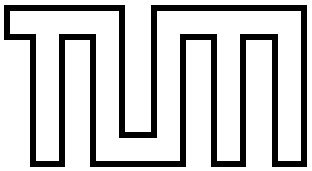

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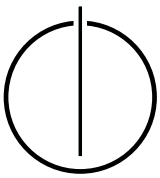
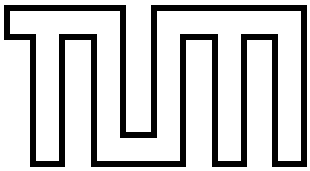
Bachelor's Thesis in Informatics

Implementing a Mobile App for Object Detection

David Drews





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Implementing a Mobile App for Object Detection

Entwicklung einer mobilen App zur Objekterkennung

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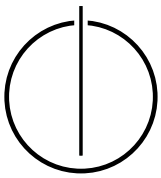
Submission Date:	15th of August 2021



I confirm that this bachelor's thesis is my own work and I have documented all sources and material used.

Munich, 15th of August 2021 David Drews

Abstract

We migrate the entire code base of the Android application TUM-Lens from Java to Kotlin. This facilitates the future development of the app as it makes the code more concise and error-proof. We elaborate on further advantages of the Kotlin language over Java and analyse how this migration lowered the lines of the existing code. Moreover, we expand the functionalities of the app by an object detection feature based on Google's open source deep learning framework TensorFlow Lite. The implementation follows in the previous TUM-Lens developer's footsteps and integrates the object detection to work entirely on-device so that no data needs to be exchanged with external servers. On the object detection theory side, we distinguish object detection from other visual machine learning tasks and survey a selection of modern deep learning architectures - both for backbone and detector networks. In addition, we study the mechanics of a specific model, the SSD MobileNet v1, as this is the model applied to the object detection task in TUM-Lens. This thesis expands Maximilian Jokel's previous work *Implementing a TensorFlow-Slim based Android app for image classification* (2020).

The repository containing the source code belonging to this thesis can be found here: `https://gitlab.lrz.de/dvrws/lens`

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Part I.

Introduction and Background Theory

1. Motivation

The aim of this work was to further develop the Android app TUM-Lens [17]. Its core function is the analysis of images that are captured by the camera of the Android device and transmitted to the app as a live feed. With the completion of this work, the pre-existing image classification capabilities of the app are now complemented by object detection.

For an optimal user experience, the analysis of the images must take place in near real time. This is the only way to ensure that the analysis results displayed always match the current content of the camera feed, which can change quickly due to panning of the camera by its user. While in many applications the analysis of image data can take place decentrally in powerful data centres, in the case of TUM-Lens the image analysis runs on the mobile device itself.

1.1. Growing Support for On-Device Machine Learning

Support for the development of machine learning (ml) and also, in particular, deep learning applications for mobile platforms is growing steadily and from different directions at the same time. Developer-friendly frameworks such as TensorFlow[1], developed by Google Brain, or PyTorch[2], developed by Facebook's AI Research Lab, are among the best-known deep learning frameworks [11]. The releases of TensorFlow Lite[3] 2017 [44] and PyTorch Mobile[4] 2019 [32] show that mobile platforms increasingly come into focus of companies providing machine learning software. In recent years, device manufacturers and operating system developers also started to provide dedicated hardware and software components for mobile machine learning. Examples include Apple's Neural Engine [45], unveiled in 2017, or Android's Neural Networks API (NNAPI) [6]. Apple's Neural Engine is a hardware component optimised for machine learning requirements. Android's NNAPI, on the other hand, is an Android C application programming interface (api) for efficient computation of ml operations and provides a basic set of functions for higher-level ml frameworks. As a result of these developments, it is becoming easier for developers to build ml applications that run efficiently on mobile devices. This support was a major catalyst for the initial and further development of TUM-Lens in the context of two bachelor theses.

1.2. Offline Usability

TUM-Lens is more independent compared to many other machine learning based apps as it does not require an internet connection to use it. Often, apps and services require a

[1] `https://www.tensorflow.org/`
[2] `https://pytorch.org/`
[3] `https://www.tensorflow.org/lite`
[4] `https://pytorch.org/mobile/home/`

connection to the internet because of the nature of the task they are meant to perform. The Amazon voice assistant Alexa can answer simple voice commands to control smart home devices or check the time without having access to the world wide web and thus already uses on-device machine learning. But even if Alexa could analyse and understand all voice commands locally, the request would still have to be forwarded to the Amazon servers in most cases. Because of the large number of possible queries, not all answers can be kept on the device, but must be retrieved from a data centre that has more storage capacity. Such queries include daily topics such as the weather report, traffic or the result of a sporting event. However, an internet connection is not required to use the full range of functions of TUM-Lens. All the information needed for image classification and object detection is stored locally on the device in the form of various already trained artificial neural network (ann). With the integration of the corresponding mobile frameworks, the image analysis can therefore be carried out locally on the device, making the app independent of an internet connection.

1.3. Improved Privacy

Using on-device ml provides a further mechanism for protecting personal data in the context of machine learning besides existing methods, such as differential privacy. Due to the growing support for mobile ml applications mentioned above, but also because of the continually increasing power of mobile devices [12], not only the use of pre-trained anns becomes possible, but also the training of new anns on the mobile device itself becomes more and more feasible and relevant [27]. If the training process takes place locally on the device itself, no data needs to be transferred to external instances, such as a company's servers. This makes it possible to develop applications that adapt more and more individually to the user as they are used, while guaranteeing a maximum level of data protection. An example of the development of such an application is DeepType [47]. DeepType attempts to predict the next word used when the user enters the keyboard. While every user initially starts with the same pre-trained version of the ann used by DeepType, the application continues to train this ann with each input and thus adapts more and more to the characteristic input behaviour of the user - all without the text inputs ever leaving the device.

2. Important Concepts

It is nearly impossible to imagine our everyday life without the use of the term machine learning. The multitude of contexts in which machine learning is spoken of - some justifiably and some unjustifiably - makes it important to create a common understanding of some machine learning-related concepts used throughout the theoretical chapters of this work. Therefore, we first introduce the term machine learning and explore a common and helpful division of the machine learning field into different subdomains. Next, we explain the concept of an artificial neural network followed by the description of a deep learning, a special class of both machine learning (ml) as a discipline and anns as a type of data processing tool.

2.1. Machine Learning

A popular definition of machine learning is attributed to Arthur Samuel describing it as the "field of study that gives computers the ability to learn without being explicitly programmed"[1]. machine learning algorithms circumvent this need for explicit programming by improving an internal model through data. This process is called training and the data used to train the model is often regarded to as the model's experience [29]. As depicted in figure Figure 2.1, ml can be divided into the subfields supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning.

2.1.1. Supervised Learning

In supervised learning, the learning machine is provided with input data as well as the output that is expected for the given input [21]. In the classical example of spam filtering, the input can be a collection of emails and the expected output is a label attached to each email that either classifies it as spam or as non-spam. The learning machine is then fed all e-mails as input data and learns to recognise which information in the input is important to produce the correct classification. As the system knows the correct answer for each training input, it can process an email, predict whether or not it is spam, and then use the known answer to change its structure in a way that will make it more likely to lead to a correct prediction and less likely to lead to a false prediction the next time it is presented with similar input (more on this adaptation process in Section 2.2).

[1] Althought cited in popular machine learning material like Andrew Ng's ml course at Stanford [30] the quote appears neither in Samuel's 1959 [36] nor his 1967 paper [37].

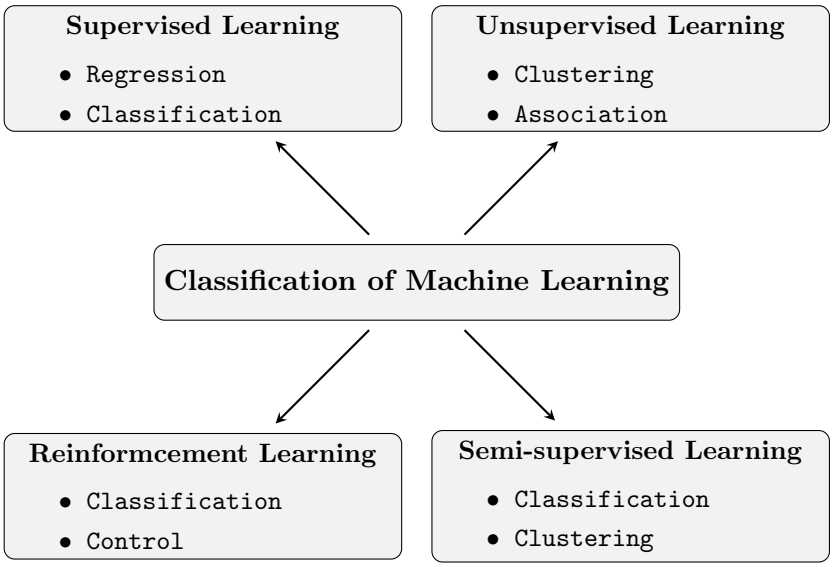


Figure 2.1.: The field of machine learning divided into subfields by the characteristics of the underlying learning process. Also indicates the learning problems that are typically tried to be solved by applying the respective learning process.

2.1.2. Unsupervised Learning

Detecting hidden patterns and structuring data is where unsupervised learning comes into play. Learners of this type do not need to be provided with an expected output while being trained [38]. A scenario for the application of unsupervised learning is the problem of dividing a customer base into subgroups in order to treat every subgroup according to their specific needs. An employee might help the machine learning system by providing the number of subgroups she wants the system to generate. The learner then builds up its representation of the internal structure of the entire data set with every input it processes. After having processed enough customers, it will most likely have identified the key metrics that distinguish customers into the different groups.

2.1.3. Semi-Supervised Learning

One use for semi-supervised learning is cluster analysis, which was already used as an example in the previous paragraph. In the case of semi-supervised learning, the system no longer has to work out the different groups (also known as *clusters*) from the unlabelled data alone. Instead, it can use a small set of already labelled customers as a reference and build its internal representation of the entire dataset (labelled and unlabelled) around the clusters indicated by the pre-labelled data. This is especially useful because in many domains, collecting or creating labelled data is difficult, expensive, or both [49].

2.1.4. Reinforcement Learning

Reinforcement learning is "learning what to do - how to map situations to actions - so as to maximize a numerical reward signal" [42]. Systems are trained via reinforcement learning to

learn how to behave in dynamic environments. The tasks in these environments can stretch from playing a video game [46] to driving an autonomous car [35]. These exemplary tasks show two characteristics that distinguish reinforcement learning from the other subfields of ml: The reward signal is often delayed and attribution to single actions is difficult. Only once a game is won or the car has arrived safely at its destination the system knows if all the decisions it made along the way lead to a positive outcome. *Trial-and-error* is therefore a term that summarises this learning paradigm quite precisely.

2.2. Artificial Neural Networks

An artificial neural network - often just referred to as neural network - is a data processing concept that is inspired by biological neurons and their interconnectivity. As figures Figure 2.2 and Figure 2.3 show, the artificial neurons (also called *nodes*) in an ann are grouped in *layers*. There are three important types of layers: The *input layer*[2], the *output layer* and an arbitrary number of *hidden layers* in between the input and output layer. Similar to neurons in human brains, nodes of different layers can be connected. In anns, the nodes exchange signals in the form of numbers. Each node outputs a number that is computed by applying a non-linear function to its inputs. The output signal can then be a new input for other nodes, or it can be part of the result returned by the output layer. The connections between nodes are also known as *edges* and typically carry a weight. When a signal travels from one node to the next, it is typically multiplied and thereby changed by the weight of that edge. With anns, the training process that is typical for all machine learning systems is the adjustment of these connection weights. The weights and other variables of the ann are grouped under the term *parameters*. In summary, an ann transforms an input vector into an output vector through a series of non-linear functions, where both the calculation of the output and the training process are characterised by the specific structure of the ann and its parameters.

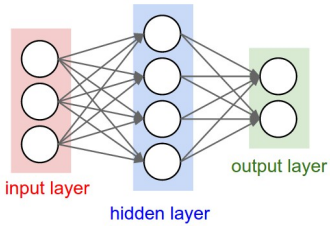


Figure 2.2.: 2-layered ann. It is called fully connected as every node from the previous layer is connected to every node in the next layer.
Source: [22]

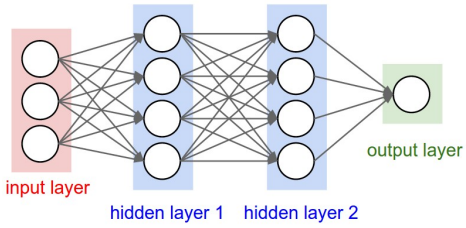


Figure 2.3.: 3-layered ann. In anns, nodes in one layer are connected to nodes in other layers but not to other nodes in the same layer.
Source: [22]

[2]Note that the input layer is usually not counted towards the total number of layers in an ann.

2.3. Deep Learning

Deep learning is a subarea of machine learning. Deep learning is characterised by the use of anns with many hidden layers. The more hidden layers a network has, the deeper it is. The deeper a network is and the more nodes the network has per layer, the more complex the computations that the ann can successfully perform [10]. As the number of layers and nodes grows, so does the number of parameters. Their large number is the reason deep learning requires extensive amounts of data to provide adequate results compared to other sub-disciplines of machine learning. Networks of this genus have the ability to perform extraordinarily complex computations at the expense of a resource-intensive training process.

3. Object Detection

The field of computer vision (cv) encompasses numerous distinct problems and an even larger number of potential solutions. In the following, object detection as a typical task in the cv context is distinguished from other cv tasks that are closest to it in terms of learning objectives. We then give an overview of a selection of modern object detectors, including their internal structures and differentiating factors. We close this chapter with a description of the model applied to the object detection task in TUM-Lens.

3.1. How Object Detection Differs from Related Tasks

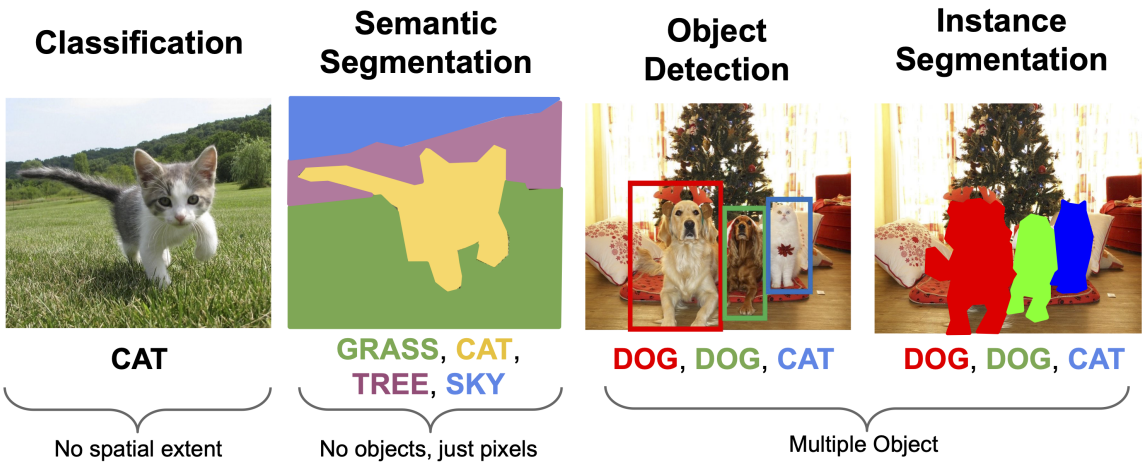


Figure 3.1.: Object detection differs conceptually from other related cv tasks regarding spatial information, the concept of objects and the number of detections in a scene.
Source: [23]

3.1.1. Semantic Segmentation

In semantic segmentation, each pixel of an image is assigned a class. However, there are no objects. This means that if there are several objects of the same class in the image, all the associated pixels receive the same class label. Therefore, the different objects cannot be distinguished based on the result of the semantic segmentation.

3.1.2. Image Classification

In image classification, the result of the detection is a single class. In rare application variants, a bounding box for one object of the detected class is also returned - as a rule, however, no spatial extent is associated with the task of classification.

3.1.3. Object Detection

Object detection deals with the identification of any number of objects within an image. For each object, a class label and its position are returned as the coordinates of a rectangle enclosing the object. It is noteworthy that, as depicted in Figure Figure 3.1, several objects of the same class can also be recognised. Contrary to semantic segmentation, the different objects of the same class can be differentiated.

3.1.4. Instance Segmentation

The instance segmentation essentially fulfils a better variant of the object detection. Again, several objects of different classes are detected and the positions of the classes are also part of the output. However, the positions are not marked by bounding boxes as in object detection, but each pixel belonging to an object receives a label of this object. The objects are therefore even more sharply separated from the image areas that do not contain an object and, in contrast to semantic segmentation, individual objects of the same class remain distinguishable.

3.2. Object Detection Frameworks

State-of-the-art object detection frameworks run predominantly on deep learning architectures [2]. The bachelor's thesis preceding this work, *Implementing a TensorFlow-Slim based Android app for image classification* [18], already explains how convolutional neural networks (cnns) work and why they are the most important building blocks for deep learning frameworks solving perceptual tasks. This explanation will therefore not be pursued here once more. Instead, we survey a range of modern object detection frameworks. Each framework is defined by the combination of a backbone and a detector. Table Table 3.1 shows a selection of popular detectors. The selection was not put together at random, but is based on popularity and performance in standard object detection benchmarks [4].

backbone	first publication	detectors
AlexNet	2012 [20]	HyperNet [19]
VGG-16	2014 [40]	PFPNet-R512 [K]
GoogLeNet	2014 [43]	YOLOv1 [33]
ResNets	2015 [13]	BlitzNet512 [8], CoupleNet [50], RetinaNet [26], Faster R-CNN [34]
MobileNet	2017 [16]	SSD [28]

Table 3.1.: Overview of a few modern cnn backbone networks and detectors that build upon them. The number of backbones and detectors is steadily increasing because existing architectures get improved over time or entirely radically new architectures are invented.

3.2.1. Backbones

The term *backbone* in the context of anns might be used differently depending on the task pursued. In the case of visual tasks and this thesis, the backbone is the part of an object detection framework that extracts features from the input data. This encapsulation of the feature extraction task in its own set of cnns allows the designer of the object detection pipeline to swap and test different backbones for the task at hand [4]. In order to demonstrate how backbones of two types can differ, we will look at the special characteristics ResNets and MobileNets.

ResNet

While the baseline ann described in Section 2.2 only connects adjacent layers, residual neural networks (ResNets) are a special subclass of ann that introduces *shortcut connections* [13]. Shortcut connection are edges in the network that skip one or more layers.

MobileNet

As the name suggests, MobileNets were developed especially for mobile or embedded computer vision applications. The key innovation of the MobileNet architecture is the combination of two elements:

1. utilisation of depth-wise separable filters [39]
2. a network structure that enables the developer to scale the model size down by adjusting only two hyper-parameters

Firstly, using depth-wise separable filters leads to a significantly lower number of parameters the model needs to learn during the training phase. Secondly, the easy shrinking of the model by adjusting the two hyper-parameters (named *width multiplier* and *resolution multiplier*) allows the model-builder to scale the model down to exactly the size that is appropriate for solving the problem the model is applied to [16]. Both of these features are incredibly valuable for a neural network that needs to run and perform on a mobile device with limited storage and computing resources. This is also the reason a MobileNet is part of the detection framework implemented in TUM-Lens.

3.2.2. Detectors

Two-Stage Detectors

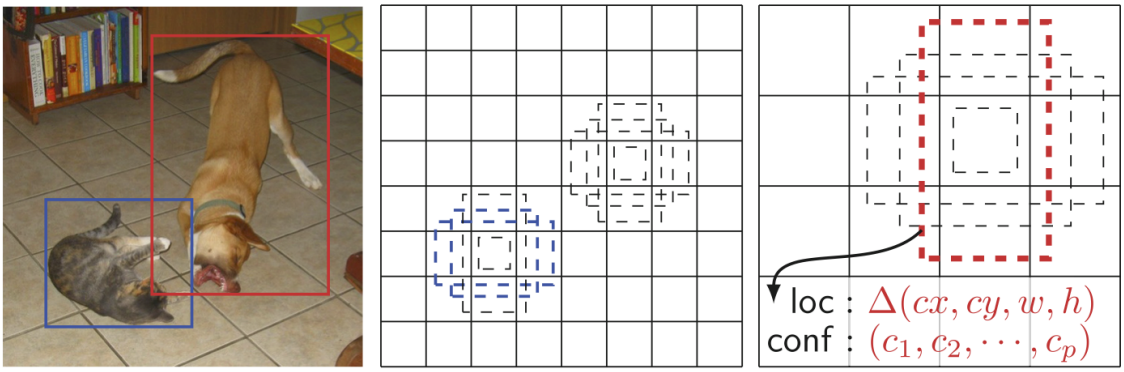
This class of detectors separates the object detection task into two distinct stages [41]. The network of the first stage (named Region Proposal Network (RPN) in the R-CNN detector family [9]) uses the image data to generate region proposals. The second stage is a separate network that takes these region proposals (or ROI - short for regions of interest), potentially decreases the final number of ROI using mechanics that depend on the specific detector, and then performs the classification on each of the final regions. All classified regions are then returned as the detected objects. Two-stage detectors tend to have a higher localisation and object recognition accuracy than single-stage detectors but can only achieve that at the cost of considerably slower inference speed [14]. Well-known representatives of this type are members of the R-CNN family.

Single-Stage Detectors

Detection frameworks are considered to have only a single stage when they comprise one deep neural network only and compute the objects (bounding box coordinates and category) in a single pass through that network. By eliminating the explicit generation of region proposals, single-stage detectors outperform their two-stage competitors with respect to speed while sacrificing a bit of detection accuracy, if at all [28]. This speed improvement makes single-stage detectors the preferred choice for applications running on mobile or embedded devices or in applications that require real-time image detection. Alongside detector implemented in TUM-Lens is described in Section 3.3, RetinaNet [26] and YOLO (You Only Look Once) [3] are established single-stage detectors.

3.3. The TUM-Lens Object Detector: SSD MobileNet v1

The SSD MobileNet v1 is the TensorFlow-Lite model used for the new object detection functionality integrated into TUM Lens. The model is pre-trained on the COCO dataset[1] and available on TensorFlow Hub[2]. Since the most important characteristics of MobileNets have been covered in subsubsection 3.2.1, we focus on the core concepts of the Single Shot MultiBox Detector (SSD).



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Figure 3.2.: The combination of bounding boxes in varying aspect ratios and multi-scale feature maps allows the SSD to detect objects in different sizes and orientations.
Source: [28]

The SSD consists of a backbone and the *SSD head*. In theory, the backbone can be any of the networks mentioned in Subsection 3.2.1 although the choice is not limited to this selection. When SSD was first introduced in 2015, the authors used the VGG-16 network as the backbone [28]. In the case of the specific SSD variant implemented in TUM-Lens, a MobileNet is used as a backbone. The reasons for the particular applicability of MobileNet in our Android app use case are described in Subsection 3.2.1. Independent of the specific type of backbone, it is first trained on publicly available image data, e.g. from a database

[1] `https://cocodataset.org/`
[2] `https://tfhub.dev/tensorflow/lite-model/ssd_mobilenet_v1/1/metadata/2`

like ImageNet[3]. Once the network is pre-trained, the final layers that originally handled the classification are then replaced by the SSD head.

The SSD head is the part of the detector that computes category scores and box locations. It is a characteristic of SSD to work with a fixed set of default bounding boxes. To account for the different sizes in which objects might appear in an image, SSD applies a sequence of comparatively small convulational filters to the feature map returned by the backbone network. Each of the feature maps obtained by this process represents a different receptive field and allows the network to detect objects at different scales. Consequently, the SSD computes predictions for all of these feature maps and for each of its pre-defined aspect ratios. It then fuses the predictions of the different aspect ratios and scales in order to improve detection accuracy. The range of aspect ratios and scales, although predetermined, enables the SSD to detect objects in various shapes and sizes. Its multi-scale feature maps are a core differentiator from other single-stage detectors like YOLO [28, 33] .

[3] `https://image-net.org/`

Part II.

App Development

4. Previous State of the Application

The practical part of this work was built in top of the already existing Android application TUM-Lens in its version 1.0. In that version, the app is already cable of classifying images received from the live camera stream in real-time. It can also classify images that are loaded from the disk of the Android as an alternative operational mode to the camera stream classification. Moreover, the user can choose between different TensorFlow-Slim[1] models to classify the images. This enables the user to do two things: she can compare the speed of similar detectors and she can also change the type of objects that can be detected as some of the available networks were trained on different data and with different class labels [18]. The most impactful design decision of the former developer of TUM-Lens was to run the entire classification locally on the Android device.

[1] `https://github.com/google-research/tf-slim`

5. Design Updates

We also took the chance to introduce some design updates to modernise the app. The fresh look of the `DetectionActivity` can be seen in Figure 5.1 and an overview of all newly introduced screens next to their counterpart from the previous app version (if applicable) can be found in Figure A.1 in the appendix. Two major advances of the updated design are the slight transparency added to the bottom sheet and the expansion of the camera preview behind the status bar. The first update is not merely a UI decision. It also leads to a better user experience because the bottom sheet in the `DetectionActivity` can easily cover the entire screen. Still, being able to see a bit of what the camera is currently capturing helps to understand, e.g. the different classification results shown. The second update regarding the transparent status bar makes the experience of the app more immersive. In fact, we also implemented a truly full-screen mode making the navigation bar transparent as well and extending the image preview to the entire area of the display. However, this behaviour is reserved for a small number of special use cases like e.g. gaming or image gallery apps. Therefore, we reverted that change as soon as we realised it did not fit to the use case of TUM-Lens.

Figure 5.1.: Current Design of the App

6. Migration from Java to Kotlin

During the Google I/O conference 2017 Google announced that they are making the programming language Kotlin a first-class citizen in Android [7]. Two years later, Google refined this statement annunciating that Android development will "be increasingly Kotlin-first" and, at the present day, the Google Developers website recommends developers to choose Kotlin when they start building a new Android app [5]. This alone can be reason enough to migrate an application to Kotlin - especially while its code base is still as manageable as the code base of TUM-Lens. To provide further explanations for the soundness of such a step, we will first look at the advantages of Kotlin over Java - with particular emphasis on the context of TUM-Lens being developed by students as part of their final theses. After that, we look at the code conversion process from Java to Kotlin, which is backed by powerful functionality integrated into Android Studio. We will also see an example of a pitfall that can be easily overlooked in such a semi-automated conversion process. In Section 8.1, we will also analyse how the number of lines of code changed from the Java files in app version 1.0 compared to the current state of the project being fully migrated to Kotlin.

6.1. Advantages of Kotlin

Continuing the development of TUM-Lens in Kotlin has several advantages. As the is app currently exclusively developed by students, Kotlin's enhanced expressiveness and conciseness over Java makes it easier for students to understand the entire application within the scope of a bachelor's or master's thesis. Moreover, students can learn more in the given amount of time they spend working on the app because they can focus more strongly on the implementation of additional features instead of having to write boilerplate Java code. As students are more error prone than professional developers, they surpassingly benefit from the safety features integrated into the Kotlin language. The most common cause for crashes of Java applications is the null pointer exception [15, 48]. With Kotlin being a strongly typed language, a lot of these null pointer exceptions will be avoided because Kotlin's safety features help the developer to identify potential sources of such errors easily. Google itself claims that Android apps are 20% less likely to crash when they contain Kotlin code [5].

6.2. Converting Java Files to Kotlin Files

Android Studio offers a convenient way to convert files from Java to Kotlin. On macOS, we first have to open the Java file we want to migrate in Android Studio. Next, we select *Code* from the menu bar and then the menu item *Convert Java File to Kotlin File*. If we have not yet configured Kotlin in your project, Android Studio will prompt us to either do so or abort the migration process. Once Kotlin is set up, Android Studio will immediately start the

conversion. At the end of the process, we are prompted with a dialogue asking "Some code in the rest of your project may require corrections after performing this conversion. Do you want to find such code and correct it too?" which we confirm by clicking on the yes-button. The file has now been converted from Java to Kotlin. In some cases, the resulting Kotlin code works right away, but in the context of TUM-Lens manual adjustments were mandatory in every file because of several reasons.

For a start, Android Studio could not always infer all types automatically. With Kotlin being strongly typed, it was necessary to restructure the code so that the compiler could know each variable's type or safely cast a variable to the appropriate type (called *Smart Cast* in Kotlin). We solved this situation using two different approaches, distinguished by the importance of the successful execution of the respective code block. In the case of non-critical functionality, using Kotlin's safe call operator `?.` to access properties that might be null was sufficient. For core functions, wrapping such functionality in an additional safety check was the better option. This not only capacitates the compiler to be certain that a mutable property had not accidentally become null before being accessed. It also enables us to react appropriately if the safety check fails.

```
1 var <propertyName>[: <PropertyType>] [= <property_initializer>]
2   [<getter>]
3   [<setter>]
```

Listing 6.1: Kotlin's declaration syntax for a mutable property. Getter and setter are optional. The property type is only optional when the compiler can infer it from the context (meaning either from the initializer or from the return type of the getter).

There is one part to Android Studio's built-in code migration tool-chain that actually tricked us into introducing a bug: the conversion of getters and setters. Listing 6.1 shows the syntax for the declaration of a property in Kotlin. Every property has default public getters and setters if not explicitly defined otherwise. Java, on the other hand, conventionally defines methods like `public variableType getVariableName()` and `public void setVariableName(variableType newValue)` for every variable of a private class that shall be retrieved or overwritten from outside that class.

Listing 6.2 contains the original Java code and Listing 6.3 shows the final solution that we implemented in addition to Kotlin's property accessors. The default Kotlin getter is not enough here as it would omit the crucial conversion task. However, this is exactly what happened during the auto-conversion: only the default getter was available after the conversion had successfully finished. As a result, other parts of the logic broke because the `rgbBytes` object could not be properly processed, which, in turn, lead to the application not working as expected. In this special case, some accessors of the particular property required the image conversion while other accessors did not. Therefore, we did not put the image conversion into a custom getter because we did not want to call `imageConverter!!.run()` every time the property was used. Retrospectively, placing it in the separate method `getConvertedRgbBytes()` has been an excellent decision for us.

```
1  protected int[] getRgbBytes() {
2    imageConverter.run();
3    return rgbBytes;
4  }
```

Listing 6.2: Java code that lead to the introduction of a bug after using Android Studio's built-in Java to Kotlin conversion command. The bug was created when this code block was substituted with a default getter in Kotlin omitting parts of its logic.

```
1  protected fun getConvertedRgbBytes(): IntArray? {
2    imageConverter!!.run()
3    return rgbBytes
4  }
```

Listing 6.3: Complementing the default Kotlin getter with this method solved the problem.

7. Implementing Object Detection Using the TensorFlow Lite Framework

As described in Chapter 4 the core feature of TUM-Lens v1.0 is image classification. Most notably, the classification task is not outsourced to some remote server but performed offline on the device itself. We adhere to this decision and built our logic on top of Google's TensorFlow Lite example app for object detection [24, 25]. The detection task is therefore carried out locally using the same TensorFlow-Lite API as the image classification. We also integrate our detection results into the images received from the camera live-stream so that the user of the app can experience the object detection in real-time. This being said, there is some discrepancy to the existing set of functionalities built around the image classification. Only one model for object detection is currently available within the app and the detection logic cannot be applied to images that have been loaded from the storage of the device.

7.1. Expansion of the Existing App Architecture

In order to make the structure of the app more accessible to new developers, we put the core classes responsible for image classification and object detection into two distinct packages. The project now includes the four packages `classification`, `detection`, `fragments` and `helpers`. Only the two base activities `StartScreenActivity` and `PermissionDeniedActivity` remained on the top-level. The UML diagram depicted in Figure 7.1 is a good starting point for interested people who want to familiarise themselves with the newly added contents of the app. Most of the code that was added is located within the `detection` package. However, adjustments in other parts of the app where necessary in order to integrate the new functionalities into the existing project.

7.2. Detection and Tracking

Just as the `ClassificationActivity` is the core activity that handles the image classification of the camera feed, the new `DetectionActivity` is the central activity for object detection. The user can easily switch between the different mode of image analysis by using a toggle button on top of the screen. We decided to use a toggle switch here since there are exactly two operating modes (classification and detection) and they are working mutually exclusively in order to best utilise the computation power of the device. This design decision may be revised later when the scope of the app is expanded to cover more visual tasks (see Section 3.1 for examples of such tasks). Another reason for a rework can be the fact that mobile devices might have enough computing power so that solving multiple tasks in parallel does not make a noticeable difference for the app user, meaning images are still processed in real-time. In this section, we will not explain the code step by step as this can be done be

reviewing the code itself and reading the comments further explaining important parts it. Instead, we will explain a few key concepts and classes so that people scanning the code after reading this thesis know what to look for.

7.2.1. Inheritance for Receiving and Rendering of Images

The `DetectionActivity` inherits from the abstract class `CameraActivity` and implements the `OverlayView.DrawCallback` interface. The `CameraActivity` handles all communication with Androids camera api and implements the proper setup and behaviour of the elements in the bottom sheet. The `DrawCallback` interface provides a single function definition that the `DetectionActivity` overrides in order to render the detected objects as rectangles in a layer on top of the preview of the camera image stream. The actual drawing is delegated to an `MultiBoxTracker` object as we will see in Subsection 7.2.3.

7.2.2. Bitmap Conversion

Since TUM-Lens can run on a multitude of devices with varying combinations of camera and display resolution, the `DetectionActivity` uses matrices to convert the image data back and forth between the different formats the data is needed in. For contemporary Android devices, the potential resolution of the camera is usually above the maximum resolution of the display. This is also the case for the Xiaomi Mi 9 on which we tested the application during its development (see Appendix B for its technical specifications). It is the developers' task to decide in which quality the camera input is displayed. Sticking to the example of Xiaomi Mi 9, the images captured by the camera have 20 (selfie camera) or 45 (main camera) megapixels and are scaled down to less than 2.5 megapixel to be displayed on the device screen. After that, they are again scaled down to a bitmap of 300x300 pixels[1] as this is the appropriate input size for the implemented detection framework described in Section 3.3. Once the detector returns bounding boxes for the objects detected in its input image the coordinates of these rectangles in turn are scaled back up to mark the corresponding areas in the higher resolution image shown on the device display.

7.2.3. DetectionActivity and MultiBoxTracker

The `DetectionActivity` also orchestrates the two most fundamental tasks of the object detection process: object detection and, since the images are derived from a continuous camera stream, object tracking. It instantiates the object `detector` of the class `TFLiteObjectDetectionAPIModel` to handle the interactions with the TensorFlow Lite api and a `MultiBoxTracker` object `tracker` that tries to assign each rectangle drawn on the screen to its related recognition result across successive input images. This is important because the bounding boxes that are drawn as an overlay on the camera view use different colours for different objects. If no tracking would happen, the colour that is assigned to an object will change randomly with every new image the detector processes. This would be very confusing for the user. Therefore, the recognition results returned by the detector are not

[1] The image received by the detector might indeed be even smaller than 300x300 pixels as the camera input is usually not square and the aspect ratio is kept throughout the image conversion pipeline. Therefore, the 300 pixels denote the larger dimension (width or height) of the actual content of the input bitmap.

directly rendered on the screen but first processed by the `tracker`.

The `tracker` guarantees two properties: Firstly, empty or degenerated recognition results are skipped and not tried to be displayed. Secondly, the 15 colours the `tracker` can assign to the remaining objects are allocated in the same order every time the old drawings are cleared from the canvas and new ones are drawn. This process of detecting objects, clearing old rectangles from the screen and drawing new ones happens with every image the detector processes. While the tracking is far from perfect, the order in which recognitions are returned by the detector stays roughly the same. This happens because they are ordered by the coordinates of their bounding boxes. Depending on the camera settings, the camera can usually stream 30 to 60 frames per second. If the user does not move the camera surpassingly fast, the coordinates of the recognition results stay close enough together so that they get assigned the same colour across the changing camera frames. New objects appearing in the scene (or existing ones becoming larger as the user gets closer) are currently the major cause of inconsistent object colouring. However, as long as no new objects are recognised, the existing ones tend to keep their colours. This is already a significant achievement given the tracking is purely based on properties of the TensorFlow Lite api and does therefore add effectively non-existent overhead to the object detection pipeline.

The detection threshold is currently defined in a constant and set to 0.5 in order to display the most relevant objects. Hence, only recognition results received from the `detector` that have a confidence score of 0.5 or higher are handed to the `tracker`. This further improves the user experience supplementary to the object tracking.

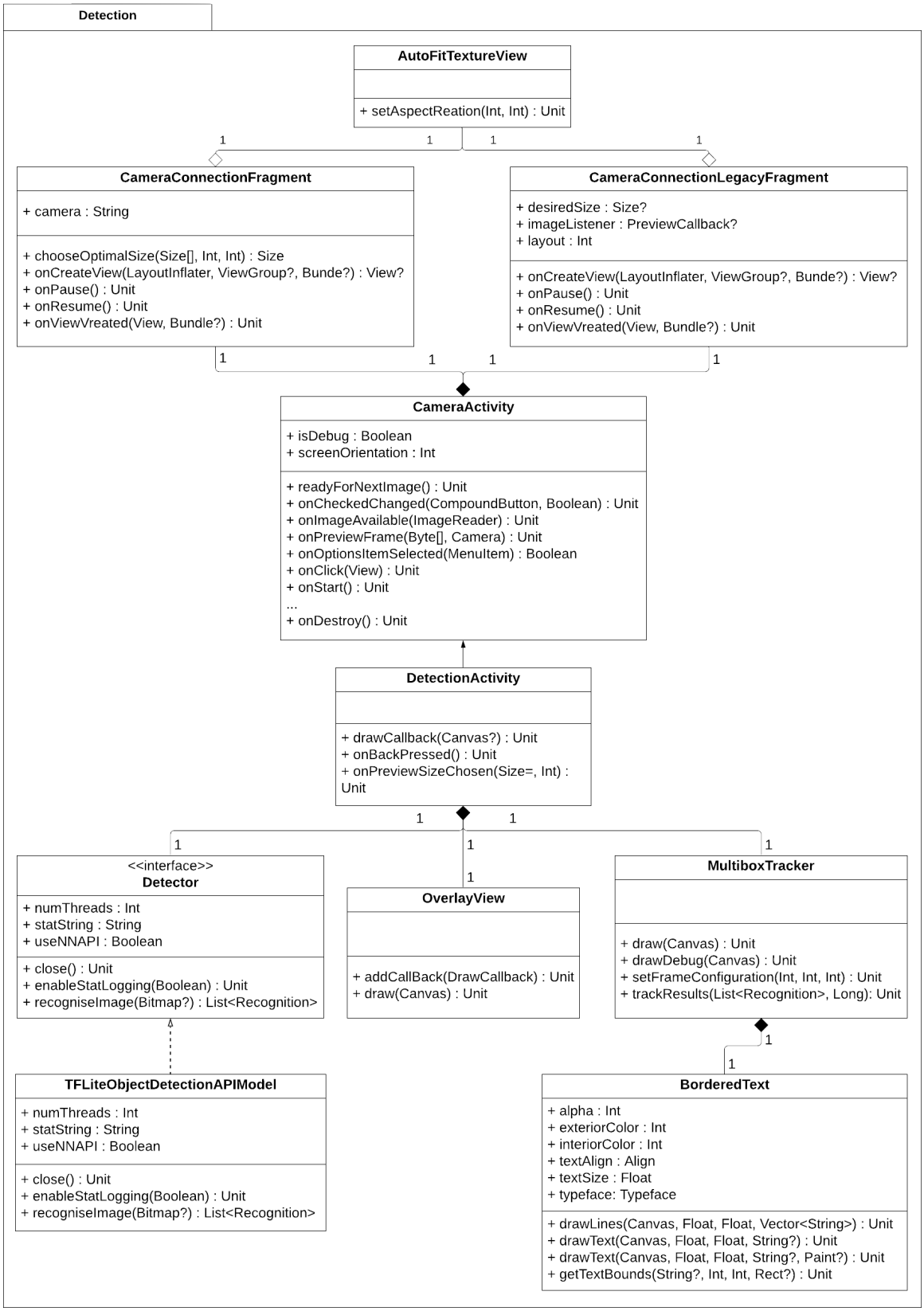


Figure 7.1.: UML class diagram of the new detection package. Only public properties and methods are shown.

Part III.

Results

8. Evaluation

We are going to evaluate two metrics in this chapter. First, we will have a look at the impact of changing the programming language from Java to Kotlin regarding the number of lines of code. Second, the performance of the application is evaluated based on the goals that were set before we took on the topic of this thesis.

8.1. Project Size after the Migration to Kotlin

Using the npm distribution of the tool Count Lines of Code (cloc)[1] we can easily count lines of Java and Kotlin code while ignoring blank lines and comment lines. This enables us to monitor how the shift from Java to Kotlin influenced the number of lines of code. With Perl, Node and npm installed on our machine, we run the following command which prints its output to stdout:

```
1  (base) david@DDs-MBP lens-david % npx cloc --by-file --git-diff-rel --
       match-d='main' --include-lang=Java,Kotlin -csv f6a18e0f 031a26a7
```

Listing 8.1: npx cloc command with its options and arguments. Prints the lines of code analysis comapring files before and after the Java to Kotlin conversion. The output was also saved as cloc.csv and can be found in lens-david/thesis/raw_data.

The `--by-file` option enables us to compare each Java file with its Kotlin equivalent directly as it changes the output so that the results are returned for every source file encountered. `--git-diff-rel` interprets the command line arguments as git targets and compares only files which have changed in either commit which is exactly what we need to measure the change in the number of lines of code. Only files in the main directory are of our concern, so we let cloc only search this directory using the option `--match-d='main'`. This excludes e.g. the test directory from being searched. With `--include-lang=Java,Kotlin` we limit the output to files written in the languages we seek to collate. Other files (like Android's XML layout files) are not of interest for this analysis. Finally, we provide two git commits. `f6a18e0f` is the last commit pushed by the previous developer of TUM-Lens and `bf0dbf7f` is the more recent commit that does not contain Java files anymore but replaced them with their respective Kotlin substitute. Table 8.1 shows the results of the cloc output. Overall, the total size of the original Java codebase shrank because of the migration to Kotlin. This is particularly impressive as understandably further logic was added to existing classes in order to account for the new object detection functionality.

[1] Original cloc project by Al Danial: `https://github.com/AlDanial/cloc`
cloc npm distribution by Kent C. Dodds: `https://www.npmjs.com/package/cloc`

Files in TUM-Lens v1.0 migrated from Java to Kotlin	Delta in lines of code
CameraRoll	-34
Classifier	4
ListSingleton	-9
PermissionDenied	-8
StartScreen	-12
ViewFinder	-7
fragments/CameraRollPredictionsFragment	9
fragments/CameraSettingsFragment	-15
fragments/ModelSelectorFragment	5
fragments/PredictionsFragment	4
fragments/ProcessingUnitSelectorFragment	-7
fragments/SmoothedPredictionsFragment	6
fragments/ThreadNumberFragment	-6
helpers/App	1
helpers/CameraEvents	0
helpers/FreezeAnalyzer	-6
helpers/FreezeCallback	0
helpers/ImageUtils	43
helpers/Logger	6
helpers/ModelConfig	-2
helpers/ProcessingUnit	-2
helpers/Recognition	-26
helpers/ResultItem	-21
helpers/ResultItemComparator	-2
cumulative delta over all relevant files	**-79**

Table 8.1.: This table presents the results from the command line prompt in Listing 8.1. Packages are shown as a prefix to the file name to resemble the original project structure of TUM-Lens v1.0 and file extension are omitted.

8.2. Performance

One goal of this work is the expansion of TUM-Lens by integrating a real-time object detection feature running entirely on the device itself. With that in mind and judging by the updated version of the app we have produced, this goal is fully achieved. For those who want to test the new app and its performance themselves, the updated version of the app can be installed on an Android device by cloning our GitLab repository[2]. We will also release the updated version 2.0 to the Google PlayStore[3] to make it accessible for a broader audience. Hereafter, we will outline how we conduct a test in which we detect objects with TUM-Lens and log the detection timings to prove that the detection can indeed be regarded as performing in *real-time*.

[2] `https://gitlab.lrz.de/dvrws/lens`
[3] `https://play.google.com/store/apps/details?id=com.maxjokel.lens`

8.2.1. Test Environment

We measure the real-time characteristic of our implementation not only subjectively by assessing what we see on the screen when we run the app. We also track the time it takes the app between the moment the camera api returns a new image and the bounding boxes of the recognitions returned by the detector are actually drawn on top of that image. While the detection time can vary based on the input data it needs to process, we did not try to measure this influence. However, we conduct our test in a private home which actually matches the types of categories the SSD MobileNet can detect quite well (e.g. bottle, cup, chair, couch, bed, dining table, tv, refrigerator, ...). This makes us confident of our analysis being viable for the assessment of the real-time quality of the object detection we implemented.

8.2.2. Data Collection

We log the Android system trace on the test device directly[4] (specs in Table B.1) because it allows us to walk around and capture different scenes without having to be attached to a computer. Once we are done collecting input, we attach the test phone to our computer and retrieve the data with the following command:

```
1  (base) david@DDs-MBP lens-david % cd thesis/raw_data && adb pull /data/
       local/traces/ .
```

Listing 8.2: The android-developer-tools (adb) offer a convenient way to retreive trace files saved on an Android device. This command transfers the system trace from our test device to the development machine it is attached to via an usb cable.

The command creates a new folder *traces* in the given directory if it does not already exist. Since our device runs Android 10, the trace files saved in the new folder have the `.perfetto-trace` format. We use Google's open source trace analysis platform Perfetto[5] to open and process the trace file we recorded while walking through the apartment. The Perfetto UI[6] offers a powerful and convenient tool to visualise the data stored in the trace file. Moreover, it also allows to query the data using SQL commands. Executed within the Perfetto UI, the query in Listing 8.3 returns a list of the three types of tracked events we are interested in: `imageAvailable`, `recogniseImage` and `DrawFrame` including their ids, names, a timestamp indicating the beginning of their execution (ts) and their entire duration (dur).

```
1  SELECT id, name, ts, dur
2  FROM slice
3  WHERE type = 'internal_slice' and
4  (name = 'imageAvailable' or name = 'recognizeImage' or name = 'DrawFrame')
```

Listing 8.3: SQL command to query object detection related events tracked with Android's system tracing.

[4] https://developer.android.com/topic/performance/tracing/on-device
[5] https://perfetto.dev/
[6] https://ui.perfetto.dev/

The source code includes carefully placed `Trace.beginSection([SectionName])` and `Trace.endSection()` function calls so that these events are properly tracked. All timings were measured with the default configuration of using 4 CPU-cores for the object detection which can also be seen in Figure 8.1 - the *recognizeImage* slice is traced in the main detection thread and three further threads support it.

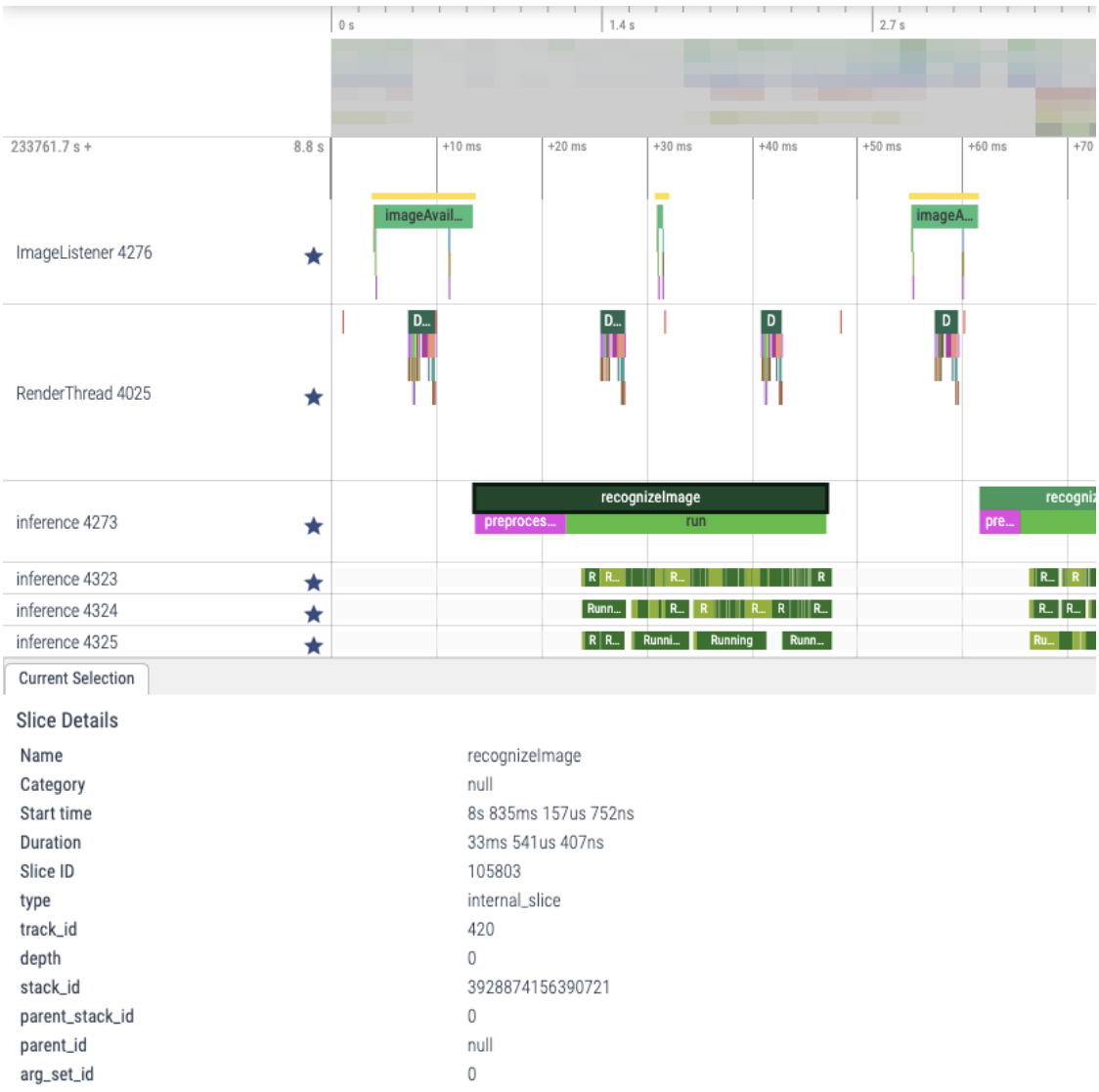


Figure 8.1.: The image shows a systrace visualisation using the Perfetto UI. The horizontal axis shows the relative time (starting at 0 seconds) and the vertical axes lists important types of events. These events are sorted to reflect their chronology as close as possible.

We imported the output of the Perfetto SQL query into a Microsoft Excel spreadsheet[7] (located in the project repository under `thesis > raw_data > traces > systrace.xlsx`. Two observations can be drawn from Figure 8.1 that we want to explain because it puts the measurements into context and makes them easier to understand.

1. The device renders images at an almost fixed rate taking whatever input is currently available. We used the systrace output to verify this and measured an average of 55 frames per seconds to be displayed on the screen. The `DrawFrame` tracking event can be found in in Figure 8.1 in the row *RenderThread 4025* (its name is cropped because of its short duration).
2. The code that contains the `imageAvailable` section will be entered every time a new input image is returned from the camera api. However, it only executes fully if the previous recognition process has already finished as only one image is processed at a time. In case a new image arrives while an old one is still being processed, the execution of the code that contains the `imageAvailable` trace stops almost immediately. This behaviour can also be visually tracked in Figure 8.1.

8.2.3. System Trace Analysis

We look at the systrace entries of the `recognizeImage` event from two different angles. First, we calculate the mean of the duration of the `recognizeImage` task which is 36,110,754 nanoseconds (ns). This can be converted to potential frames a detector with this speed provides which is 28 frames per second (fps) on average. This is a decent performance and can definitely be considered real-time (as a reference: movies are usually recorded with 24 fps). Moreover, it is also close to how academic papers usually measure the performance of neural networks. However, this is not congruent with what the user experiences as it implies that the detector is working non-stop - which it does not. Thus, we measure a second metric to access the performance closer to what a user experiences. This second metric measures the average time from the start of one `recognizeImage` event to next. Thereby, we automatically include both the additional time needed to retrieve the image from the camera and also the downtime in which no detection is being computed but also no new image data is available. The average time for this metric is 61.500.325 ns translating to around 16 fps. This time is low enough for the bounding boxes to track the corresponding objects accurately and therefore qualifies as real-time. However, it is not low enough for the tracking to appear complete stutter-free which would be the ideal case. The average joint time of a non-aborted `imageAvailable` and its subsequent `recognizeImage` is 43.100.228 ns or 23 fps. In order to achieve the maximum visible performance on the test device, this time needs to be lowered to less than 15.640.005 ns (or over 64 fps) which is the average time between `DrawFrame` events - while also being in perfect sync with the latter. This is a challenge to be taken on in a new project for someone who wants to optimise the current code for performance or when further detection frameworks become available.

[7] For people who do not have excel installed: Google Docs offers a spread sheet functionality under `https://docs.google.com/spreadsheets` that can read and manipulate .xlsx files as well

9. Outlook

9.1. Possible Applications

As touched upon in Chapter 1, there are at least two major drivers that will fuel future development efforts. Protecting the sphere of privacy will definitively be a major motivation to build apps running machine learning frameworks locally. We have already introduced this idea by alleging the example of DeepType in Section 1.3. The second driver for an increase in on-device machine learning applications has been introduced in Section 1.2. It is the need for machine learners that can act independently of an internet connection. This is important as it is simply impossibly to guarantee such a connection in some circumstances. We will expand this line of thought by adding the requirement for increased speed that some challenges have. We will use the following paragraphs to introduce a wide range of potential applications centred around the idea of on-device machine learning partitioned by their major drivers.

9.1.1. Autonomy and Speed Inspired Use Cases

We will not go into too much detail in this section as this work emphasises the importance of low latency performance for object detection on Android devices in multiple occasions already. Still, we want to highlight the case of on-device machine learning application requiring both autonomy and speed that will change our life in the most profound way.

Autonomous Navigation

Many applications in the field of autonomous navigation will greatly benefit from both aspects of on-device computation - autonomy and speed. Driving (or rather being chauffeured by) an autonomous vehicle is the showpiece of on-device machine learning. Firstly, it needs the fast reaction time provided by algorithms running on embedded hardware to minimise the distance and thereby time the data needs to travel when it is captured by the car's myriad of sensors. This facilitates the car's decision engine to compute decisions in real-time. Given the high speed at which cars can travel and the unpredictability of other traffic participants, it is of utmost importance to react to changes in the environment in real-time. Secondly, a connection to some remote instance that analyses data online might not be given in all situations. Cars must pass tunnels, rural areas might have poor network coverage, or the network itself might have an outage because of unforeseen events such as climate catastrophes, terrorist attacks or cyber attacks. In any of these cases, the car must not lose control but be able to continue to navigate smoothly and safely. The core of its data processing and machine learning pipeline must therefore function decoupled from all external networks.

Having said this, autonomous cars are not the only use case for navigation relying on on-device machine learning. We can also conceive other areas such as deep sea exploration, drone navigation and even space travelling where either offline usage, minimal latency or both is required for successful autonomous navigation.

9.1.2. Privacy Inspired Use Cases

Biometric Data

Some company like Apple and Snap[1] are already heavily influenced and driven by privacy concerns - at least in specific areas of their business practices. Apple's Face ID is a well-known security feature of Apple's smartphone and table division. It relies purely on on-device machine learning to pick up all the important details that make a face unique and thereby successfully secures the device without transferring sensitive user data to the cloud. Snapchat uses on-device machine learning to power its manifold filters so that user data only gets transmitted once the user actively shares a photo or video via the app. Protecting biometric user data has already become a mainstream use case for big tech companies. However, these large firms can afford to employ a considerable amount of machine learning experts to ensure their artificial neural networks can also run on mobile devices with their limited storage and computing capabilities. Smaller firms, on the other hand, rarely have the capacity to hire many machine learning engineers. It is these firms that exceedingly benefit from on-device machine learning getting ever more accessible and increasingly easy to implement even for small teams.

Health Data

Since smartphones are just a subcategory of mobile devices, different hardware opens the door for new types of applications. Health care is an industry that can benefit from on-device machine learning as health data is among the data categories that are most worthy of protection. Today, there is already an astonishing variety of devices that capture health data - each of which also comes in a "smart" version that not only collects this data but also sends it to decentralised servers for storage and processing: smart watches, scales, portable electrocardiogram (ecg) and electroencephalography (eeg) devices, blood pressure monitors, glucometers, thermometers and many more. Future developments might combine more and more of such tools into personal health companion devices that can capture and track every aspect of our health condition. Combining these various inputs to a coherent assessment of one's health status is an ideal use case for the application of machine learning. Since the data is sensitive and can easily tell a story people might want to keep private, it is a reasonable assumption that there will be a market for health companions that perform their analysis offline without sharing any data with a third party.

Further Dimensions

Listing all application domains of on-device machine learning would exceed the scope of this work. It can be observed, however, that there is not only the dimension of machine learning

[1] Snap Inc. is the developer of Snapchat, a mobile app known for its various and peculiar filters that users can apply to manipulate the images captured by the smartphone camera.

task along which different applications can be found (image classification, object detection, natural language processing, ...) but also other dimensions such as hardware on which the machine learning algorithm is deployed (smartphones, gadgets, robots, ...) or industries benefiting from customers being less scared about privacy breaches (entertainment, media, public sector, ...).

9.2. Future Work

To wrap up this thesis, we want to suggest a variety of topics that have not been covered by this work or its predecessor and might interest to students at TUM. By doing so, we hope to inspire other students to continue the development of TUM-Lens. In the eyes of the author, this app is a fertile ground for students striving for both challenging and interesting tasks ranging from state-of-the-art mobile development up to training custom neural networks for mobile devices.

Replace Deprecated Code and Fix Bugs

A first improvement can be the replacement of deprecated code. We have already achieved substantial progress in modernising the app by migrating it to Kotlin but there is still a significant number of outdated code that can be modernised by the next student working on the TUM-Lens project. Unfortunately, the app is also not entirely bug free. One bug we have found in version 1.0 that we were not able to fix is the changeability of models once an image has been loaded from storage. This does currently not trigger a re-classification with the newly selected network and should be fixed in a future release.

Enable Input Freezing and Analysis of Images Loaded from Storage

These tasks primarily aim at aligning object detection features with those available for image classification. In the future, a double tap while being in object detection mode shall thus freeze the detection process and keep the frozen results on screen. Furthermore, the user shall be able to select an image from the device storage and the app shall display the detected objects recognised for that specific input.

Load New Models from Remote Servers and Increase Number of Available Models

This might sound counter-intuitive to the goal of this thesis but downloading models and the corresponding label file from an online resource would further improve the usability of the app. Currently, a new app version needs to be published in order to add a new neural network to the app. This is the case because as of now, all models must be saved to the assets folder of the application before it is built. Lastly, the user should have the option to choose from multiple object detection framework available within TUM-Lens just as in the image classification case.

Expand The Set of Features of TUM-Lens

The final tip is the expansion of the features of the app. With image classification and object detection we already cover two major disciplines in computer vision. In a follow-up

project, instance segmentation could be implemented to further increase the capabilities of TUM-Lens. While this would add an entirely new feature, improvements to existing function are also possible. On the easier side of the enhancement spectrum are further customisation options for the user. In the current state of the app, the user can adjust the number of threads to utilise for carrying out the object detection tasks. More options like changing the minimum confidence threshold a detection must have to be displayed are also conceivable. Ranked among the more difficult advancements is the implementation of better tracking than the mechanism currently implemented and described in Subsection 7.2.3.

9.3. Conclusion

We have delivered an updated version of TUM-Lens that now also provides a real-time object detection function running locally on the device. Moreover, we have modernised the app both design wise and with regards to the programming language it is written in. In summary, it can be stated that we have achieved all goals that had been set in the beginning of this work. With every new contribution to TUM-Lens, the number of new directions in which one can take the app is only growing. We therefore encourage fellow students to follow suit and continue to evolve this project.

Part IV.

Appendix

A. Screenshots of the Application

(a) Classification v1.0 (b) Classification v2.0 (c) Detection v2.0

(d) Bottom sheet in classification v1.0 (e) Bottom sheet in classification v2.0 (f) Bottom sheet in detection v2.0

Figure A.1.: Development of app visuals from version 1.0 to 2.0. The bottom sheet is now slightly transparent and the camera preview stretches into the status bar.

B. Test Device Specifications

The development of TUM-Lens v2.0 was tested on a Xiaomi Mi 9. Development and testing occurred April to August 2021. The most relevant specifications are as follows.

Brand and name	Xiaomi Mi 9
CPU	Octa-core: 8 Kryo 485 cores with respective clock speeds of 1x2.84 GHz, 3x2.42 GHz and 4x1.78 GHz
GPU	Adreno 640
RAM	6.00 GB
Screen resolution	1080 x 2340 pixels ($\approx$ 2.5 MP)
Screen aspect ratio	19.5:9
Screen size (diagonal)	6.39 inches
Main camera (triple)	48 MP, f/1.8, 27mm (wide), 1/2.0", 0.8µm, PDAF 12 MP, f/2.2, 54mm (telephoto), 1/3.6", 1.0µm, PDAF 16 MP, f/2.2, 13mm (ultrawide), 1/3.0", 1.0µm, PDAF
Selfie camera (single)	20 MP, f/2.0, (wide), 1/3", 0.9µm
Model identifier	M1902F1G
MIUI version	MIUI Global 12.0.5 (QFAEUXM)
Android version	10 QKQ1.190825.002
Release Date	25th of March 2019

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Bibliography

[1] *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Las Vegas, NV, USA). IEEE Computer Society, Dec. 2016. ISBN: 978-1-4673-8851-1.

[2] Shivang Agarwal, Jean Ogier Du Terrail, and Frédéric Jurie. "Recent Advances in Object Detection in the Age of Deep Convolutional Neural Networks". In: *arXiv preprint arXiv:1809.03193* (Sept. 2018).

[3] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. "YOLOv4: Optimal Speed and Accuracy of Object Detection". In: (Apr. 2020). URL: https://arxiv.org/abs/2004.10934v1.

[4] "Convolutional Neural Networks Backbones for Object Detection". In: *Image and Signal Processing. ICISP 2020. Lecture Notes in Computer Science* 12119 (June 2020), pp. 282–289. DOI: 10.1007/978-3-030-51935-3_30.

[5] Android Developers. *Android's Kotlin-first approach*. 2021. URL: https://developer.android.com/kotlin/first (visited on 07/31/2021).

[6] Android Developers. *Neural Networks API*. 2021. URL: https://developer.android.com/ndk/guides/neuralnetworks (visited on 07/31/2021).

[7] Google Developers. *Google I/O Keynote (Google I/O '17)*. May 2017. URL: https://youtu.be/Y2VF8tmLFHw?t=5245 (visited on 07/31/2021).

[8] Nikita Dvornik et al. "BlitzNet: A Real-Time Deep Network for Scene Understanding". In: *Proceedings of the IEEE International Conference on Computer Vision* (Venice, Italy). Vol. 2017-October. Institute of Electrical and Electronics Engineers Inc., Oct. 2017, pp. 4174–4182. URL: https://arxiv.org/abs/1708.02813v1.

[9] Ross Girshick et al. "Rich feature hierarchies for accurate object detection and semantic segmentation". In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition* (Nov. 2014), pp. 580–587.

[10] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep Learning*. MIT Press, 2016. URL: http://www.deeplearningbook.org.

[11] Jeff Hale. *Deep Learning Framework Power Scores 2018*. Sept. 2018. URL: https://towardsdatascience.com/deep-learning-framework-power-scores-2018-23607ddf297a (visited on 07/31/2021).

[12] Matthew Halpern, Yuhao Zhu, and Vijay Janapa Reddi. "Mobile CPU's rise to power: Quantifying the impact of generational mobile CPU design trends on performance, energy, and user satisfaction". In: *Proceedings - International Symposium on High-Performance Computer Architecture* (Apr. 2016), pp. 64–76. DOI: 10.1109/HPCA.2016.7446054.

[13] Kaiming He et al. "Deep Residual Learning for Image Recognition". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Las Vegas, NV, USA). IEEE Computer Society, Dec. 2016, pp. 770–778. ISBN: 978-1-4673-8851-1. DOI: 10.1109/CVPR.2016.90.

[14] Wang Hechun and Zheng Xiaohong. "A Survey of Deep Learning-Based Object Detection". In: *2nd International Conference on Big Data Technologies* (Jinan, China). Association for Computing Machinery, Aug. 2019, pp. 149–153. DOI: 10.1145/3358528.3358574.

[15] Andras Horvath. *Which Java exceptions are the most frequent?* June 2018. URL: https://blog.samebug.io/which-java-exceptions-are-the-most-frequent-f830b113c37f (visited on 07/31/2021).

[16] Andrew G. Howard et al. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications". In: (Apr. 2017). URL: https://arxiv.org/abs/1704.04861v1.

[17] Max Jokel. *TUM-Lens*. Version 1.0. July 31, 2021. URL: https://play.google.com/store/apps/details?id=com.maxjokel.lens.

[18] Maximilian Jokel. "Implementing a TensorFlow-Slim based Android app for image classification". Bachelor's thesis. Garching: Lehrstuhl für Wissenschaftliches Rechnen, Technische Universität München, Nov. 2020. URL: https://mediatum.ub.tum.de/1579885.

[19] Tao Kong et al. "HyperNet: Towards accurate region proposal generation and joint object detection". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Las Vegas, NV, USA). IEEE Computer Society, Dec. 2016, pp. 845–853. ISBN: 978-1-4673-8851-1. DOI: 10.1109/CVPR.2016.98.

[20] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "Imagenet classification with deep convolutional neural networks". In: *Advances in neural information processing systems* 25 (2012), pp. 1097–1105.

[21] Erik G Learned-Miller. "Introduction to supervised learning". In: *I: Department of Computer Science, University of Massachusetts* (Feb. 2014).

[22] Fei-Fei Li, Ranjay Krishna, and Danfei Xu. *CS231n: Convolutional Neural Networks for Visual Recognition*. 2021. URL: https://cs231n.github.io/neural-networks-1/ (visited on 07/31/2021).

[23] Fei-Fei Li, Ranjay Krishna, and Danfei Xu. *Detection and Segmentation*. May 2021. URL: http://cs231n.stanford.edu/slides/2021/lecture_15.pdf (visited on 07/31/2021).

[24] Yuqi Li et al. *TensorFlow Examples*. 2016. URL: https://github.com/tensorflow/examples/tree/master/lite/examples/object_detection/android (visited on 07/31/2021).

[25] Google Ireland Limited. *Object detection — TensorFlow Lite Examples*. URL: https://www.tensorflow.org/lite/examples/object_detection/overview (visited on 07/31/2021).

[26] Tsung Yi Lin et al. "Focal Loss for Dense Object Detection". In: *Proceedings of the IEEE International Conference on Computer Vision* (Venice, Italy). Vol. 2017-October. Institute of Electrical and Electronics Engineers Inc., Oct. 2017, pp. 2999–3007. DOI: 10.1109/ICCV.2017.324. URL: http://arxiv.org/abs/1708.02002.

[27] Jie Liu et al. "Performance Analysis and Characterization of Training Deep Learning Models on Mobile Device". In: *Proceedings of the International Conference on Parallel and Distributed Systems - ICPADS* (Dec. 2019), pp. 506–515. DOI: 10.1109/ICPADS47876.2019.00077.

[28] Wei Liu et al. "SSD: Single Shot MultiBox Detector". In: *Lecture Notes in Computer Science* (2016), pp. 21–37. ISSN: 1611-3349. DOI: 10.1007/978-3-319-46448-0_2. URL: ttp://dx.doi.org/10.1007/978-3-319-46448-0_2.

[29] Tom M. Mitchell. *Machine Learning*. Ed. by Erick M. Munson. McGraw-Hill, Mar. 1997, p. xv. ISBN: 0-07-042807-7.

[30] Andrew Ng. *Machine Learning Course by Stanford University*. 2021. URL: https://www.coursera.org/learn/machine-learning (visited on 07/31/2021).

[31] *Proceedings of the IEEE International Conference on Computer Vision* (Venice, Italy). Vol. 2017-October. Institute of Electrical and Electronics Engineers Inc., Oct. 2017.

[32] Team PyTorch. *PyTorch 1.3 adds mobile, privacy, quantization, and named tensors*. Oct. 2019. URL: https://pytorch.org/blog/pytorch-1-dot-3-adds-mobile-privacy-quantization-and-named-tensors/ (visited on 07/31/2021).

[33] Joseph Redmon et al. "You Only Look Once: Unified, Real-Time Object Detection". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Las Vegas, NV, USA). IEEE Computer Society, Dec. 2016, pp. 779–788. ISBN: 978-1-4673-8851-1. DOI: 10.1109/CVPR.2016.91.

[34] Shaoqing Ren et al. "Faster r-cnn: Towards real-time object detection with region proposal networks". In: *Advances in neural information processing systems* 28 (2015), pp. 91–99.

[35] Ahmad EL Sallab et al. "Deep reinforcement learning framework for autonomous driving". In: *Electronic Imaging* 2017 (2017), pp. 70–76.

[36] A. L. Samuel. "Some Studies in Machine Learning Using the Game of Checkers". In: *IBM Journal of Research and Development* 3 (3 July 1959), pp. 210–229. DOI: 10.1147/RD.33.0210. URL: http://ieeexplore.ieee.org/document/5392560/.

[37] A. L. Samuel. "Some Studies in Machine Learning Using the Game of Checkers. II - Recent Progress". In: *IBM Journal of Research and Development* 11 (6 Nov. 1967), pp. 601–617. DOI: 10.1147/RD.116.0601.

[38] R. Sathya and Annamma Abraham. "Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification". In: *International Journal of Advanced Research in Artificial Intelligence* 2 (2 2013), pp. 34–38. ISSN: 2165-4069.

[39] Laurent Sifre. "Rigid-Motion Scattering For Image Classification". PhD thesis. École Polytechnique, CMAP, 2014. URL: https://www.di.ens.fr/data/publications/papers/phd_sifre.pdf.

[40] Karen Simonyan and Andrew Zisserman. "Very Deep Convolutional Networks for Large-Scale Image Recognition". In: *3rd International Conference on Learning Representations* (San Diego, CA, USA). ICLR, Sept. 2014. URL: https://arxiv.org/abs/1409.1556v6.

[41] Petru Soviany and Radu Tudor Ionescu. "Optimizing the Trade-off between Single-Stage and Two-Stage Object Detectors using Image Difficulty Prediction". In: *20th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing* (Timișoara, Romania). Institute of Electrical and Electronics Engineers Inc., Sept. 2018, pp. 209–214. URL: https://arxiv.org/abs/1803.08707v3.

[42] Richard S. Sutton and Andrew G. Barto. *Reinforcement Learning: An Introduction*. Ed. by Frances Bach. second edition. The MIT Press, 2018. ISBN: 9780262039246.

[43] Christian Szegedy et al. "Going deeper with convolutions". In: *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (Boston, MA, USA). IEEE Computer Society, June 2015, pp. 1–9. ISBN: 978-1-4673-6964-0. DOI: 10.1109/CVPR.2015.7298594.

[44] James Vincent. *Google's new machine learning framework is going to put more AI on your phone*. May 2017. URL: https://www.theverge.com/2017/5/17/15645908/google-ai-tensorflowlite-machine-learning-announcement-io-2017 (visited on 07/31/2021).

[45] James Vincent. *The iPhone X's new neural engine exemplifies Apple's approach to AI*. Sept. 2017. URL: https://www.theverge.com/2017/9/13/16300464/apple-iphone-x-ai-neural-engine (visited on 07/31/2021).

[46] Oriol Vinyals et al. "Grandmaster level in StarCraft II using multi-agent reinforcement learning". In: *Nature* 575 (2019), pp. 350–354.

[47] Mengwei Xu et al. "DeepType: On-Device Deep Learning for Input Personalization Service with Minimal Privacy Concern". In: *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2 (4 Dec. 2018), pp. 1–26. DOI: 10.1145/3287075. URL: https://dl.acm.org/doi/abs/10.1145/3287075.

[48] Alex Zhitnitsky. *The Top 10 Exception Types in Production Java Applications - Based on 1B Events*. June 2016. URL: https://www.overops.com/blog/the-top-10-exceptions-types-in-production-java-applications-based-on-1b-events/ (visited on 07/31/2021).

[49] Xiaojin Zhu and Andrew B. Goldberg. "Introduction to Semi-Supervised Learning". In: *Synthesis Lectures on Artificial Intelligence and Machine Learning* 3 (June 2009), pp. 1–130. DOI: 10.2200/S00196ED1V01Y200906AIM006. URL: https://doi.org/10.2200/S00196ED1V01Y200906AIM006.

[50] Yousong Zhu et al. "CoupleNet: Coupling Global Structure with Local Parts for Object Detection". In: *Proceedings of the IEEE International Conference on Computer Vision* (Venice, Italy). Vol. 2017-October. Institute of Electrical and Electronics Engineers Inc., Oct. 2017, pp. 4146–4154. DOI: 10.1109/ICCV.2017.444. URL: https://doi.org/10.1109/ICCV.2017.444.

Acronyms

adb android-developer-tools.

ann artificial neural network.

api application programming interface.

cnn convolutional neural network.

cv computer vision.

ecg electrocardiogram.

eeg electroencephalography.

ml machine learning.

NNAPI Neural Networks API.

ResNet residual neural network.

Glossary

application programming interface set of functions and procedures allowing the creation of applications that access the features or data of an operating system, application, or other service (Oxford Dictionary).

differential privacy property of a learning algorithm that uses personal data for training while guaranteeing that an individual's data cannot be reverse engineered by analysing the algorithm while potentially even having access to the data of all the other individuals. In other words, the differentially private algorithm behaves very similar (if not entirely identical) regardless of whether a particular personal information was used during training..

electrocardiogram time-voltage-graph of the electrical activity of the heart measured by electrodes touching the skin.

electroencephalography measures electrical signals emitted by the brain to observe brain activity.