scissor
1502 Image Samples
Webcam
Upload
Folding-Knife
1594 Image Samples
Webcam
Upload
Straight Knife
819 Image Samples
Webcam
Upload
Multi Tool Knife
1622 Image Samples
Webcam
Upload
Utility Knife
1643 Image Samples
Webcam
Upload
Gun
78 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Scissor
Foldin... Knife
Straig... Knife
Multi Tool Knife
Utility Knife
Gun
100%

Bill of Materials

#	Material	Unit Cost
1	Samsung SM-T500NZAAXA 10.4" Galaxy Tab A7 32GB Gray(Refurbished) Link	$189.99
2	Print Enclosure	$5.00
3	Webcamera	$18.99
4	Smart-See-Thru Software	$0.00
5	Windows PC or Mac Computer	Required
6	Shipping and Handling Cost	$10.00
	TOTAL COST OF SOLUTION	**$223.00**

Software used

Operating System:Windows 10,macOS Monterey
Teachable Machines: https://teachablemachine.withgoogle.com/train
Python: https://www.python.org/

Testing Solution

How will you test your solution? The BEST way to test your solution is to build a working model or a prototype that you can actually use. Or you can guess how your solution will work BASED ON your research. Which method will you use and why?:

After we built the prototype, we decided to test the accuracy of each prohibited object in our two datasets, and built 6 to 10 models for each scenario. Our goal is to get the prediction accuracy of these objects close to 1.0, better than manual levels. We captured the prediction accuracy of each object in the tables below.

Testing Dataset: OPIXRay-Set

Dataset: OPIXRaySet

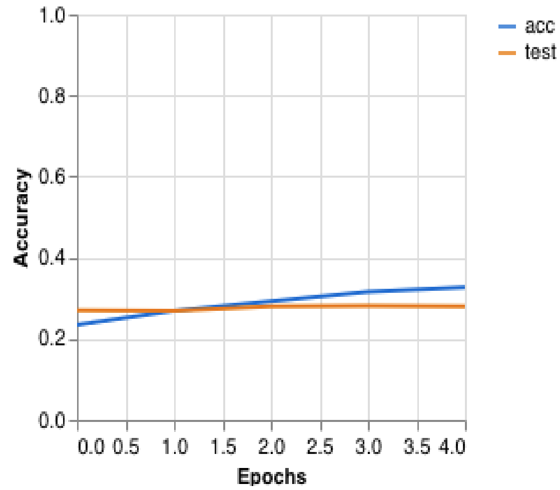
Object Category	Total Number of Images	Images used for Model Training
Scissor	1494	10
Folding Knife	1589	10
Straight Knife	809	10
Multi-Tool Knife	1612	10
Utility Knife	1635	10

Test-01: Number-of-Epochs = 5, Batch-Size=16

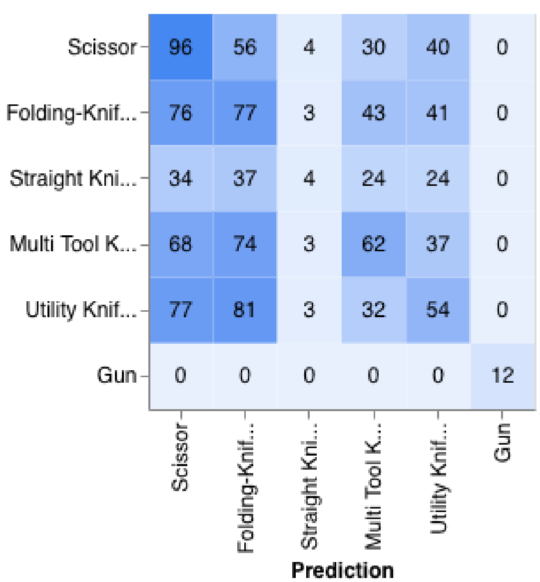
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.42	226
Folding-Knife	0.32	240
Straight Knife	0.03	123
Multi Tool Knife	0.25	244
Utility Knife	0.22	247
Gun	1.00	12

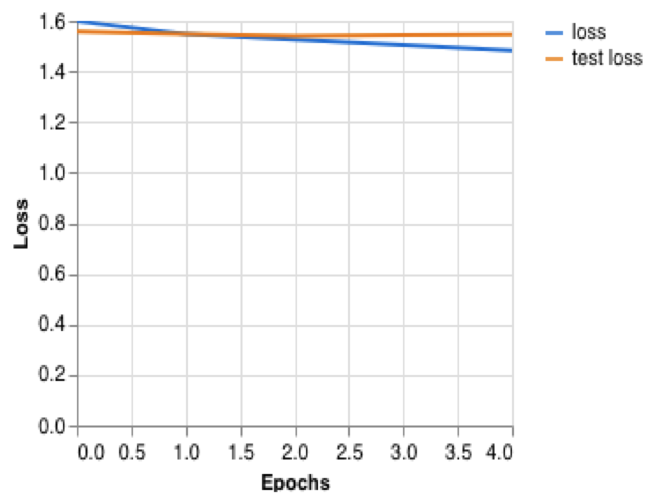
Accuracy per epoch



Confusion Matrix



Loss per epoch

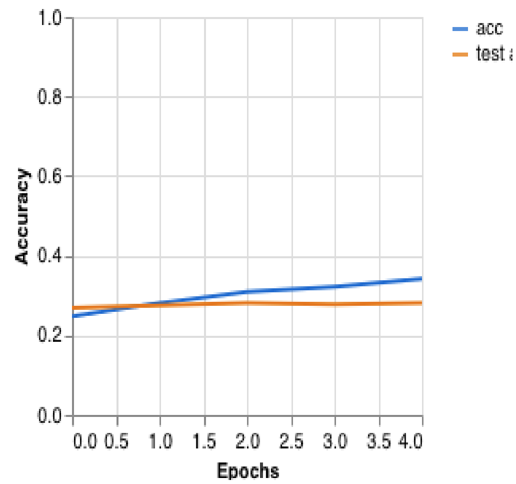


Test-02: Number-of-Epochs=5, Batch-Size=64

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.29	226
Folding-Knife	0.07	240
Straight Knife	0.04	123
Multi Tool Knife	0.70	244
Utility Knife	0.14	247
Gun	1.00	12

Accuracy per epoch

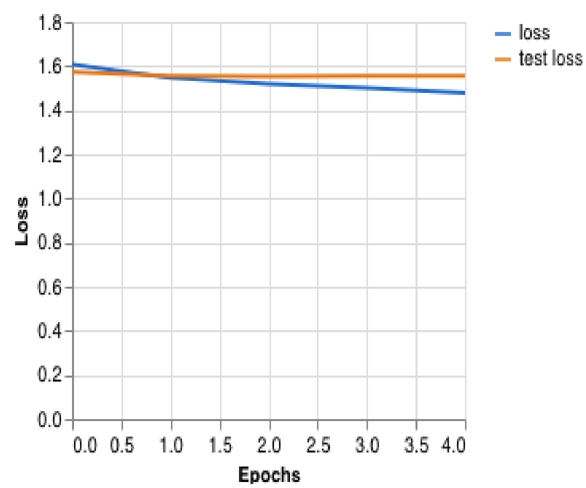


Confusion Matrix

	Scissor	Folding-Knif...	Straight Kni...	Multi Tool K...	Utility Knif...	Gun
Scissor	66	15	2	113	30	0
Folding-Knif...	42	18	4	148	28	0
Straight Kni...	30	8	5	68	12	0
Multi Tool K...	26	17	1	171	29	0
Utility Knif...	49	18	7	138	35	0
Gun	0	0	0	0	0	12

Prediction

Loss per epoch

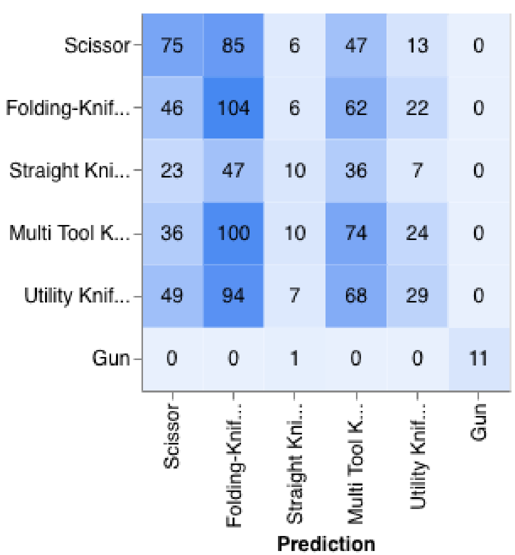


Test-03: Number-of-Epochs=10, Batch-Size=16

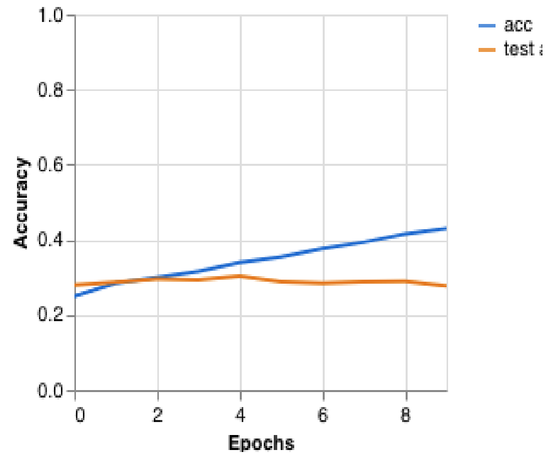
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.33	226
Folding-Knife	0.43	240
Straight Knife	0.08	123
Multi Tool Knife	0.30	244
Utility Knife	0.12	247
Gun	0.92	12

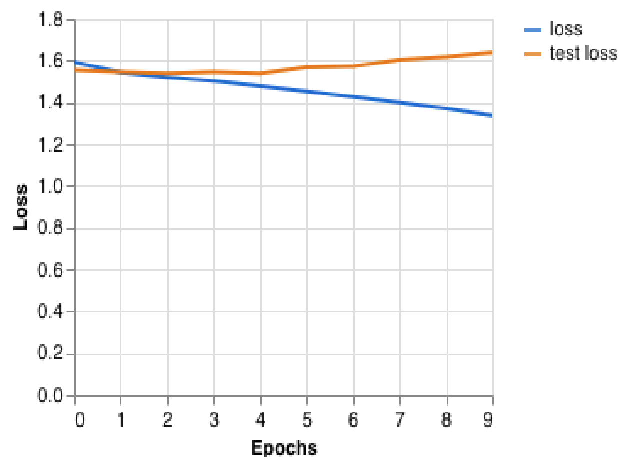
Confusion Matrix



Accuracy per epoch



Loss per epoch

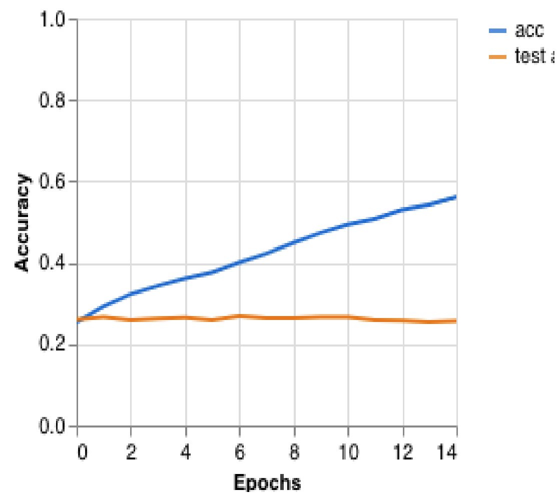


Test-04: Number-of-Epochs=15, Batch-Size=16

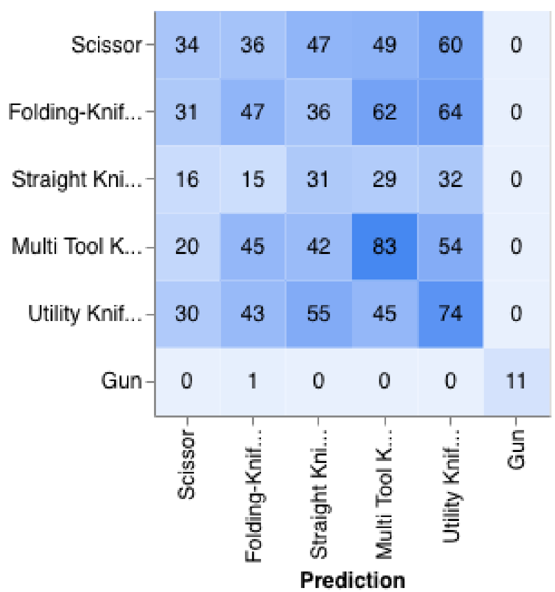
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.15	226
Folding-Knife	0.20	240
Straight Knife	0.25	123
Multi Tool Knife	0.34	244
Utility Knife	0.30	247
Gun	0.92	12

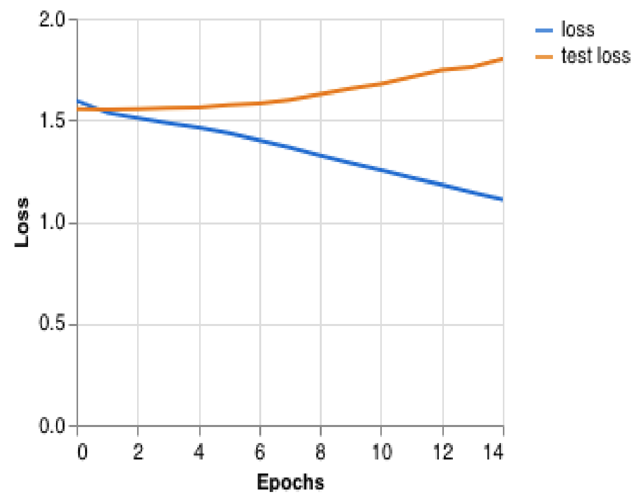
Accuracy per epoch



Confusion Matrix



Loss per epoch

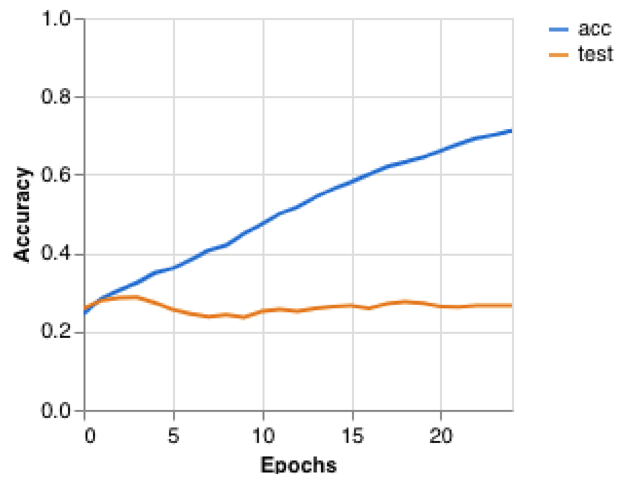


Test-05: Number-of-Epochs=25, Batch-Size=16

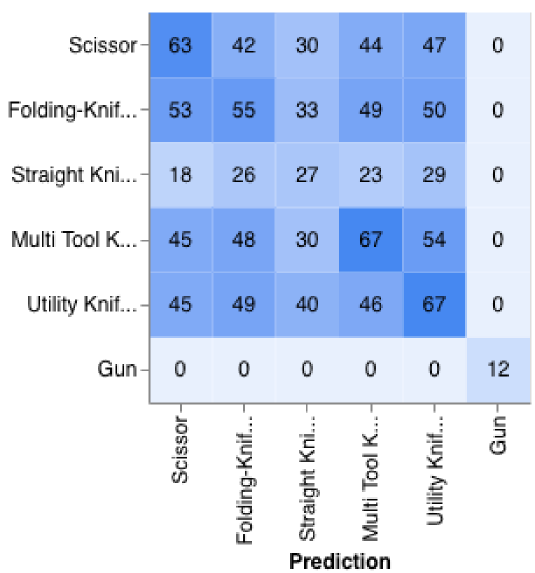
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.28	226
Folding-Knife	0.23	240
Straight Knife	0.22	123
Multi Tool Knife	0.27	244
Utility Knife	0.27	247
Gun	1.00	12

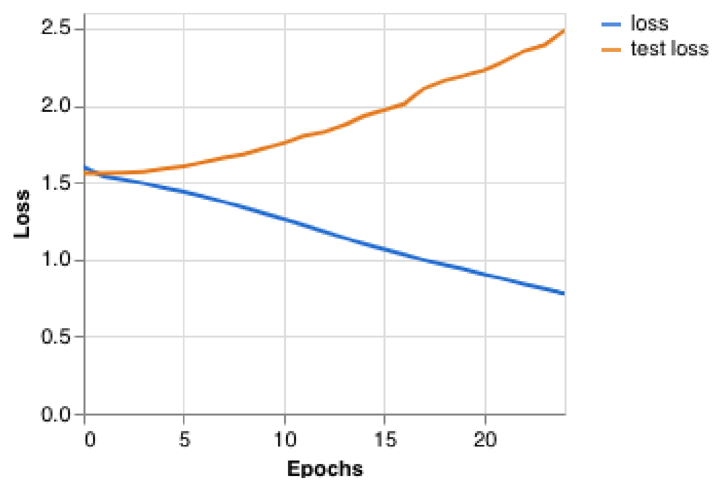
Accuracy per epoch



Confusion Matrix



Loss per epoch

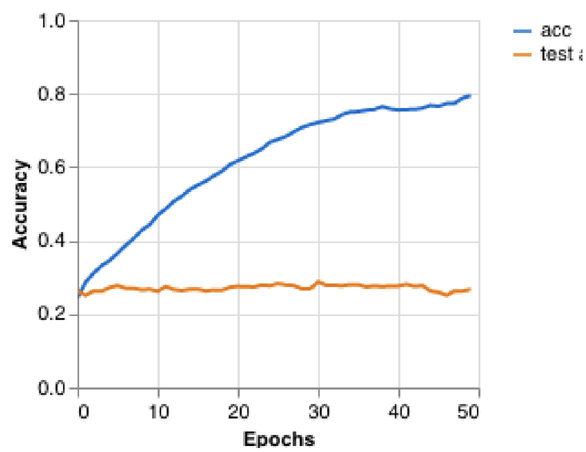


Test-06: Number-of-Epochs=50, Batch-Size=16

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.17	226
Folding-Knife	0.34	240
Straight Knife	0.13	123
Multi Tool Knife	0.16	244
Utility Knife	0.42	247
Gun	1.00	12

Accuracy per epoch

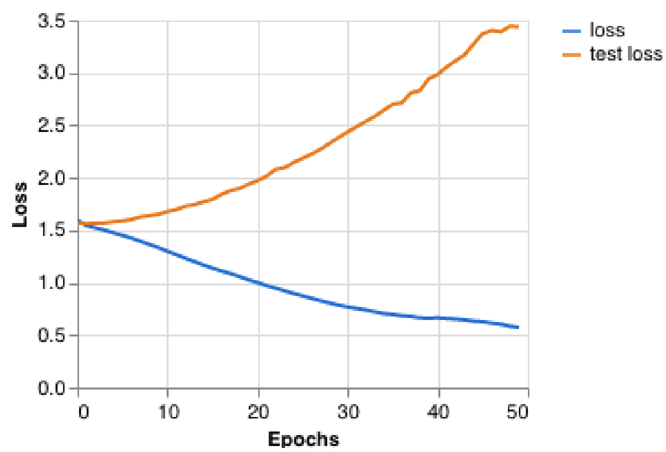


Confusion Matrix

	Scissor	Folding-Knif...	Straight Kni...	Multi Tool K...	Utility Knif...	Gun
Scissor	39	70	19	14	84	0
Folding-Knif...	31	81	12	25	91	0
Straight Kni...	21	31	16	16	39	0
Multi Tool K...	33	75	24	40	72	0
Utility Knif...	34	70	24	15	104	0
Gun	0	0	0	0	0	12

Prediction

Loss per epoch

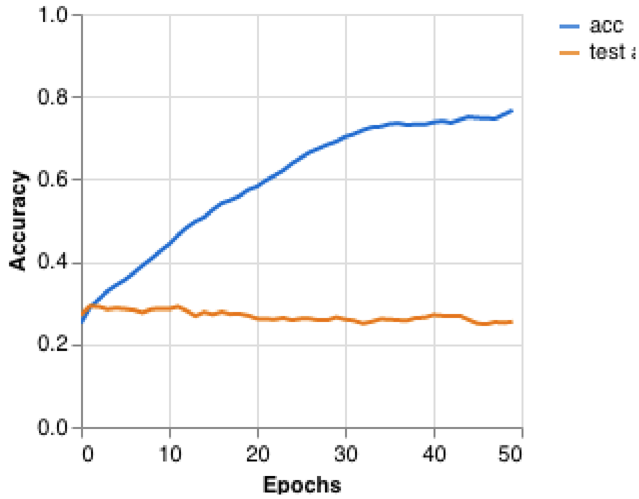


Test-07: Number-of-Epochs=50, Batch-Size=32

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.37	226
Folding-Knife	0.28	240
Straight Knife	0.12	123
Multi Tool Knife	0.14	244
Utility Knife	0.28	247
Gun	0.92	12

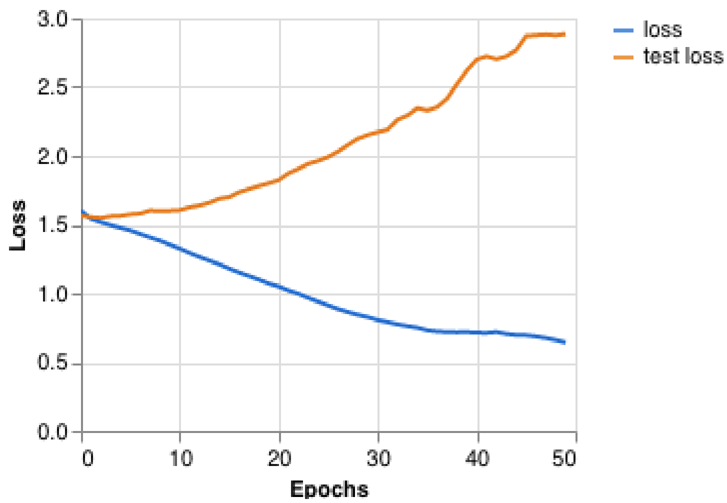
Accuracy per epoch



Confusion Matrix

	Scissor	Folding-Knif...	Straight Kni...	Multi Tool K...	Utility Knif...	Gun
Scissor	84	43	26	27	46	0
Folding-Knif...	68	66	35	24	47	0
Straight Kni...	37	31	15	9	31	0
Multi Tool K...	61	71	23	34	55	0
Utility Knif...	83	49	33	14	68	0
Gun	0	0	0	0	1	11

Loss per epoch

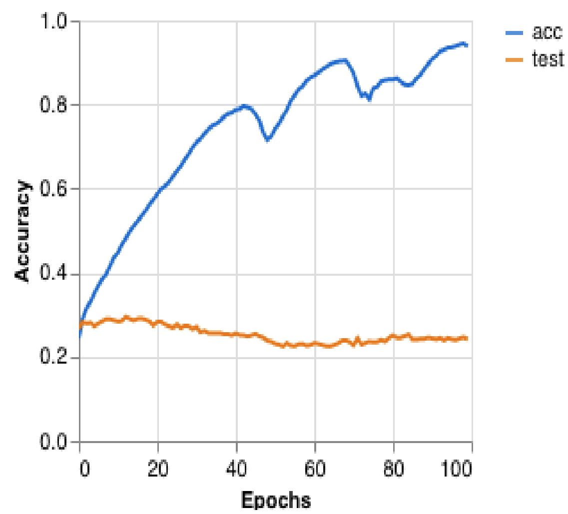


Test-08: Number-of-Epochs=100, Batch-Size=32

Accuracy per class

CLASS	ACCURACY	# SAMPLES
Scissor	0.18	226
Folding-Knife	0.12	240
Straight Knife	0.19	123
Multi Tool Knife	0.49	244
Utility Knife	0.16	247
Gun	0.92	12

Accuracy per epoch

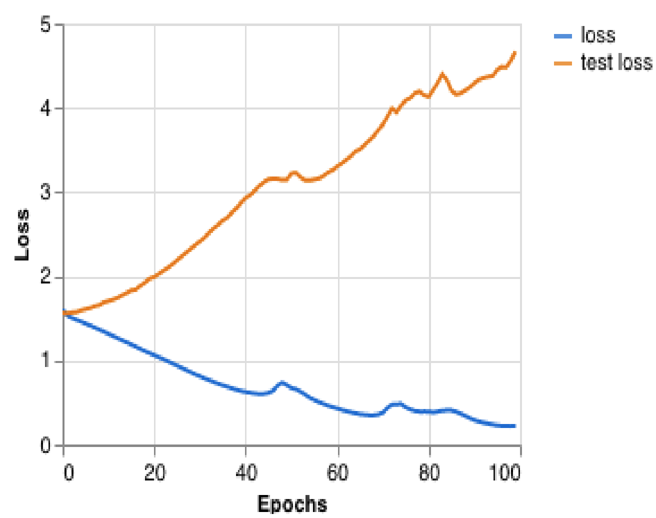


Confusion Matrix

	Scissor	Folding-Knif...	Straight Kni...	Multi Tool K...	Utility Knif...	Gun
Scissor	41	27	30	96	32	0
Folding-Knif...	40	29	23	101	47	0
Straight Kni...	16	14	23	51	19	0
Multi Tool K...	31	27	25	120	41	0
Utility Knif...	27	24	41	115	40	0
Gun	0	1	0	0	0	11

Prediction

Loss per epoch

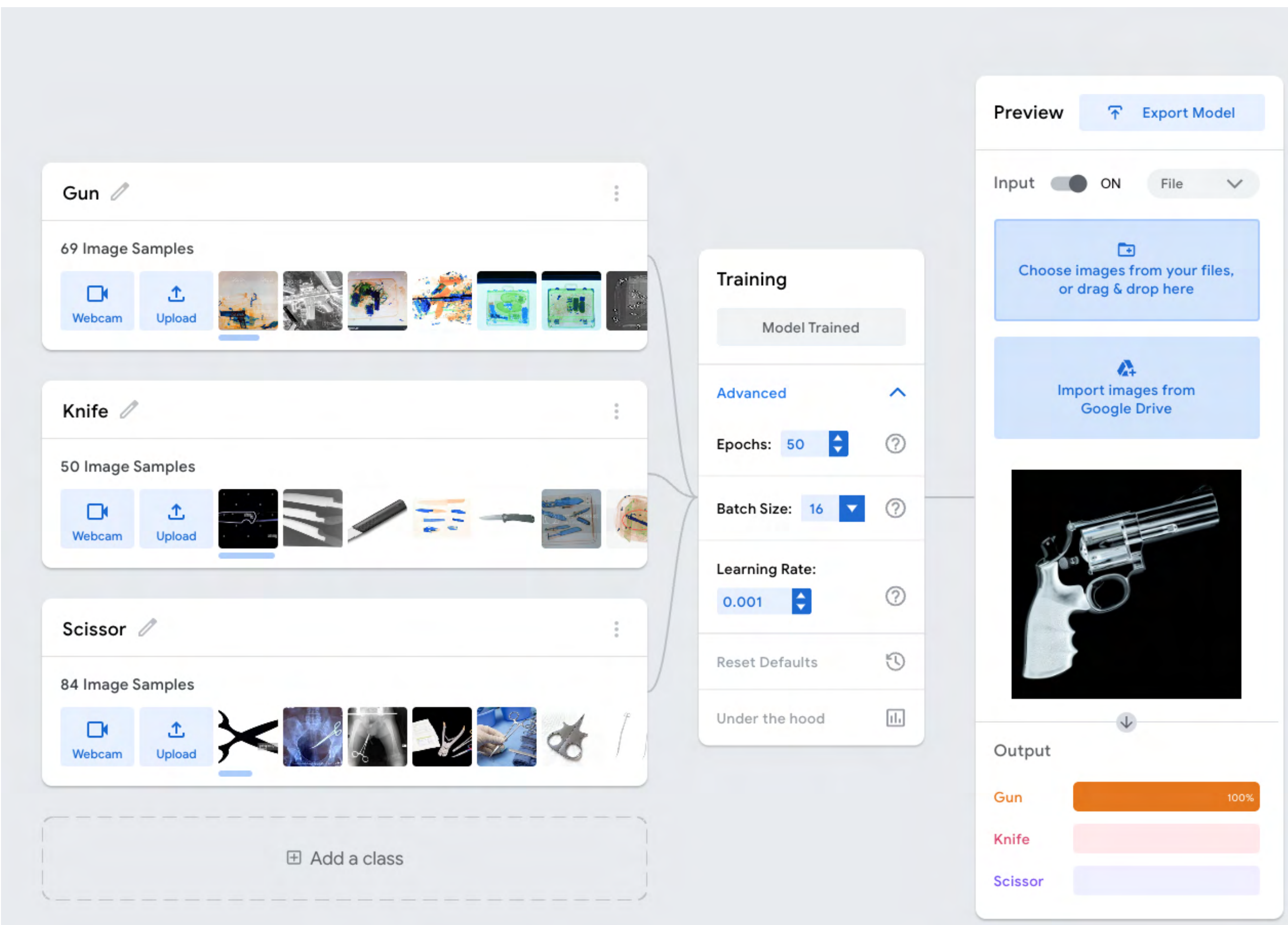


Testing Dataset: XraySet

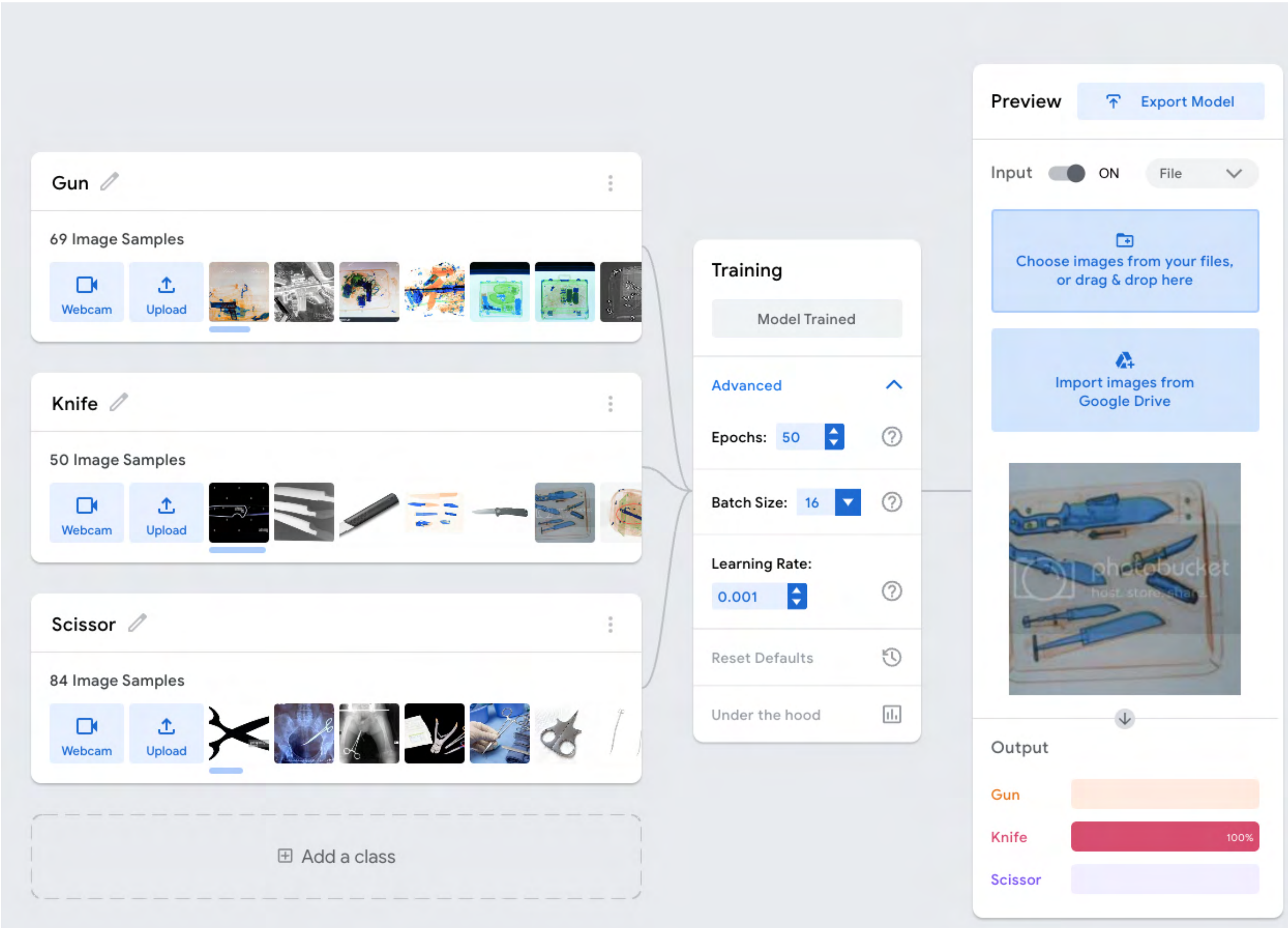
Dataset: XRaySet

Object Category	Number of Images
Gun	69
Hammer	70
Scissor	84
Knife	50

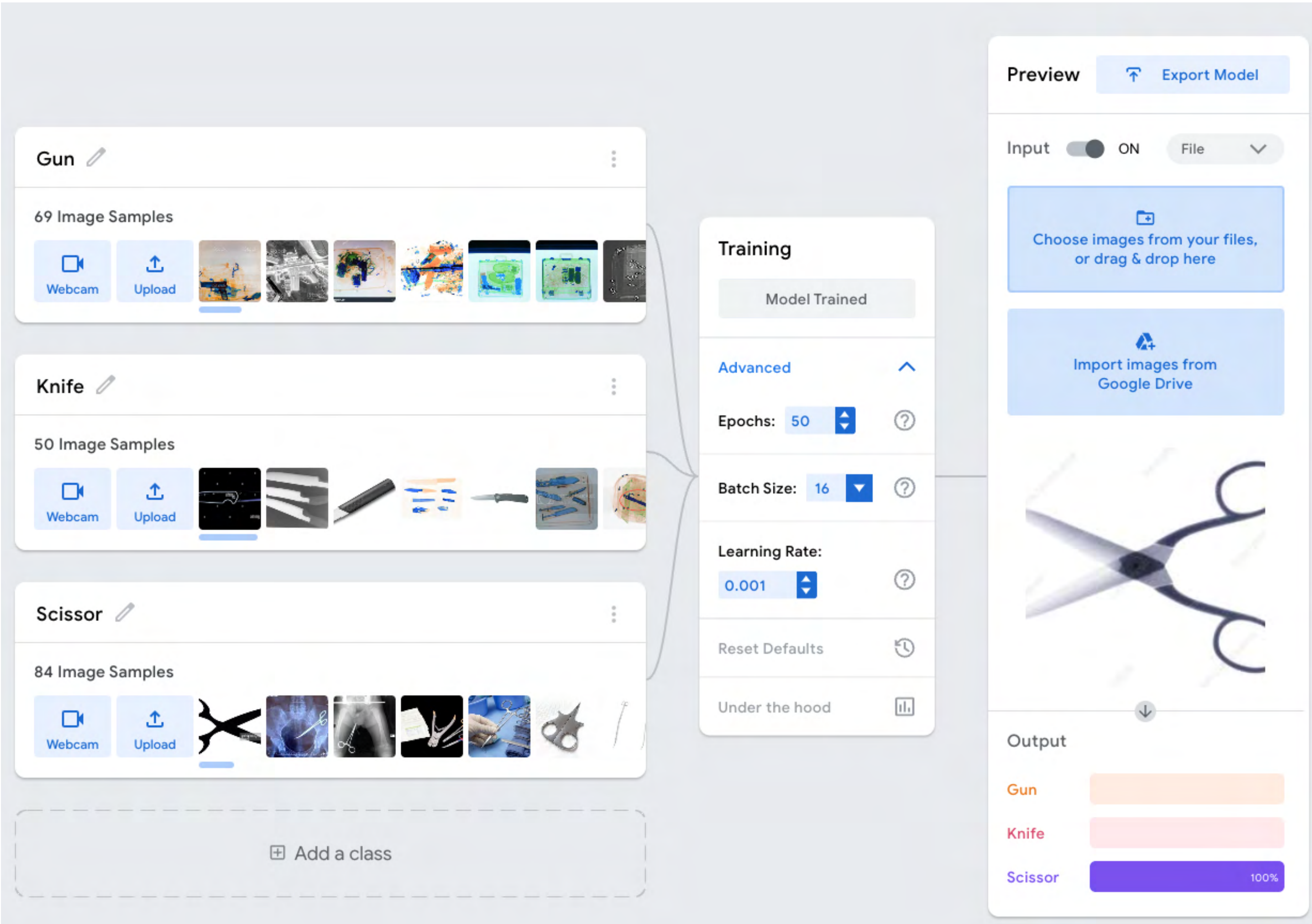
Test-1: Detect Gun



Test-2: Detect Knife



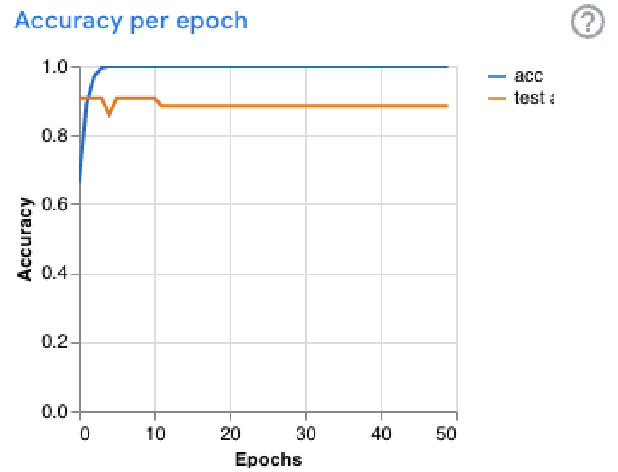
Test-3: Detect Scissor

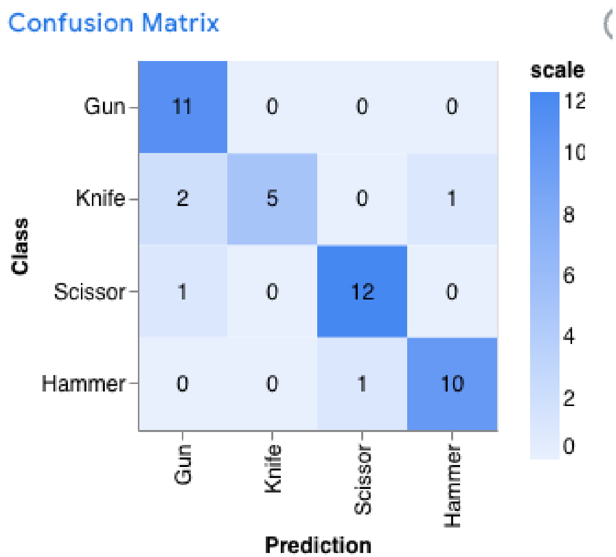


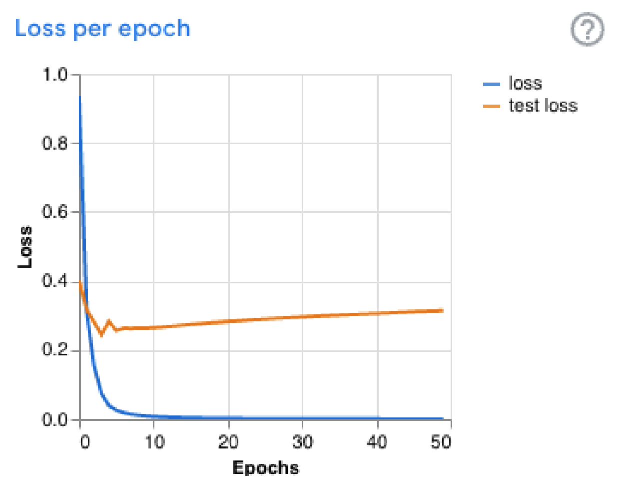
Test-4: Analyze Data Accuracy

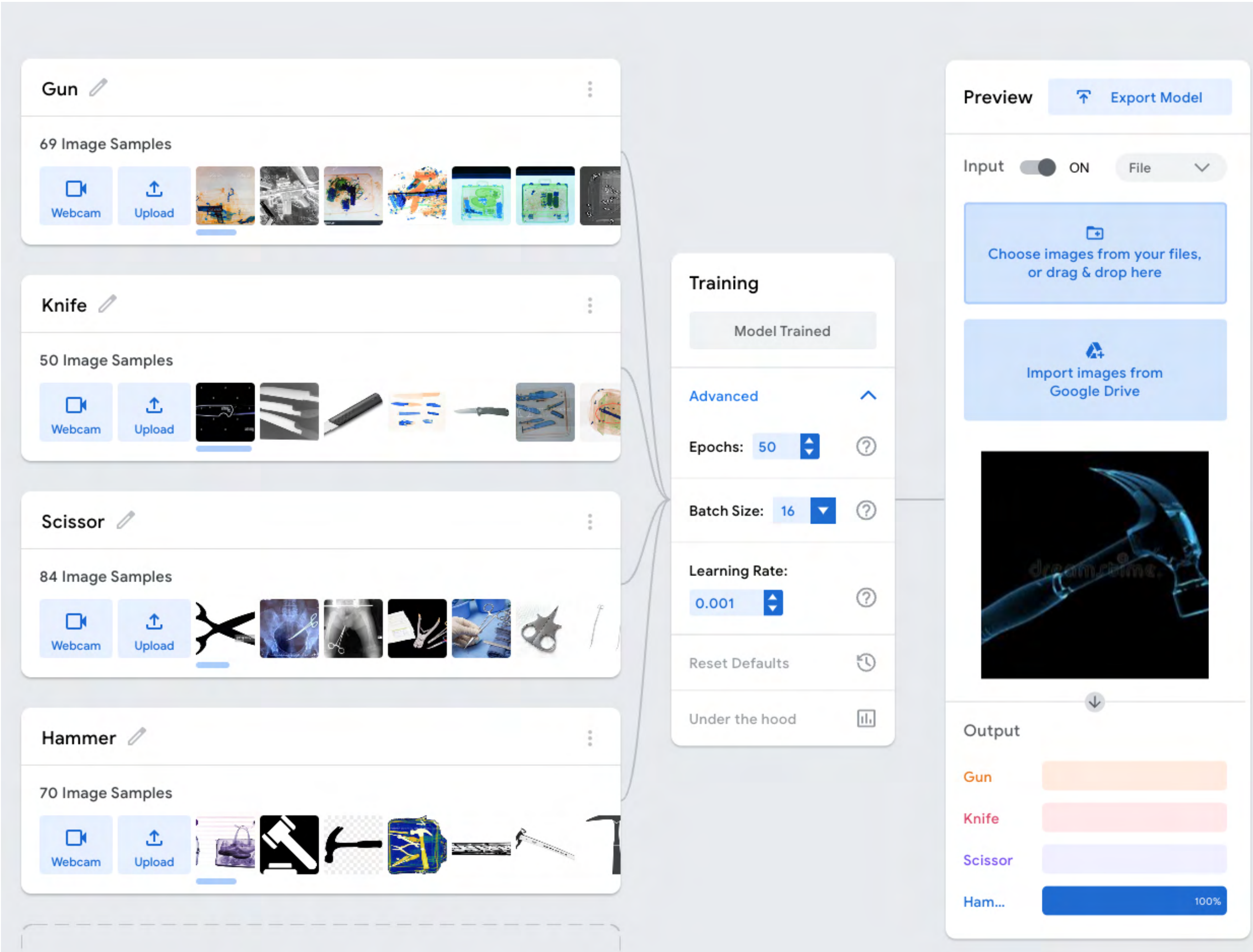
Accuracy per class

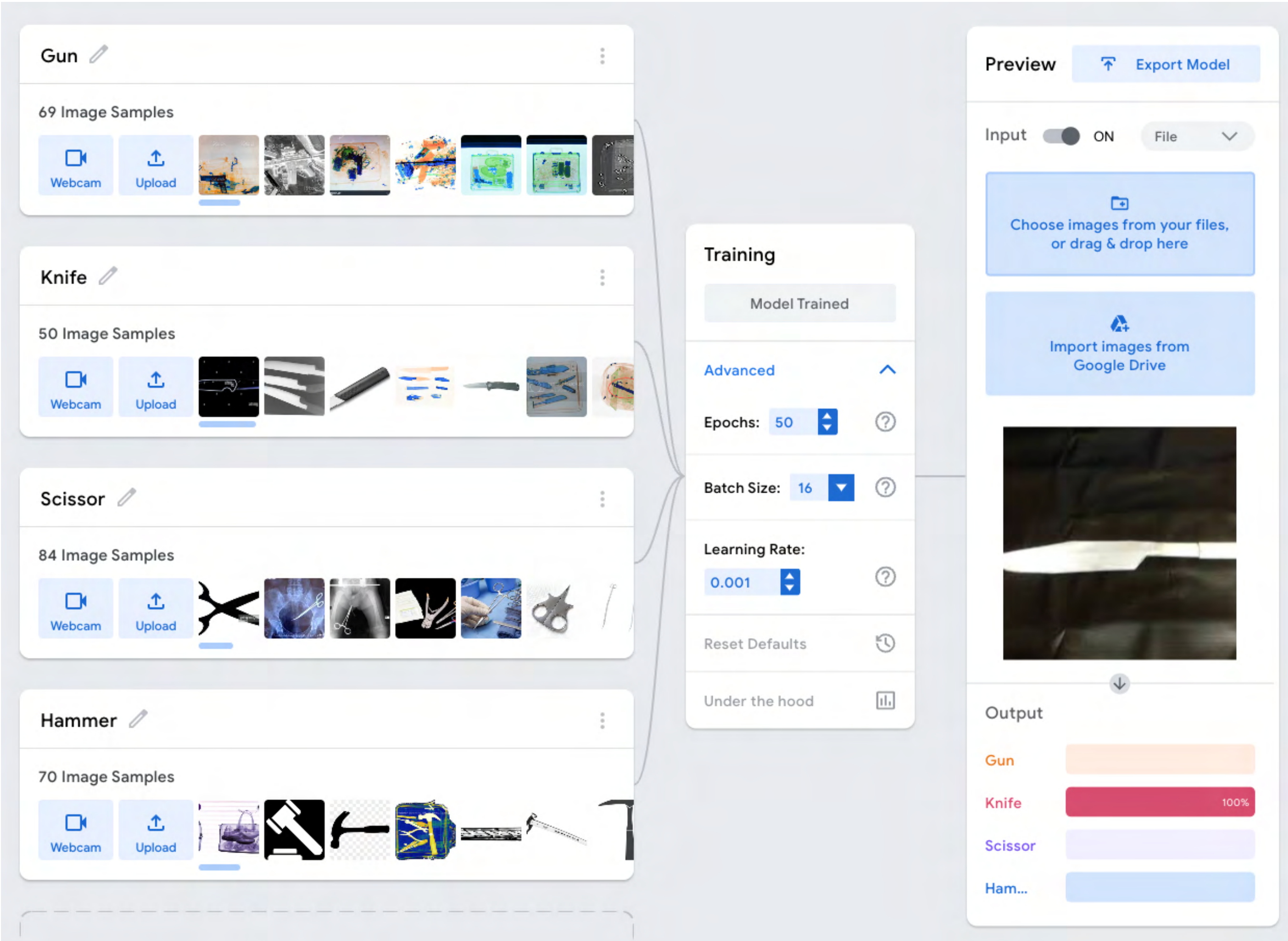
CLASS	ACCURACY	# SAMPLES
Gun	1.00	11
Knife	0.63	8
Scissor	0.92	13
Hammer	0.91	11

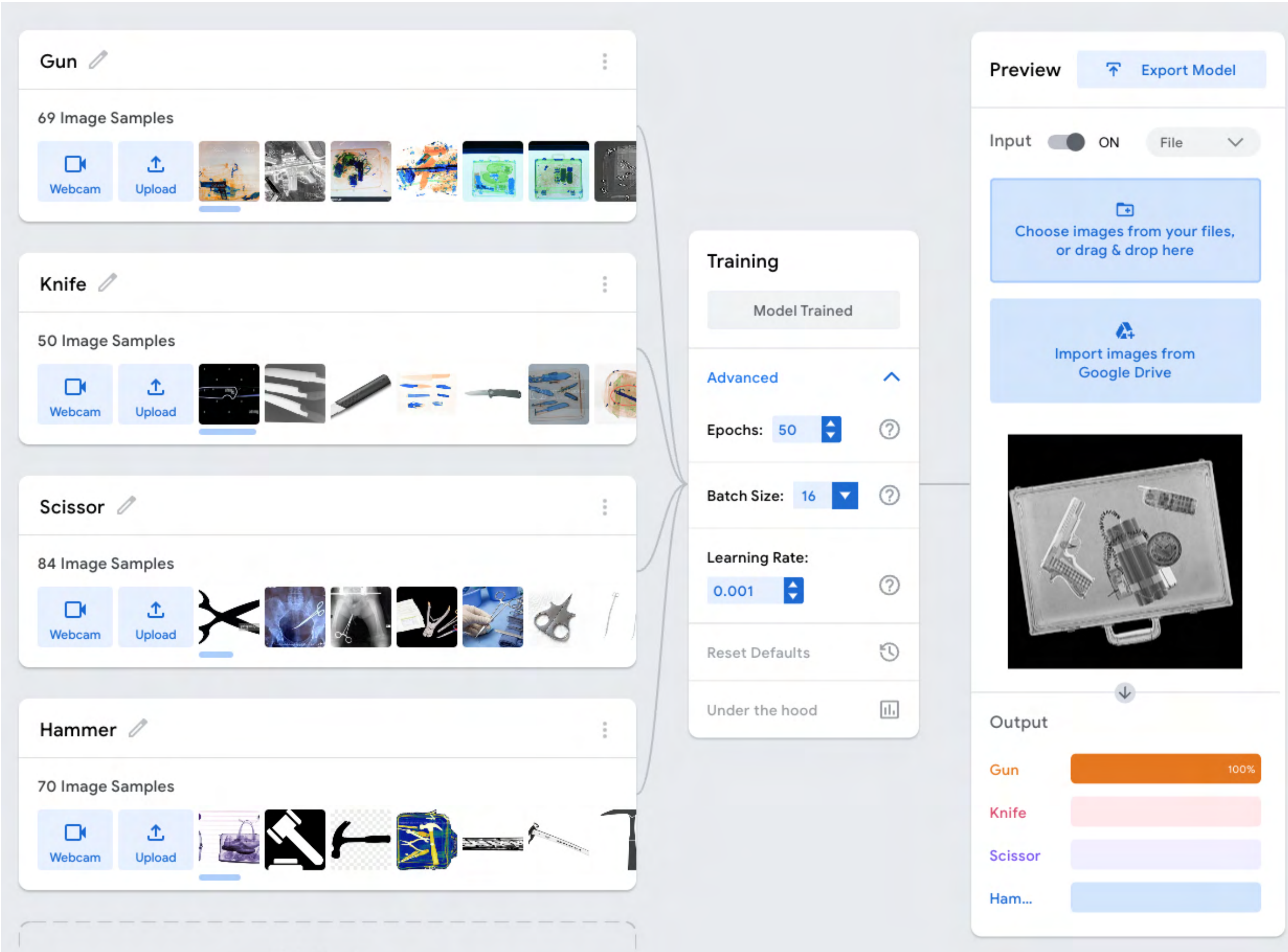







Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Epochs: 50
Batch Size: 16
Learning Rate:
0.001
Reset Defaults
Under the hood
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Gun
Knife
Scissor
Ham...
100%


Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Epochs: 50
Batch Size: 16
Learning Rate:
0.001
Reset Defaults
Under the hood
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Gun
Knife
100%
Scissor
Ham...


Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
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Batch Size: 16
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0.001
Reset Defaults
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Preview
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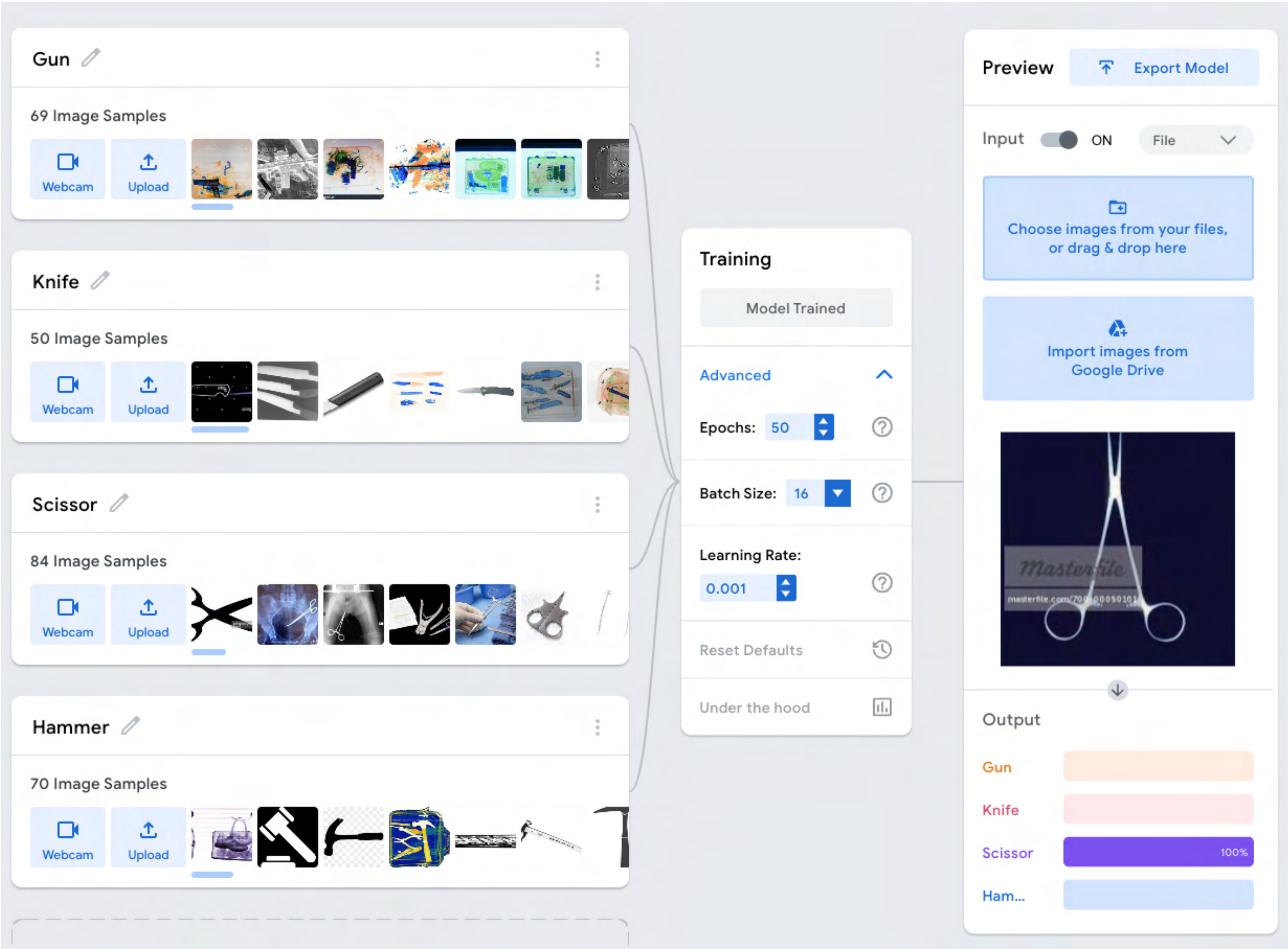
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Gun
100%
Knife
Scissor
Ham...



Gun
69 Image Samples
Webcam
Upload
Knife
50 Image Samples
Webcam
Upload
Scissor
84 Image Samples
Webcam
Upload
Hammer
70 Image Samples
Webcam
Upload
Training
Model Trained
Advanced
Epochs: 50
Batch Size: 16
Learning Rate:
0.001
Reset Defaults
Under the hood
Preview
Export Model
Input
ON
File
Choose images from your files, or drag & drop here
Import images from Google Drive
Output
Gun
Knife
Scissor
100%
Ham...

Google Drive to Web Service Conversion

www.drv.tw [Google Drive HTML file to Web service conversion]

Admin Panel

Congratulations!

In a moment, you will find links to your shared web pages below.

Your pages are cached by us for faster access. As a result, your edits may not be shown immediately. **After you change your content, you may press CTRL-F5 or SHIFT-F5 in your browser to refresh your page.**

Read the **DriveToWeb Docs** and learn about:

- **Blogging** with static generators;
- Using a **your own domain name** to build your branded website;
- Using a **CDN** to accelerate content access and provide security.

You can access this administrative panel when you sign in from **DriveToWeb**. This admin page is only visible to you, the owner of this cloud drive account.

Have a suggestion for improvement? **Tell us** by email. Please send us your generous **support**.

Your web pages

You can now share the following web pages to everyone. Click to open:

https://zqapw5vbkhe8rzarfujnsq-on.drv.tw/sst-02262022.html

Test Case Scenarios

We developed the following test plan to comprehend both the hardware and software aspects of our solution. In addition, we have developed a test plan for the web connection with the device at home to move, store and process the collected data for recommendations.

Setup

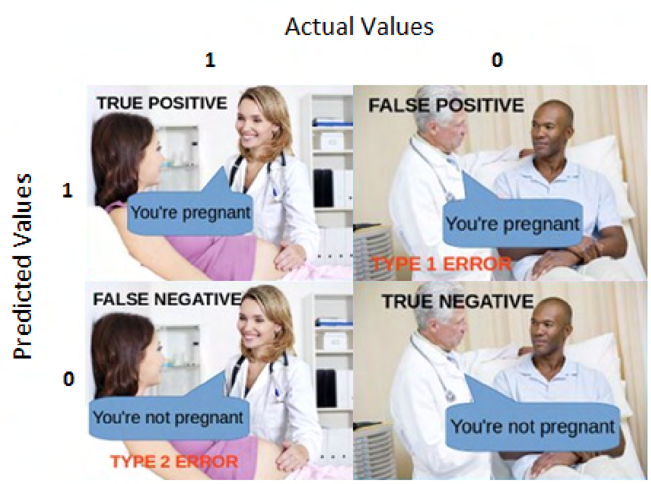
We extracted new images, one for each prohibited object category, and used them to test the accuracy of our models. We saved the extracted images with specific names to reflect their object type. For example, the test image for a gun is named as a gun-test-image, and the test image for a scissor was named a scissor-test-image. In the teachable machines, after the model was trained, we chose, upload test file option, to test the accuracy of each prohibited object.

Data Collection

Confusion Matrix

Confusion Matrix is a performance measurement for machine learning classification problems where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN



True Positive:

Interpretation: You predicted positive and it's true.
You predicted that a woman is pregnant and she actually is.

True Negative:

Interpretation: You predicted negative and it's true.
You predicted that a man is not pregnant and he actually is not.

False Positive: (Type 1 Error)

Interpretation: You predicted positive and it's false.
You predicted that a man is pregnant but he actually is not.

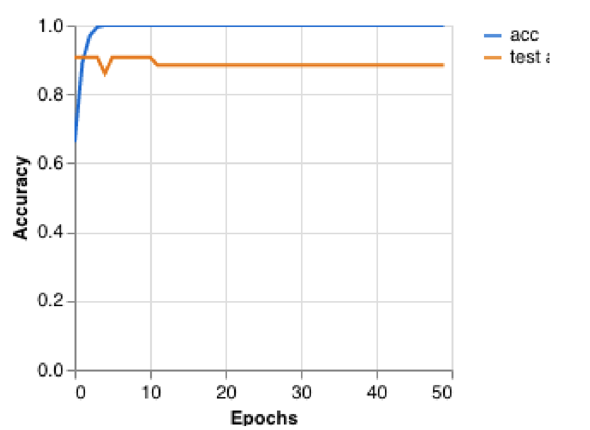
False Negative: (Type 2 Error)

Interpretation: You predicted negative and it's false.
You predicted that a woman is not pregnant but she actually is.

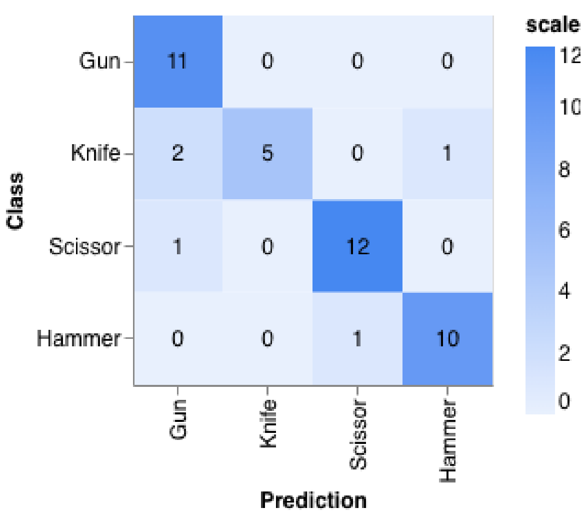
Accuracy per class

CLASS	ACCURACY	# SAMPLES
Gun	1.00	11
Knife	0.63	8
Scissor	0.92	13
Hammer	0.91	11

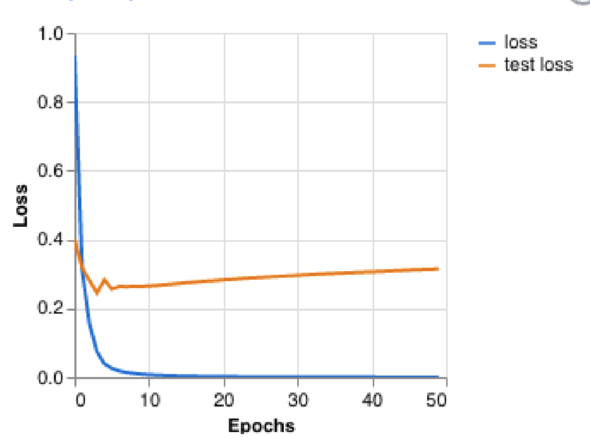
Accuracy per epoch



Confusion Matrix



Loss per epoch



Interpreting Confusion Matrix for Test-11

In our test data set of ~100 images in each prohibited object category,
Gun: There were 1 Scissor and 2 Knives that had somewhat similar properties of guns.
Knife: There were 0 knives that showed properties of other objects
Scissor: There was 1 hammer that showed properties of scissors
Hammer: There was one knife that showed properties of knives

For the test data set size of ours, the above confusion matrix is very good, and the corresponding training and testing accuracy confirms that the prediction accuracy for the four trained objects will be more than 80% correct.

Exporting Model as a Web Service

https://teachablemachine.withgoogle.com/models/qmQ5olrko/

```
<div>Teachable Machine Image Model</div>
<button type="button" onclick="init()">Start</button>
<div id="webcam-container"></div>
<div id="label-container"></div>
<script src="https://cdn.jsdelivr.net/npm/@tensorflow/tfjs@1.3.1/dist/tf.min.js"></script>
<script
src="https://cdn.jsdelivr.net/npm/@teachablemachine/image@0.8/dist/teachablemachine-image.min.js"></scrip
t>
<script type="text/javascript">
    // More API functions here:
    // https://github.com/googlecreativelab/teachablemachine-community/tree/master/libraries/image

    // the link to your model provided by Teachable Machine export panel
    const URL = "https://teachablemachine.withgoogle.com/models/qmQ5olrko/";

    let model, webcam, labelContainer, maxPredictions;

    // Load the image model and setup the webcam
    async function init() {
        const modelURL = URL + "model.json";
        const metadataURL = URL + "metadata.json";

        // load the model and metadata
        // Refer to tmImage.loadFromFiles() in the API to support files from a file picker
        // or files from your local hard drive
        // Note: the pose library adds "tmImage" object to your window (window.tmImage)
        model = await tmImage.load(modelURL, metadataURL);
        maxPredictions = model.getTotalClasses();

        // Convenience function to setup a webcam
        const flip = true; // whether to flip the webcam
        webcam = new tmImage.Webcam(1024, 1024, flip); // width, height, flip
        await webcam.setup(); // request access to the webcam
        await webcam.play();
        window.requestAnimationFrame(loop);

        // append elements to the DOM
        document.getElementById("webcam-container").appendChild(webcam.canvas);
```

```
        labelContainer = document.getElementById("label-container");
        for (let i = 0; i < maxPredictions; i++) { // and class labels
            labelContainer.appendChild(document.createElement("div"));
        }
    }

    async function loop() {
        webcam.update(); // update the webcam frame
        await predict();
        window.requestAnimationFrame(loop);
    }

    // run the webcam image through the image model
    async function predict() {
        // predict can take in an image, video or canvas html element
        const prediction = await model.predict(webcam.canvas);
        for (let i = 0; i < maxPredictions; i++) {
            const classPrediction =
                prediction[i].className + ": " + prediction[i].probability.toFixed(2);
            labelContainer.childNodes[i].innerHTML = classPrediction;
        }
    }
</script>
```

Testing Criteria

Explain how you tested your prototype or model. Be sure to include every step of your testing including all safety precautions that were taken. If not stated it will be assumed no safety precautions were taken. If you are using research to guess how your solution will work, explain step-by-step how it will work and why:

We tested every single component in our prototype for specific criteria. For the various security prohibited object categories, we followed procedures carefully using safety precautions. In the below sections we explain our testing criteria and constraints.

Criteria: Get the accuracy number of all prohibited objects close to 1.0 by varying the number of epochs, batch-size and Learning Rate values.

Dataset: XRaySet

Test #	Epochs	Batch-size	Learning Rate	Gun	Knife	Scissor	Hammer
1	10	32	0.001	1.00	0.75	0.77	0.73
2	50	32	0.001	0.82	0.63	1.00	1.00
3	100	32	0.001	0.82	0.75	0.92	0.82
4	200	32	0.001	1.00	0.88	0.85	1.00
5	500	32	0.001	1.00	0.75	0.92	0.82
6	1000	32	0.001	1.0	0.63	0.92	1.00

Dataset: OPIXRaySet [10 images per category]

Test #	Epochs	Batch-size	Learning Rate	Folding Knife	Utility Knife	Multitool Knife	Straight Knife	Scissors
1	10	32	0.001	0.00	0.50	0.00	0.50	0.00
2	50	32	0.001	0.50	0.00	0.00	0.00	0.00
3	100	32	0.001	0.00	0.00	0.00	0.00	0.50
4	200	32	0.001	0.00	0.00	0.00	0.50	0.50
5	500	32	0.001	0.00	0.00	0.50	0.00	0.00
6	1000	32	0.001	0.00	0.00	0.00	0.50	0.00

The accuracy of above models with 10 images per category did not result in acceptable accuracy levels.

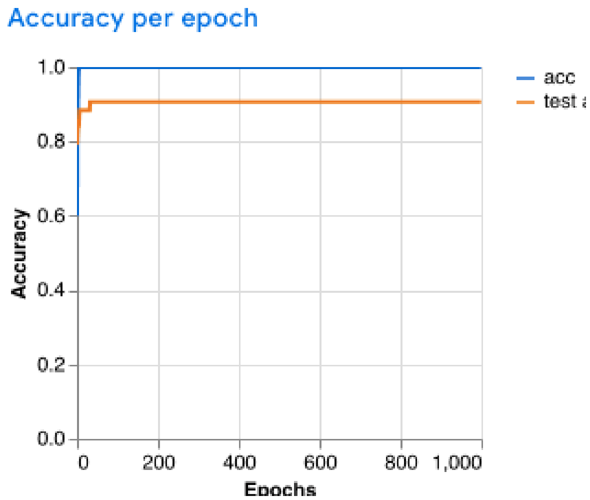
Dataset: OPIXRaySet [50 images per category]

Test #	Epochs	Batch-size	Learning Rate	Folding Knife	Utility Knife	Multitool Knife	Straight Knife	Scissors
1	10	32	0.001	0.00	0.25	0.13	0.13	0.25
2	50	32	0.001	0.25	0.25	0.38	0.38	0.13
3	100	32	0.001	0.25	0.13	0.13	0.50	0.38
4	200	32	0.001	0.38	0.25	0.25	0.13	0.13
5	500	32	0.001	0.25	0.25	0.50	0.25	0.25
6	1000	32	0.001	0.25	0.34	0.25	0.25	0.25

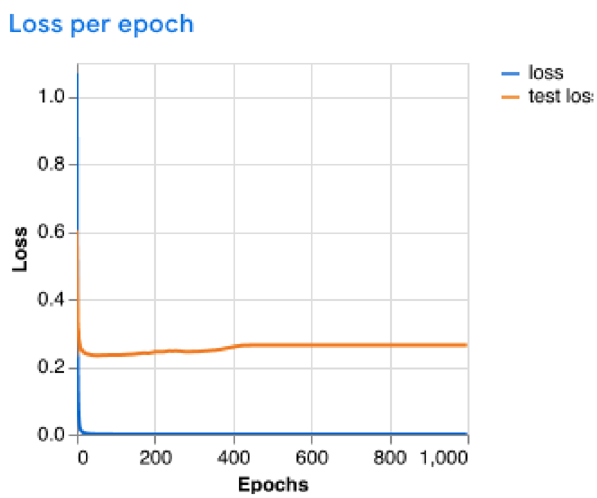
Data, Error Analysis and Charts

CLASS	ACCURACY	# SAMPLES
Firearm	1.00	11
Knife	0.63	8
Scissor	0.92	13
Hammer	1.00	11

For the four prohibited images category in the Xray-Set Dataset the 1000 epoch model resulted in the best possible accuracy for 3 out of 4 categories.

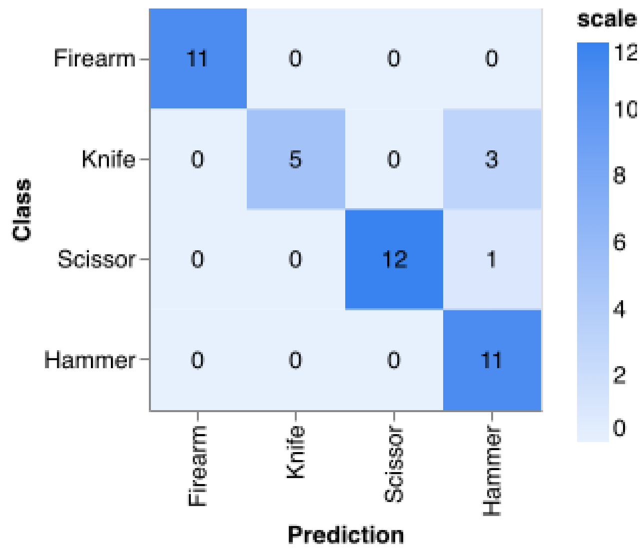


For the 1000 epoch test with Xray-Set Dataset the accuracy during the epoch increased steadily and stayed above 80% from the 25th epoch.



The training error loss for the 1000 epoch test run decreased steadily as expected from 60% during the first 5 epochs to below 0.25 as expected through epoch 1000.

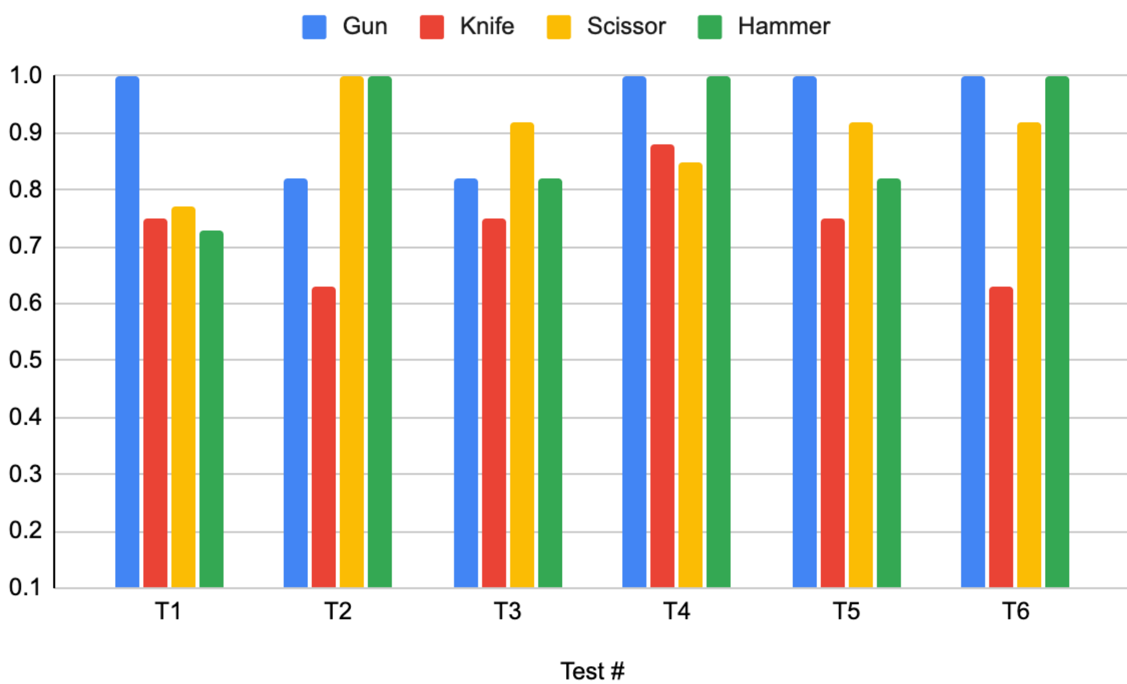
Confusion Matrix



With the tested Xray-Set Dataset the four prohibited object categories showed cleaner confusion matrix. For example, of the 11 Hammer images, 1 showed similar properties of a scissor and 3 images showed similar properties of a knife.

Outlier Error Ranges

Only Test T6 produced acceptable results of greater than 90% accuracy for 3 out of 4 object categories. Test T4 produced results of greater than 85% accuracy for all 4 object categories.



Errors

What problems did you find with your solution? Be specific since you will need to redesign based on these problems:

Our Smart-See-Thru solution should automatically detect the prohibited security objects at or above 80% accuracy levels to be usable, matching human expert accuracy levels.

For the two datasets we used, XRay-Set and OPIXray-Set we observed various accuracy levels of object detection based on the number of images that were in the two datasets for each object category, usually, higher the better.

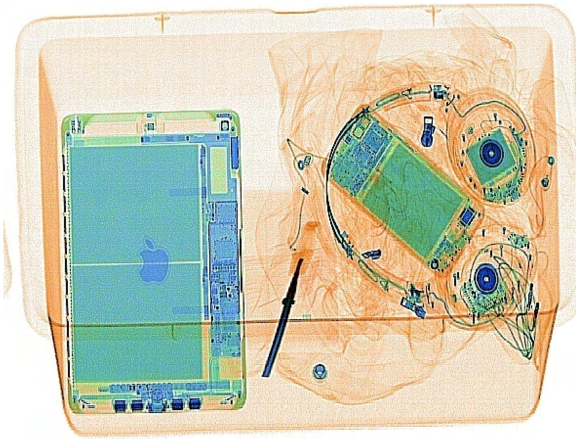
When we did not have more than 50 images in our sample dataset for each category, the object detection accuracy fell below 50%, which is unacceptable.

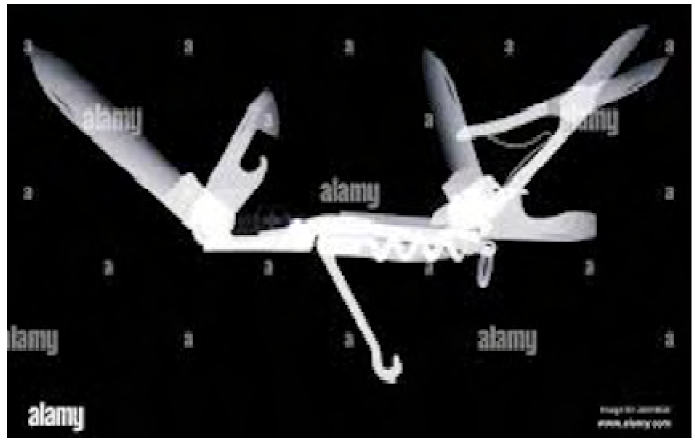
We increased the number of epochs, which is the test iteration for model training to offset for the lower quantity of images we had in specific object categories, however, that did not improve the overall object detection accuracy.

To minimize errors we redesigned the prototype by developing more than five machine learning models to pick the one that produced more than 80% accuracy for all four object categories.

Describe all of the changes you made to your prototype or model (or proposed prototype) after your first test. Why will these changes improve your solution?:

Problem-1: Poor Object Resolution of input images





Solution-1:

We gathered additional high resolution images for each prohibited object category and retrained the machine learning model, which improved the object detection accuracy.

Problem-2: Insufficient Training Data Samples

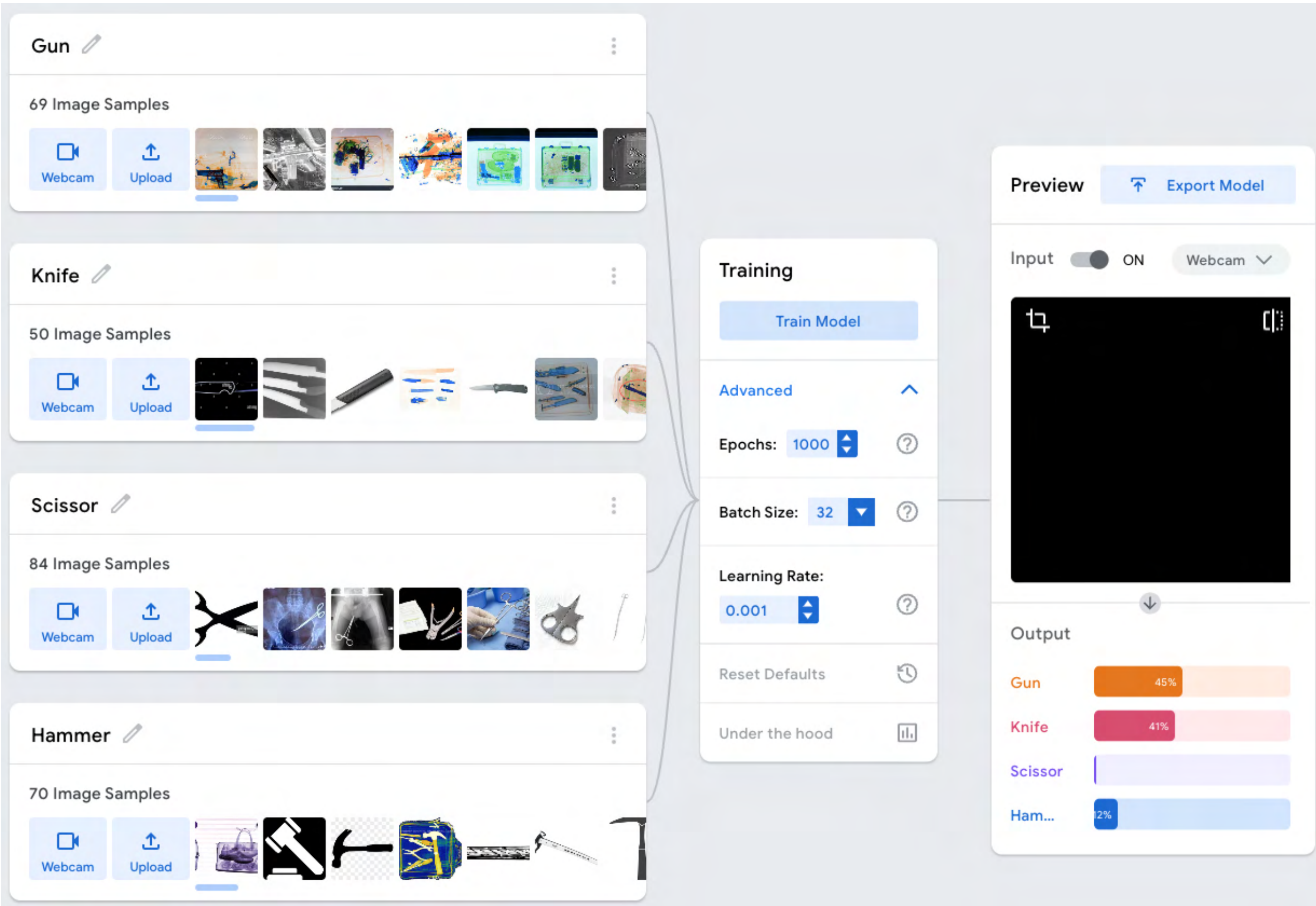
Test #	Epochs	Batch-size	Learning Rate	Folding Knife	Utility Knife	Multitool Knife	Straight Knife	Scissors
1	10	32	0.001	0.00	0.25	0.13	0.13	0.25
2	50	32	0.001	0.25	0.25	0.38	0.38	0.13
3	100	32	0.001	0.25	0.13	0.13	0.50	0.38
4	200	32	0.001	0.38	0.25	0.25	0.13	0.13
5	500	32	0.001	0.25	0.25	0.50	0.25	0.25
6	1000	32	0.001	0.25	0.34	0.25	0.25	0.25

For the OPIXRay-Set dataset, we trained machine learning models with 50 images per each object category. We realized, even at 1000 categories, the object detection accuracy was below 50% which was unacceptable.

Solution-2:

Increase the input dataset for each object type to maximum available, and set the number of epochs to more than 50 to increase the object detection accuracy levels to acceptable levels.

Problem-3: Web Camera Background Noise



Teachable machines by default use the web camera in the computer. When the image size of the prohibited object was smaller than the camera view area, it picked up additional objects in the background, thus negatively impacting the object detection accuracy for certain categories.

Solution-3:

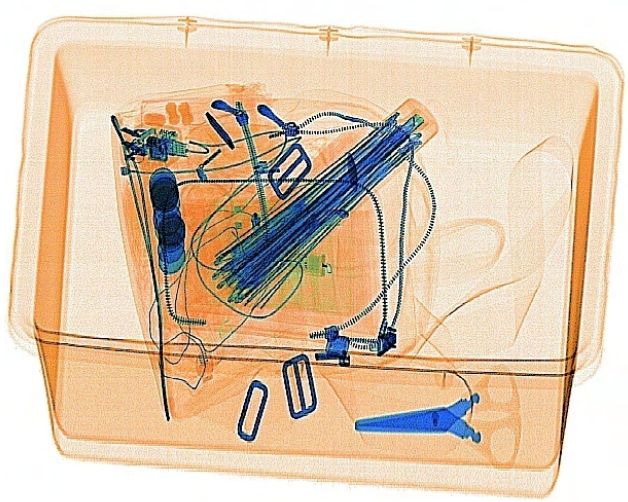
We used an external web camera and mounted it to a box to provide a clear background. This eliminated the background noise, and improved the object detection accuracy level.

Potential Sources of Error

What are your potential sources of error? Remember, this doesn't mean "Did everything work?", all tests have potential sources of error, so make sure you understand what that means. Explain how these sources of error could have affected your results:

We identified the following potential sources of errors:

- **Training Data Image Resolution**
  - When the resolution of the images in the input dataset is lower than recommended, the training accuracy dropped significantly
  - Each image in the training dataset should be at least 256x256 pixels with clearly visible prohibited objects in the X-ray image
- **Training Data Coverage**
  - When we did not have sufficient data samples for each object category, the machine learning accuracy was lower than desired
  - When we ensured each of the prohibited object categories has at least 50 images in their respective training dataset category, we were able to demonstrate more than 80% prediction accuracy
- **Lighting condition**
  - Without a consistent light source, the accuracy of the data set decreased
  - For low resolution images, the lighting source played a pivotal role in determining the accuracy
  - If the webcam is not recalibrated for the room lighting conditions, it can cause deviation in the prediction accuracy levels
- **Misclassified image set in the Training Dataset**
  - The Training dataset we had collected from research papers had multiple images with misclassified objects, for example, the image had a knife but was incorrectly tagged as scissor, and the image that had a scissor was incorrectly tagged as a gun. More misclassified we had in the Training dataset, the steeper the drop was in the object detection accuracy



Conclusion

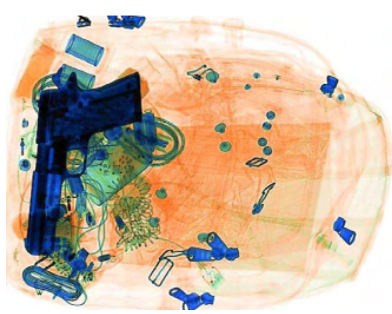
What conclusions can you draw based on the data you gathered during your tests?:

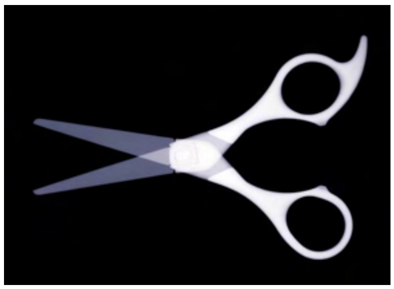
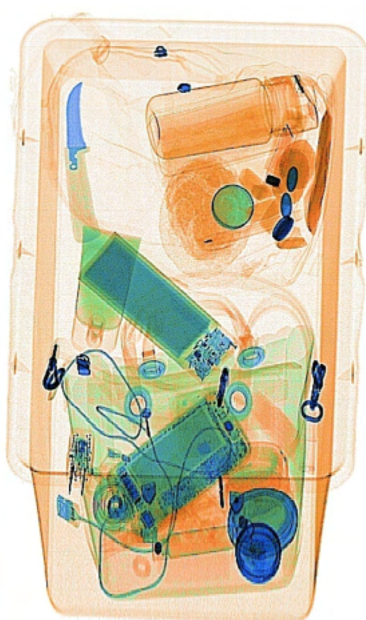
We set our hypothesis to prove or disprove, “can we offer a cost-effective and reliable method to detect security prohibited objects automatically at or above human expert levels?”. We scoped our research to specifically eight object categories: gun, knife, hammer, scissor, utility knife, straight knife, folding knife, and multi-tool knife.

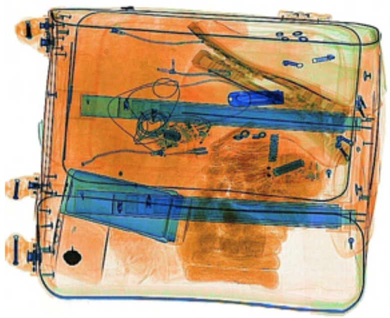
Using the freely available Machine Learning software and a web camera which cost less than $250 and the software we developed using Teachable Machines and Javascript on Windows or Mac computers (desktop/laptop) we proved that we can automatically detect security prohibited objects automatically in a cost-effective and reliable way, with accuracy levels above 70%.

Through experiments we conducted, we successfully concluded that for 7 out of 8 prohibited objects, our Smart-See-Thru solution was able to detect objects reliably with more than 70% accuracy levels. For the knife object, we were not able to increase the detection accuracy above 63% when tested at 1000 epoch level, but we believe, with the additional test images in our training dataset we can improve the object detection accuracy.

We successfully proved that the automated security prohibited object detection can be comparable to TSA human expert level audit accuracy, primarily because our solution relies on training computers to learn from human expert learnings and performs consistently, unlike humans who can be fatigued by looking at the X-ray computer screen for more than a few hours consecutively.

Object	**Image**	**Accuracy**	**Is prediction accuracy > 70%**
Gun		100%	YES

Knife		63%	NO
Scissor-1		92%	YES
Hammer		100%	YES
Utility Knife		82%	YES

Folding Knife		73%	YES
Straight Knife		23%	NO
Multi-Tool Knife		83%	YES
Scissor-2		90%	YES

We have successfully proved that seven out of eight object categories can be supported reliably and cost-effectively using our “Smart-See-Thru” solution. As a next-step, we plan to increase our test coverage to multiple additional objects and also invest more in our software application development to improve the prediction accuracy. Subsequently, we plan to expand coverage to additional prohibited objects such as lighters, bombs, etc.

Community Benefits

Explain how investigating the problem your team chose will help the community. Be sure to include the impacts your research will have on individuals, businesses, organizations, and the environment in your community (if any). Make it very clear why solving this problem would help your community:

Lower Security Inspection Cost: TSA continues to invest Billions of US dollars in improving security checks. Smart-See-Thru solution uses Artificial Intelligence and Machine Learning techniques to detect prohibited items reliably and cost-effectively for less than $250. This can be integrated with existing security scanners at the airports, to augment TSA professionals, thus reducing the number of required TSA professionals at the security gate.

Improved Airport Passenger Safety: According to the Transportation Security Administration (TSA), nearly 2 Million passengers, 5.5 Million Carry-on items and 1.4 Million checked items are screened daily. The number of Firearms detected at security checkpoints per million passengers traveled annually has been consistently increasing year over year. In 2015, a study conducted revealed that 95% of security trials failed to detect firearms at dozens of the nation's busiest airports. Smart-See-Thru solution detects 7 different prohibited objects at human expert or above level accuracy reliably and consistently, thus improving passenger safety and transportation security.

Faster Security Checks at Airports: According to Times, in 2021, nearly 70,000 passengers, including some of our team members, missed flights due to long security lines. Our fully automated Smart-See-Thru solution offers a reliable method to accelerate security checks at the airports.

Historic data collection and analysis: Another major benefit of our solution is that it allows the TSA professionals to add newly identified prohibited objects to the training dataset, and to retrain the machine learning model to improve the accuracy levels. By monitoring and providing history of various detected prohibited objects, we have the opportunity to improve the automated object detection accuracy levels.

Improved Transportation Security: Our Smart-See-Thru solution can be deployed at any Transportation security checkpoints, air, sea, road. Additionally, other places, such as shopping malls, hospitals, government offices, schools etc can also benefit from deploying our solution to improve the overall national security.

Cost-Benefit Analysis Projection

Assumptions

Data	Figures	Source
Number of Passengers in a given day (US)	2,000,000	www.tsa.gov
Number of Passengers missing flights due to long security lines (annually)	70000	https://time.com/4349766/airline-70000-passengers-missed-flights-due-to-security-lines/
Total cost of Delay (US, annual)	$33B	Derived from Cost of delay estimates, FAA study, 2019 (4 key causes: Flight delays, cancellations, schedule buffers, missed flights/connections)
Total cost of Delay - Passenger cost (US, annual)	$18.1B	
Total cost of Delay - Passenger cost due to missed flights (US, annual)	$4.5B	
Total cost of Delay - Passenger cost due to missed flights from long security lines (US, annual)	$226M	Derived from https://www.thetravel.com/16-most-common-reasons-travelers-miss-flights-7-not-so-common/, https://skyrefund.com/en/blog/ten-reasons-for-flight-delays
Total cost of Delay - Passenger cost due to missed flights from long security lines (US, annual) / Passenger	$3,232	Derived from above assumptions; These include change/rebooking fees and cost of time lost
Passenger traffic growth (US, Domestic, past 10 yrs - pre pandemic)	3%	Derived from https://www.statista.com/statistics/197790/us-airline-domestic-passenger-enplanements-since-2004/
Earliest time frame by which the solution can be implemented	2023	
% reduction in passengers missing flights due to long security lines after implementation of Smart See Thru solution	5-25%	We expect as we mature the solution, at-least 10-25% reduction in number of passengers missing flight due to long security lines in 3 years

Model

Summary

Cost		
Prototype Cost	$223	
Implementation Cost (at each airport)	TBD	To be analyzed as part of next steps
Deployment Cost (at each airport)	TBD	To be analyzed as part of next steps
Testing Cost	TBD	To be analyzed as part of next steps
Training Cost	TBD	To be analyzed as part of next steps
Maintenance Cost	TBD	To be analyzed as part of next steps
Benefits		
Conservation Roll Out Scenario	$25M	
Aggressive Roll Out Scenario	$80M	

References

Research your problem. You must learn more about the problem you are trying to solve and also what possible solutions already exist. Find AT LEAST 10 different resources and list them here. They should include books, periodicals (magazines, journals, etc.), websites, experts, and any other resources you can think of. Be specific when listing them, and do not list your search engine (Google, etc.) as a resource:

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