Vision

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Summary

Super Resolution problem, SR for short, which is essentially just taking a low resolution picture and converting it to a high resolution picture, with magic of course. It might seem like an easy problem to solve; because of the fact that the requirement are simple, but it’s not easy, it’s simple, but not easy, there are a lot of details that we have to care of in order to produce the same details in both the lower resolution picture and the higher resolution one, to give an example, if the lower resolution picture is a picture of a licence plate of a car, we have to make sure that we keep that license plate correct and not lose some information from it.

Introduction

Imagine taking an amazing picture, and you get home exited to put that picture on a huge monitor in your living room, so you can show it off to people who come to your house, to find out that when you put a small picture on a big screen, most of the details in the picture are lost, which leads to a blurry picture, that does not look good. Now that happens when you just have fun and take normal pictures, imagine when that picture is important to a crime, or for getting important information, or a memory of someone, you can't just get back in time to get a better looking picture with higher resolution, the time machine has not been invented yet, and we also can't just try to guess what that blurry part of the picture is and assume the information we need. We have to solve this problem, which is not limited to only pictures, but videos as well.

That problem is called the Super Resolution problem, SR for short, which is essentially just taking a low resolution picture and converting it to a high resolution picture, with magic of course. It might seem like an easy problem to solve; because of the fact that the requirement are simple, but it's not easy, it's simple, but not easy, there are a lot of details that we have to care of in order to produce the same details in both the lower resolution picture and the higher resolution one, to give an example, if the lower resolution picture is a picture of a licence plate of a car, we have to make sure that we keep that license plate correct and not lose some information from it.

System Description

Our system is quite simple to describe, which also leads to better scalability, higher availability and fault-tolerance, and an efficient way to solve the problem. The system has three main components,

1. User Interfaces
2. Distributed System of processing units
3. Deep learning Models

The user interface, also called the front-end, is responsible for taking care of the full user experience, from uploading the picture or the video, to displaying the new higher resolution image or video. It will be a Flutter application, which handles the mobile version, both IOS and Android, Desktop Application for Windows, macOS, and Linux, as well as a web version. This will make sure that we cover almost all platforms, so people can use it whenever they want, fast and easy.

The distributed system of processing units will handle all the temporary data operations, why temporary?, might ask, because these units will be stateless meaning that they shouldn't know which request is which and user data or save anything. These processing units should also make sure the whole system is resilient, in case of a failure, as well as handling huge amounts of requests with a small amount of resources.

The deep learning Model, the cherry on the cake, will have our main algorithms and learning models to convert the user's lower resolution picture or video to a high resolution picture or video, using state-of-the-art deep learning models, and APIs. Why are we using deep Learning, not just normal image processing algorithms ? or why not use the traditional methods to enhance resolution ?, you might ask, well first of all, traditional methods don't really work for the general case, meaning that they are restricted to certain types of pictures, and even with that, they don't always keep the details of the picture that we talked about earlier. Second of all, deep learning models, or even normal Machine learning models, learn from every picture that is fed into them, that is why they are called learning models, which leads to automatic development and scale, and make it adaptable to new types of data. In addition, the problem itself isn't traditional, we can't just create an algorithm that always works fast, and achieve a high resolution picture with all the important details, we don't know how to fill the extra pixels in the image after we convert it to a high resolution, so we need some sort of learning model to choose the best thing to fill those pixel, and also keep learning on it's own, based on previous positive experience.

System Purpose

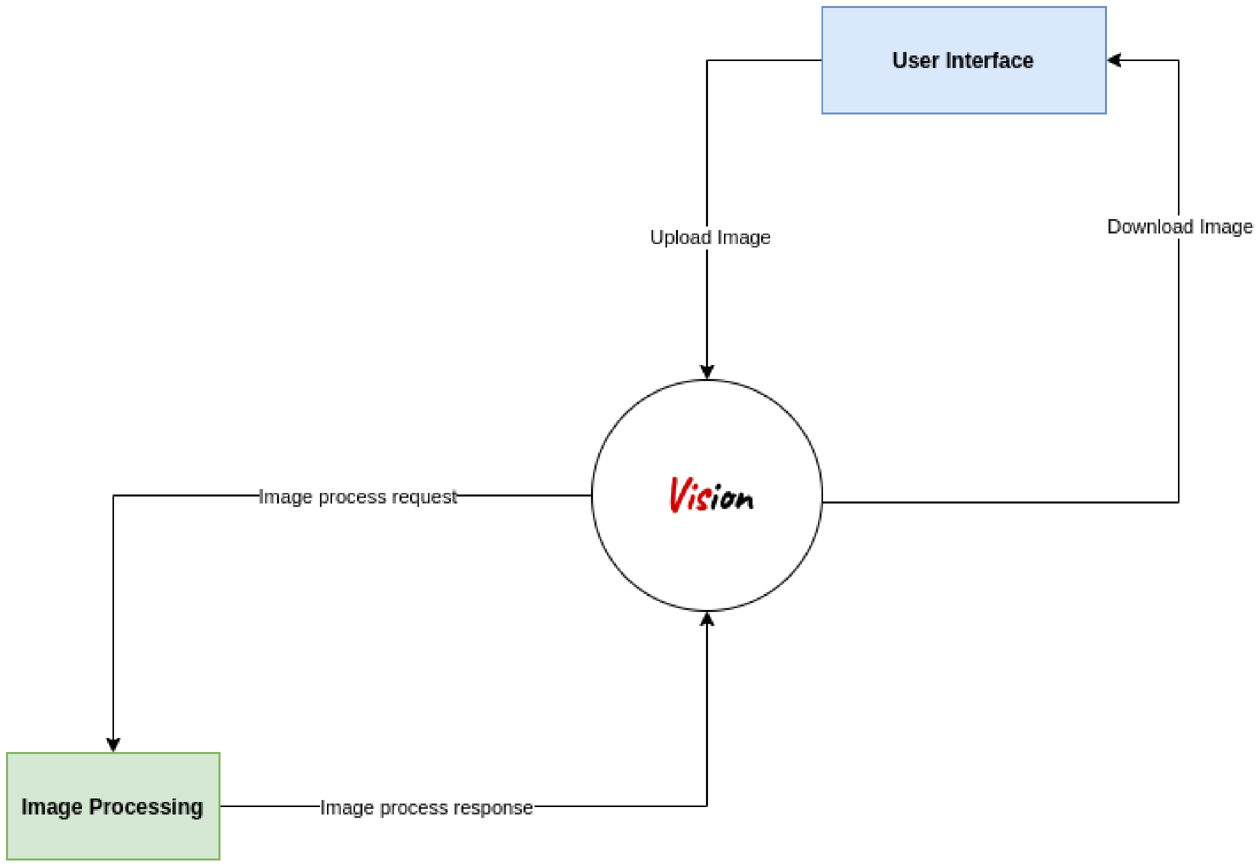
The purpose of the system is simple, the system takes an image or a video from the user, processes it, and finally returns the processed image or video to the user. This, of course, needs to happen in milliseconds, even when the system is under load. And when the system experiences failure, it needs to meet it with elegance rather than disaster, and stay highly responsive, giving users effective interactive feedback. This is because our system has critical values to the users, and they need the results as soon as possible. Also one thing that we should provide is security, we don't want other people getting into users' data, so we are going to provide a stateless application to make sure we, the system, don't have data to leak or something like that. As well as, making sure that our network interactions with the user is also secure, to be able to receive and send data securely.

Problem Statement

The main problem is converting a lower resolution (lower Pixels per inch) image, to a higher resolution (high Pixels per inch) image. Which also can be extended to videos, because of the fact that a video is just a sequence of images called frames. And it’s the same for our requirement, Pictures and DVR videos.

So if we have a frame, image or a frame from a video, called X, we have to return X' ; such that X' has a higher resolution than X with the details from existing in X'. So given a frame, produce a frame of larger size, and with noticeably more pixels, as well as higher image quality.

The System Context View



Literature Review

Deep Learning for Single Image Super-Resolution: A Brief Review

This review brings a new perspective on how we should look at the deep learning models on solving problems, but in the context of the Super Resolution problem of course. It reviews representative deep learning models that relate directly to the Single Image Super Resolution, SISR for short, and then group them into two colors, relative to their contribution to two core aspects of SISR, the first one being, the exploration of efficient neural network architectures for SISR, and the second being, the development of effective optimization objectives for deep SISR learning. It highlighted some benchmarks of deep Architecture for SISR, which show some amazing numbers of how deep learning enhances the SISR operation.

Image Super-Resolution Using Deep Convolutional Networks

This paper proposed a deep learning method for single image Super Resolution, it directly learns an end to end mapping from the low resolution image. That mapping is done using Convolutional Neural Networks, CNNs for short. It showed an amazing proof of how traditional sparse-coding based Super Resolution methods can also be seen as CNNs, however, unlike traditional methods that handle each component on it's own, their deep learning model jointly optimizez all layers and components, with a lightweight structure, and maintaining state-of-the-art quality. All of that with the idea of working efficiently and having real online applications across the industry.

Photo-Realistic Single Image Super-Resolution Using GANs (Twitter)

Twitter researchers, Twitter Cortex research group to be exact, showed that some deep learning methods for Super Resolution are good, but there are some issues in them, despite the breakthrough in accuracy and speed that people got from Convolution Neural Networks. One of the questions that remains unanswered is, how do we recover the finer texture details when we super resolve at large upscaling factors? So they introduced SRGAN, a Generative Adversarial Network for Super Resolution that solves this problem.

iSeeBetter

Three researches figured out that although the learning-models have enhanced the performance of a single picture Super Resolution, yet applying those methods, the single picture Super Resolution methods, consecutively to each video frame is going to cause a lack of temporal coherency, which is something that we don’t want to have for sure. Convolutional Neural Networks, CNNs, outperformed traditional methods in almost every way, but Generative Adversarial Networks, GANs, offers a competitive point for us, which is begin able to mitigate the issue of a lack of finer texture details, usually seen with CNNs when super resolving at large upscaling factors. So iSeeBetter used GANs in order to be able to produce Super Resolution videos, VSR, that renders temporally consistent VSR.

RAISR: Rapid and Accurate Image Super Resolution (Google)

This is my personal favorite paper about Super Resolution, because it really shows how many important applications the problem has, not just the fictional movies image enhancement kind of thing, to give a few about the applications of the Super Resolution, Google showed it in many of its products, the Pixel 2 phone used it in its digital zoom, which showed amazing result over the years. Google+ (RIP) used up to 75% **less** bandwidth per image when using RAISR, and they’re applying RAISR to more than 1 billion images per week, reducing these users’ total bandwidth by about a third. Not just that, it also produces high quality restoration while still being faster than the current leading algorithms by a factor of two, with an extremely low memory footprint. This way it can be executed on a smartphone offline, rather than on a server or a heavy machine to handle it.

Challenges

1. Brand New!

   Students don't normally just get into AI and Machine learning, and whatever is around it, easily. So it was hard to understand these kinds of stuff, and how to be able to connect the basics that we know, from math basics, computer basics, with what we are trying to solve. We can easily find working code online, but we also would like to understand the Math behind it, the Theory, its Applications, its History, and all that sweet stuff that makes Computer Science what it is.

2. Simple yet Hard to solve!!

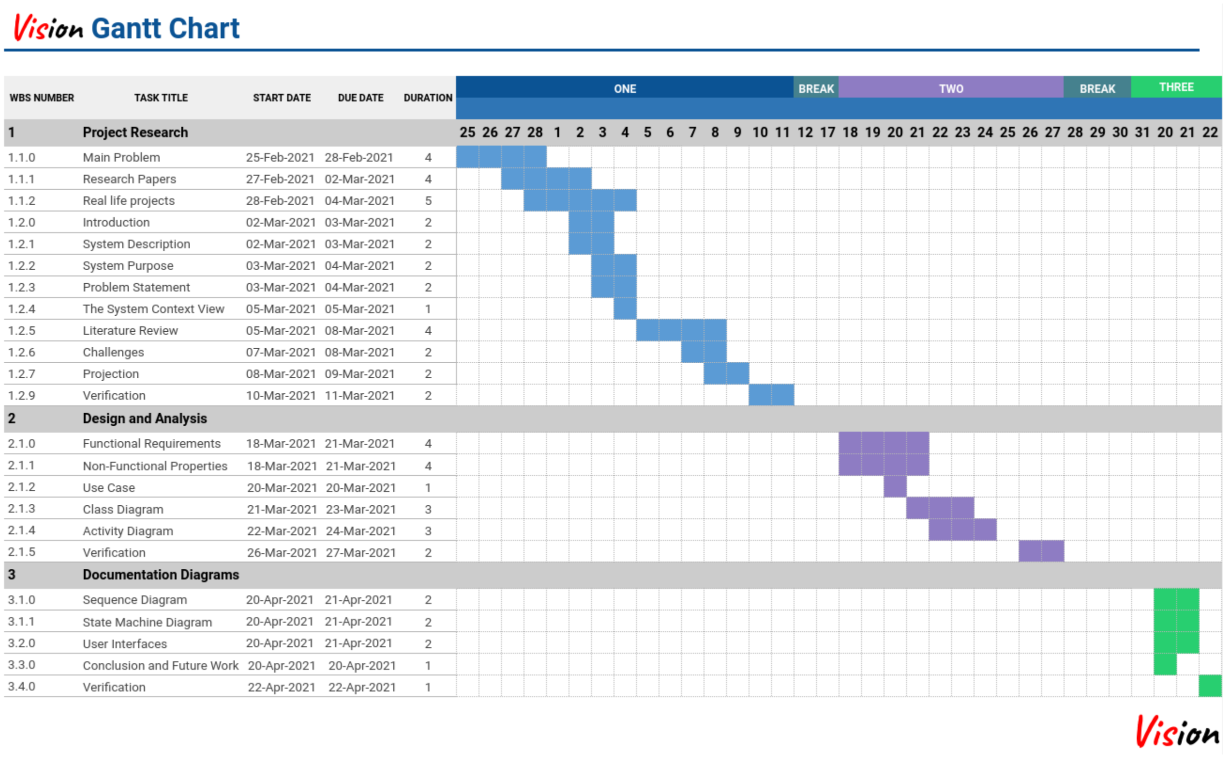
   The way I think about it is that it's trivial to explain to anyone what the Super Resolution is, like for real, get me a group of 3 year olds and I am sure that 99% of them will understand it. But algorithmically, it is very hard to solve, yet we need an algorithm that works on a smartphone or something to that extent, with a small amount of memory, which is, again, "sweet stuff that makes Computer Science what it is", so we are glad to be able to try and solve these kinds of problems.

3. Proof of Concept, PoC, without a working application is hard!!!

   This is a combination of Simple yet hard and Brand New, like yeah we know that this kind of deep working algorithms are used in high tech companies and it works, but how to prove that it will work in our case, or just even prove it at all, so we need to implement it and show that it works in most cases at least; because the use of it will be important to so many people, especially for the requirement of our system.

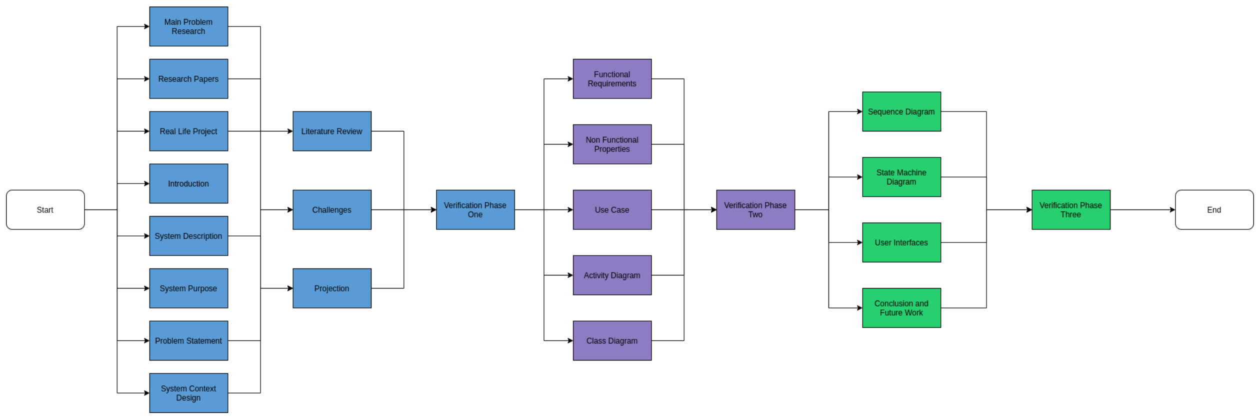
Projections

Gantt Chart



WBS NUMBER	TASK TITLE	START DATE	DUE DATE	DURATION
1	**Project Research**			
1.1.0	Main Problem	25-Feb-2021	28-Feb-2021	4
1.1.1	Research Papers	27-Feb-2021	02-Mar-2021	4
1.1.2	Real life projects	28-Feb-2021	04-Mar-2021	5
1.2.0	Introduction	02-Mar-2021	03-Mar-2021	2
1.2.1	System Description	02-Mar-2021	03-Mar-2021	2
1.2.2	System Purpose	03-Mar-2021	04-Mar-2021	2
1.2.3	Problem Statement	03-Mar-2021	04-Mar-2021	2
1.2.4	The System Context View	05-Mar-2021	05-Mar-2021	1
1.2.5	Literature Review	05-Mar-2021	08-Mar-2021	4
1.2.6	Challenges	07-Mar-2021	08-Mar-2021	2
1.2.7	Projection	08-Mar-2021	09-Mar-2021	2
1.2.9	Verification	10-Mar-2021	11-Mar-2021	2
2	**Design and Analysis**			
2.1.0	Functional Requirements	18-Mar-2021	21-Mar-2021	4
2.1.1	Non-Functional Properties	18-Mar-2021	21-Mar-2021	4
2.1.2	Use Case	20-Mar-2021	20-Mar-2021	1
2.1.3	Class Diagram	21-Mar-2021	23-Mar-2021	3
2.1.4	Activity Diagram	22-Mar-2021	24-Mar-2021	3
2.1.5	Verification	26-Mar-2021	27-Mar-2021	2
3	**Documentation Diagrams**			
3.1.0	Sequence Diagram	20-Apr-2021	21-Apr-2021	2
3.1.1	State Machine Diagram	20-Apr-2021	21-Apr-2021	2
3.2.0	User Interfaces	20-Apr-2021	21-Apr-2021	2
3.3.0	Conclusion and Future Work	20-Apr-2021	20-Apr-2021	1
3.4.0	Verification	22-Apr-2021	22-Apr-2021	1

Network Diagram



Functional Requirements

Denoising Image

Function ID: V-00

Denoising images, especially when these images are taken at night, is crucial to our system, we can enhance the image as far as we can, but without the denoising, it’ll still be not so clear. There are various sources of noise in an image, it can be through compression, network transmissions, and the way the image is saved from hardware components to zeros and ones can cause noise as well. So how are we going to represent noise in an image, the answer is, drum rolls please….., MATH, as scary as the word MATH sounds, it’s actually provide a simple and neat definition of how noise can be represented in an image,

$$m(x) = o(x) + u(x),\ x \in \Omega$$

where $o(x)$ is the original image without noise, $u(x)$ is the noise that was applied through some source, or various sources, to the image, and finally, $m(x)$ is the input image with noise. x is a set of pixels, and $\Omega$is a collection of pixels, which is the entire image basically.

With basic algebra math we can see that we can obtain the original image accurately by subtracting the noise $u(x)$ from the input image $m(x)$. But as the saying goes “Names are not always what they seem.” ~Mark Twain, unless there is some magic way to figure out where the noise(s) came from, we can’t just invert them, not to mention the fact that seeing if an image has noise or not is hard, we as humans think it’s intuitive, but computational wise, it’s really not.

How are we going to solve it ? How are we going to implement it ? This is such a complex problem oh my god!!!!!!!. Convolutional Neural Networks, CNNs, to the rescue. It just makes sense to use Artificial Intelligence in general to solve these kinds of problems, and it even makes more sense to use CNNs as a method to implement this problem, we are mapping a known input to a known output. How do we know the output?, one might wonder, easy, and simple answer: we know how to add noise to an image, so we get a bunch of datasets that have high quality images in it, add some noise to it, and *Voila*! We have a bunch of noisy images, plus, we can also use this to evaluate our model output, because as I said we know the output.

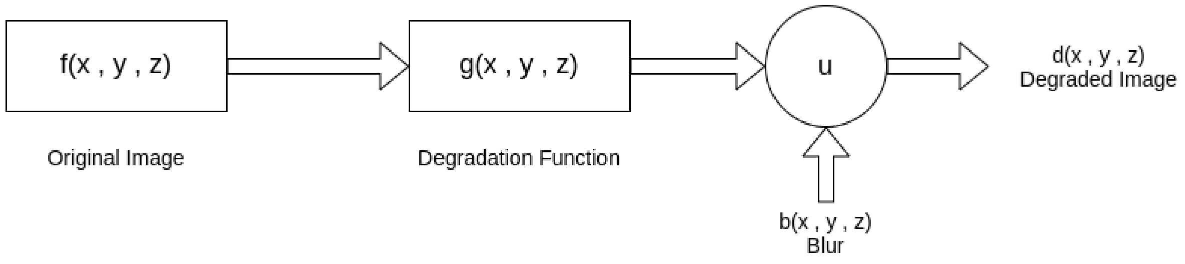
To train this network (sometimes called model) we need a dataset, fortunately, there are many open source datasets that we can use, we used many of them from different categories, faces, normal natural images, and many more, like for example we used the SIDD dataset which has 30,000 pairs of noisy images that have different lighting conditions using different cameras, and the original image. As well as the FFHQ dataset, which has more than 70,000 high quality human faces images with different variations in terms of age, ethnicity, background, glasses, hats, and more.

Enhance Image

Function ID: V-01

This is quite literally half of the core to our system, we heavily rely on image enhancing to get the job done for our users. For that reason, we need to be careful when we solve the super resolution problem, sometimes called the Single Image Super Resolution Problem or SISR for short, because there are high standards that are set for this kind of feature. Some of the standards that are set for this feature is, producing a high quality image with the same details in the original image, delivering single-digit millisecond performance at any scale, having low memory footprint in both the user side and the server side, and many more.

At the SISR problem it is also a mathematical model, just like any other computer science problem, to understand how to derive a mathematical model we first have to understand some concepts that relate to it. First is, Degradation Modeling, degradation modeling is an effective reliability analysis tool for things with failures caused by degradation; images degradation can come in different forms such as noise, camera misfocus, motion blur, …, etc. To give an example, a simple image degradation model can be like this one,



In our problem, the Single Image Super Resolution, the linear degradation model is formulated by,

$$i = A_s Bx$$

Where $i \in R^{M \times N}$ is the input image, $x \in R^{M_s \times N_s}$ is the high resolution image that we want. $B \in R^{MNs^2 \times MNs^2}$ is the linear operator that blurs the high resolution image, x, with the decimation in a factor of s in each axis, which is the outcome of the multiplication by $A_s \in R^{MN \times MNs^s}$.

We are solving for the unknown x, which is the high resolution image, and recover it from the known measurement i, which is the input image. We also have to pay attention that the model doesn't always have to be linear, for example: due to compression, noise, or even some other unknown(s).

We are going to use an Enhanced Super-Resolution Generative Adversarial Networks, ESRGANs for short, we talked about SRGANs in Phase one, it was from the Twitter Cortex research group, and it showed some really interesting results. Yet a group of chinese computer scientists won first place in the PIRM2018-SR Challenge and showed even better results, and guess what they called their model ? that's right, ESRGAN, they found some flaws in the original model, fixed them, enhanced the model, and gave better results, simple right ?, well yes but actually no, there are more behind how they actually enhanced the model and kept consistency with the old model.

The normal SRGANs was very influential in the Super Resolution problem; which is an important part of the computer vision industry, and it showed very promising capabilities of creating and generating realistic image textures.
However, there were some details in the image that didn't improve, so the group of chinese computer scientists found some areas to improve and enhance, which is the network architecture, the adversarial loss, and the perceptual loos, so they added the Residual-in-Residual Dense Block (RRDB) without batch normalization as the building unit of the neural network, which lower the computational complexity of the network. As well as got some influence from other types of GANs, and from there they were able to enhance the SRGANs.

For the training data we used a high quality dataset, the DIV2K dataset that contains 800 images. As well as some other datasets to make the model diverse, such as the Flickr2K dataset, which has more than 2000 2K images.

Image to Data

Function ID: V-02

This is an extra feature to make use of images, and to provide our users with some insights from the image. Some of these insights can be licence plates recognizing, faces detections, object detections, and more to come. It can also assist users to see details that they can't recognize, or some object they didn't pay attention to.

We are going to use Amazon Rekognition, for its simplicity and ease of use, in addition to having a well documented APIs. Nevertheless, if we need to, we are going to implement some features that the API doesn't have.

Denoising Video

Function ID: V-03

Just like in images, denoising in video has the same degree of importance. In addition to that, most of our system data will be videos, that's what the project description said. Nonetheless, we showed that it's not efficient if we process videos frame by frame, or a batch of frames, to be treated like images. So we simply treat videos as they are and process them as a whole.

We also showed that Conventional Neural Networks, CNNs, can solve complex problems where we map from a known input to a known output, so we are going to use it. Why not use GANs? GANs can also be used to solve this problem, but it would be tedious to use it, as it is too complex for this kind of problem, along with, the state-of-the-art models right now also use CNNs to solve this problem.

Training was done using the DAVIS dataset, in addition to other datasets that help the model with diversity.

Enhance Video

Function ID: V-04

This is the other half of our core, which puts the cherry on top of the cake for our system, and it’s also the most complex problem in our system, yet. The name of the function itself is scary, imagine what the model will look like.

There was an interesting paper that we reviewed, iSeeBetter, this paper was a grad student project in fall 2019, in the CS230 Deep Learning course in Stanford University led by Andrew Ng to be exact, and it showed some really amazing results. It makes practical and effective use of GANs, along with the concept of Recurrent Back-Projection Networks, RBPN for short, as its generator, and its known for the RBPN to solve the video super resolution problem. It also uses a four-fold loss function (Adversarial, Perceptual, Mean Squared Error, and Total-Variation) to avoid the problem of misrepresentation of perceptual quality. With this solution it easily set a new bar for the other state-of-the-art models.

Training was done using the Vimeo90K dataset, and many other datasets to make sure we have a general model, so that we can enhance all kinds of videos, no matter the background, the object, and all the different details in the video.

Non-Functional Properties

Usability

Ease of use is an essential part of every system, you can't afford bad user experience because the system isn't intuitive for some users. Ease of use does not relate to only user experience but also to developers and software engineers who are going to make the system better, it takes less time when the system is easy to understand and use.

When we talk about user experience in our system, then our system is simple, meaning that anyone can use it intuitively, and get their desired results in no time. Why is that?, you might ask, because of the fact that uploading an image or a video to an application is easy, plus our user interface will make sure that everything is straightforward.

When we talk about the developer or the software engineer side of view, our system has simple problems to understand, but hard to solve, like for example, most of the ways we use to solve problems is AI, Machine Learning, and Deep learning, as well as some data engineering concepts, cloud computing, and more computer science topics. So it might not be very straightforward to understand how the system was built. However, the layers of abstractions that we provide will make sure that we make it easier to understand, like for example some data visualization so it's easier to look at, without knowing much of how things happen behind the scenes, plus some APIs to handle communicating with the models and other components for the system, and more.

Performance

Performance is key to all systems nowadays, users want their response as soon as possible, and software engineers want their system to have the capability to handle more load as the system grows. It's a very important quality attribute that can tell alot about any system. Furthermore, it affects many other non functional properties, we can't have an ease of use with the system taking too long to respond, we can't have reliability of a system talking too much memory from every single request, and many more properties that won't hold under poor performance.

Our system will hold performance easily, we use state-of-the-art Deep Learning models that provide single-digit milliseconds responses, along with relying on cloud computing to not worry about extra overhead from poor server configurations, as well as to distribute our system to also distribute the load into many machines. Not to mention that we will have a small memory footprint which helps with many operations and reduce the size of our running processes.

Security

Let's assume that security wasn't important, whether it's user data, or the system as a whole. Users images and videos would be just visible to everyone who can look at the network, moreover, we, the software engineers would also have access to user's data, some engineers say that "it's okay" so we can make the product/system better for the user. Now throw that assumission out of the window, burn it, and walk away like you did not see anything.

User's data MUST be visible to the user only, we have to make sure that no one is allowed to view that data, unless it's theirs of course. So, our plan is to have our deep learning model run on the client side; to prevent network calls and data transmissions. However, for now we will deploy our models on the cloud and secure our network, until we find an efficient way of running deep learning models on the client side; because they might be heavy to load in every client device (web, mobile, desktop).

Overall, we are going to make sure that we secure our system, and that our cloud provider has a secure network, as well as not having a registration system for our users, How are we going to know our users?, you might ask, the answer is, that is the whole point, we should not know which image belongs to who, the request response API model will handle who to route these without having to store which user is which. Caching might expose some data, so we also won't use it, plus caching won't help us make that much sense figuring out if two images are the same is a whole problem itself.

Reliability

Reliability isn't a very clear concept when you compare it to performance, security and these kinds of things in the system; meaning that it's not a very initiative property to understand. So to lay some groundwork and make sure we are on the same page of what reliability is we will start with a definition,

Reliability refers to the probability that a system performs as it's designed, correctly, during a specific time duration, or a period of time, and during this time no repair should be performed, and the system adequately follows the defined performance specifications.

Reliability is a must in any system in this day and age, our system is expected to perform at its top performance at all times, even when the load is at its peak. That is one of the many reasons we chose to be cloud native, which means run everything on the cloud, so we don't need to handle server maintenance, network recovery and what not. This way we can almost guarantee that we have high reliability probability and operate as we should.

Availability

This property is sometimes confused with the reliability property, although all properties are connected in some way or another, but still every one of them has its own definition and how they relate to others; meaning that they are not the same of course.

Availability is the probability that a system performs as it's designed, correctly, at a specific point of time, time instance. Some things might go wrong before or after the point of time (where we calculated the availability), but the system MUST be operational, and adequately satisfy the defined system specifications.

So, Availability is a very critical concept in any system, especially in our system, users can't afford having the system down when they're enhancing a video or an image, the same way we can't afford bad user experience.

Scalability

Having a system that is built for a big user base is very important, however, not all products are Google products where the starting number of users are more than a million users. Instead, normal products start with zero users, or the number of developers who are testing them, so having a system that is already scalable can be expensive, both in time and money.

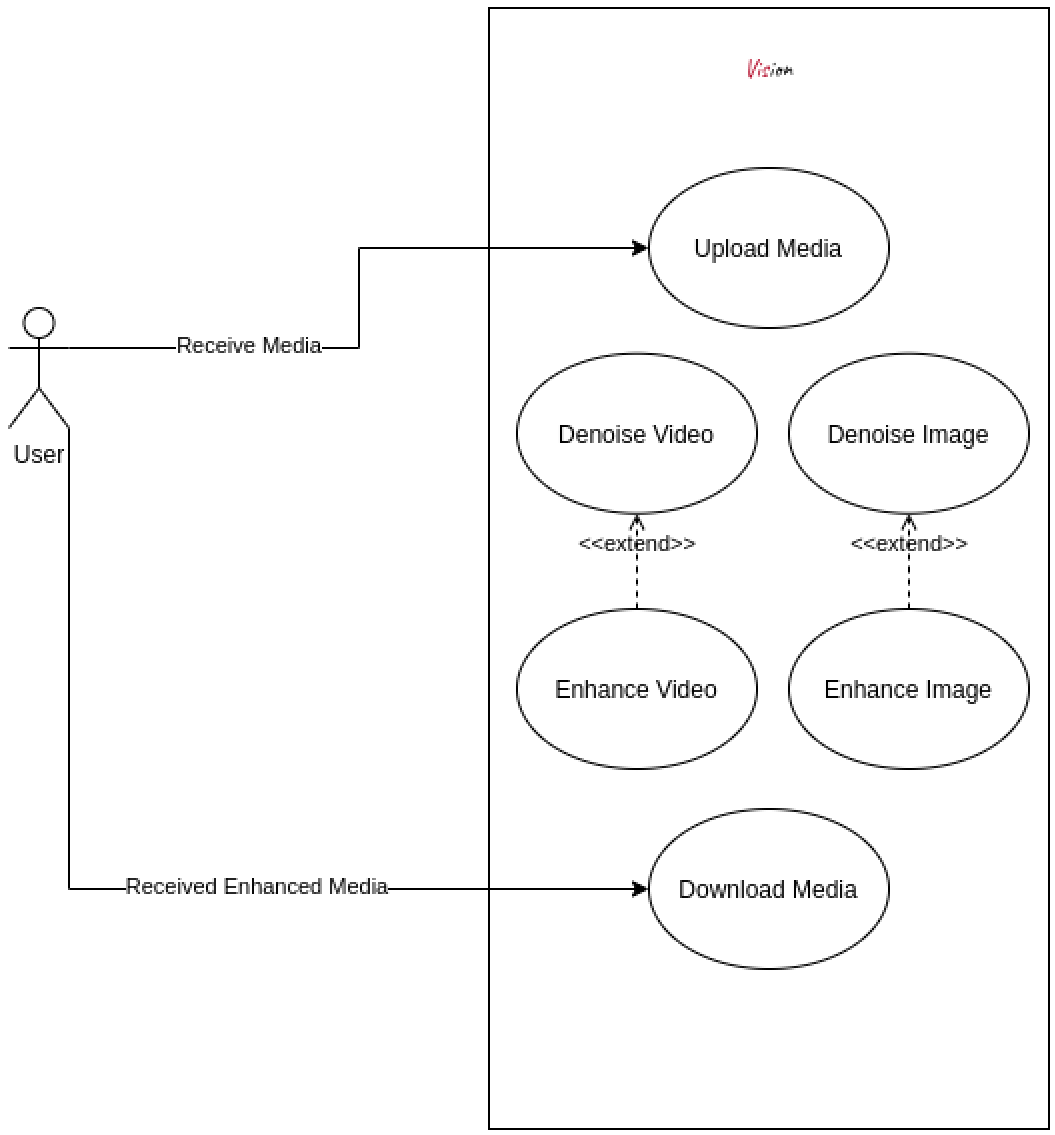
Vision, the system, is not build for a big user base from the start, but is build to grow as the user base grows, I like to call it the infinite ballon scale, where the system is a balloon that can get as big as you want (infinite), and as the load grows, the balloon grows, and as the load decrease the balloon decrease its size as well. This way we make sure we can handle our system peaks like a piece of cake, and handle when the system doesn't need to handle a lot of requests and reduce system resources such as CPU power, memory, disk I/O, and more.

Maintainability

Maintainability is something that many software engineers leave behind in many projects, it doesn't get that much attention. Nonetheless, we will make sure our system is maintainable to make sure that if we want to extend some extra features, or make sure that other people understand how the system works and add their own touch of creativity to the system.

It's also important to make sure the system itself is maintablite, meaning that deployment, bug fix, and stuff like that should also be easy to maintain in the future. This way we handle the technical side of maintainability as well as the development side of it.

Use Cases


Vision
Upload Media
Receive Media
User
Denoise Video
Denoise Image
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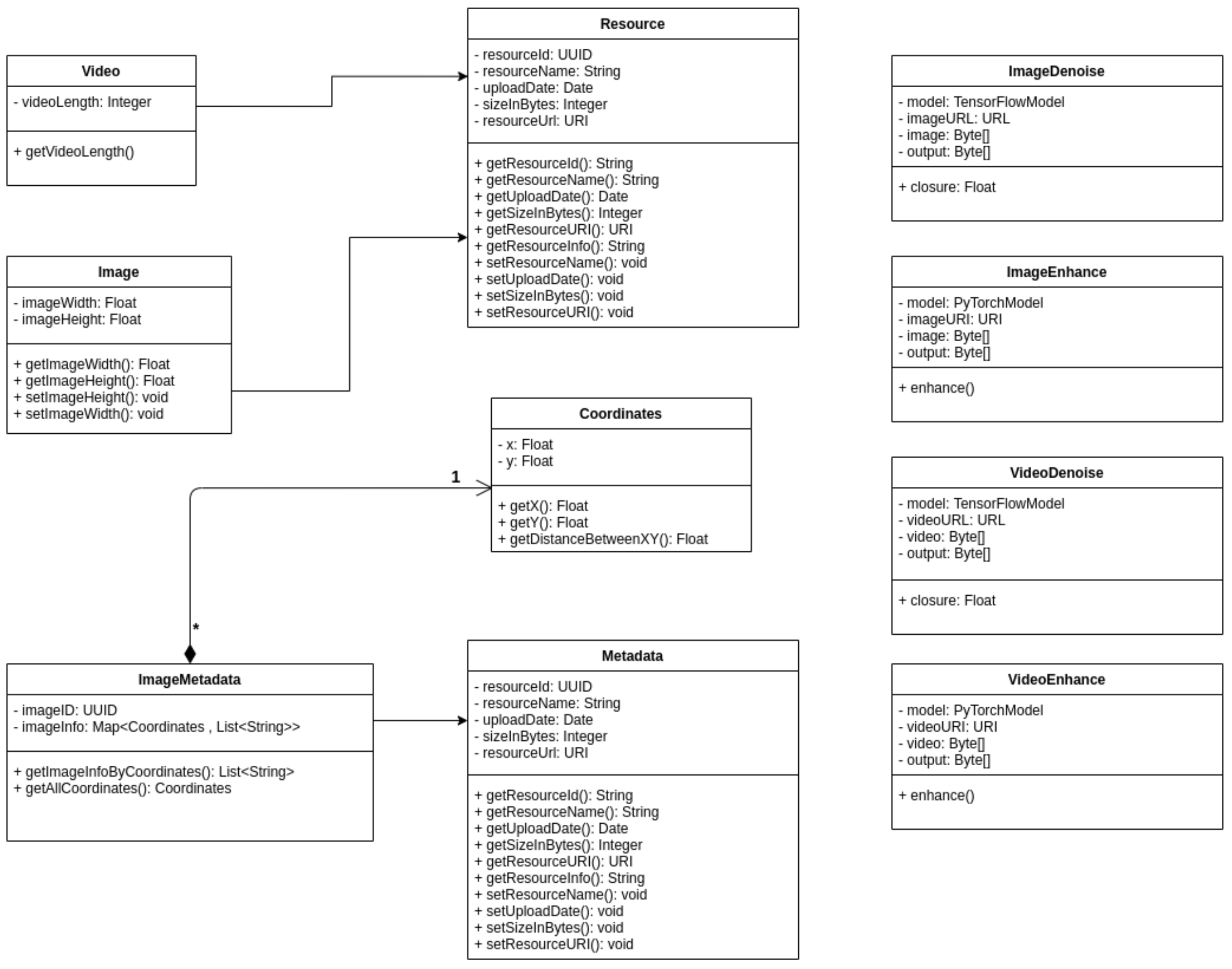
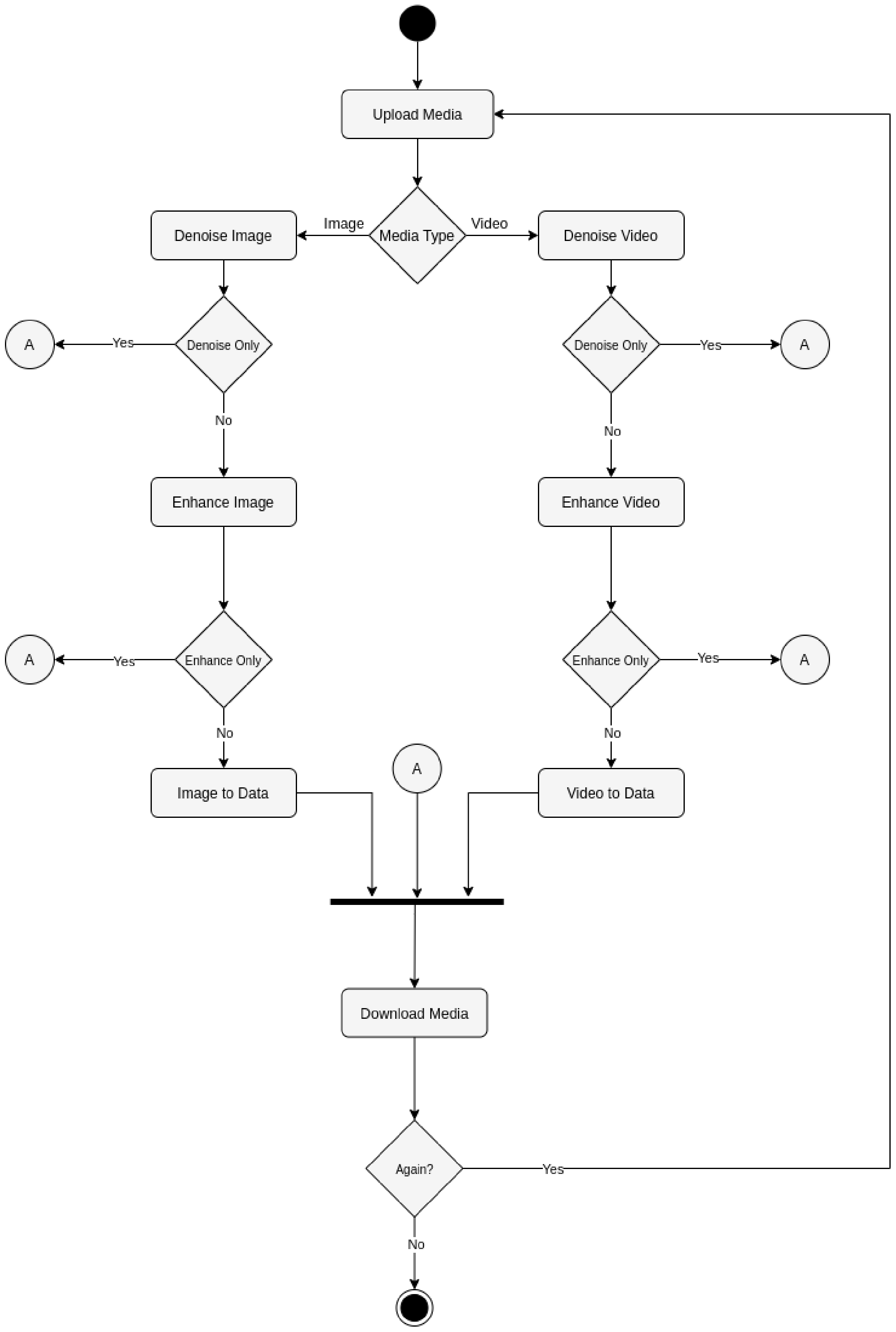
Enhance Video
Enhance Image
Received Enhanced Media
Download Media

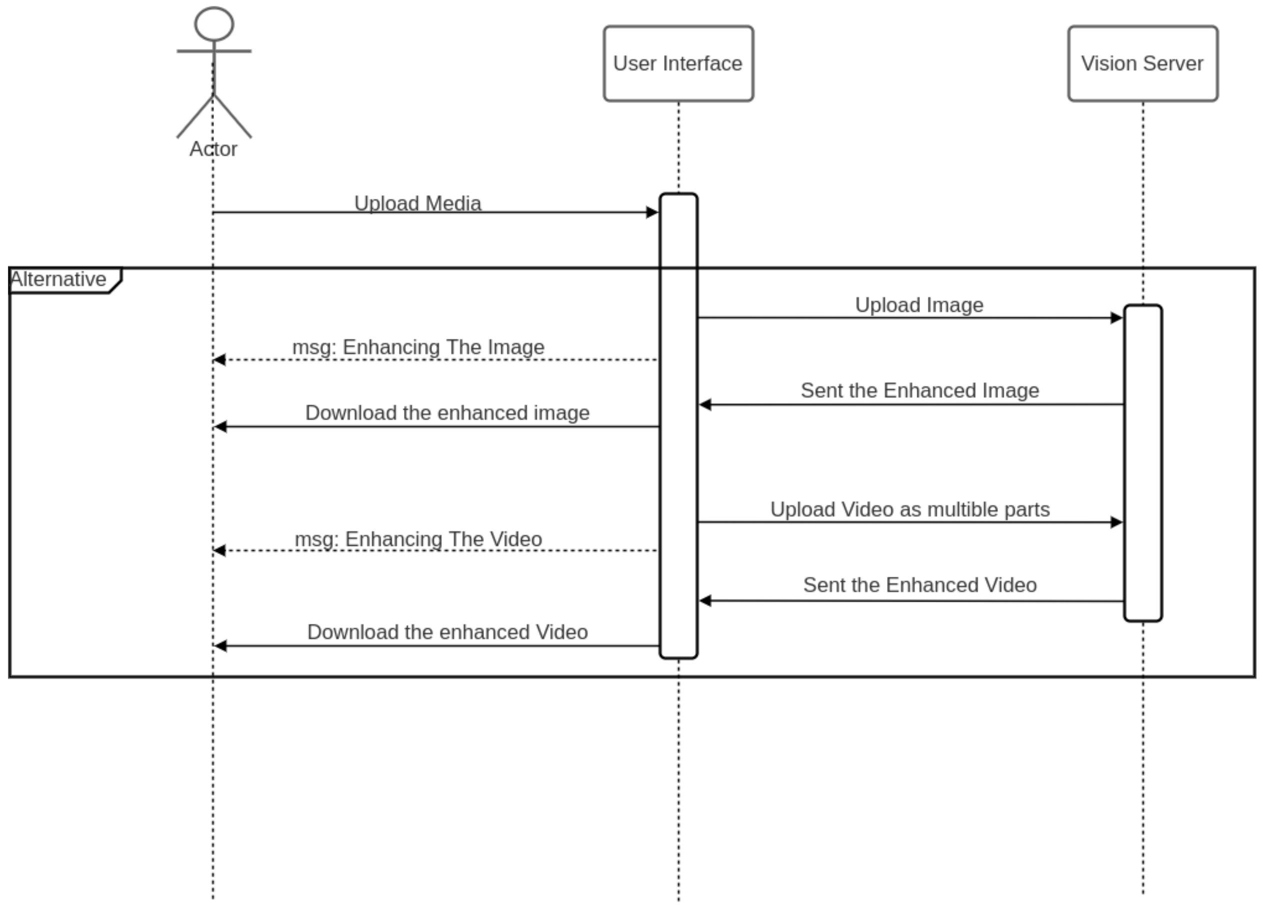
Class Diagram



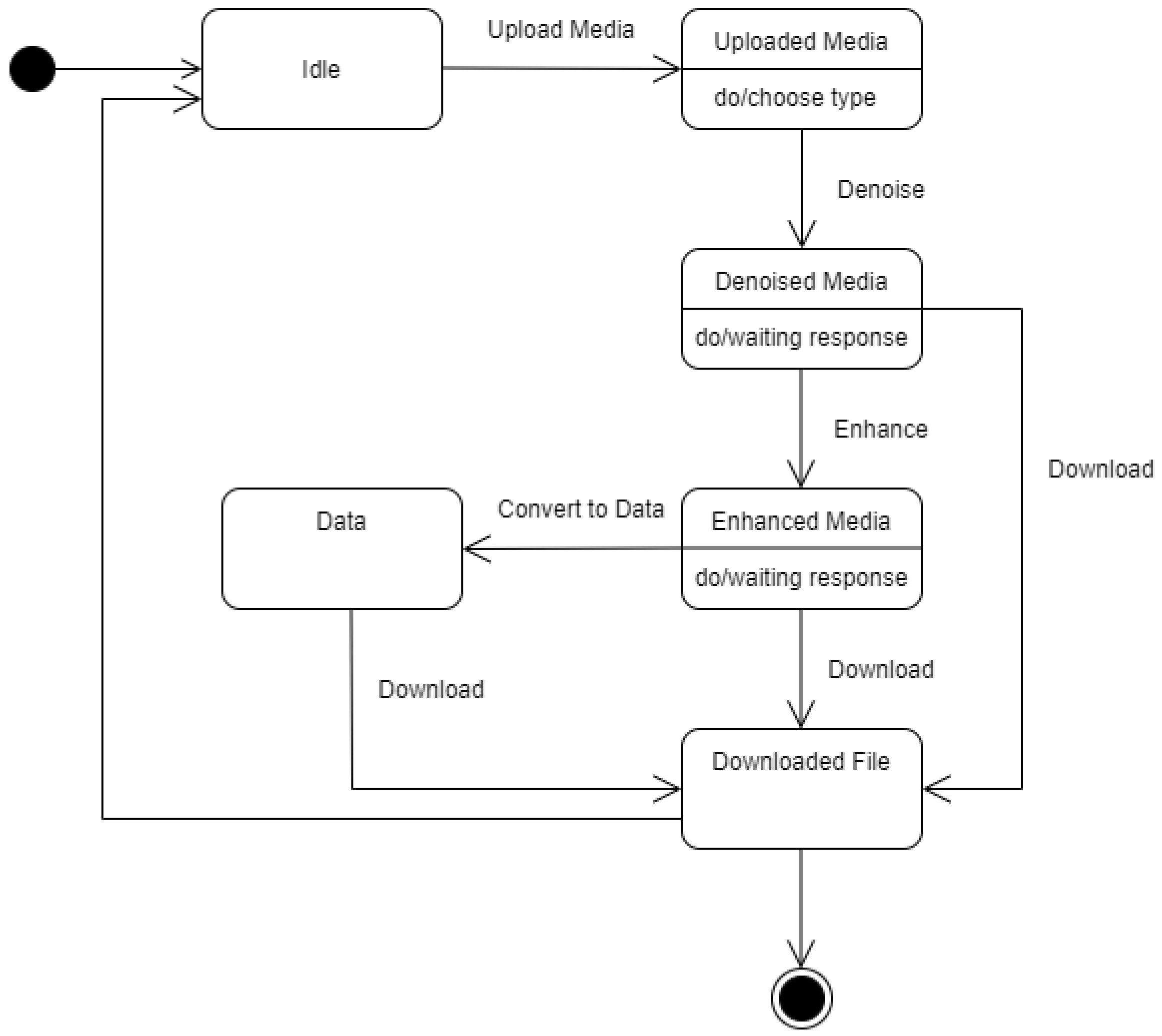
Activity Diagram



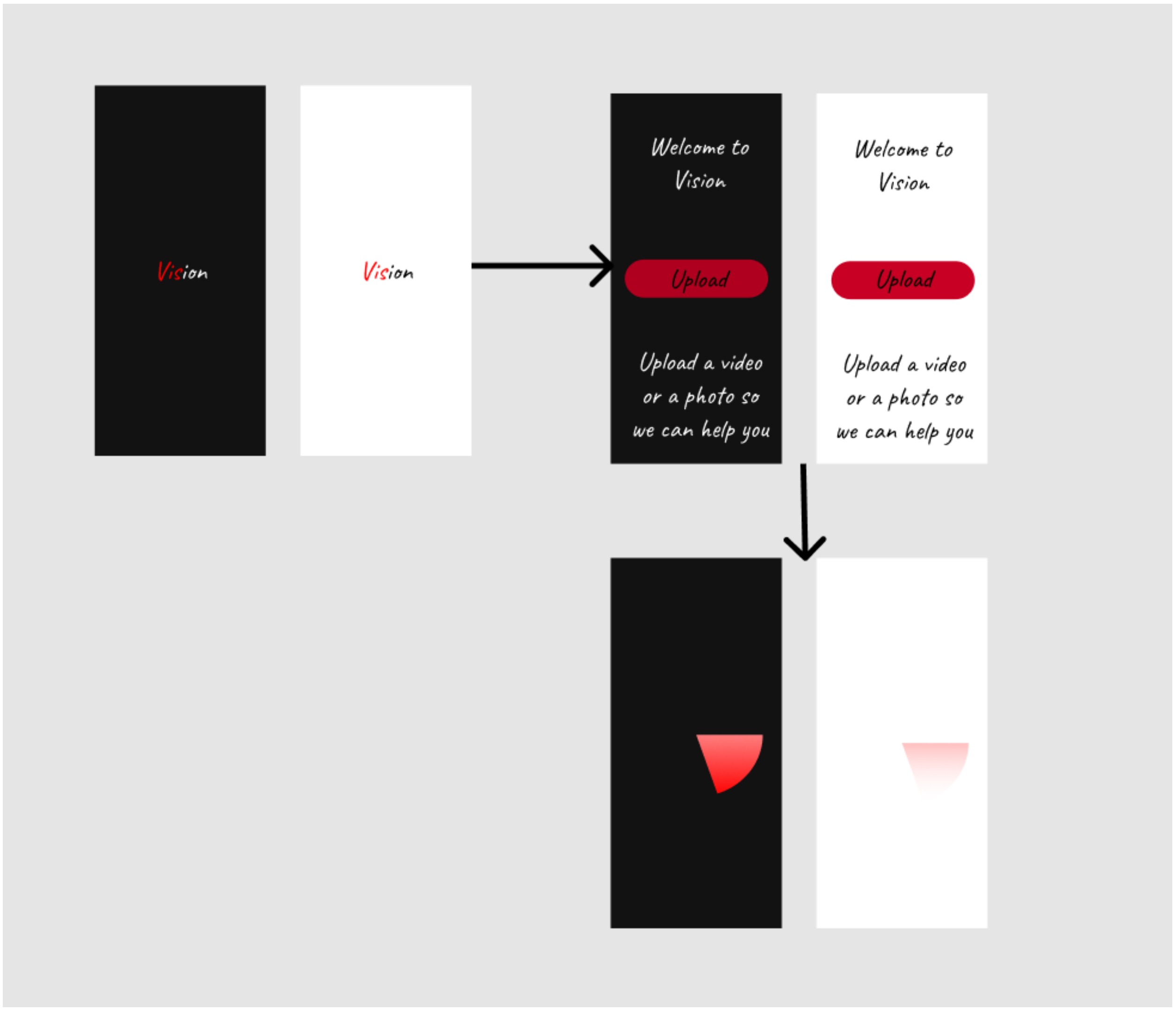
Sequence Diagram



State Machine Diagram



User Interfaces


Vision
Vision
Welcome to Vision
Upload
Upload a video or a photo so we can help you
Welcome to Vision
Upload
Upload a video or a photo so we can help you

Conclusion and future work

The future of any project depends on its power to innovate, simplify and create solutions that solve the user’s problems. And we’re definitely going to do just that, from enhancing current solutions to discovering new and ambitious problems. To give a small example, our current algorithm to solve the super resolution problem is very complex in both runtime and the way it works, as well as the process of making the pictures or videos ready to be sent to our server and sending them back to the user is still not the best which also add time to how much a user wait to get their result back.

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