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FAKULTA INFORMAČNÍCH TECHNOLOGIÍ

DEPARTMENT OF INTELLIGENT SYSTEMS
ÚSTAV INTELIGENTNÍCH SYSTÉMŮ

DEEPFAKE DETECTION FRAMEWORK

FRAMEWORK PRO DETEKCI DEEPFAKES

MASTER'S THESIS
DIPLOMOVÁ PRÁCE

AUTHOR **Bc. JAN BERNARD**
AUTOR PRÁCE

SUPERVISOR **Mgr. KAMIL MALINKA, Ph.D.**
VEDOUCÍ PRÁCE

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Master's Thesis Assignment

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Institut:	Department of Intelligent Systems (UITS)
Student:	**Bernard Jan, Bc.**
Programme:	Information Technology and Artificial Intelligence
Specialization:	Cybersecurity
Title:	**Deepfake Detection Framework**
Category:	Security
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Assignment:

1. Learn about deepfakes (voice and video). Explore the current state of deepfakes detection methods (voice and video).
2. Learn about the technologies needed to create web extensions and technologies for creating scalable server applications.
3. Learn about existing deepfake detection solutions (e.g. other commercial web browser plug-ins)
4. Design an extensible framework (server-client or client-only) for deepfakes detection (support for at least 3 detection methods (voice and video)). Design a web extension for deepfakes detection that will use this framework. The solution should support multiple browsers and allow the detection of displayed content and uploaded files.
5. Implement the tool according to the design.
6. Test the functionality and reliability of the resulting implementation. Perform testing on at least two independent publicly available deepfakes datasets.
7. Discuss usability, detection efficiency and possible extensions.

Literature:
Puspita Majumdar, Akshay Agarwal, Mayank Vatsa, and Richa
Singh, “Facial retouching and alteration detection,” in Handbook of Digital Face Manipulation and Detection, pp. 367–
387. Springer, 2022
FIRC Anton a MALINKA Kamil. The dawn of a text-dependent society: deepfakes as a threat to speech verification systems. In: Brno: Association for Computing Machinery, 2022

Requirements for the semestral defence:
Items 1 to 4.

Detailed formal requirements can be found at https://www.fit.vut.cz/study/theses/

Supervisor:	**Malinka Kamil, Mgr., Ph.D.**
Consultant:	Ing. Anton Firc
Head of Department:	Hanáček Petr, doc. Dr. Ing.
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Abstract

Deepfake creation has improved a lot in recent times and hence is a dreaded menace to society. Deepfake detection methods have also responded with development, but there are still not enough good tools available to the general public. This work focuses on creating a deepfake detection framework that will be easily extended by other detection methods in the future, yet simple and accessible to the general public.

Abstrakt

Tvorba deepfake se za poslední dobu velmi zlepšila a tudíž je obávanou hroznou pro společnost. Detekční metody odhalující deepfake také reagovali rozvojem, ale stále není široké veřejnosti dostupné dostatečné množství dobrých nástrojů. Tato práce se zaměřuje na vytvoření frameworku na detekci deepfake, který bude jednoduše rozšiřitlený dalšími detekčními metodami v budounu a přitom jednoduchý a dostupný široké veřejnosti.

Keywords

deepfake, framework, deepfake detection, containerazation, web plugin

Klíčová slova

deepfake, framework, detekce deepfake, kontejnerizace, webový doplňek

Reference

BERNARD, Jan. *Deepfake Detection Framework*. Brno, 2022. Master's thesis. Brno University of Technology, Faculty of Information Technology. Supervisor Mgr. Kamil Malinka, Ph.D.

Deepfake Detection Framework

Declaration

I hereby declare that this Master's thesis was prepared as an original work by the author under the supervision of Mgr. Kamil Malinka Ph.D. The supplementary information was provided by Ing. Anton Firc. I have listed all the literary sources, publications and other sources, which were used during the preparation of this thesis.

.....
Jan Bernard
January 27, 2023

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I also owe a debt of gratitude to my family, especially my parents, friends for their wonderful support throughout my studies.

Contents

Chapter 1

Introduction

Deefake is the buzzword that has no agreed-upon technical definition. It consists of two words deep and fake. Deep is referring to deep learning machine learning, which is used for creating of fake voices, images, or even videos. It is a fast-growing technical field of study and could be big threat for society. We are living in information era and creation of unrecognizable fake media affects us all. Deepfakes could be found on social media, news portals, etc.

There are many different deepfake categories for face swap to full puppet and more. Most of the detection methods are focused on a single domain, which means they are capable of detecting only a one deepfake category. There are few tools in market targeting to undemanding/inexperienced users, and some of them are not free to use.

The goal of this work is to examine the current state of deepfakes, first, generally, with later focus to detection methods. Based on the acquired knowledge design and develop the fake detection framework and client application utilizing it.

Chapter 2

Deepfakes

The creation of fake media and their detection have been a problem since photography was invented. Digital photography or video with tools such as GIMP, Adobe Photoshop or Adobe After Effects allows more people to create fakes than before, still some experience in this area is needed. Media that have been modified or otherwise manipulated are called synthetic media, and they do not depend on whether it is an analogue or digital medium. Deepfakes also fall under this category [9]. Tools powered by deep learning allow unexperienced users to easily create trusted fakes.

The quality of deepfakes reached a level when a trained person or even an experienced researcher in this field has a problem of spotting them. This fast development allows creating realistically looking assets to art photography or movie production, unfortunately, it can be used for malicious purposes like creating fake porn videos to blackmail people or manipulate public via fake news. There are many use cases where deepfakes can be applied.

It is putting huge pressure on researchers to develop new forensics tools or any technology which will prevent malicious usage of deepfakes. As mentioned before, creating fakes is not new, and a whole field of study engaged in spotting fakes and developing techniques over 15 years. Despite continuous research efforts in the past, the advent of deep learning changed the rules of the game. [24]

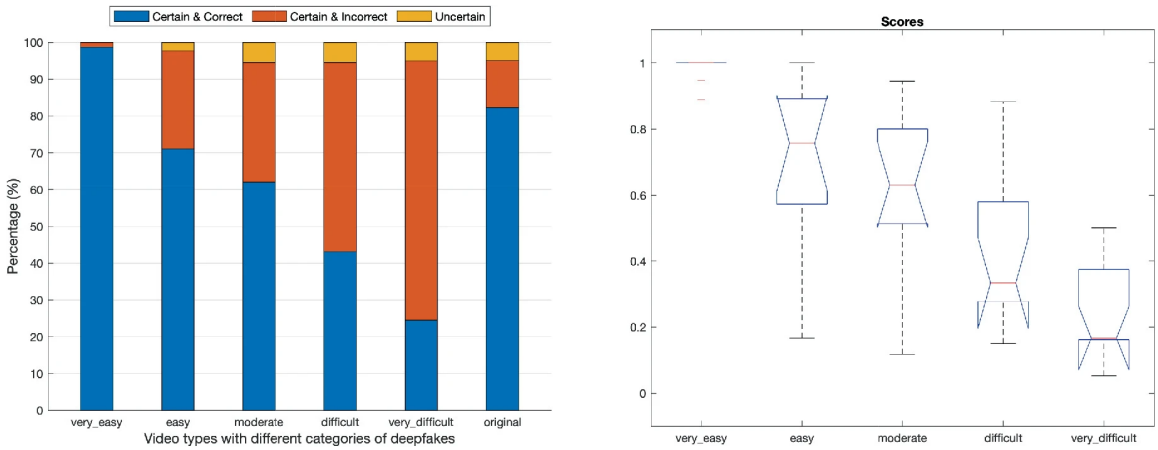
2.1 Human capabilities of deepfake detection

The human ability to recognize fake materials from the originals is in contradiction to their quality. Korshunov and Marcel confirmed this in their research. They created a questionnaire containing several videos, and the subject (interviewee) had to answer after watching the video whether the person in the video was genuine, fake, or they are uncertain. The videos were manually divided into five categories (very easy, easy, moderate, difficult, and very difficult, original).

Videos were split into several categories manually by researchers probably without usage of any metrics but based on their experience and feelings. Afterwards ANOVA test shows there is an overlap in several categories, so several videos could be moved to different category. However, the categories are still significantly different.

The results of test in Fig. 2.1 certainly demonstrate that people's recognition ability decreases significantly as the quality of deepfakes increases. Also, the audience of this test knows they are looking for fakes, otherwise we can expect worse results if there will be unsuspected audience (e.g. deepfakes on social media). It is quite alarming that the correct

answers in the category of "very easy" reach only 71,1 %. The quality of deepfake increases over time, thus it can be expected that human recognition ability will continue to decrease. [12]



(a) Subjective answers

(b) ANOVA test

Figure 2.1: Subjective answers and median values with error bars from ANOVA test for different deepfakehttps://www.overleaf.com/project/6373f30660c2425f4720defb categories. Retrieved from [12].

Another research tested only recognition of audio tracks and they were comparing humans versus computer programmes. Attendees had a correct classification between fakes and origins 67 % after the first several rounds. Their accuracy increased while listening and answering to more tracks, but the value stabilizes to 80 %. On average, trained AI performs about 10 % better than human, but this result highly depends on difference of learning and test dataset. Still, it shows that the computer can outperform humans in spotting deepfakes. [16]

2.2 Potentional risks

Humans are not good at recognizing deepfakes, but "why should we be worried?". Almost every technology humankind created could be used for good or bad – deepfake is no exception. There are plenty different deepfake categories, and each has its own attack vector or use case. This section is describing potential risks of those categories and their closer description will be covered in next section 2.3.

Deepfakes are about gaining someone's trust or influence him. For the last couple of years there has been an increasing trend of scamming people, mostly via phone or computer [3]. Targeting only one person/victim, for example, to gain their money or information. Those attacks are getting better and more credible and using deepfake to impersonate close friend of victim could be next step how to improve it, if it is not already happening.

Creating "fake news" to influence a large audience is the most common use case of deepfakes because we live in an information era. There are many targets of "fake news" such as rigging elections, demoralizing military units, or manipulating the stock market. In this case, politicians, celebrities, and significant personalities will be used in deepfakes to influence audience. We can only imagine what one person or high quality deepfake can

change with enough media reach. For example, after one tweet from Elon Musk about Tesla's stock, sends shares down more than 10 % almost immediately [22]. [9]

A real example of deepfake is famous video with Barak Obama insulting Donald Trump, which should spread awareness regarding the fast developing category of new thread [1]. Several years later another video stating Volodimir Zelenskyj talking about surrendering, it was proved that it is a manipulated video, and its purpose was to demoralize Ukraine army and make them capitulate [2].

Another field where deepfakes could be used is to tricky biometrics systems in which the attacker is a different person to the gain access (banking, building, ...) [6], to secured equipment, etc. It was proven that biometrics system is not ready to deal with deepfakes, and it will probably require to add a new module to authentication pipeline which will be detecting deepfakes [10]. Face or voice biometrics recognition systems are in greatest danger. The falsification of documents is related to this topic and there was a case of smuggling people across borders with an official passport containing morphed photos of two individuals [20].

These cases are only the tip of the iceberg, and in the future, everyone should ask if video on social media with film celebrity is real or even worse, if the evidence in courts is trustworthy or not. The solution for this is using tools capable of detecting deepfakes. Those tools have to be created with caution for unskilled users.

2.3 Types of deepfakes and their creation process

There are plenty of methods on how to create deepfakes, and as its name suggests some of them are based on deep neural networks, but not exclusively. This section describes most common types of learning networks used for creating image/video or voice deepfakes. One of the most popular types for face deepfakes is Generative adversarial network (GAN), and it is used to create completely new faces or face manipulations.

Each method leaves traces in the medium that can then be detected. This is one way to recognize deepfakes so understanding process of creation is an advantage. Detecting will be described in more detail in Chapter 3.

2.3.1 Neural networks

All the facts regarding neural networks were retrieved from [15]. Neural networks are composited from neurons arranged in layers, and each layer is connected sequentially via synapses. Synapses are weighed, and the process of finding the proper value of all weights is called a learning neural network. To obtain results from the input of n-dimensional x process `forward-propagation` is used to propagate x through each layer.

Input to layer is vector a of values calculated by previous layer or in case of first layer x itself. That means result of each layer is also vector calculated by activation function $f(a * W + b)$, where f is activation function (Sigmod, ReLU, etc.), a is input vector, W is matrix of weights between layers i and $i + 1$ and b is dimensional bias. Dimensional bias is a constant offset that helps the network shift the activation function toward the positive or negative side [1].

[1] https://www.buzzfeed.com/craigsilverman/obama-jordan-peele-deepfake-video-debunk-buzzfeed

[2] https://www.youtube.com/watch?v=X17yrEV5sl4

Now let's consider the neural network M as a black box and denote its execution as $M(x) = y$. Supervise learning to train M is using paired samples with from (x_i, y_i) and loss function L is defined. Loss function is to generate a signal at the output of M and propagate him back to find error of each weight in synapses.

Optimalization algorithms such as gradient descent are then used to calculate new weights of M for the number of epochs. As a result of this process, the network learns the function $M(x_i) \approx y_i$ and is capable of making prediction on unseen data. More detailed descriptions of this could be found in the work of Y. Mirsky and W. Lee [15].

Next list shows types of neural networks used for generating deepfakes [15]:

- Generative Adversarial Networks (GAN) – Consist of two neural networks working against each other. One layer is generator and second is discriminator. Generator producing fake features trying to fool discriminator, on the other hand, discriminator is learning to distinguish between real sample and fake one.
- Encoder-Decoder networks (ED) – Contains at least two networks, encoder and decoder. It has narrowed layers towards its center. If encoder En and decoder De are symmetric and they are trained as $De(En(x)) = x$, then the network is called autoencoder. Generating deepfakes using ED trained with function $De(En(x)) = x_g$, where x_g is fake generated features. There is possibility to use multiple different ED chained after each other or using specific variant of ED called variational autoencoder.
- Convolutional Neural Network (CNN) – CNN is learning pattern hierarchies in the data. For deepfakes purposes, it learns filters applied over the input and forming an abstract feature map as the output.
- Recurrent Neural Networks (RNN) – RNN can handle variable length data and it is remembering stat after processing which can be used in next iteration. RNN are mostly used in audio.

Each architecture has its own subcategories that have small modifications or using some techniques from different architecture. All above mentioned neural networks types are shown in 2.2 and 2.3

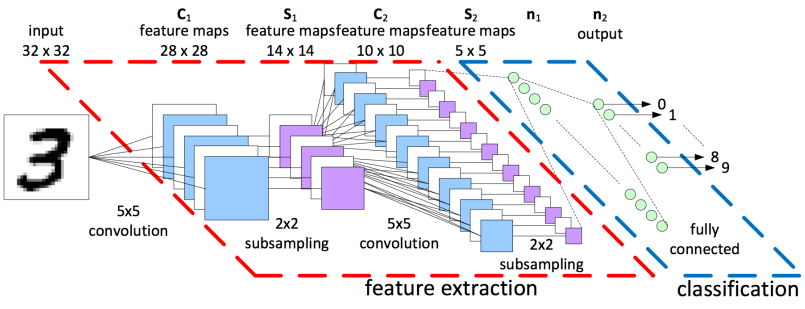


Figure 2.2: Architecture of convolutional neural network. Retrieved from [4].

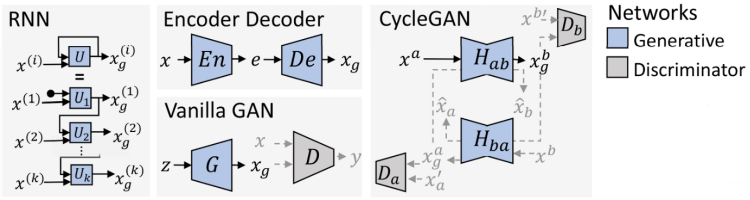


Figure 2.3: Basic neural network architectures (RNN, ED, GAN). Retrieved from [15].

2.3.2 Voice deepfakes

There are three different modalities for speech synthesis: text-to-speech (TTS), voice cloning (VC), and replay attack (RA). [25] The last fine is based on the capture victim voice and the replay of it. It is quite easy and cheap to perform because it only requires capture and replay device (today we can use for example smartphone) and current methods for voice recognition still have accuracy issues. [14] First two are using AI-synthesis with content regeneration which makes them more indistinguishable for naked ears. [25]

Text to speech (TTS) converts written text to artificial speech, on the other hand voice cloning consumes source voice. Both methods produce synthesis voice saying desired phrases specified by the input, high-level diagram how those methods works could be seen on Fig. 2.4. Voice deepfakes are used independently or with deepfake video (e.g. full puppet). Creating synthesis voice is computationally challenging and one of the goals is making real-time voice cloning. There are several projects that are trying to accomplish this 3 4.

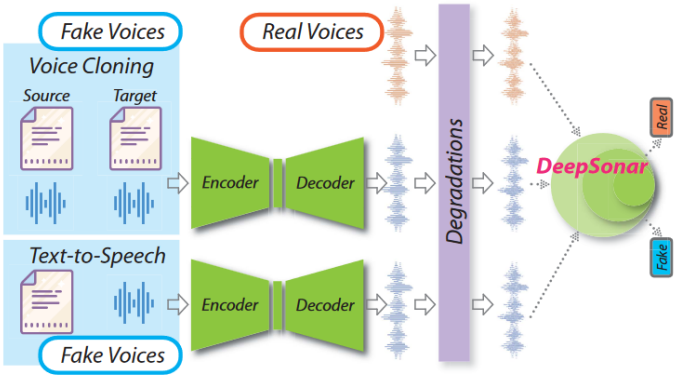


Figure 2.4: Text-to-speech and voice cloning data flow diagram. Retrieved from [25].

2.3.3 Image or video deepfakes

The list of the following deepfakes is based on the work R. Tolosana, et al. [11]:

- Identity swap – Replacing the face of subject with the face of target as shown in Fig. 2.5. There are two different approaches, classical computer graphics-based technique and deep learning technique. Generally, the process of swap could be described as face detection, cropping, extraction of intermediate representations, synthesis of new face, and blending the generated face.

Figure 2.5: Examples of real and fake identity swap images. Retrieved from [11].

- Full puppet – Method related to identity swap allows creation of so-called puppet. One person (master) is source of facial expression and body movements that are mapped onto target person as shown in Fig. 2.6. [9]

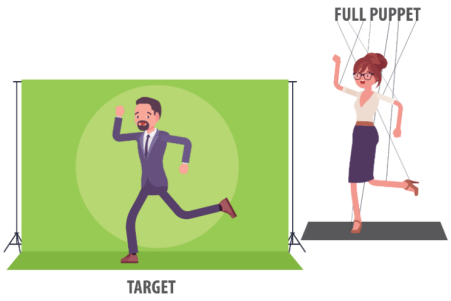


Figure 2.6: Full puppet technique visualisation. Retrieved from [12].

- Morphing – It is a type of manipulation that is used to create artificial biometric face samples. Final face contains resemble biometric information of two or more individuals. It should be possible to be successfully verified by biometrics systems for all individuals who were source for given deepfake. Fig. 2.7 shows an example of a morphed image.

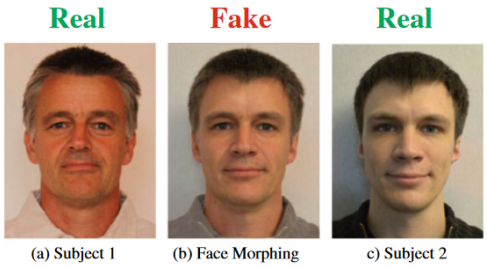


Figure 2.7: Examples of fake morphed identity from Subject 1 and Subject 2. Retrieved from [11].

- Attribute manipulation – Face editing or face retouching technique involves modifying some attributes such as length or color of hair, color of skin, sex, age, adding glasses or other artefacts, and more. Fig. 2.8 shows an example of this technique.

Figure 2.8: Examples of real and fake attribute manipulation category. Retrieved from [11].

- Expression swap – Modifying facial expression of the subject as shown in Fig. 2.9. This technique is used as one of part for full puppet.

Figure 2.9: Examples of real and fake expression swap category. Retrieved from [11].

- Audio/text to video – This method related to expression swap synthesising facial expression from audio or text. It is also known as lip-sync deepfakes. Diagram in Fig. 2.10 shows how this method works.

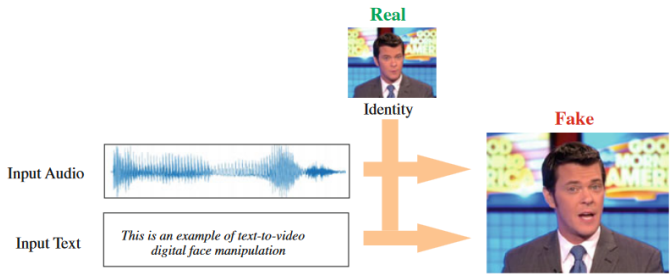


Figure 2.10: Examples of real and fake audio/text to video fake category. Retrieved from [11].

Creating deepfakes nowadays is complex task and many deepfakes is using more techniques so that they could be included into more than one category. Attackers could create deepfake that will fall under identity swap category and after that use attribute manipulation to tune final results.

Chapter 3

Deepfake detection

As we stated, humans are not good at recognizing deepfakes. Creating deepfakes could leave visible defects (e.g. blurring or misalignment on edges in the image). A. Firc summarizes the list of features to focus on when spotting fakes for humans [5].

- Facial features – eyes and their movement, eyebrows, glasses, facial expression, hair and facial hair, skin, lips, teeth
- Body features – body position and posture, body movements
- Voice features – unusual tempo, end of words, fricatives, conversation
- General indices – blurring or misalignment on edges, inconsistence noise or audio

This list points to most critical parts of deepfakes where some defects could be spotted created by creation process. Generation of deepfakes is getting better and other masking techniques are used. Huge problem for deepfake detection is lossless compression, several chained resize of a image, application of noise, etc. Basically, all methods that led to some data loss but still maintained main information with no notable change for naked eye or ear. Manual post-processing could be used for polishing results (images – Photoshop, GIMP, etc.) when previous methods are still not good enough.

Machine detection could be divided into two categories: standard algorithms looking for physical inconsistency, digital integrity, using same features as A. Firc described. Other methods are based on machine learning. The same "masking" techniques listed before have the same effect on machine-based detection because there is data loss, preventing usage of reliable methods like frequency analysis. Still, computers perform better than humans, because they can also use different features (e.g. pixel level features), especially neural networks trained for deepfake detection. In case where we are not looking only for deepfakes but we expend input set to all synthetic media we can use similar methods. The difference will be in the learning process (training data) or feature selection. The worst case scenario is only recognizing suspicious images containing traces after possible masking techniques such as double compression traces, noise patterns, etc. [24]

Another problem of detection algorithms is bad generalization. Most of methods are trained on single domain deepfake (e.g. identity swap), which means they are not able to recognize deepfake from different category. When methods are trained on multi-domain datasets accuracy is going down. [13]

3.1 Image/Video detection methods

As stated, before most of methods for deepfake detection are targeting only single domain. This section will describe examples of proposed detection methods for image/video deepfakes. There are more conventional approaches and also more "exotic".

P. Majumdar, et al. referring to multiple detection methods for image retouching (makeup, filters) and alternation (fully synthetize faces, morphing) [13]. Most of them use the same pattern which could be described as specific feature extraction followed by support vector machines (SVM) for classification. One of the methods proposed detection of images using face patches as input in the deep Boltzmann machine for feature extraction and SVM for binary classification. Another method uses softmax probabilities as features in the SVM. Other methods, for example, using convolutional neural networks. [13]

L. Spreeiwers, et al. made research on using local binary pattern with SVM for morphing detection [23]. A single LBP histogram contains 59 feature values, which means that for a 3×3 layout, the feature space has 531 dimensions. The SVM classifiers are trained on between 650 and 1,000 samples. They also stated that EER increases to above 20 % while adding Gaussian noise to the deepfakes images.

Non-conventional detection method is heart rate estimation (remote photoplethysmography) by J. Fierret [8]. They are trying to estimate heart rate from video and evaluating frame-by-frame. There are other human physiological processes that could for be used instead heart rate such as blood oxygen or breath rate. The score oscillates during the video and final decision is based on the mean/median/QCD score.

There are many other methods, and each will have its pros and cons, but as we can observe, SVM classification with large range of different feature extractors. Another rising group of detectors is using CNN. There are not many researches using CNN as SVM but results seems to be promising as we can see in researches [19] [17].

3.2 Voice detection methods

Voice detection complicates different languages; it is similar story to image/video deepfakes. There are face swaps, morphing, etc., and for voice there are different languages and dialects. Voice detection methods also copying trend from image/video detection methods. Support vector machines (SVM) with different feature extractors or CNNs.

Z. Almutairi and H. Elgibreen refer to multiple methods [2]. One of them uses the SVM model with Random Forest to predict synthetic voices based on a feature called Short-Term Long-Term. In this research, they compared SVM with many other classifiers such as Linear Discriminant, Quadratic Discriminant, Linear SVM, weighted K-Nearest Neighbors, and SVM outperforms all of them. Other referred work uses combination of two CNN, 1-D CNN and Siamese CNN. The Siamese CNN contained two identical CNNs that were the same as the 1-D CNN but concatenated them using a fully connected layer with a softmax output layer. [2]

3.3 Analysis of existing tools for detecting deepfakes

Tools for deepfake detection are slowly getting from command line tools for experts to online tools with user-friendly interface. There are not many tools of this kind and some of them are not free to use. The following lines describe two available tools in a market.

3.3.1 Deepware

The Bosnia and Hercegovina recognize danger of deepfakes, while their parent company researched methods to develop an AI-based antivirus engine. Deepware company was founded to develop scanner for deepfake recognition.

Deepware provides REST API with web UI [1], mobile android application. The backend of this project with pre-trained models is accessible on their GitHub as Python command line tool [2].

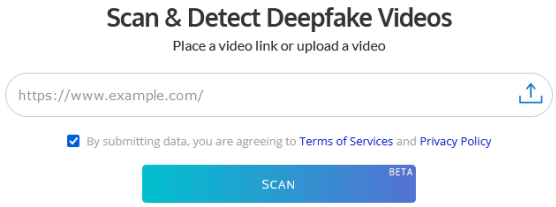


Figure 3.1: Deepware scanner input form

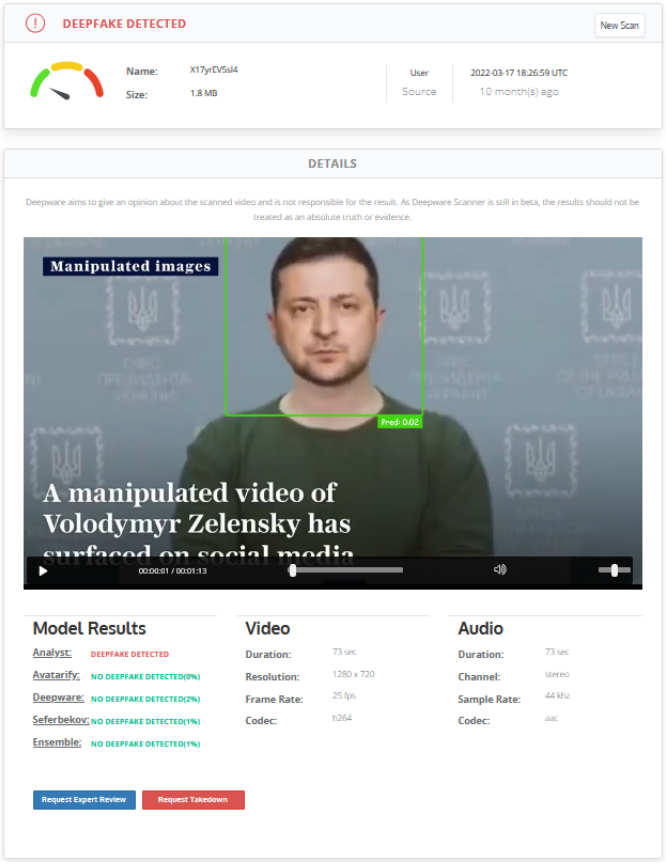


Figure 3.2: Results of Deepware scanner containing probability of deepfakes from multiple detection methods

[1] https://scanner.deepware.ai/
[2] https://github.com/deepware/deepfake-scanner

The Web application is stating that the project is in Beta, but unfortunately the last commit to the GitHub repository was mad on 7th of June reported at the time of writing this thesis.

The tool provides a simple user interface to scan only videos. The user can input the link to the video (e.g. YouTube) or upload the video file directly as shown in Fig. 3.1 . There are many supported video formats. The only limitation is the length of the video, which does not have to be longer than 10 minutes.

Processing of approximately 1 minute long video takes several seconds (3-10 seconds). Results contains video and audio metadata, results of multiple detection methods/models, and deciding whether it is a deepfake or not with gauge chart of confidence as we can observe in Fig 3.2. To use their Rest API, you need to request authentication token. API provides the same functionality as web UI via three methods.

- POST /video/scan
- GET /url/scan
- GET /video/report

The first two methods execute scan on a video file or link and return report ID. Results report could be retrieved by last method and results are returned as JSON. Documentation also code samples for multiple programming languages on how to use API properly. The provided API can be integrated to other processes like mail communication scans or file upload filters.

3.3.2 Sensity

Sensity is very similar from the user perspective to Deepware. Based on the post on Sensity blog [21] from 2021 we can explore web UI of their application. The application is not publicly accessible and to obtain access, you need to request it. Sensity provides more tools related to cybersecurity, person identification, and verification.

Sensity allows for detection of images and videos by inserting files or referencing them via a URL link as shown in Fig. 3.3. Sensity allows processing of quite small group of file types (png, jpeg, jfif, tiff, mp4, mov). Another limitations are for videos regarding their size (up to 30MB), length (10 minutes), and quality of videos (1440p). [21]

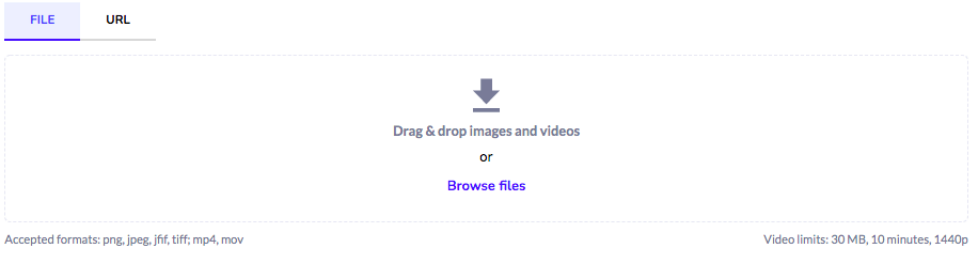


Figure 3.3: Sensity deepfake detection tool input form. Retrieved from [21].

The tool is capable of recognize only face swap and fully synthesized faces by GAN. It is not able to recognize morphed images or other deepfakes. For GAN-genereated faces, it is sometimes able to classify model generator. If deepfake is recognize tool show how

confident he is, all shwon in Fig. 3.4. Compared to Deepware, it provides image scans; on the other hand, it does not have mobile application.

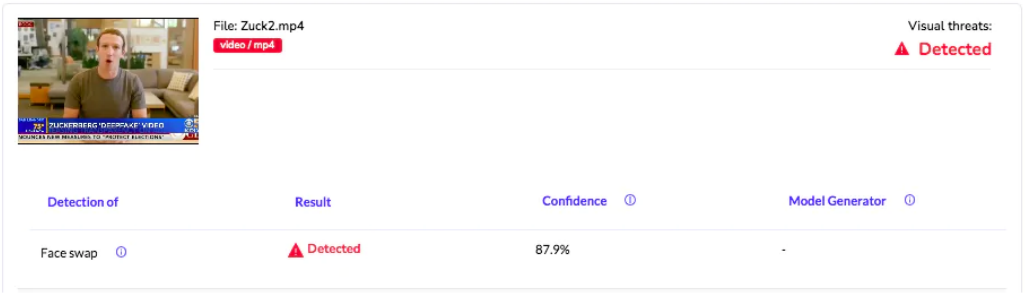


Figure 3.4: Sensity deepfake detection tool results. Retrieved from [21].

Chapter 4

Architecture and technologies analysis

The goal of this work is to develop a deepfake detection framework capable of serving various client applications and an exemplary web plugin subscribing this framework. We already analyze the market and test existing tools. Because there is no external contracting party defining their need, we will define requirements by ourselves. Requirements will be divided into two categories, functional and non-functional requirements. It is important to define not only functional logic, but also some limits on processing time, number of users, etc.

4.1 Requirements

As we already said, the framework has to support multiple clients, so there needs to be a properly defined communication interface between the client applications and the framework itself, which will act as server in this case. Framework allows dynamic changing detection methods, which means it is able to add, remove, or edit detection method. This implicates multiple detection methods at one time for image, video, and even voice deepfake detection. Editing detection method means updating the model or constant parameters.

The platform should support as many file types as possible and adding a new method should not affect methods already presented in the framework, within supported file types. Different detection methods have different models depending on their design, so model management will be wrapped completely into the detection method.

The framework should collect statistics and hardware metrics, but the collection of personal information should be omitted. All collected metrics will be used for future improvements of detection methods and optimizing operating costs and performance. We would like to have a short response time with as low operating costs as possible. Those two parameters are in contradiction, so there has to be some balance between them. Scalability of the framework or some computationally intensive parts of the framework will help with these requirements. From a perspective number of users, the platform will handle up to hundreds of users at one time, and with enough resources the framework should handle even more.

The client application has to be simple so that anyone can use it. Users should be able to upload files or put a link to a file. The Web plugin allows access to DOM of the webpage so an optional extension will be selection of web elements and retrieval from metadata of

it automatically. Because it should cover a large group of possible users, results have to be easy to understand and also provides information for experienced users. Last but not least, the client application should enable users to send feedback. There are several web browsers in market that cover almost all audience, it will be nice that the developed web plugin will be portable among multiple web browsers.

Today it is standard, but it is necessary to mention that the application should be secured. It will affect code of framework, client application, and environment itself (hardware, operating systems, ...). All work is open-source and accessible on the public GitHub repository.

Summary of functional requirements:

- Adding, removing, and editing (changing parameters and models) detection methods
- Multiple detection methods at once
- Collecting statistics and feedback
- Detection of image, video, and voice
- Detection of file, URL link, or selected HTML element (optional)
- Understandable presentation of results
- Security

Summary of non-functional requirements:

- Scalability
- Small response time
- Low operating costs
- Portability of the web plugin among multiple web browsers (optional)
- Open source

4.2 Containerazation

The framework requires dynamic management of the detection methods. It means that the framework can contain one or twenty different detection methods. Each method could be developed using different programming languages or technologies. Also, model management will be integrated into the detection method. This leads to some isolation of each detection method with a defined communication protocol. Another requirement requires scalability of framework, and all this together will be reached via containerization.

There are many technologies dealing with containers, such as Docker, Podman, LXC. When we start counting orchestration with automatic scalability, the number of technologies drops down. Cloud solutions such as AWS, Azure offer Kubernetes for orchestration of Docker containers. In addition, Docker is probably the most widely used technology for containerization. Because of the huge community and good support of different cloud platforms, we can possibly run framework, we will stick with duo Kubernetes and Docker.

4.3 Framework

The framework is a collection of detection methods, an interface for the client application (receiving requests, sending report response), and orchestrates/arranges all communication. It will be built into several containers and one of the containers will be providing client application interface. It could be Rest API, GraphQL or custom protocol. It is not a good idea to develop a custom communication protocol, so we will stick to the most used Rest API. For this purpose, we can use a huge number of different technologies such as ASP.NET Core, Flusk, Django, Ruby on Rails, etc.

Basically all named technologies meet defined requirements (response time, number of users, ect.) because most of them are covered by microservice design and containerization described in chapter X. Our choice is ASP.NET Core because it has a huge community, Linux support, many external libraries, it is suitable for bigger projects, and it has good speed of program development.

4.4 Web browser plugin

Web plugins are based on web technologies such as HTML, CSS, JavaScript, TypeScript, etc. There are also technologies like WebAssembly which allow development of web applications in languages like C++ without usage of web framework. Because of portability and good integration we will choose HTML, CSS, and Typescript. Typescript is a strict syntactical superset of JavaScript and adds optional static typing to the language. It is also compiled into JavaScript. With those technologies we could be able to create portable web plugin for Chromium base browsers and Firefox.

Chapter 5

Framework architecture

The architecture must reflect that each detection method could be developed in different architectures. We can isolate the detection methods from each other and wrap them into independent services. We do not need communication among all detection methods because they do not cooperate or share any data. In this case, the microservice architecture meets all defined requirements.

5.1 Microservice architecture

Microservice architecture is the style of developing applications. Example of design can be observe in Fig. 5.1. The microservice allows the application to be separated into smaller logical independent parts. The service then has its own realm of responsibility and they can communicate with each other. Containers are a well-suited microservice architecture example. [7]

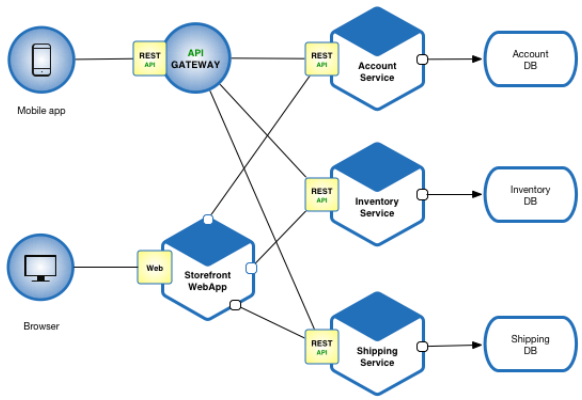


Figure 5.1: Microservice architecture of fictitious e-commerce application

Microservices improve fault isolation that non-functional service should not affect others, in best case scenario. In real cases microservices depend on each other and this might lead to a problem. For example, if one service contains a memory leak, it is not propagated into other ones. Another benefit was already mentioned, and it eliminates commitment to one technology stack. One service has better maintainability because it should be small (better understandability, faster tools), which leads to more productive developers. [18]

This architecture also has several drawbacks. It increases the complexity of architectural design and additional implementation of cross-service communication. When saving data to database, developers have to deal with distributed system because each service has its own independent database. [18]

5.2 High-level architecture

The user communicates directly with the Rest API endpoint. This part of the design may be labelled as master process because it is handling request, preparing and validating data, selecting which type of processing should be used. After processing is done, it collects all results and distributes them back to the user. Fig. 5.2 contains high-level design of framework with data flow.

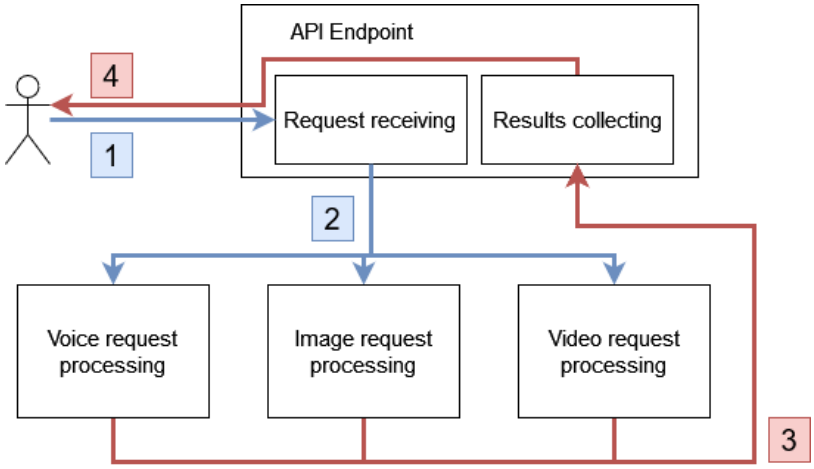


Figure 5.2: High-level design of whole framework

The architecture separates voice, image, and video detection into an independent unit. Each unit contains a processing queue where the request will be assigned by the master process/Rest API. The queue is serviced by one or multiple processing units that contain all related detection methods as shown in Fig. 5.3.

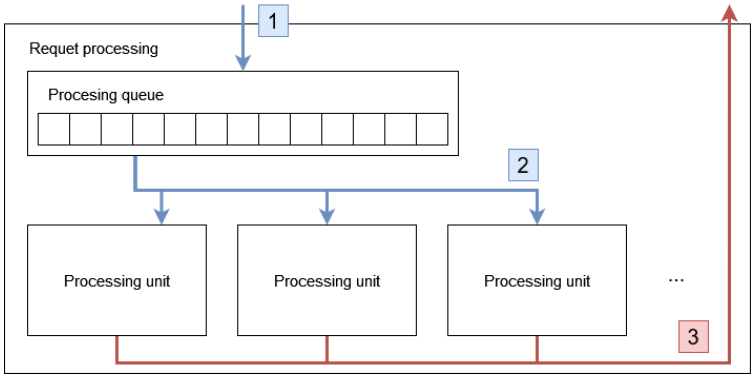


Figure 5.3: Request processing detail

The processing unit works as a parallel pipeline. Closer look at design is in Fig. 5.4. Some detection methods require input data in specific format, so the first step is optional data preparation. Some methods are wrapping data preparation by themselves. The next step is the detection method that decides whether the input data contains deepfake or not. Detection methods are different, so are their results, so we need to properly generalize and also normalize them.

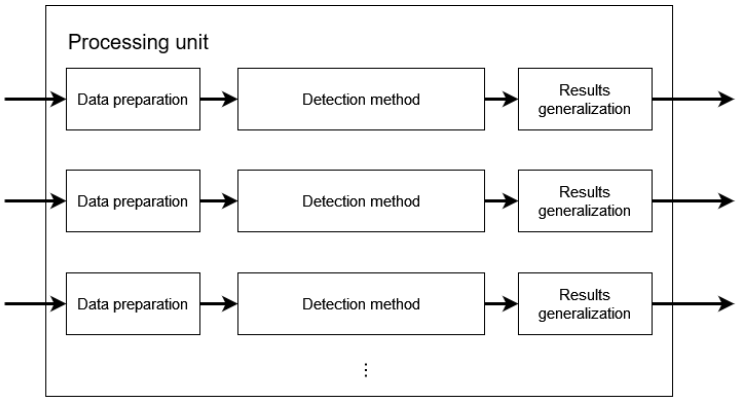


Figure 5.4: Processing unit pipeline

5.3 Containerization and scaling

Detection methods have to be containerized, and to decrease complexity data preparation and results generalization will be encapsulated together with detection method. The processing unit then will be the collection of containers/pods.

The processing unit then can be clone/scale up when needed to process more requests. Scaling up can be done automatically by setting specific rule in container orchestrator. To save costs we can scale down when a peek of request disappeared.

5.4 API Endpoint

As mentioned before, API endpoints communicate directly with user application and with backend processing mechanism. Processing takes same time, so user application creates request and wait asynchronously to be processed by the framework. The API for this purpose contains “detect” and “request” methods. “Detect” methods start processing and“requests” methods manage already running process. There are other support methods for possible health check or providing feedback. All methods are described in following list:

- /ping
  - GET /ping – healtcheck endpoint
- /detect
  - POST /detect/file – creates request with file in HTTP request body
  - POST /detect/link – creates request with link to a file in HTTP request body

- /request
  - GET /request/stop/<request_id> - stops running request
  - GET /request/results/ – returns results of processed request or empty results if request is in process
- /feedback
  - POST /feedback/<request_id> - collects user feedback with optional parameter request_id

Each detection method has different processing times. There are two options to return results to user: partial results from the detection methods already completed or returns only when everything is completed. Because there is no need to show partial results, the second option will be used. This requires the use of another queue for respons or some sort of database. The framework needs to calculate the overall score and this requires all results from all methods. Calculating the total score requires considering the univariate methods as well as their domain differences. A single method will usually focus on a single domain (e.g. face swap). We leave the exact definition to the implementation section.

The method `/request/results` could be possibly replaced by websockets which will increase complexity, but on the other hand a user application could better report status of the running process. It is one of the possible extensions to the framework.

5.5 Request processing and processing unit

API endpoint placing all new requests in the request queue. One of the available processing units takes the first request form queue. This request contains all the information such request ID, data for detection, and metadata for this data.

The first step in the processing pipeline is optional data preparation. The detection method could be trained only on a specific resolution of the video/image or on a specific length of the voice sample. This means data processing unit has to be designed for a given detection method. When data are prepared for detection, they continue to the detection unit.

After detection, the same case as optional data preparation is optional data generalization/normalization. Because results need to the be correctly presented to user and the framework needs to calculate over all scores, all results need to the be normalized to same scale and "units". When results contain more specific information, in this case it needs to be generalized. Results could contain field with additional/extra information about results which could also be presented to the user. Results are then pushed to the results queue or database, depending on implementation.

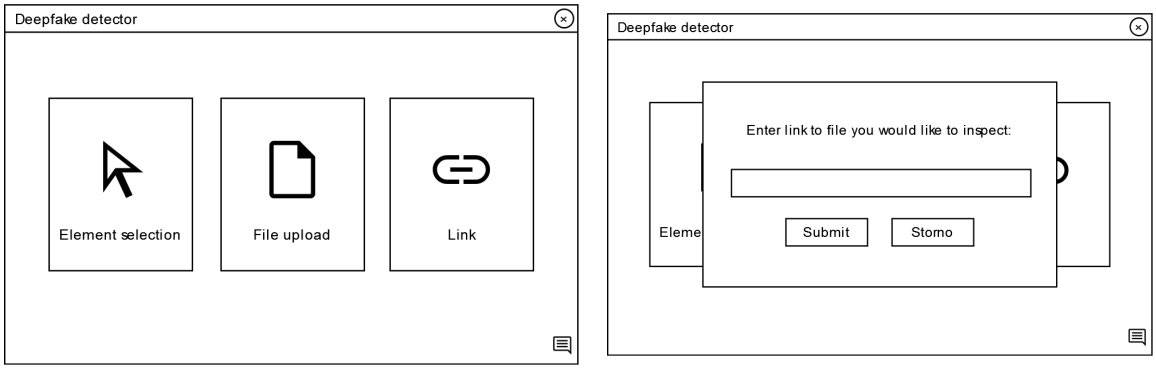
Chapter 6

Client architecture

The use case of the client application is straightforward, so there does not need to be use case or data flow diagrams. The application will try to prepare the file for inspection and send it to the server framework. The next section contains several wireframes of how the client application should look like with description.

6.1 Web browser plugin

It should allow the user to insert a file via file upload, link, or HTML element containing a targeted file. In Fig.6.1 we can see type insertion selection, for file upload the user will be prompted by system file upload picker. When user pick link as input, floating windows will pop up, and user then can insert URL to file. Those two selections are the same as other tools in market also provide. Optional improvement will be element selection which switches the application to interactive mode where user can point to HTML element and application will try to retrieve metadata of image or video directly from HTML.



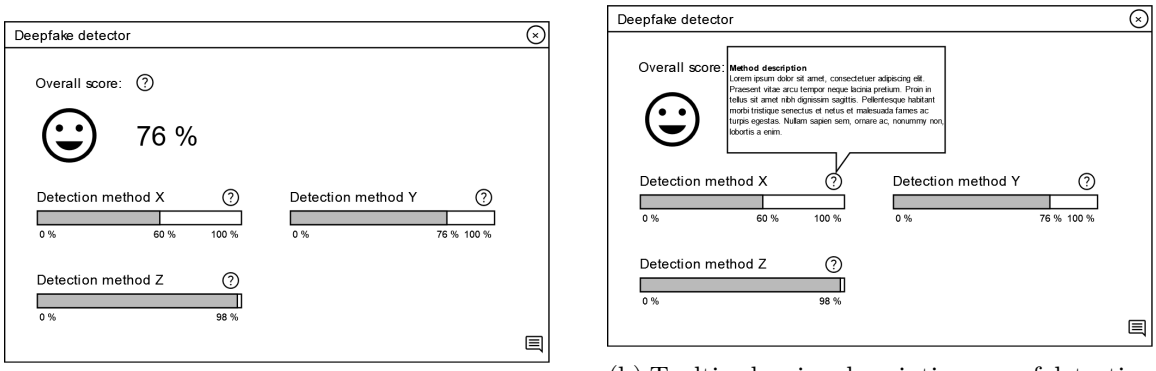
(a) Input type selection

(b) Link input in floating window

Figure 6.1: Input type selection screens

Because detection framework will contain several detections method we need to show the result of each method independently. It could be a little confusing for user so there will also be overall score which interprets/generalizes all the results of each method. The overall score will indicate the results as a percentage and as emoticon. The palette will contain four emoticons shown in Fig 6.3. For better understanding there are question marks in the

UI that after mouse hover shows tooltip with description. Whole results screen can be view in Fig. 6.2.



(a) Results view

(b) Tooltip showing description one of detection method

Figure 6.2: Results view screens

Figure 6.3: Palette of emoticons indicating if inspected file contains deepfake or not

At the bottom of each screen there is an icon that enables the user to the send feedback to application. After clicking on this icon floating window will appear, shown in Fig 6.4. When user will be sending feedback on the result page, the internal result ID will be added as an additional parameter to the feedback message.

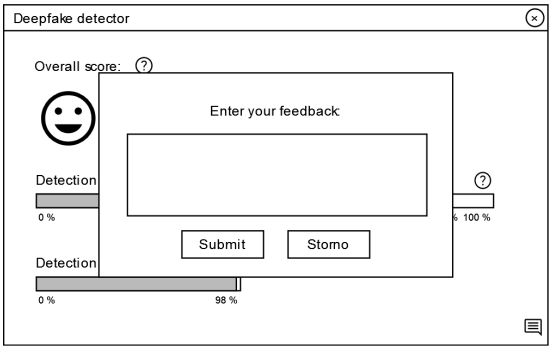


Figure 6.4: Feedback form in floating window

Chapter 7

Conclusion

As Theodor Roosevelt once said: “Believe you can and you’re halfway there.” I believed and now this thesis is halfway to finish line. All set requirements and set goals were met, so we can consider the first part to be successfully completed.

The thesis covers general knowledge about deepfakes and their generation and describes several methods for detecting them. At the end there is an architectural design of the detection framework and also client app utilizing it.

The next steps will include extending little bit deeper architecture, finding a suitable detection method for integration to framework. When all this will be finished, implementation itself can be started. There is still a lot of work to do and hopefully all subsequent steps and intermediate results will be promising and lead to a successful end.

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