Technologies of Object Recognition in Space for Visually Impaired People

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Abstract

Eyesight is a person's unique ability to visually notice obstacles in their path. But, unfortunately, this statement does not apply to everyone. Moving from one place to another cause many challenges for visually impaired people. In the period of the rapid development of artificial intelligence systems, as well as the expansion of the capabilities of mobile devices, there is an excellent opportunity to find an affordable and effective solution necessary to solve the problems of blind people. Development of applications that allow detecting objects in the user's environment is one of the priority approaches to this problem. The mobile application can warn the user of obstacles in his path and help him to move from one place to another, as well as giving user the opportunity to avoid unwanted collisions and stumbling. The target devices for deploying such applications are smartphones running on the Android operating system. The reason for this is the breadth and high availability of this devices. Android smartphones of any price segment are almost everywhere. Also, the choice of just such a popular category of devices allows to save time on the development and testing of new special gadgets for navigation, which could serve as an alternative in this solution. Therefore, this article proposes a model that allows to use the smartphone, a popular device accessible to everyone, on which there will be installed software that can help the visually impaired person to detect objects in his environment and help him navigate his way to destination place. The user will be able to receive all the original processed information in sound form, provided in the form of navigation instructions or a short description of the object.

Keywords 1

detection scheme, convolutional neural network, machine learning, TensorFlow API, Google Cloud Vision.

1. Introduction

Due to the rapid development of deep learning technologies, engineers have been able to create complex machine learning models designed to detect objects in images, regardless of their features and geometric shape. It also facilitated the replacement of existing heuristic-based systems in favor of machine learning models with better performance and speed. The massive spread of mobile phones and smartphones among users around the world, as well as the ever-increasing demands and expectations for greater performance, have challenged the industry to more widely use the latest and greatest technologies to meet demand. One of the topical solutions is the use of machine learning algorithms for object detection in space [1]. Learning is the phase where a model, usually a neural network, learns to behave in a certain way based on certain sets of data. This step can be easily implemented in the cloud and shared on mobile devices, where trained models can be used to train from previously unknown data. When using more advanced technologies and algorithms on a mobile device, one of the problems is the limited computing power of its equipment. In such a case, it is important that the operations performed are optimized for mobile devices. With the original mobile

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version of TensorFlow, namely TensorFlow Mobile, and the updated mobile library TensorFlow Lite, developers can use pre-built mobile device models for training, optimized for mobile hardware.

The object of study is a study of the means for deploying intelligent object detection and spatial navigation systems.

The subject of study is a TensorFlow machine learning technology capable of building and training neural networks to identify and decipher patterns and correlations.

The purpose of work is an analysis of the implementation of machine learning technologies in the area of object detection and spatial navigation implemented on devices running the Android operating system. Unfortunately, in the modern world, there are not many available tools that could make life easier for people with visual impairments. And thanks to the constant development of machine learning technologies and the growth in the number of platforms for their implementation, there is a great prospect to find the optimal solution to this problem. Therefore, the main purpose of this work is the study of applied tools for determining objects and spatial navigation, as well as analyzing the operation of convolutional neural networks, which make it possible to introduce an accessible and understandable software solution for this category of people.

2. Theoretical analysis

2.1. Visual Processing

The ability to see clearly depends on how well the components of the human eye are functioning. Light rays are reflected from all objects. The eyes receive light rays and transmit detailed information to the brain, which interprets them as images. Each part of the eye plays its own role in the transmission of these images. The sclera is a dense, opaque, protective protein membrane. In front is the cornea (cornea), a transparent window that allows light to enter the eye. Around the cornea is a thin, transparent membrane called the conjunctiva that helps protect the rest of the eye from the front and inside under the eyelids. [2]. Behind the sclera is the middle layer - the choroid. It is dark in color to prevent light from reflecting inside the eye and contains primarily the blood vessels that feed the eye. The front part of the choroid is the iris, which gives the eyes their color. At the center of the iris is the pupil, a round hole that looks like a black dot. The muscles in the iris control the size of the pupil by letting in more or less light. in bright light, the pupil shrinks to a small size to prevent too much light from entering. In low light or darkness, the pupil is enlarged to allow more light to enter the eye [3]. The task of the retina is to collect light information that the main nerve of the eye (optic nerve) sends to the brain in the form of nerve impulses [18]. The brain then transforms these messages into images. The retina has two types of light-sensitive cells - rods and cones, that capture rays of light. Rods help to see in dim light, while cones help to see details and colors. The transparent and flexible lens of the eye also plays an important role in the visual process. It focuses light on the retina. For precise tasks, light is focused at the center of the retina, in an area called the macula. The muscles around the lens control its shape, allowing the human to see objects at different distances. The cavity between the lens and the cornea contains a fluid called aqueous humour. A jelly-like substance called aqueous humour fills the cavity behind the lens. The aqueous humour and vitreous give the eyes their shape. By changing its shape, the lens provides clear vision at different distances. To focus on near objects, the muscles of the eye contract and the lens becomes rounder. When a person looks at a distant object, the same musculature relaxes and the lens is flattened [4].

The retina consists of 10 layers of photoreceptor cells, 6 of which are layers of light-sensitive cells. The 2 types of photoreceptors have a special shape, which is why they are called cones and rods. The rods are extremely sensitive to light and provide black-and-white perception and night vision to the eye. The cones, in turn, are not so sensitive to light, but they are able to distinguish colors - the optimal performance of the cones is noted during the daytime. Thanks to the work of photoreceptors, light rays are transformed into complexes of electrical impulses and are sent to the brain at an incredibly high speed, and these impulses themselves overcome over a million nerve fibers in a fraction of a second. The communication of photoreceptor cells in the retina is very complex. The cones and rods are not directly connected to the brain. Having received the signal, they redirect it to bipolar cells, and they redirect the signals already processed by themselves to the ganglion cells, more than a million axons (neurites through which nerve impulses are transmitted) of which make up a single optic nerve through which the data goes to the brain [5]. After the processed visual information enters the brain, it begins sorting, processing and analyzing it, and also forms a whole image from the individual data. With the help of two eyes, two "pictures" of the world that surrounds a person are formed - one for each retina. Both "pictures" are transmitted to the brain, and in reality a person sees two images at the same time. Image separation and highly complex optical pathways make it possible for the brain to see with each of its hemispheres separately using each of the eyes. This allows human to speed up the processing of the flow of incoming information, and also can provide vision only with one eye, if suddenly a person for any reason ceases to see with the other. This whole process of collecting analysis and processing visual data by the human brain is called visual processing [6].

2.2. Human vision and blindness

- Human vision is the process of visually detecting images and the location of objects in the surrounding world. The human visual system consists of two separate parts. The eyes act as a receiving channel of visual information from the outside world. Their main function is to capture and transform light rays into signals transmitted to special areas of the brain that are able to process these signals and perform them in the form of images [18]. As a result, thanks to the information received from the eyes, forms an internal picture of the surrounding space visible to a person. During the visual information processing, brain removes "blind" spots and distortions caused by the micromovement of eyes, blinking and a narrow viewing angle, offering the person an adequate integral image. Despite the lack of a clear distribution of function between the brain and eyes, it is still possible to consider each of the components of the visual system separately [7].
- Limitations of Human Vision:
- limited memory, a human cannot remember a quickly flashed image
- limited to visible spectrum
- illusion

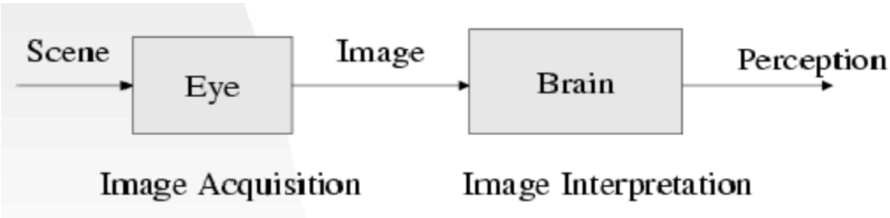

Figure 1: Stages of image processing by human organs

The World Health Organization (WHO) notes an increase in the number of people with visual impairment, who are characterized by moderate to severe visual impairmentю. For such categories of people, the use of contact lenses or regular glasses is not relevant and effective. As a result, a person loses the ability to fully function when performing routine tasks or completely loses his robotic ability. Blindness is a condition characterized by an absolute loss of vision, temporarily or permanently. Various diseases of the central nervous system, such as meningitis, encephalitis, and toxic brain damage, can lead to blindness. In the elderly, a sharp decrease in vision is often associated with degenerative-dystrophic changes in the retina and optic nerve.

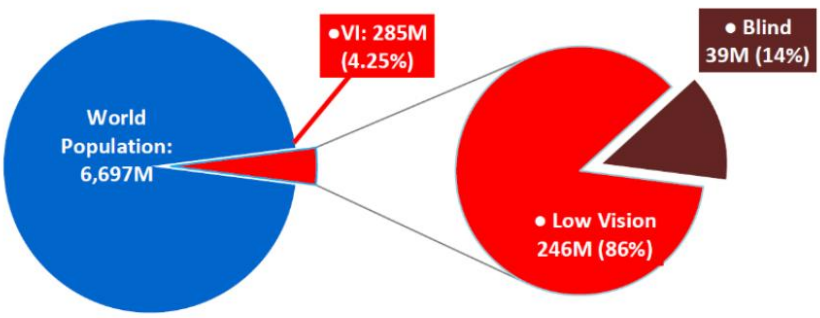

Figure 2: Global estimate of visual impairment (World Health Organization data for year 2012)

According to the 2012 WHO criteria, a global estimate suggests that of the 285 million people with visual impairments, approximately 39 million are blind. Most often, vision problems occur in people living in developing countries. In these countries, the main cause of many cases of blindness (about 48% of cases) is cataract (partial or complete opacity in the lens of the eye). Most often, vision problems occur among the elderly. Globally, women are at greater risk than men. If the treatment is started correctly and on time, about 85% of cases of visual impairment can be avoided, and about 75% of cases of blindness can be prevented or cured [8, 13].

2.3. Computer Vision

Computer vision is an interdisciplinary field that deals with the extraction of information from digital images and videos, regardless of their type and format. The purpose of this area is the automation of processes and tasks in the field of computer technology, which are performed by the human visual system.

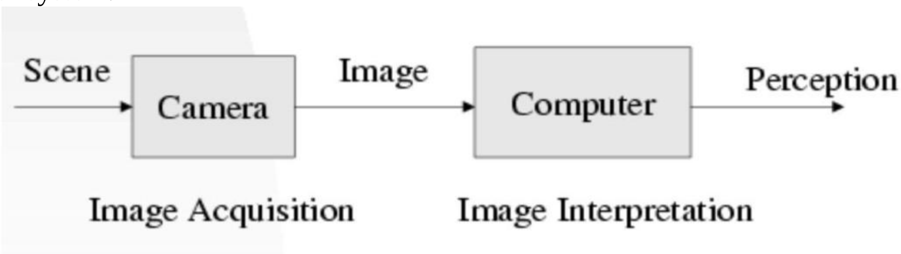

Figure 3: Stages of image processing performed by computer vision

The task of computer vision is to find optimal methods for analyzing and processing images and presenting it in the form of multidimensional models, digital and symbolic data or equations. The information that different algorithms extract from images in computer vision can have different nature and type. Some algorithms simply split the image into parts corresponding to individual objects or different parts of objects. The concept of understanding digital images is based on the principle of distributing symbolic information and image data using models built on the theory of physics, statistics, geometry and machine learning [18, 15].

In object classification, it was known that the work of the human brain is characterized by know-how in the semantic area, that is, semantically significant elements are equivalent to line segments, its shape and boundaries. In any case, even with the use of later data processing techniques, such components still cannot be accurately recognized by a computer, so it is still difficult with computer vision to represent visual data the way humans do. A computer needs to prepare visual data in an information space framed by significantly disparate but less important components, for example, shades, surfaces, and other. Thus, the philosophy of working with visual objects in computer vision is not at all the same as in humans. That is, if a person is able to perceive the visible picture integrally in his consciousness, the computer in its logic relies on the differences between the elements of the image.

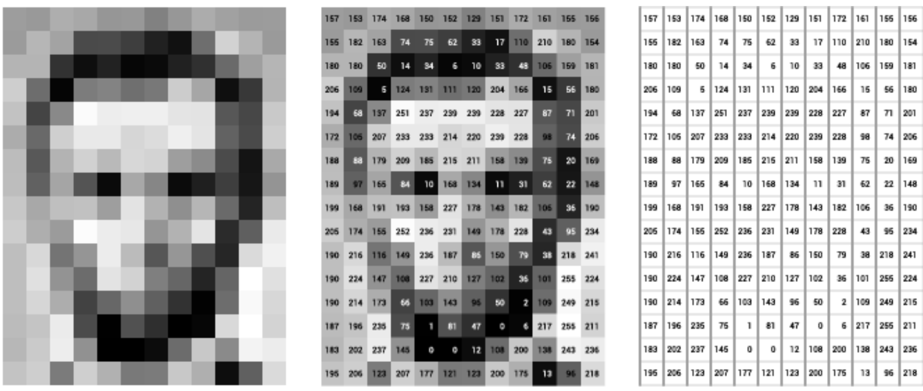

Figure 4: Example of computer vision image recognition

Computer vision is used in the tasks of automatic analysis, processing and understanding of useful information obtained from an image or sequences of several frames. First, it is necessary to agree on the theoretical foundations of the approach and prepare the algorithmic basis for achieving automation of the understanding of visual data. In its work, computer vision relies on the technology of applying machine learning in the field of identifying objects in images. The effectiveness of computer vision solutions is constantly growing, regardless of their field of application. Computer vision is widely used in various sectors of industry and social life, from medicine (medical scanners) and security equipment (CCTV cameras) to the military industry (missile guidance optics) and the automotive industry (autopilot and other innovations). The end result of applying machine learning models and theories in this discipline is the creation of automated computer vision systems.

The field of machine learning models for visual recognition emerged in the late 2000s and now dominates the area of computer vision. Due to the large amount of labeled data, complex algorithms and increasing computing power, these models are able to classify objects without human intervention. Currently, the most common algorithm for detecting objects in the field of computer vision are convolutional neural networks, for which it has been proven that their ability to classify images exceeds the human level [9, 17].

The computational characteristics of artificial neural networks are similar to those of graphical computations in real time when rendering objects in video games, where operations such as matrix animation and splitting are performed per pixel in parallel. Around 2005, researchers realized the potential benefits of deploying and training artificial neural networks on a graphics processing unit rather than a central processing unit, resulting in faster computations and better performance. This allowed the researchers to add more layers in neural networks, also known as deep neural networks, and use more data while maintaining optimal execution times [10, 20].

3. Architecture diagram

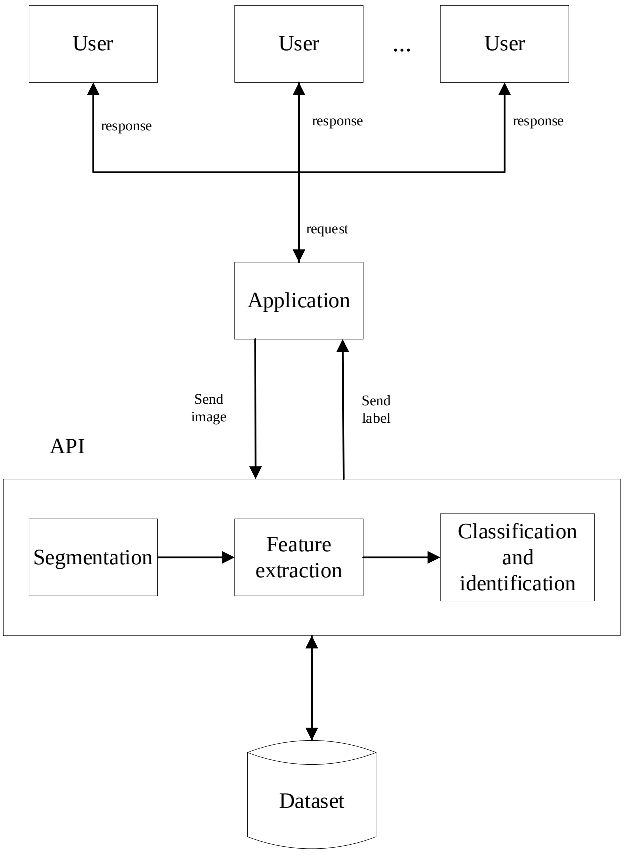

Figure 5: System architecture

The above diagram is a four-layer architectural / conceptual diagram of the system. This conceptual diagram shows the interaction between different parts of the proposed system by dividing them into four separate components. This division more accurately represent the relationship of different elements in the scheme and allows better understand the structure of the system. The outer layer of this architecture is represented by the user layer and is the system entry point. The figure also shows the interaction between users and the Android application, which is the middle layer of the architecture. The Android application contains the user interface of the system, it also receives requests from users and sends them to the API for further processing. The API uses a dataset that contains thousands of labelled images to process requests. In this case, the system compares the current image received from the user with the images in the data set. After classification and identification, the API sends to the application a label and a detection accuracy parameter of the current image.

4. About system and methods

4.1. Classification and object detection

The process of determining which of the k possible categories some x input belongs, is called the problem of classification. This can be described by the function $f\colon R^n \rightarrow \{1, \ldots, k\}$. The result can be transferred by a class, or by a vector from the distribution of values of all classes. Classification of the image - the process of establishing the classification of the category, before which the object should be placed on the image [20].

Object detection is the process of detecting objects in an image; it applies a recognition algorithm on all sub-windows of the original image, ranging from one to several classes of objects [11]. Object detection can be used to detect faces, pedestrians or vehicles in an image. For example, image detection in the YOLO network preforms the process of dividing images into subsets [12]. To identify objects, it is necessary to localize objects within the image that do not have a classification. At first YOLO architecture image is divided into a grid, and then this grid is used to evaluate multiple image sub-windows.

If there is performed video analysis, that consists of several images (frames) per second, and detection is performed in real time, then such an algorithm is considered an algorithm for detecting objects in real time. Analyzing multiple images per second in object detection puts a lot of emphasis on efficient algorithms as the processing power required increases.

In machine learning, the training stage is the stage where the parameters of the model θ are optimized to minimize the cost function, and essentially learns the mapping function f^* from input to output. The inference phase of the machine learning model is that the fully trained model, that shows some input value x, and outputs some initial value y obtained from the composition of the proper function.

4.2. Mean Average Precision

The most common metric for object detection performance is the mean Average Precision (mAP), as defined by the PASCAL VOC. Best performance is reported as a higher mAP value based on the ideal expected result field and class data for the object detection task. Before using mAP to detect an object, all predicted fields and classes are sorted in descending order of probability and aligned with the fields and classes of the ideal expected result. If the prediction classes and the ideal expected result are the same, and their intersection on the union (IoU, also known as the Jaccard index) is greater than or equal to 0,5 (0,5IOU), then the prediction is considered a match. A match is considered true if and only if it has not been used before to reduce duplicate object detection [13]. The ranking quality metric is calculated using numerical integration as the ratio of the area under the precision and recall curve, and then the mAP result is achieved by calculating the ranking of all classes.

To get mAP, we have to calculate the precision and calculate all the objects in the images. We also need to consider the precision result for each object detected by the model in the image. There is a necessity to consider all the assumed limiting fields with a precision result above a certain threshold. Bounding boxes that are above the threshold are considered to be positive, and any provided bounding boxes below the threshold are considered negative. So, the higher is the precision threshold, the lower mAP will be.

5. Experimental part

The typical software used for machine learning tasks on Android devices is TensorFlow Lite. It is widespread because it offers an interface for implementing common machine learning algorithms and executable model code. Models created in TensorFlow can be ported to heterogeneous systems with little or no change to devices ranging from mobile phones to distributed servers. This software was created and maintained by Google and is used internally for machine learning purposes. TensorFlow performs computation as a data flow graph with states.

Google designed TensorFlow Lite to be able to run on heterogeneous systems, including mobile devices. This was due to the problems of transferring data between devices and data centers where calculations could be performed on, without involvement of particular device. TensorFlow Lite allowed developers to create interactive programs without the need for backward network latency for related computation [14, 18].

Since the machine learning task is computationally expensive, model optimization is used to improve performance. TensorFlow Lite minimum hardware requirements for random access memory (RAM) size and processor speed are low, and the primary bottleneck is computation speed, since latency is desirable for mobile applications. For example, a mobile device with hardware capable of 10 gigaflops per second (FLOPS) floating point operations is limited to running a 5 gigaflops model at 2 frames per second, which may make the desired program performance impossible.

Some of the optimizations included in TensorFlow Lite include hardware acceleration through the silicon layer, templates such as the Android Neural Network API, and optimized mobile ANNs such as MobileNets [15] and SqueezeNet [16, 19]. Learned TensorFlow models are automatically converted to TensorFlow Lite model format.

Also, an important component of such a system is the use of the Google Cloud Vision API, which allows you to identify a specific object in the digital image using machine learning models in the REST API. It quickly characterizes the image in a large amount of classifications (for example, "helicopter", "Statue of Liberty", etc.), highlights special features and images within the image itself, and finds the printed words contained within. It can be used to build metadata on the image index, target malicious content, or enhance new advertising scenarios by examining image ratings. The image from the request is analyzed and integrated with the image storage in Google Cloud Storage.

At the initial stage of the Android applicationdevelopment, that use TensorFlow Lite technology, we need to import the required software libraries into the application. To do this, we add the following line to the dependency section of our build.gradle file:

```
compile 'org.tensorflow:tensorflow-lite:+'
```

In order to load the model and configure it start up, we need to import the TensorFlow Lite interpreter, which also provides a set of inputs. Then in TensorFlow Lite it will be possible to execute the model and set the outputs.

```
import org.tensorflow.lite.Interpreter;
```

Then we create and loadan instance of the Interpreter into the MappedByteBuffer.

```
protected Interpreter tflite;
tflite = new Interpreter(loadModelFile(activity));
```

To load the model, we must also use the getModulePath () function, which returns a string that points to a file in the assets folder. To classify images, we need to call the launch method on the interpreter, and pass it an array of labels and image data:

```
tflite.run(imgData, labelProbArray);
```

The classifyFrame () method contains the core of the TensorFlow Lite library:

```
private void classifyFrame() {
  if (classifier == null ||
   getActivity() == null ||
    cameraDevice == null) {
  showToast("Uninitialized Classifier")
  return;
}
```

Then we loada raster mapfor the classifierand scale it to the required size. After that, to get a list of the 3 best classes, we need to use the classifyFrame () method, which will return the text of the class labels and the calculated weights.

```
Bitmap bitmap = textureView.getBitmap(
  classifier.getImageSizeX(), classifier.getImageSizeY());
String textToShow = classifier.classifyFrame(bitmap);
bitmap.recycle();
showToast(textToShow);
```

Precision predictions are made using the Intersection over Union method. The object detection system makes predictions in terms of the timing of the bounding boxes and class labels. IoU measures the overlap between two limits. We use this to measure the percentage of the predictable area overlap the location of the object with its real area (real feature of the object). In some datasets, we pre-define the IoU threshold (let say 0.5) by classifying whether the prediction is True Positive or False Negative.

Figure 6: Overlapping areas of predicted and ground truth bounds

Below are the results of identifying objects on a smartphone with an installed experimental application. In the resulting images, you can observe the overlap of bounding boxes on certain objects, object labels and the accuracy of the detection in percent. Based on the results, it can be argued that TensorFlow Lite technology is capable of qualitatively and fairly accurately identifying objects in the image.

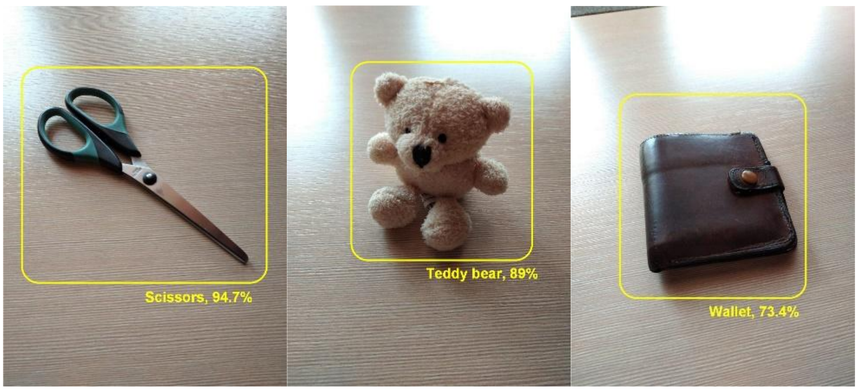

Figure 7: Results of object detection

For transmission of sound information about certain objects from the screen can be used the functionality of the TalkBack service, often used by people with visual impairments on their smartphones. This service is a Google screen reader pre-installed on Android devices. TalkBack provides voice prompts so that the user can use the device without looking at the screen.

6. Conclusions

The main driving factors in the analysis and testing of this software were the motivation and the idea to find the optimal solution to the problems of people with visual impairments. This article reviewed modern technologies for detecting objects in digital images, which include the TensorFlow Light and the Google Cloud Vision API libraries. The main object of the research was the use of the TensorFlow Light library, which contains many useful algorithms for processing, analyzing and classifying images. This technology has demonstrated a wide range of tools for machine learning and object detection. The Google Cloud Vision API uses a COCO dataset, which contains millions of pictures, that can be compared with the input image. All Google Cloud images are sent and processed in the cloud. Also, choosing the Android operating system from Google as the target platform for distributing the application eliminates the possibility of unpleasant compatibility issues.

Among the main limitations of this system are the necessity to keep the user smartphone always turned on, a stable Internet connection and a sufficient battery level. The user must carry it with him at all times. A good addition could be a special hook-on case for a smartphone, and then a person's hands would become free.

7. References

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