DATA SHED

An Interactive Learning Journey Through Data

By

ADIT VERMA

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ABSTRACT

This research explores how the data collection process has accelerated in the past decade through artificial intelligence, leading to data being a major part of our digital economy. Understanding data and its implications has become crucial for individuals to make informed decisions in their daily lives as technologies have become more and more embedded in our everyday lives. The research aims to encourage users to take control of their data and understand it. I have created an interactive installation named Data Shed that gathers latent data from them and shows how it is collected and visualised, with the user offered the option to own their data. Research-creation was used as the methodology for constructing Data Shed.

Keywords: data collection, data ownership, latent data, data shedding, machine learning, generative art, interactive installation.

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TERMINOLOGIES

Latent data

The term Latent data used throughout this thesis refers to those data that exist around someone without their knowledge. These kinds of data are usually hidden and require some form of process or tool to access or extract. A prime example of latent data is a person's movement data when they are using a GPS-enabled device while taking a walk.

Data Shedding

Data shedding is an idiom that I coined. Data shedding is described as the fall-off of data that happens like a natural process, extracting its meaning from the ways that a snake sheds skin.

Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that aims to create intelligent machines that can learn and adapt like humans.

Machine Learning

Machine Learning (ML) are systems that are designed to be trained on a data set to learn or improve its performance.

Computer Vision

Computer Vision is an offshoot of AI and Machine Learning that enables a computer to see and extract data from multimedia which can be images or videos. Computer Vision has opened new frontiers in how data can be collected and processed which are object recognition, and facial recognition to name a few (Rand et al. 68).

CHAPTER 1: INTRODUCTION

As data has become ubiquitous in our lives; data are all around us, and we are constantly generating data without even realising it. Some argue that data has become the new oil of our digital economy where almost anything we see like a Tesla on the road is driven by data.

On one hand, data are used to make many of our day-to-day activities easier but on the other hand, data is used to target ads and sell us more things. As more organisations start collecting these data, there is a growing need for people to understand this hidden force acting on their behalf, making decisions for them, and how all this data is being collected with the use of new algorithmic systems.

Contemporary life continues to be dominated by smart machines in some way or the other, any interaction that we have with these machines leads to **data shedding**, which is the transfer of data explicitly or implicitly from the individual to the machine.

Data shedding can happen through various interactions with machines or any time we encounter technology, such as using a search engine, social media, or even online shopping. For example, a person purchasing a transit ticket in many places around the world provides the data from the station they are boarding and the destination station. The data generated gives insights, for example identifying the stations that see higher footfall, which can be then used to design stations depending on the footfall at different stations.

This is an example of how a small interaction can lead to data generation in an implicit manner, where the users are not aware they generated data through their interaction with the system in place. This data can be seen as **latent data** that exists around the user without them knowing about it.

Data shedding can have severe implications for our privacy, as it can lead to information leakage and unwanted tracking of our activities. Modern algorithmic systems like computer vision have become the norm of data collection in our modern world. Computer vision is a subset of artificial intelligence that enables machines to see and interpret objects by analysing visual inputs such as images and videos. It has enabled facial recognition, object detection, autonomous driving, medical diagnosis, etc.

Computer vision technology is used to collect data from various sources such as surveillance cameras, drones, satellites, and even mobile phones. This data can be used for a variety of purposes such as security and safety applications or retail analytics. For example, CCTV cameras are used to detect potential threats or suspicious activities in public places. Similarly, drones are used for collecting aerial imagery which can be used for mapping terrain or detecting crop health.

Data collected by computer vision systems not only help evaluate the physical environment better but also provide insights into human behaviour which can be useful in marketing strategies or policy-making decisions. In addition to this, machine learning algorithms use these data to improve their accuracy over time thus making them more reliable and efficient in decision-making tasks, but the accuracy of these algorithms heavily depends on the historical data that they were trained on. It could be argued that a machine learning algorithm is as good as its training data set.

Therefore, it is evident that data collected by modern algorithmic systems like computer vision plays an integral role in our everyday life and will continue to dominate the way we interact with machines in the future.

This research tries to empower users by teaching them about data shedding and latent data that they generate whenever they come in contact with technology that can capture data. This includes the ways that modern algorithmic systems can collect data and build a picture or a “Data double” of them in the ubiquitous networked system where technologies are so well woven into our lives that a life without them is unimaginable (Haggerty et al. 605). Any data that we generate has ripple effects in this digital environment; it is like a big machinery with small components which are all connected helping the machinery churn and machine function. People usually do not understand how the data that they generate is shaping their decisions. If they do understand they do not want to tinker with trying to control that data, as it can lead to the system having holes and the machine not working because we are so dependent on technologies.

This research aims to strengthen data fluency by creating an interactive installation that tracks users to find the latent data around them that they generate while engaging with the system in place. Through an engaging, hands-on experience users can gain a deeper understanding of the privacy implications of some data collection methods that exist enabled by the machine learning algorithms like body-scan from a camera feed, face detection etc. The goal is to enable the user to become more conscious of how they interact with some of the digital services of our connected world. Ultimately, this research highlights the potential for interactive installations to help people better understand the complexities of today's digital environment in a visual way.

RESEARCH SUMMARY

PROBLEM STATEMENT

As technologies are advancing at an unprecedented speed, there are new algorithms and technologies that are being developed fuelled by the rapid breakthroughs in the research of artificial intelligence and machine learning driven by data. This leads to our problem that despite having all these data and access to such powerful tools we understand so little about how data is collected and how data directs our decisions and choices in this well woven digital environment. Data fluency is the key to unlocking knowledge and understanding how data has become the main ingredient of the digital age.

HYPOTHESIS

Data Shed can improve users' comprehension of how contemporary algorithms gather data through simple hardware such as a camera. Through this interaction and decision-making experience, users can gain a better understanding of data and privacy. Data Shed further enables users to understand privacy as it is an assumed privilege that people think they have whenever they are in a public space or come in contact with smart technology. It does so by giving agency to the user so they can control their presence while collaborating with the machine.

GOALS AND OBJECTIVES

The goal of this research is to create an interactive installation that visualises the complex relationship between people and intelligent machines so that people can be made more aware of their data and understand the essence of data; how data is collected; how it is analysed and what we can do to control our data.

RESEARCH QUESTIONS

How can an interactive installation encourage users to take control of their data and lead to data fluency?

Secondary

How could modern algorithmic systems lead to awareness of explicit and implicit data handover by the user?

How can data visualisation and art installation lead to awareness of users' data?

How does providing choices to the user push them to take ownership of their data?

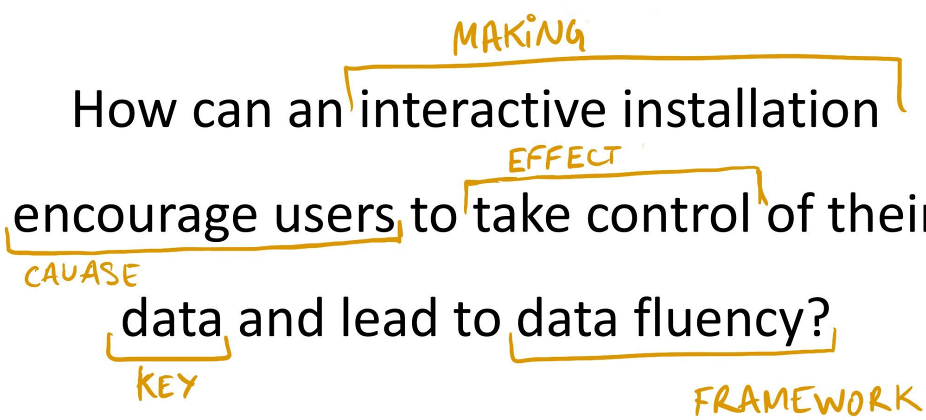

Figure 1: Breaking down the primary research question

Breaking The Primary Question down into parts to look for the answers to the research questions. This directs us to consider installation being the medium to encourage users to take control of their data so that they better understand their data and lead to data fluency.

SCOPE AND LIMITATIONS

The scope of this research is working with technology that already exists and adapting it for an audience to create the installation. The research does not cover the following:

- As technologies are evolving, so fast that it is hard to keep up with new machine learning techniques that are more effective and efficient or could house multiple models in one system. Systems were used at a point in time and continue to evolve.
- As this is a small-scale project it does not cover how to design a machine learning system that is able to handle complex and large datasets.
- As the research uses existing models, any biases that they contain are not uncovered in this research.
- Due to the time constraint of this research an in-depth literature review about understanding people's behaviour using computer vision technology was out of scope.

The limitations of this research are:

- Due to the time constraint, this research was limited to only computer vision technology.
- As the concept of data shedding happens as a natural process, staging this collection of data is a challenge as it separates the viewers from the real world contexts where data are shed.
- A significant limitation is the computation power needed for large scale data analysing and dynamic collection of data from different models and devices.

CHAPTER 2:
LITERATURE AND CONTEXTUAL REVIEW

The literature builds from the fields of data collection, data analysis, data narrative interpretation of information and builds on the visualisation approach from the contextual works. The literature starts with the ways that data has become the building block of our connected economy and how modern algorithmic systems have accelerated the creation and collection of data. This is followed by a deep dive into understanding data from a multidimensional perspective. This includes looking into how data creates biases, understanding data at the granular level and finally, having a critical perspective on data. The literature then looks at how modern algorithms combined with an artistic approach to data can help to bring back a balance between humans and technology. People will have a better understanding of the data and can use it to make better decisions.

I explore means to mix and combine various sources of data and display them visually. Additionally, I investigate the ways that a visual interface can improve communication between users and machines.

DATA IN THE MODERN AGE

In the past decade, we have seen a tremendous increase in the use of artificial intelligence (AI). AI systems are evolving so fast that it has become increasingly possible to build an intelligent computer system that is programmed to do a single task. For example, a camera can extract data regarding what people are wearing to analyse the number of people who wear a tie during the day.

Keith Downing described machine intelligence as a branch of computer science that deals with the design and development of intelligent computer systems. Intelligent computer systems are those that can reason, learn, and solve problems like humans (4). As these intelligent machines incorporate modern machine learning algorithms for data collection, they are therefore heavily focused on the results and not on the process. An intelligent computer system programmed to find people in a scene and isolate them, as a result, can segment people from a scene and capture only the person. It does not show how it profiled people in the scene.

Similar intelligent machines are being built that yield results, accelerating the data collection process several folds and creating a gap in the knowledge of the process and the data collection process. Data that used to take months to gather now just takes days. This emphasis on efficiency pushes data to the forefront of our digital economy as "The amount of data in the world doubles every two years" (Call for Code). Arguing, "Data is the new oil," British mathematician Clive Humby stated that data drives everything in our digital economy. Though it does not make sense in an unrefined state, it starts making sense when we try to connect all the data around us, which makes it very crucial to start looking at data as an entity. Although latent to us, data with the help of algorithms are making decisions for many of our day-to-day activities. For example, all the advertisements we see and all the new people we meet online through social networking sites are driven by the data associated with us in this connected ecosystem (Pitoura 1). Organisations are constantly collecting data and looking for ways to make use of this data. Traditionally, one way of using this data was to sell us more things through targeted advertisements (Johnson 128). But in this era, it is essential for us to seek more ethical and conscientious methods of utilising the vast amount of data collected.

ALGORITHMS CHANGING DATA COLLECTION

As defined by Knuth, an algorithm is “a set of rules for getting a specific output from a specific input. Each step must be so precisely defined it can be translated into computer language and executed by machine” (63). Modern algorithms are increasingly being used to collect data as they can process enormous amounts of data quickly and accurately. In addition, these algorithms can filter data and find the needed information quickly.

Much data currently derives from machine learning algorithms that are actively trained on historical data to help the algorithm understand context based on historic decisions. This has led to a boost to the data collection process significantly enabled by machine learning algorithms.

The more data these algorithms access, the more accurate they can be in their predictions. This leads to the question: how is the data used to train these algorithms biased? Data can be incorrect and make the system favour the results that closely represent the data it was trained on (Pitoura 1).

New algorithms within the field, like computer vision, can produce data from multimedia which can be used for object recognition, facial recognition, and motion recognition. However, as discussed in the following section, systems designed with these machine learning algorithms are not perfect and can sometimes make mistakes which will be discussed in the following sections.

DATA BIAS AND THE PROBLEM

Discrimination in algorithms is a critical issue of our time. In her book, Weapons of Math Destruction, Cathy O'Neil scrutinises the ways that algorithmic decision making can worsen existing inequalities and keep them in place.

She examines the ways in which algorithmic decision-making can be used to create and enforce structural inequalities. She argues that these automated systems are being used to oppress people by reinforcing existing societal disadvantages based on factors such as race and gender. Ultimately, these "weapons of math destruction" have the potential to amplify discrimination and cause harm to those who are already disadvantaged or marginalised. (O'Neil 10)

The problem has deep roots in our modern algorithmic society as most of the decisions made for us are dominated by AI systems and ML models which act on historical decisions that were used to train these models. Thereby these models do not work well with outliers or with data that was not widely available to the model in the first place while training which further adds to the problem of data bias in such systems.

> *There is a well-documented history of learned bias in computer vision models, resulting in lower accuracies and correlated errors for underrepresented groups, with consequently inappropriate and premature deployment to some real-world settings (*Bommasani et al. 33)

As I am working with vision-based ML models, it is important to establish that the models are not perfect and that they can be biased. Bias is relevant to the thesis as it reminds the reader that anything that is produced by the model is not absolute truth. The aim of this research is not to correct bias but rather lay out the problem of bias in the system to help better understand data.

DATA FLUENCY

Data Fluency can be defined as the ability of an individual to understand the structural meaning of data and be able to effectively conclude the meaning of data as well as understand data at a more granular level (Gemignani et al. 24). We can think of data fluency as being fluent in data as we are fluent in a language. Data fluency involves being able to recognize patterns in data, interpret and use the knowledge to make better decisions and translate it to others (Herzberg). It is a result of the need to keep up with the data-driven world.

Although we have become more concerned about how our data is handled, managed, and used by organisations, our behaviour still does not reflect this concern as we continue to tick consent boxes as though they do not matter (Chakravorti). This behaviour is known as the “Privacy Paradox” (Naughton).

The Privacy Paradox can be attributed to the fact that we do not understand the nature of the data-driven systems that are in place. We sometimes try to comprehend the data and try to value our privacy at the same time, which is difficult to do as the systems do not give the user the leverage to choose what they want to share. The other problem is that the organisations that hold our data have become an integral part of our life and therefore, they see little incentives and offer little to no leverage to the users to control their own data and even if they do, it is buried under the many layers of settings that an average user is not aware of.

We can say **Data is intangible** and **We are data** as anything that we do online generates data, although invisible to us it is still harvested and made visible to us through marketing offers and ads (Chakravorti).

This points us to the gap in knowledge that people have about how data can be used in shaping recommendations we receive and making other decisions for us of which we are not even aware. We can recognize these invisible data points through the advertisements we see online; For example, I see an ad for cloud storage because I was searching for some cloud storage solution; this shows that I generated some data while searching for a solution for myself that ended up being a data point for targeted advertisement for cloud storage. A recent article by the New York Times named “These Ads Think They Know You,” used targeted advertisement to show the ads from a data point of view i.e., what data points triggered that specific ad (Thompson). If we look closely at the sample advertisements, the advertisement reads “This ad thinks you’re **trying to lose weight** but **still love bakeries.**” The ad uses information likely from the user's browsing history and credit card history. It tried to promote knowledge discovery by making data more accessible to the user so that they can pinpoint those data points. If the advertisement created enough discomfort in the user's mind about the collection of their data, it would thereby provoke the user to ask the right questions and look for those answers.

This leads to the question if the user is given a choice to opt-out of data collection would they take ownership of their data and understand what they are sharing with the world. A prime example would be that we continue to agree to all the terms and conditions of every website and social media platform we use without giving a second thought about the data that we are giving away. That is the Privacy Paradox. But on the same hand if we are given the agency to decide if a service tracks us or not, we might choose to opt out of it. As seen in the iOS 14.5 update by apple which gives agency to the user to make the decision to own their data by a pop-up that says, “Ask App Not to Track” (Apple).

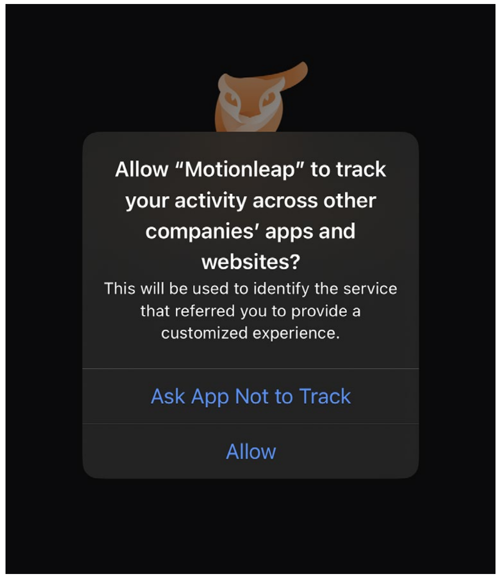

Figure 2: Screenshot of the pop-up that 'ask app not to track'

I could assume that any user who gets an option to ask an app not to track would select the option to opt out rather than allowing it to track their information unless they like the highly personalised experience that tracking provides by understanding and knowing what the user is doing on their device.

Lack of control over data can be attributed to the lack of data fluency which in turn results in less control over data as we do not ask the right questions. This directs that there is a gap between the user's understanding of the data that is being shared and the ability to opt out. This research aims to explore how this gap can be bridged and help the user to gain more control over their data.

CRITICAL DATA STUDIES

Critical Data Studies as defined by Craig Dalton and Jim Thatcher calls for the use of a critical perspective on data (Dalton et al.). They consider the ways that modern society is dominated by data and data has become a backbone for modern algorithms, giving rise to "algorithmic culture" which is the phenomenon of expressing human thought through the logic of big data and large-scale computation (Striphas). It has become complicated to analyse and interpret data in a meaningful way, as there is a divide between the person that is generating the data and the person that is reading the data (Dalton et al.). The whole data generation and collection process is often seen as a flat process that does not take into consideration the other hidden aspects that influence data production, there is a growing faith in 'big data' as a solution for all problems and that data is the key to unlocking human understanding.

In the article "Critical Data Studies: A dialogue on data and space" by Dalton, an example is used to describe how data production is influenced by place, with London having a more developed atmosphere than cities such as Mauritania. It also explains how a lack of supplementary data can make it difficult for analysts working remotely to read Big Data accurately, and that important chunks of the Mauritanian data sphere exist in analogue form (Dalton et al.). This is referred to as a problem of missing data and taking into consideration the limitations of the reader would be the limit of the data, so having holes in data could not portray the full picture to the reader who might be making decisions based on the data at some remote location.

Even with models and theory, big data analytics cannot answer every research question, and therefore cannot overthrow or replace other, more established qualitative and quantitative research methods as it fails to take into consideration hidden or invisible data points. It can never provide the depth and detail that comes with qualitatively learning about and understanding someone's standpoint by asking them about a place and their feelings and motivations. Building on this idea, I want to point the audience to understand that algorithmic data collection does not lay the full picture and the datasets generated by the algorithm can never replace these hidden data points.

Additionally, as we have access to more data and more ways to analyse it the question arises. "**What is to be done with 'big data?' Data's role in targeted marketing and the surveillance state are clear, but what other purposes could it serve?"** (Dalton et al.). Can this data help us to understand people through artworks and artefacts, but how does this data relate to people in real life?

UNDERSTANDING USERS THROUGH GENERATIVE ART PIECES

The literature is divided into two sections: the first section contains the evidence that generative artworks could be used to determine the preference of a user and the second section contains the conceptualisation of how a similar approach could be followed to use interactivity in a similar context and use art visualisations to help to gain insight about the user.

Examining the literature on how generative artworks help to understand the user and their behaviour and how these artefacts can be used to gain insight about the users. Parikh explored a similar idea of using generative art works to understand creators as they used the generative artwork tool to create artworks. She then used these generative artworks to predict a user’s preference depending on the configuration and the type of generative artwork the creator chooses. This allowed her to gather a lot of insights about the users based on their choices. The study concludes “We do find evidence that preferences of a user creating art using an interactive generative art tool are predictable from choices they make " (Parikh).

Can such an approach of using data to understand and find latent data be followed for understanding the user with the help of interactivity? As concluded earlier choices the user makes tell us more about them, their preferences, and their behaviour. What if the data drives the artworks that come up on the screen and the trivial interactions a user has with the art piece generates data about them? These small interactions can then be used to gather data about the user in a manner that they would not actually anticipate. For example, they may learn that they like a certain colour palette because they chose the colour while interacting with the generative art piece and like a certain shape because the facial expression changes when a certain shape is shown on the screen.

Consciously or not, one limitation that the users might face would be the bias and the assumption about the data they generate either through the researcher or the machine learning algorithms. As talked about earlier, the data may be biased, and the data may be inaccurate. Hence the insights obtained from it may be skewed. Also, the assumptions that the researcher is making may also be incorrect. Hence, it is important that we note that the data generated is not absolute and not the ultimate truth about the user but an approximation of the user's behaviour and preferences.

HUMAN AND ARTIFICIAL INTELLIGENCE COLLABORATION

Human and Artificial Intelligence Collaboration has opened a new realm of creativity. As AI systems become increasingly sophisticated, they can now be used to create these hybrid flows for collaboration where the creation would have not been possible without the combination of human ingenuity and AI technologies.

> *Organisations that continue to manage AI and humans on parallel tracks will continue to be able to make moderate gains in efficiency, while organizations that choose to integrate humans and AI into super teams can realize much greater value by redesigning work in transformative ways* (Mazor).

This collaboration has allowed for unique and innovative forms of expression which would not have been possible. By collaboration I mean the application of AI tools to create engaging new ways to create.

> *Casual Creator is an interactive system that encourages the fast, confident, and pleasurable exploration of a possibility space, resulting in the creation or discovery of surprising new artifacts that bring feelings of pride, ownership, and creativity to the users that make them* (Compton et al.).

This synthesis of workflows between the tools and artists has created systems that have opened the pathways for these new tools that enable creators to create with these new tools and technologies. One form of this collaboration is when an artist works with an AI system to co-create an artwork and generate images based on certain parameters that they provide; the artist then incorporates these into their own artwork. This typical approach has been on the rise lately after the introduction of tools such as Midjourney[1]

[1] "Midjourney." https://midjourney.com/. Accessed 19 Mar. 2023.

and Dalle 2[2]. People have been naming these workflows in diverse ways such as 'Human-AI' and 'AI-Human-AI' depending on the workflow and whether it was input by the artist or the AI system that led to the creation of the artwork (Tan).

Living in this era where we can use the power of technology to our advantage to communicate and create with the machine. Artists have incorporated these new tools into their workflows to create more engaging content enabled by machine learning and other technologies. Here are some examples of these collaborative workflows between artists and AI:

Move Mirror is an interactive video experiment that was created by Jane Friedhoff and Irene Alvarado, creative technologists at google creative labs (Friedhoff et al.). The piece is a video-based experiment that scans the performer's pose and tries to match the pose with thousands of images from around the world. The experiment uses an algorithm to identify the participant's pose and then using the data characteristics it tries to find images that most resemble the performer's pose.

"Body, Movement, Language: AI Sketches With Bill T. Jones" is another piece that showcases a collaboration between dancer Bill T. Jones and AI systems to create a series of dance pieces (Jones et al.). Using speech recognition and movement analysis, providing the framework for people to engage with his work with just a laptop with a camera and microphone.

In conclusion, defining 'collaboration' between humans and artificial intelligence systems is not straightforward. It could involve direct co-creation or using tools specifically developed for that purpose. However, one thing remains clear: through this type of collaboration, we can look forward to exciting new possibilities as both sides continue pushing boundaries in creativity!

[2] "DALL·E 2 - OpenAI." https://openai.com/product/dall-e-2. Accessed 19 Mar. 2023.

Summary

The literature suggests that data has become a building block for machine learning systems, specifically vision-based models. We have discussed the ways that algorithms are being used to process data and produce new information at unpresidential speeds and shortly talk about the data bias that comes into play with these models. The implication of this rapid growth is that there is a gap between the data being generated and people understanding the essence of that data. But if they do, they often do not get ownership of the data they generate as they do not get the choice to own that data. My research tries to empower individuals to understand their data and own it in a collaboration with a machine.

CHAPTER 3:
CONTEXTUAL WORKS

Thermal Drift Density Map

Figure 3: Lozano-Hemmer, Rafael. Thermal Drift Density Map, 2022. (Licensed under CC)

Thermal Drift Density Map, 2022 is an artistic installation by Rafael Lozano-Hemmer that visualises the dispersion of body heat using thermal energy emission (Lozano-Hemmer). The installation includes a thermal camera that captures and detects heat and a particle system that allows for the flow of thermal energy away from the participant. Driven by data from the thermal camera, the artwork presents a unique and interactive way to understand the movement of heat in the human body.
Through this data-driven work, viewers can gain insight into their relationship with their environment and explore new ways in which they can interact with it.

How Normal Am I?[3]

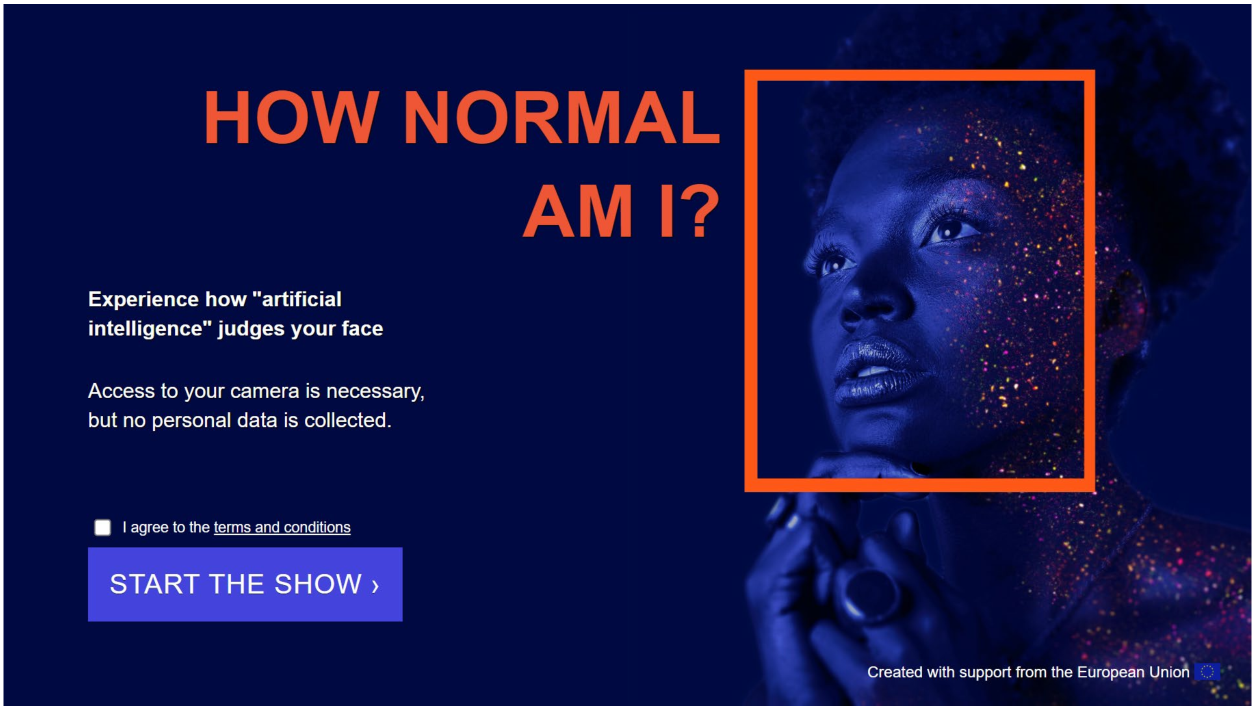

Figure 4: "HOW NORMAL AM I?" HOW NORMAL AM I? 20 Oct. 2020, www.hownormalami.eu/

How Normal Am I, 2020, is part of a series of works produced under the project SHERPA of the Horizon 2020 European Research and Innovation Programme. The series explores future ethical issues around smart information systems. This work by Tijmen Schep exposes the tension between face recognition algorithms and human privacy. The project provides a space to explore the face analysis algorithms enabled through a camera. The algorithm in the play tries to examine and understand the facial features to predict emotion, life expectancy, body mass index, beauty, age, and gender of the user. The website itself is an interactive artefact that tries to bring awareness and attention to the uses and applications of such technologies.

[3] "How normal am I?" https://www.hownormalami.eu/.

VISUALIZING ALGORITHMS[4]

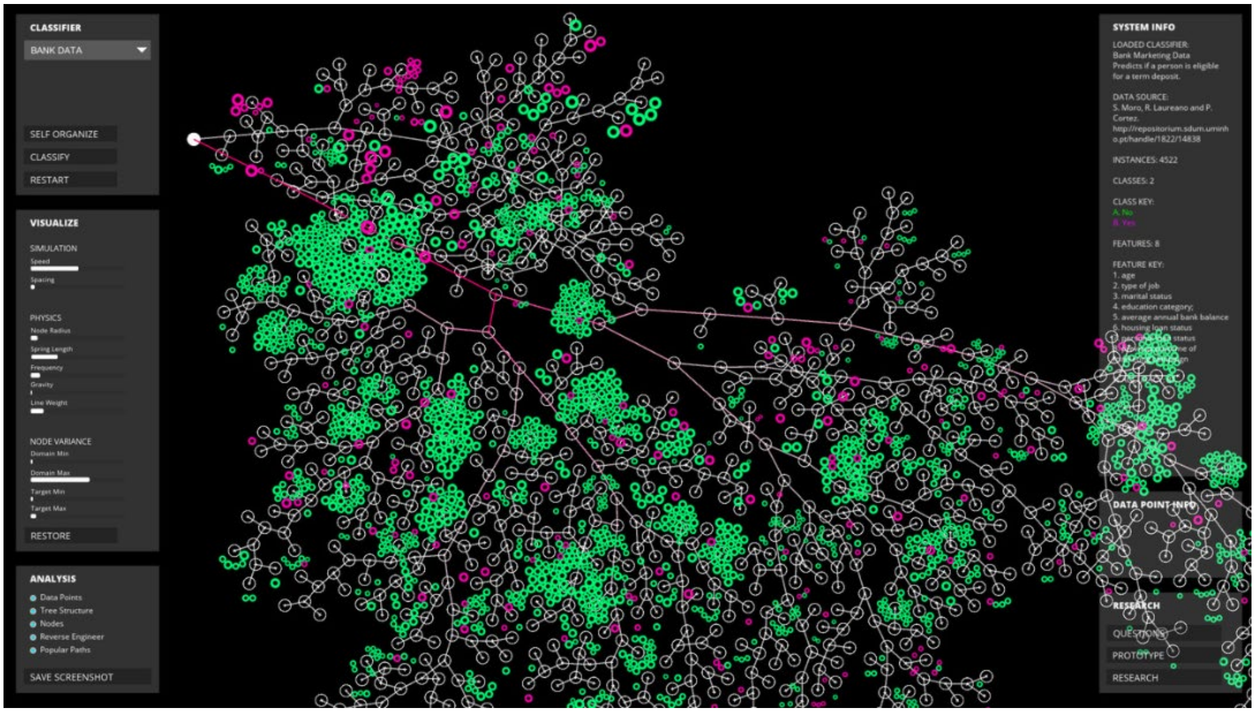

Figure 5: "VISUALIZING ALGORITHMS." VISUALIZING ALGORITHMS - Isohale, 20 Oct. 2020, www.isohale.com/VISUALIZING-ALGORITHMS

Visualizing algorithms, 2020, is a research project by Catherine Griffiths, which shows the invisible decision-making of algorithms by slowing down the speed of computation to a point where it becomes visible to the human eye. The project studies decision tree classifiers that are used in predictive classification based on training data. The artist chose to use a decision tree classifier to enable the user to understand the algorithm, as the data can be seen flowing through the algorithm's network, revealing the logic of the decision. The artwork incorporates synthetic data that is classified by the classifier.

[4] "VISUALIZING ALGORITHMS - isohale." https://isohale.com/VISUALIZING-ALGORITHMS.

Herald/Harbinger[5]

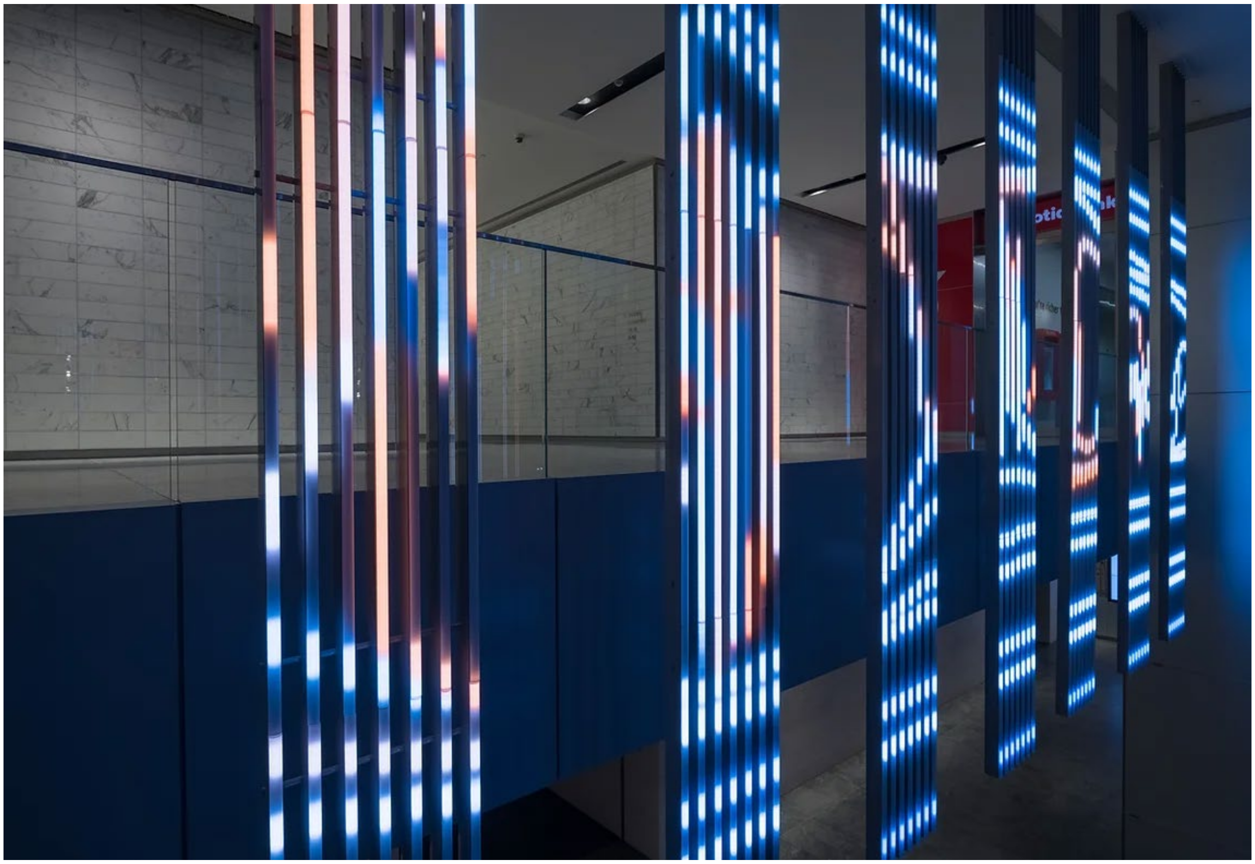

Figure 6: "Herald/Harbinger." Herald/Harbinger | Jerthorp, 25 Jun. 2018, www.jerthorp.com/herald-harbinger (photo by Brett Gilmour)

Herald/Harbinger, 2018, by Ben Rubin and Jer Thorp is a data artwork that attempts to illustrate the interrelationship between the natural system Bow Glacier in the Canadian Rocky Mountains and human activities in oil and gas sector investment in Calgary. The artwork incorporates a real time data feed from the Bow Glacier, which is geophone data measuring the movement of the bedrock. The artist says, “the artwork is a living wake” and in around fifty years the glacier would have melted and disappeared, there would be no signal from the glacier and the artwork would stop representing the glacier in the middle of the city. The artwork incorporates an LED array as a visual representation of the data from the glacier.

[5] "Herald/Harbinger | jerthorp." https://www.jerthorp.com/herald-harbinger.

ANALYSIS OF CONTEXTUAL WORKS

The contextual works explored are highly valuable to this thesis as they all share the goal of data visualisation to bring attention to latent data in a visual format. These works helped me conceptualise my ideas into an interactive installation; The ideas of interactivity, data fluency, working with live data and artwork in relation to dynamic data. The works discussed look at various aspects of visualisation depending on the data used and algorithms applied. I strike a comparison between the works to find the points of similarity and differences.

CONCEPTUAL WORKS	Interactivity	Data Fluency	Dynamic Data	Artwork	Installation
Thermal Drift Density Map	✓	✓	✓	✓	✓
How Normal am I?	✓	✓	✓	✓	
Visualising Algorithms	✓	✓		✓	
Herald/Harbinger			✓	✓	✓

Table 1: Comparison between the contextual Works for points of similarity and differences

The contextual analysis became the basis of my data visualisation approach for the installation. I decided to use a dynamic data source and explore data fluency through an interactive experience that would allow the user to be part of the installation through their own data to complete the artwork.

CHAPTER 4: METHODOLOGIES

My research seeks to develop an interactive experience for the user and contribute to the growing research on data fluency and how inanimate objects like machines or artificial intelligence systems can be used to make our lives more connected at the cost of our data. Through this research I tried to synthesise multiple aspects of the cited literature and borrow knowledge from diverse fields to look at the problem from different angles, using a mixed methods approach.

This research uses Research-Creation as the main methodology to carry out research. It further borrows from the literature on Data Fluency and Critical Data Studies to build on the concept of this thesis.

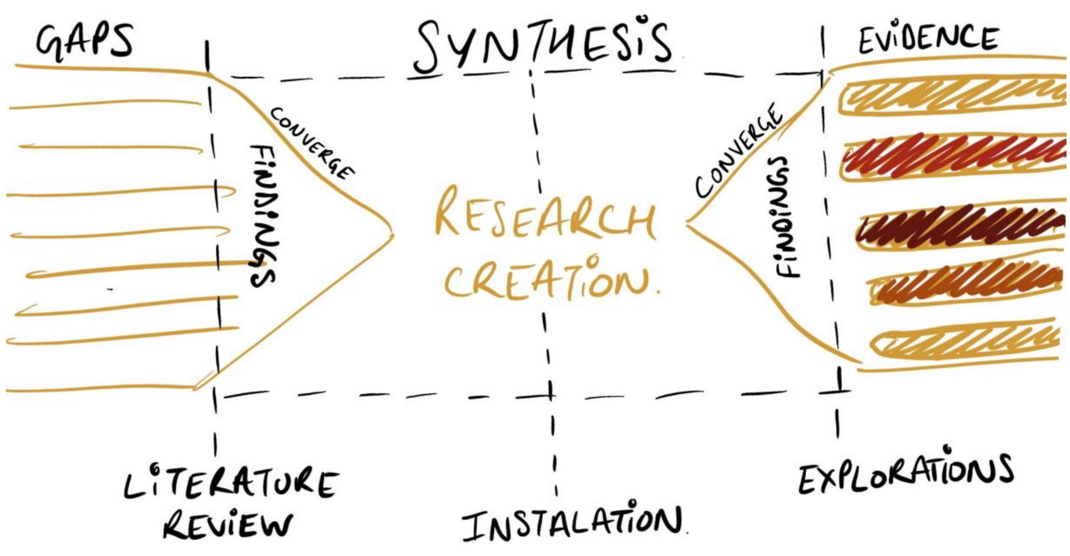

Figure 7: The conceptual framework to use Research Creation

RESEARCH CREATION

‘Research-Creation, also known as practice-based research, is a hybrid methodology that initiates research through the researcher's practice, where questions and problems are identified, and the research strategy is shaped through the creative activities and presentation to audiences to find answers. It works on the idea of knowledge building through exploration, discovery, and integration of ideas through artistic making.

> *It can be argued that artworks often embody such generalisable and transferable knowledge, so that aspect of the definition is not necessarily problematic to creative arts practitioners, though higher education administrators may find the idea that art can transmit knowledge more problematic. However, there is also an unstated implication in this definition, or at least in most interpretations of it, that knowledge is normally verbal or numerical.* (Smith and Dean, p.4)

Understanding that creating a visual language to transfer knowledge is not limited to what can be verbal or numerical, I used data visualisation to explore how knowledge can be converted to a visual language that doesn’t need verbal or numerical knowledge. It is important to note that the data in this research are not just visual data, but it is an attempt to link these data to the audience interacting with the work. The audience gives their pose data to power the generative artwork.

This method is suitable for this research as it allows exploration and building through different approaches while trying to answer the research questions. Looking at the problem of how the digital economy is built on data and the algorithms that run it, I tried to develop a methodology that would allow me to explore these technologies and their effects on our lives through the creation of an interactive installation that collects data and visualises it to teach the audience about these topics.

CHAPTER 5: EXPLORATIONS

The exploration is divided into different segments where each segment is based on the distinct aspects leading to the construction of the final installation. The explorations are based on my practice and the research done into the parts that I found to be the crucial building blocks of the final piece. The explorations are divided into five different segments: (i) Machine Learning Explorations (ii) Interactivity to collect Latent Data (iii) Data Visualization (iv) Hardware and (v) Software and Protocols for data transfer.

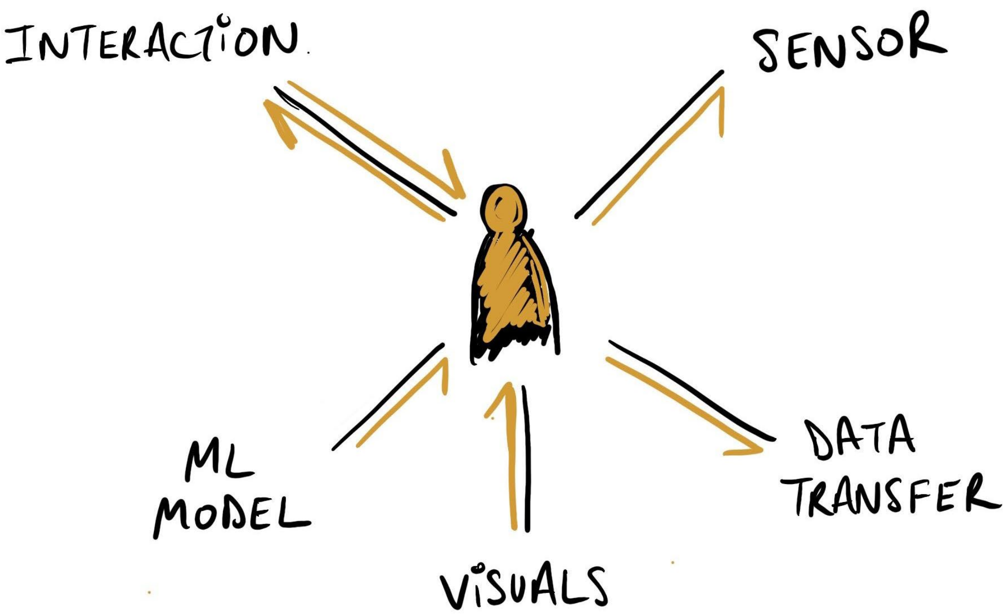

Figure 8: The data flow from the user to the different segments of the exploration

MACHINE LEARNING EXPLORATIONS

As indicated in the Literature Review, modern algorithms have changed the data collection process. Fuelled by new research in the field each day, machine learning algorithms can efficiently work in any JavaScript enabled browsers with minimal hardware and computing power. I point the focus to light JavaScript based machine learning algorithms which are easily deployable through modern browsers. This segment intends to test out the performance of different JavaScript based machine learning algorithms that are readily available and deployable in the modern browser.

There are many machine learning algorithms available. The scope of this exploration is to investigate the performance of machine learning algorithms that are based on computer vision technology. The aim is to not build a whole new model to collect data (such as training my image classification model to segment people from a scene or to detect objects in the scene) but rather, to use existing tools to collect the data and explore how effective the models already available are in terms of their results and how well they can perform. This exploration cannot cover all the available tools; this will give an idea of what is available and the capabilities of those tools. So, I will only be looking for how versatile the algorithms are and how they perform by utilising limited computing power to collect data. Although the intentions are to use tools that are easily available and deployable, I will demonstrate how simple it has become to build your image classification model and the possibilities that exist in terms of data collection. I further offer the guide that follows as a framework that other artists could use in applying simple machine learning and vision tools.

HOLISTIC MODEL[6]

This one model can generate data which normally would be done by three different models. It combines the hand tracking, face mesh and pose detection models in one model. The data generated by this model is rich enough that it can be used to predict multi-faced data in a wide array of applications.
For example, Predicting the pose of a person in relation to the expression of the person to triage the information to correctly classify the activity the person is doing.

ANALYSIS

The model was able to correctly detect my face, hands, and body. The skeleton was also quite accurate and responsive to the movement.

REFLECTION

Although the model is quite accurate, it may have some limitations under stressful conditions. As it failed to detect the left part of my hand which may be due to overlapping with other data points. As seen in Figure 9 it does not. detect my left hand properly. Although we will be looking over the smaller models that build up this model for more insights.

SUPPORT MATERIAL

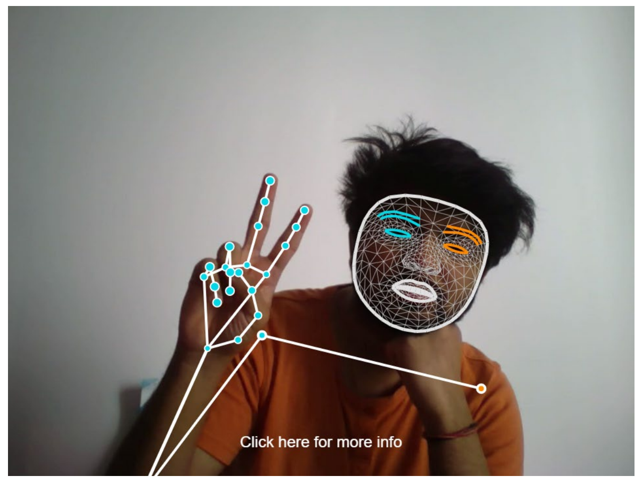

Figure 9: A screenshot of the Holistic Model

DATA POINTS

The model generates the following data:

- Face Mesh: used to track the face of a person and the movement of the face.
- Hands: used to track the movement of fingers and joints and the gestures a person makes.
- Poses: used to predict the activity the person is doing.

[6] "MediaPipe Holistic - Google." https://google.github.io/mediapipe/solutions/holistic.html. Accessed 18 Mar. 2023.

FACE MESH[7]

The model generates a face mesh by predicting the face of a person and tracking it using landmarks as part of the mesh. The mesh differentiates the part of the face be it the left side or right side, the angle of the face and the expression of the face.

ANALYSIS

The accuracy of the model is remarkably high as shown in Figure 10. The prediction on the face where the camera could not actually see the facial feature was almost right in terms of the mesh mark applied. As seen the forehead is covered with hair and the model is still predicting the forehead mesh.

REFLECTION

The predictions made by the model for the features it could not see are also very accurate. Demonstrating that the model can predict the hidden features to an extent.

SUPPORT MATERIAL

Figure 10: A screenshot of the Face Mesh Model

DATA POINTS

The model generates the following data:

- 468 3D Face Landmarks in mesh format: used to track the face and the movement of the face. The mesh could also be used to predict distinctive features like the expression or some intricate details like the BMI of the person by averaging the data in the mesh (Yousaf et al).

[7] "MediaPipe Face Mesh - Google." https://google.github.io/mediapipe/solutions/face_mesh.html. Accessed 18 Mar. 2023.

HAND DETECTION[8]

The model predicts the hand pose and generates landmarks to the hand. The model enables the tracking of hand movement and predicts gestures based on the signs and the hand motion. The landmarks are colour coded to represent different hands and joints on each hand. For instance, red signifies the left hand and blue signifies the right hand.

ANALYSIS

The model is pretty accurate in predicting the hand pose. The landmarks of the hand are very responsive and always snap to the hand skeleton as soon as the hand is detected. The model also maps these points in 3D space for better reflection in the environment.

REFLECTION

Although the model is quite accurate it sometimes under stressful conditions behaves abnormally and is not able to determine the hand pose as seen in Figure 11 both hands are red.

[8] "MediaPipe Hands - Google." https://google.github.io/mediapipe/solutions/hands.html. Accessed 18 Mar. 2023.

SUPPORT MATERIAL

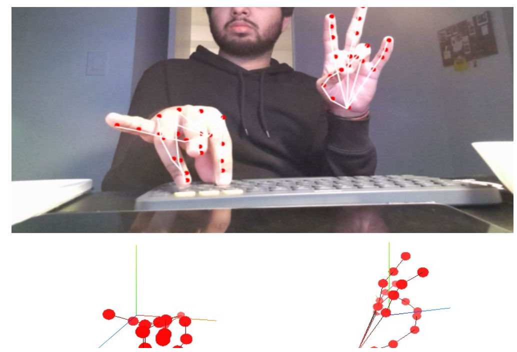

Figure 11: A screenshot of the Hand Detection Model

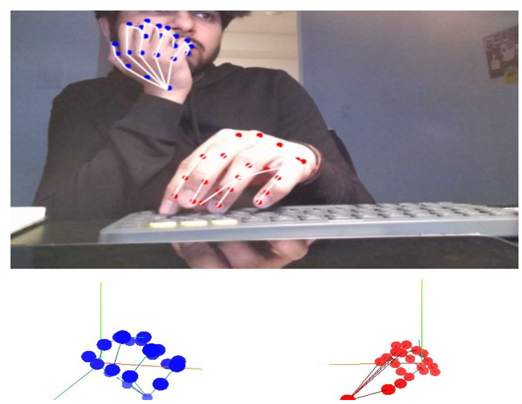

Figure 12: A screenshot of the Hand Detection Model

DATA POINTS

The model generates the following data:

- 21 3D Hand Landmarks: used to track the hand and the movement of the hand. The landmarks could be used to guess the gestures and movements of the hand.

POSE DETECTION[9]

The model predicts the pose of a person and landmarks the points of joints and the head with high accuracy. The model enables the tracking of actions and gestures based on body movement. The landmarks are colour coded to indicate which side of the body the point lies on. For instance, orange signifies the left side of the body and blue signifies the right side of the body.

ANALYSIS

The model is pretty accurate in predicting the pose of the person. The landmarks on the body are very responsive and always snap to the body skeleton as soon as the model predicts that the pose is detected. The model also maps these points in a 3D space for better reflection in the environment.

REFLECTION

The predictions made by the model for some complex poses are also very reliable. The model also demonstrates the ability to predict features that are not visible in the image or are being overlapped by other objects.

SUPPORT MATERIAL

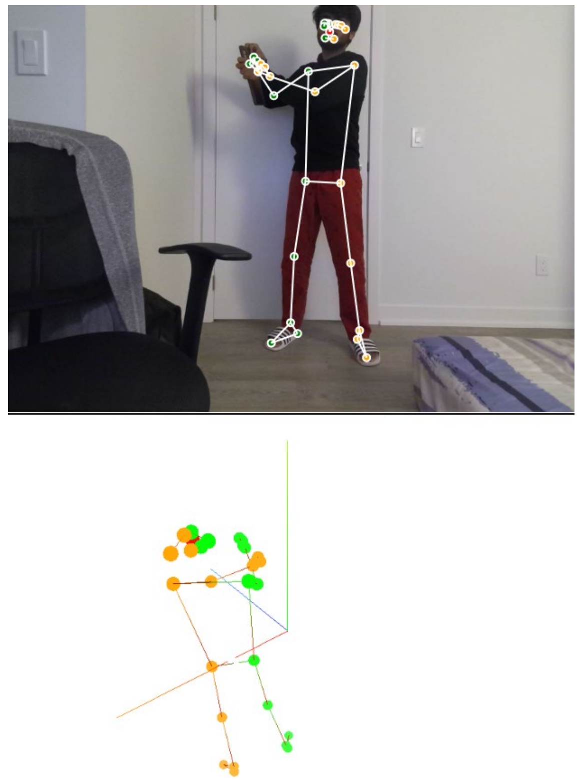

Figure 13: A screenshot of the Pose Detection Model

DATA POINTS

The model generates the following data:

- 33 3D Pose Landmarks: used to track the pose of the user. The landmarks give data about joints and head position. Data could be used to predict the action that the person is performing.

[9] "MediaPipe Pose - Google." https://google.github.io/mediapipe/solutions/pose.html. Accessed 18 Mar. 2023.

FACE DETECTION[10]

The model predicts the face and generates landmarks on the face. The model enables the tracking of head and face position. The landmarks are colour coded in blue and are placed on the face and the face is segmented with a red box.

ANALYSIS

The accuracy of the model is remarkably high as shown in Figure 14. The prediction of the landmarks and their mapping on the face are very reliable and responsive.

REFLECTION

The predictions of landmarks and face mapping are very accurate and ultrafast. The model also supports multiple face detection with the same accuracy and speed.

SUPPORT MATERIAL

Figure 14: A screenshot of the Face Detection Model

DATA POINTS

The model generates the following data:

- 6 Face Landmarks: used to track the face of the user. This data could be used to see which side the person is looking towards.

[10] "MediaPipe Face Detection - Google." https://google.github.io/mediapipe/solutions/face_detection.html. Accessed 18 Mar. 2023.

OBJECT DETECTION[11]

The model predicts and segments objects from the frame. The bounding box for the segmentation also shows confidence in how strongly the model thinks that the object is what it is being predicted as. The model is extremely fast in detecting objects and is trained to detect around eighty objects with high accuracy.

ANALYSIS

The accuracy of the model is reasonable as shown in figure 15. The model is very responsive in detecting the objects from its trained data objects. The prediction bounding boxes for the objects are reliable and get adapted to the movement of the object.

REFLECTION

Although the model has proven to be an exceptionally reliable and fast model in predicting and segmenting objects. It may sometimes be inaccurate in detecting a few objects in figure 15 the mug is identified as a donut. But that is observed for a split second and not a constant issue as the model is able to adjust accordingly and correct its prediction.

SUPPORT MATERIAL

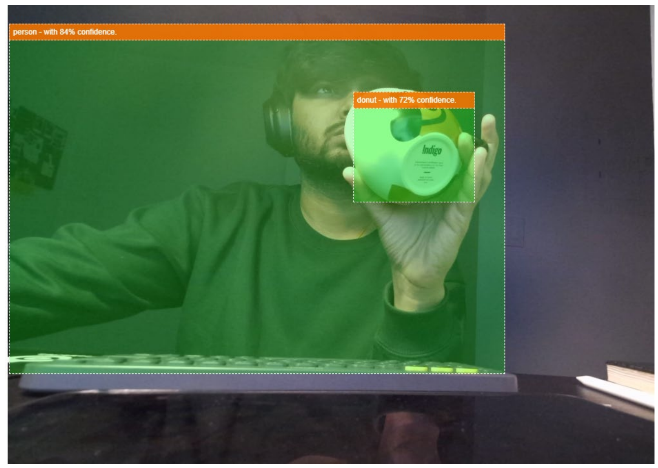

Figure 15: A screenshot of the Object Detection Model.

DATA POINTS

The model generates the following data:

- 80 Object Detection: used to segment and detect the objects from the frame. The detections could be used to spot and extract specific objects that could be illegal or for data collection.

[11] "MediaPipe Object Detection - Google." https://google.github.io/mediapipe/solutions/object_detection.html. Accessed 18 Mar. 2023.

IRIS DETECTION[12]

The model predicts the iris and the depth value of the eye from the camera. The model takes the help of the face mesh system to predict the correct position of the iris and the depth value. The model can recognize faces and iris very easily. Although it does not infer the gaze data that could be accounted for with some tweaking in the code.

ANALYSIS

The accuracy of the model is quite high as it detects the eye and the iris very well with the depth data. The landmarks for the iris and the eye are very reliable in terms of performance. The model is fast in detecting the eye and iris when it finds a face in the scene.

REFLECTION

The model also incorporates the face mesh landmarks so it could be considered a multi-detection model. The model also accounts for the hidden features that are not directly visible in the scene by predicting where they might be located.

SUPPORT MATERIAL

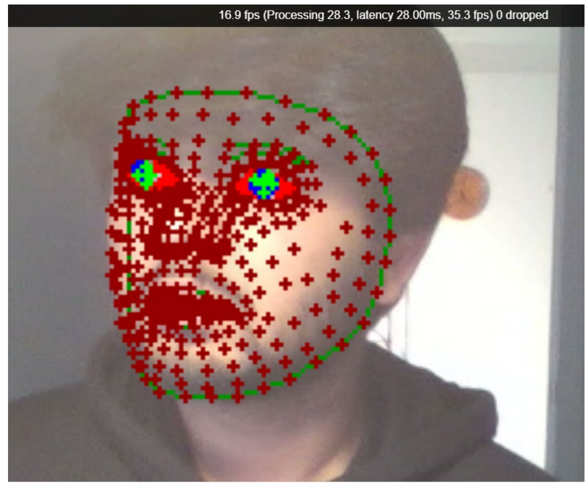

Figure 16: A screenshot of the Iris Detection Model

DATA POINTS

The model generates the following data:

- 10 3D Eye Landmarks and 468 3D Face Landmarks: used to track the face, the movement of the eye and the iris data. The detection could be used to interpret gaze data and predict where a person might be looking.

[12] "MediaPipe Iris - Google." https://google.github.io/mediapipe/solutions/iris.html. Accessed 18 Mar. 2023.

SEGMENTATION[13]

The model predicts and segments a person from the scene. The model masks the identified person from the background with an overlay. The segmented person is the only output you get from the scene.

ANALYSIS

The model performs accurately to segment the person from the scene. The model does an exceptionally job distinguishing the person and applying a mask on the background as seen in Figure 17.

REFLECTION

The model gives the data that a pose detection model does but without the skeletons and dividing the person into sectors for data points like joints and other features of the body.

SUPPORT MATERIAL

Figure 17: A screenshot of the Segmentation Model

DATA POINTS

The model generates the following data:

- The model gives back the image with an overlay at the background segmenting out the person from the background. The data could be used in other ways when combined with other tools to segment out some people from the scene.

[13] "MediaPipe Selfie Segmentation - Google." https://google.github.io/mediapipe/solutions/selfie_segmentation.html. Accessed 18 Mar. 2023.

TEACHABLE MACHINE[14]

An interactive web-based tool developed by Google to create a machine learning model fast, easy, and accessible for everyone in a few steps without the need to write code or understand what machine learning is. The goal of this section is to demonstrate how an image-based machine learning model can be created with a few steps using the teachable machine toolset.

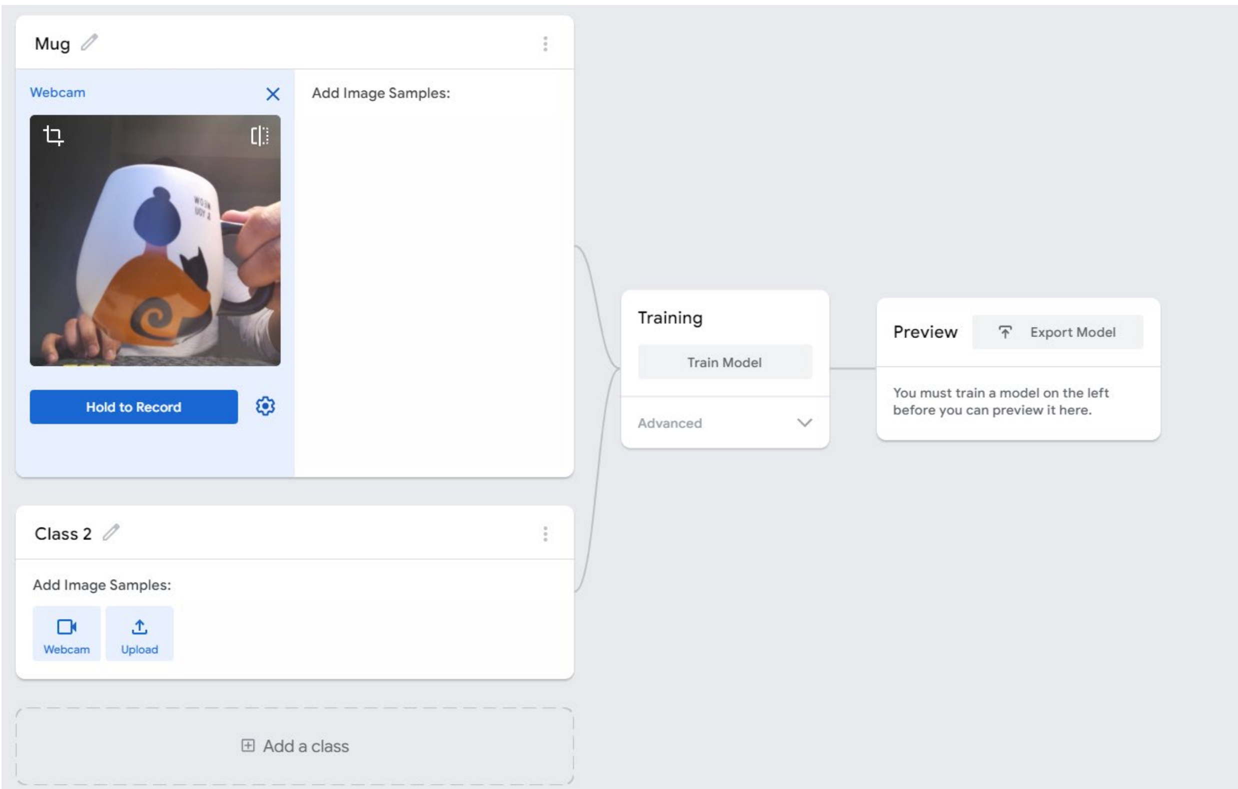

Figure 18: Teachable Machine interface

The process is very straightforward: you just record the object or thing you want the model to classify in the scene. As per Fig 18 above, you just press the 'Hold to Record' button and start to record the object from different angles and distances, you can also add some pre-recorded images if you want; add the object from fairly most angles and

[14] "Teachable Machine." https://teachablemachine.withgoogle.com/. Accessed 12 Feb. 2023.

distances and then just move on to the next object and repeat the same. Lastly just press ‘Train Model’ and voila you have made an image classifier.

SUPPORT MATERIAL

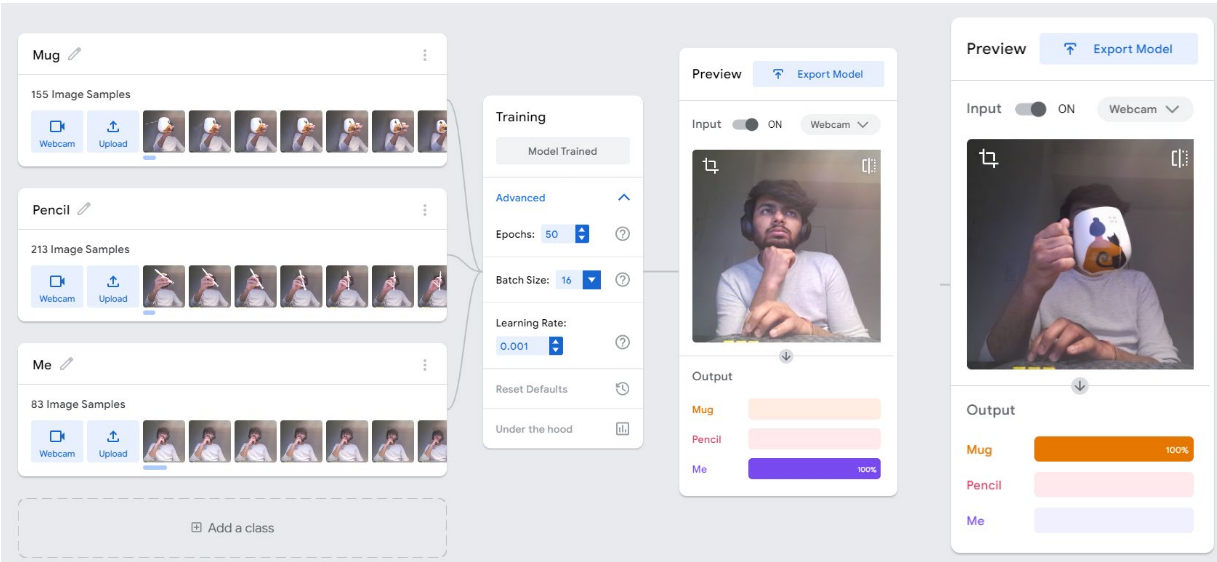

Figure 19: Teachable Machine interface and a trained model

ANALYSIS

Figure 19 shows how easy it has become to create a machine learning model to classify an object and collect data with just a few steps and without any programming knowledge. The model works very well considering the amount of data on which it was trained. The Output from the classifier is the data point that is captured from the video stream.

REFLECTION

The tool can enable the creation of a powerful machine learning model to classify and make predictions for objects and things built for specific purposes. The tool has a lot of potential in it depending on how it is used. It can be used by users to learn about machine learning and the importance of data in the digital age. It can also be used to invade people's privacy and track their activities.

Findings of Machine Learning Exploration

The exploration of the different models and algorithms that I have shown and evaluated within this section gives a fair understanding of vision-based machine learning models and what kind of data points could be extracted from the images or video frames. Additionally, seeing how easy and accessible machine learning has become enabled by Teachable Machine, it is even more evident that there is a need to make users aware of such modern algorithmic systems.

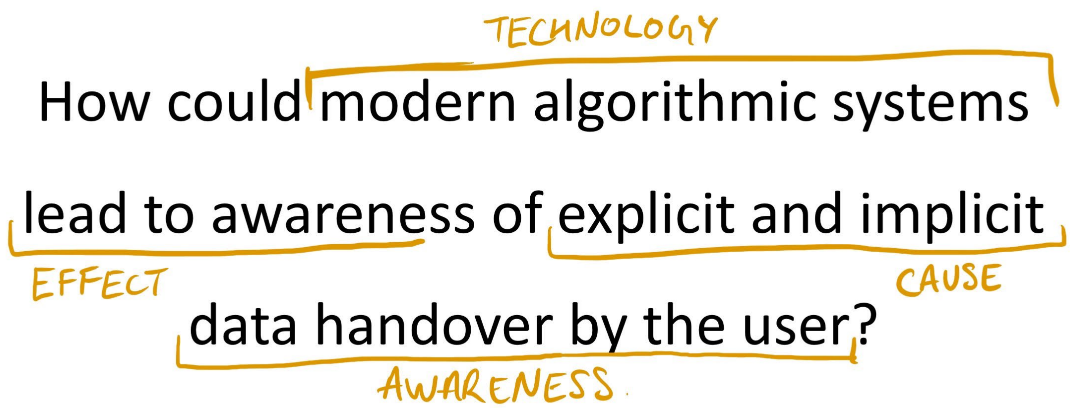

Figure 20: Breaking down secondary question.

Building upon my findings from the Machine Learning explorations and having a better understanding of the data points each model produces, I synthesised my findings and created an interactive artwork that tried to collect latent data which are the core concepts I explore in the next section.

INTERACTIVITY TO COLLECT LATENT DATA

Building on the evidence and discussion in the literature review, this section builds on the possibility of collecting latent data from the users. I will look at two ways of collecting data from the user’s using sensors and machine learning algorithms to determine the user's preferences. This way of data collection could be described as an implicit way of data collection where the user does not get asked about their preference. Rather, the interactions and the engagement with the artefact generate the user's preference. The other way of collecting data would be to ask the user explicitly about their preference. This way of data collection would be explicit data collection where the user is asked about their preference, and they respond with the input.

The choices could be triggered to help in building a decision table through the data that the user provides while interacting. The data points could be anything ranging from colour preference or wanting to learn or try new things while interacting with the interactive art piece, the latter resulting in curiosity as a data point about the user.

I will share some interactive artworks that I developed for the purpose of collecting latent data about users. The artworks are enabled with machine learning algorithms to determine the user's movement and their interaction with the art piece. The pose estimation model is used to determine distinct aspects of the user's movement by calculating a weighted combination of the spatial landmark position and orientation to create different interactions with each art piece. The interactive art pieces are made in p5.js[15] which can be used in web pages and can be hosted on the webpage. The art pieces use the camera as the main sensor that is used to track the user as we are only looking at algorithms enabled by computer vision technology. The artworks have been developed for the purpose of learning about how different models can be used with artworks to predict a user’s preference and try to determine their personality based on the interactions and the data collected.

[15] "home | p5.js." https://p5js.org/. Accessed 19 Mar. 2023.

Generative Artwork 1 (Colour Preference)

p5.js Web Editor | Color Pref (p5js.org) | Try it out!

The first piece of work creates an artwork based on a preconfigured scheme of the colour swatches that is pleasing to the eye and goes well together. The interaction with the piece is divided into three parts which are:

- Idle: When the artwork detects there is no one in the scene or if the person interacting is outside the interaction parameters, the artwork stays static and waits for the audience to enter the parameters of the interaction. The parameter is the distance of the person engaging with the artwork.
- Change: When the person engaging with the artwork is in the interaction parameter and claps, the colour scheme changes to another palette which contains completely distinct colour swatches. The person can cycle through the different palettes until they come to an artwork that they like.
- Engage: When the person is within the interaction parameter the interaction starts. The interaction starts generating a series of artworks from the given colour scheme. It makes a new artwork each second of the engagement the more artworks are created for a certain colour scheme.

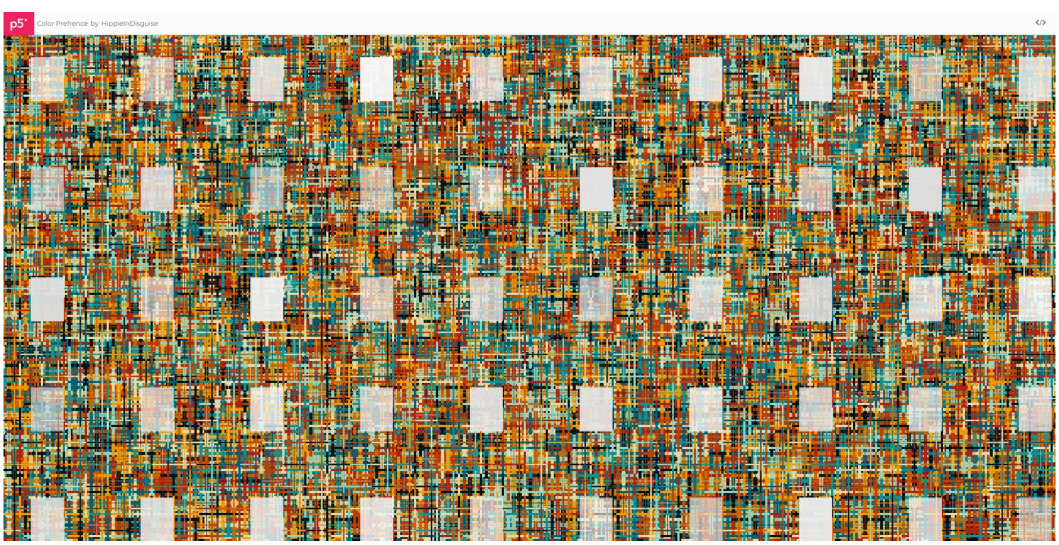

Figure 21: Generative Artwork for interaction with Colour

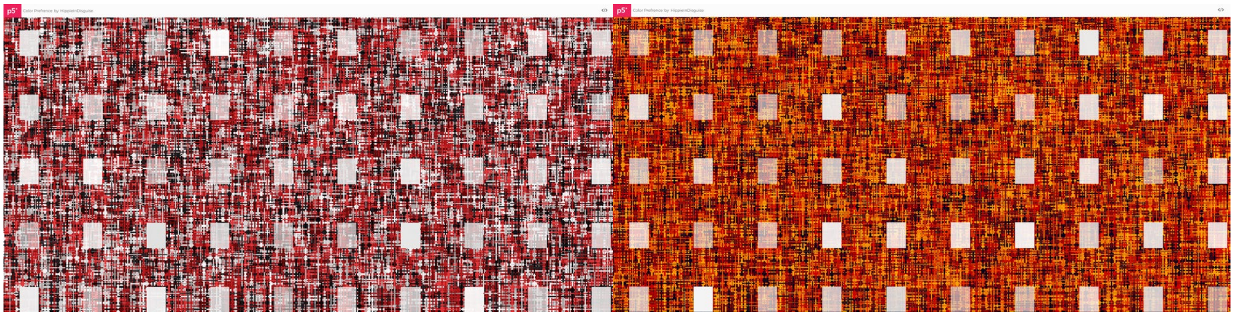

Figure 22: Generative Artworks for Interaction with Colour

The engagement with the piece generates the colour scheme for the artwork which could be used to predict what colour scheme the audience prefers. This data is analysed by calculating the average time the person is interacting with the piece and the colour scheme that they are engaging with the most time. The insights gained from the data could be used to create artworks that are more appealing to the audience like morphing the colour scheme that is preferred by an average or segment of the audience.

Generative Artwork 2 (Left-Right Preference)

p5.js Web Editor | Left Right Pref (p5js.org) | Try it out!

The second piece of work creates an artwork based on the weights applied onto circles to create a boldness characteristic to the circles. The interaction with the artwork is divided into three parts which are:

- Idle: This is the default state of the artwork, in this state the circles randomly jump around the screen and a new weight is applied to each circle based on the weight value previously assigned to each circle. Each second a new artwork is generated and presented to the user.
- Left Push: When the user wants to engage with the artwork, they use their left hand to push the weight towards the left of the screen and the circle would arrange in order of the weight applied on the circle, the circles which are closer to the left of the screen would have higher weight and the circles which are closer to the right would have lower weight.

- Right Push: When the user wants to engage with the artwork, they use their right hand to push the weight towards the right of the screen and the circle would arrange in order of the weight applied on the circle, the circles which are closer to the right of the screen would have higher weight and the circles which are closer to the left would have lower weight.

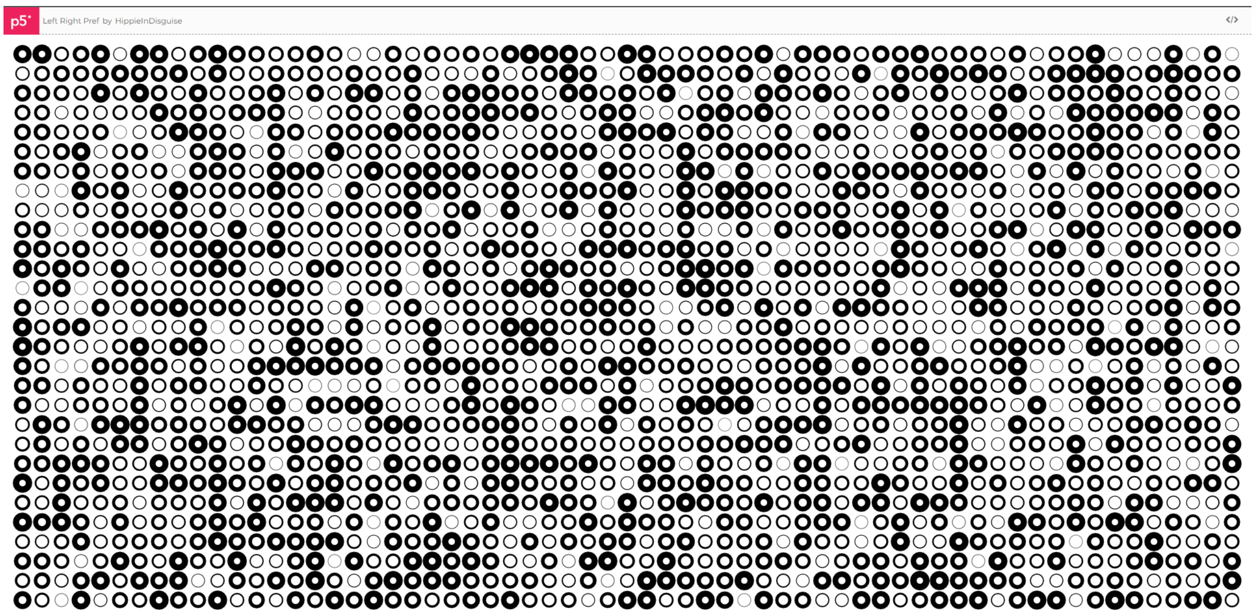

Figure 23: Generative Artwork for interaction with weight

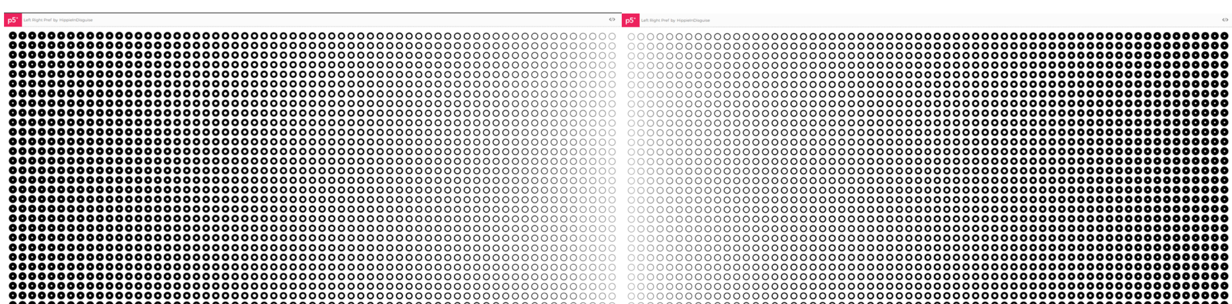

Figure 24: Generative Artwork for interaction with weight

The engagement with the artwork generates the preference of the user and exhibits the orientation that the user prefers to see the artwork. The data would be collected by seeing the movement of the user's hand. The other data point generated is how long the corresponding artwork stays on the screen differentiating the preference.

Findings of Interactivity to Collect Latent data

The limited evidence from exploring the use of interactivity and technology through the generative artworks discussed in this section point that the use of interactivity to collect latent data is a viable option in learning about user's behaviour and their reaction to the interface and how it can be used in different contexts. These data visualisations can be utilised to give visual cues to the users that their responses and interactions are morphing the artwork. This finding is important as it shows that using interactivity and technology, we can collect data to enhance the user experience and let them know that their response and interaction are being actively used to play with the work and create the visual output. The final visualisation approach builds upon this idea of interactivity to collect latent data and utilise it.

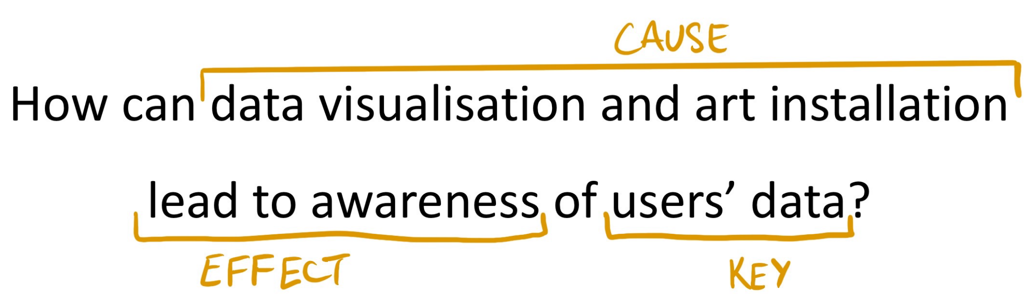

Figure 25: Breaking Down the secondary question

VISUALISATION DESIGN

How can I show data with a visual queue for the viewers? The medium should be rich enough to allow for creativity and allow for flexibility in representing something that is constantly changing and interacting.

Starting from a basic idea of the visualisation of data, the installation was originally planned for a simple touch screen-based interface and sensors on the top of the screen that would allow for the collection of data from the users while they interact on the screen.

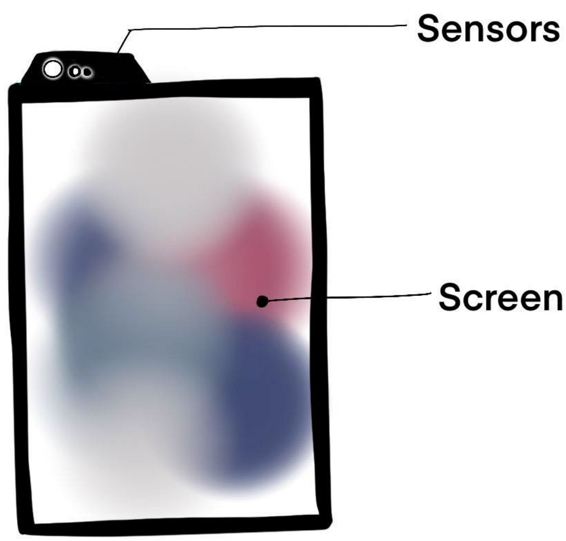

Figure 26: concept sketch of a screen-based interface

Although the screen-based approach does provide an interface, it is not as immersive in terms of user interaction as it would be limited to only one person interacting with the screen at a time. The second problem with a screen-based approach is projecting the data shed which happens when the user interacts with the interface. I made the move away from a screen graphic visualisation to make the interface more dynamic. I started ideating about how to make a LED array-based installation that would allow the user to not only interact with the installation but also have a richer visual output to the audience.

As the LEDs can be controlled individually, we can display different animations and visual effects with specific brightness parameters and also have interactions with twisting the strips to make hue and colour changes as seen in Fig 27.

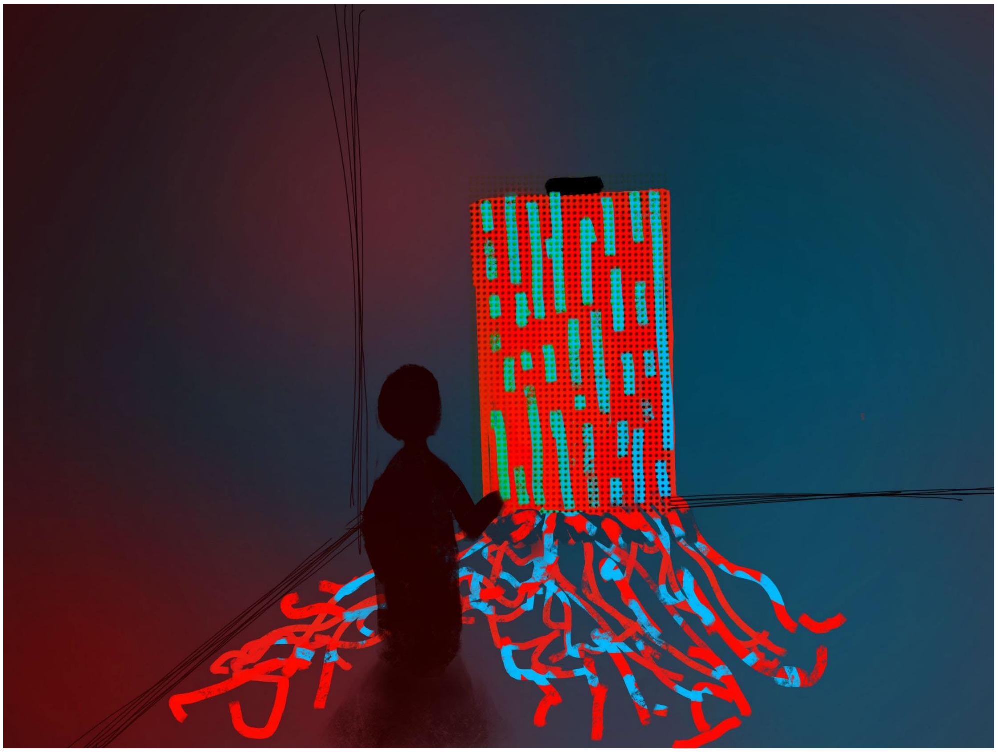

Figure 27: Concept sketch for the final interactive installation

The exploration is divided into two segments wherein one part looks at the construction of the artefact that acts as the portal to connect the user with the interactive installation and the other part looks at the selection of sensors that would act as the input from the users. The sensors are also responsible for gathering latent data from the user.

ARTEFACT

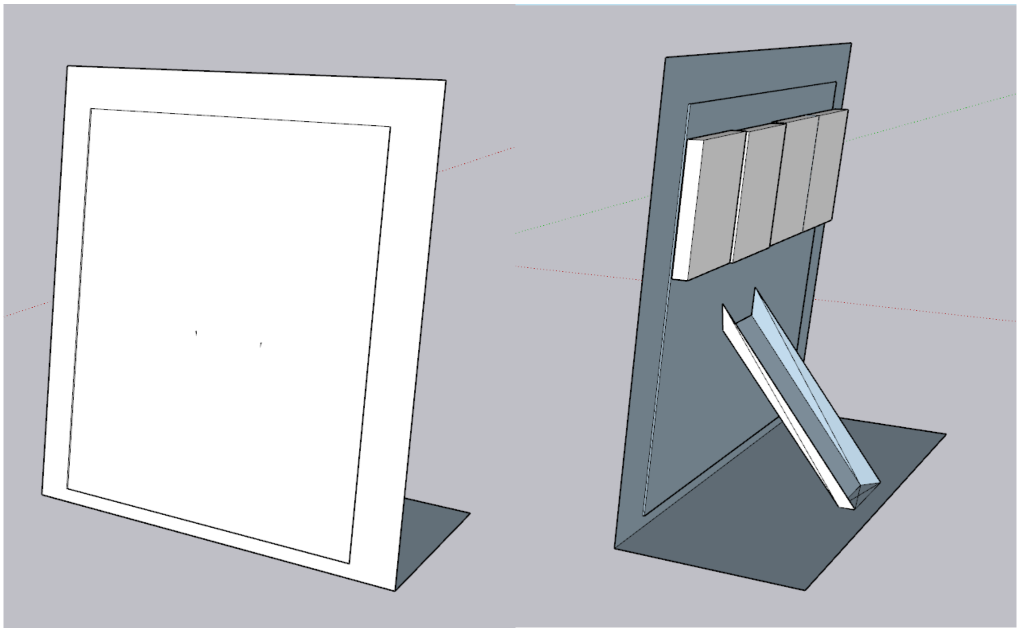

Figure 28: Concept 3D model of the physical installation

While designing the artefact I divided it into two sections. The **first section is a door like structure** with a height of approximately 6 ft constructed out of programmable LED strips of 5 metres that are connected from the top to the bottom and the remaining length of the programmable LED strips make the **second section of the artefact which lay down on the ground** to create a difference between the first section and the user. This second segment allows the addition of interactivity to the installation. It acts as the entry point for the user to understand when data transfer occurs and gives a visual queue to the user when the artefact captures data from the user. The LED strips on the ground also act as a barrier between the artefact and the sensors so that a full scan of the user is possible as what the camera sees is highly dependent on the field of view, ensuring a certain distance would always yield best results as to how the system is designed. The other advantage this distance created with the LED strips on the floor provides is to make sure that the user is inside the area where the users are required to stand as there is no other visual indicator for the user to know where to stand.

The first act was selecting the right programmable LED and the operating voltage although there are many led strips available ranging from 5/12/24 Volts. I chose the 12-volt LED strips as they have a more uniform light output as the voltage drop in higher voltage strips is very minimal so they can have longer runtimes with close to no effect on their brightness.

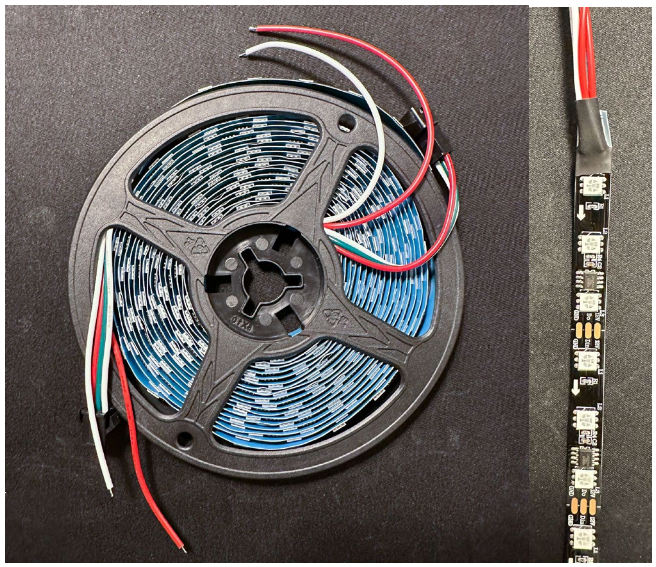

Figure 29: photo of the LED strips used

The second piece was to make sure that the LED strips are provided with enough voltage to run and power them through a power supply. The selected power supply can power around 8 LED strips without any voltage drops observed.

Figure 30: Photo of the power supply used

The last piece of the artefact is the controller that will be used to send data from the computer to the artefact to make the LED turn on and off. I used the SP801E ArtNet

Controller. The ArtNet controller is a DMX-type device that can control up to 512 universes of 512 channels each. The ArtNet controller can be programmed using the free ArtNet editor.

Figure 31: Photo of the ArtNet controller used

So, the configuration for the whole was thirty-two programmable LED strips, four power supplies and an Art-Net[16] controller.

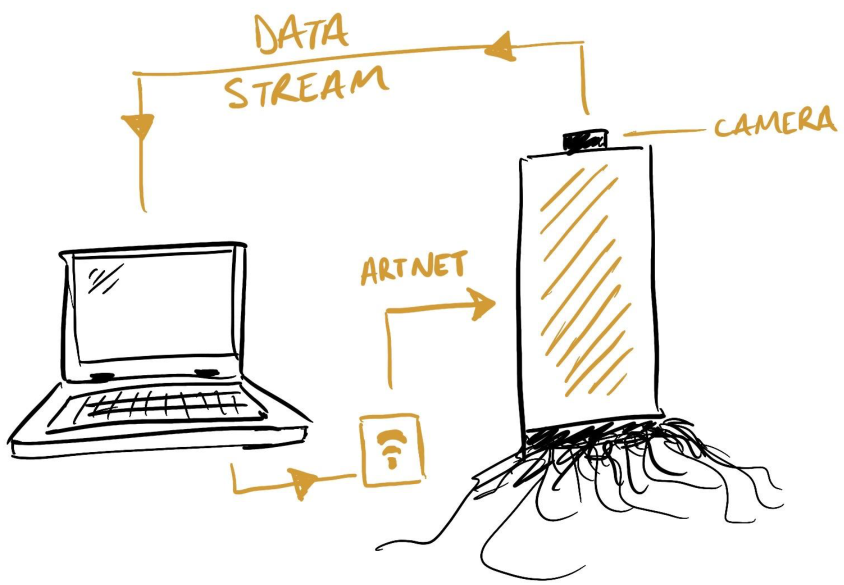

Figure 32: Data flow between the installation and the system

[16] "Art-Net 4 - Artistic Licence." https://artisticlicence.com/WebSiteMaster/User%20Guides/art-net.pdf

SENSORS

The selection of appropriate sensors for the artefact to gather the data was a key factor in the success of the installation. The primary idea for the sensor was to restrict the data to only those that can be observed by a camera as almost all the models used within the exploration were computer vision-based models or machine learning models that only need images as input. There are many diverse types of sensors that could have been used to gather data for the installation, but I chose to use Azure Kinect DK[17].

Figure 33: Microsoft Azure Connect DK Source: amazon.com

The reason for this was that the sensor provides a wide array of sensors, including depth, skeletal tracking, RGB and infrared cameras, which can capture colour data from what the camera is seeing. In addition to all the visual data that could be captured the Azure Kinect DK also provides a 7-microphone array that can capture the sound around the device.

The Azure Kinect DK also provides an added advantage over other sensors as it can compute and run machine learning models powered through the Microsoft Software Development Kit.

[17] "Azure Kinect DK – Develop AI Models." https://azure.microsoft.com/en-us/products/kinect-dk

SOFTWARE AND PROTOCOLS FOR DATA TRANSFER

This section talks about the software, protocols used for the data transfer process and analysis of the data gathered. The software used was mainly VVVV[18] after consideration of using different software such as Unity, Processing, Touchdesigner and OpenFrameworks. The other option was to write custom code to gather and process different data points such as movement, orientation and RGB colour. The reason for choosing to use VVVV was mainly due to its ability to run almost all the .NET libraries and the possibility to use custom code if needed. The other thing that swayed me towards VVVV was the fact that this was a thesis research project and building a custom piece of software to process and analyse the data gathered would have taken a lot of time and effort. The other advantage was the fact that VVVV is node based and can be scaled and deployed to windows running machines.

The other aspect of the installation was the protocol used for data transmission that helped establish the link between VVVV and the LED artefact constructed. The protocol used was ArtNet. The reason for using ArtNet was that it is a protocol specifically designed for the transmission of lightning control data over an Ethernet connection. ArtNet was also used because it can be used to control a lot of lighting equipment at the same time.

The next step was to build the framework for the system to start capturing data from the camera and the underlying machine learning models. I used OpenCV for the machine learning algorithm to track the movement of the subject and give skeleton tracking for the person engaging with the installation. After building out the data flow for the system, I ran into the issue of the model giving performance issues due to the high amount of computation that was not leveraged by the system GPU but was running on the CPU. As seen in Fig 34 the points were being plotted but not updating real time based on the pose tracking.

[18] "vvvv - visual live-programming for .NET." https://visualprogramming.net/.

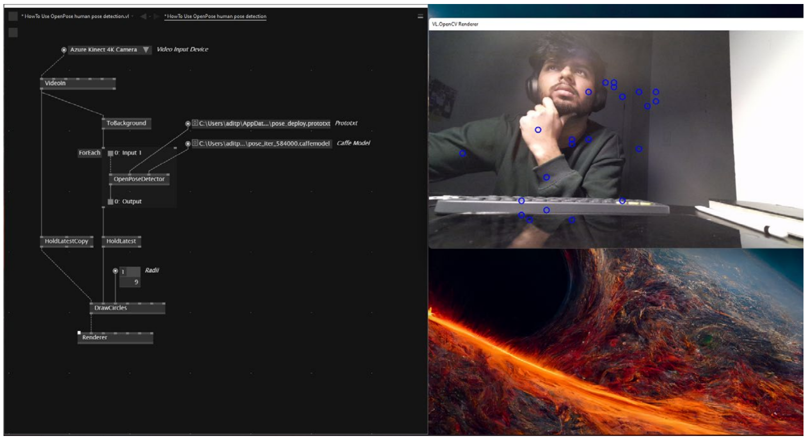

Figure 34: Workflow of OpenCV in VVVV

I made the shift from openCV to the Microsoft Azure Kinect body tracking software development kit (SDK) to tackle the performance issue and improve the processing power of the whole installation.

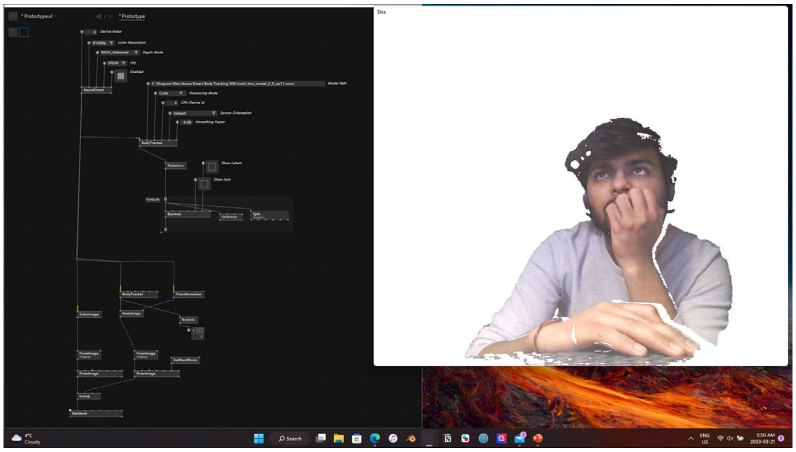

Figure 35: Workflow of Azure BodyTracker in VVVV

The segmentation of the camera image of the body was the output from all the processing of the machine learning model. Other data is also captured but is not visualised in this manner. Like Body id, the skeleton representation of the body from pose detection. However, none of the computation that happens on the computer is projected to the artefact. The artefact has its own visual art language which is generated in response to the user's interaction with the visuals which will be discussed later in the Data Visualization section.

DATA VISUALISATION

Data visualisation refers to the use of various graphical tools like charts, plots, and animations to represent data. In this way, complicated data relationships and data-driven insights are communicated in an easily comprehensible manner.[19] This section discusses the arrangement of the data collected and their analysis in a way that will help the audience understand the essence of the data collected in colour and shapes rather than the usual numbers and statistics. Data are not just numbers and statistics, however that is how the algorithms see data, as a collection of functions and calculations that have embedded meanings. Removing the complexity of interpreting and understanding what these numbers mean, I arranged the data collected into an artistic format. The visualisation is designed into two stages: (1) first data collection and classification and (2) the second stage is the analysis and visualisation of the collected data.

Data Collection and Classification

The data that I worked with was captured from the Kinect and the data is converted into data points with the help of machine learning algorithms. The data points that are collected are dynamic in nature and are updated in real time as the viewer is interacting with the installation. The data points that are captured are Pose, Body index, Segmentation, RGB and Infrared camera feeds and point cloud.

Analysis and Visualisation of the data

Data visualisation plays a crucial role in understanding the output generated by machine learning models. Various methods can be employed to represent and interpret the data effectively, providing deeper insights into the results. In this case, I chose segmentation data as the base for the visualisation. There is a random function that selects three colours from the image of the segmented persons and generates a colour palette. This colour palette is used to generate the artwork and is associated with the body index.

[19] "What is data visualization?." https://www.ibm.com/topics/data-visualization

This dictates that each person that interacts with the installation has a unique experience of the artwork.

CHAPTER 6:
INSTALLATION SYNTHESIS

The installation brings people's attention to the technology around them and lets them understand the machines and algorithms monitoring their actions. The system is built around existing machine learning models. The idea was not to design a system from scratch but use the power of the existing algorithms to create an interactive experience. The experience is meant to be a journey through various aspects of data from learning about data gathering and data shedding to the creation of an interactive artefact that brings the data together and raises awareness of what is being monitored and collected about the audience. The system developed has a modular approach as it was conceptualised from different modules and combined into a cohesive whole installation.

Specifications of the Installation:

- Software: VVVV (visual programming)
- Sensor: Microsoft Azure DK
- Machine Learning Models: Custom Configuration of Machine Learning Models
- Data Points Captured: Pose, Body index, Segmentation, point cloud, IR and RGB data from the camera.
- Data Transfer Protocol for LED: ArtNet
- LED Strips: 32 rolls of 5 metre RGB programmable strips
- LED on the wall: 32 x 100
- LED on the floor: 32 x 200

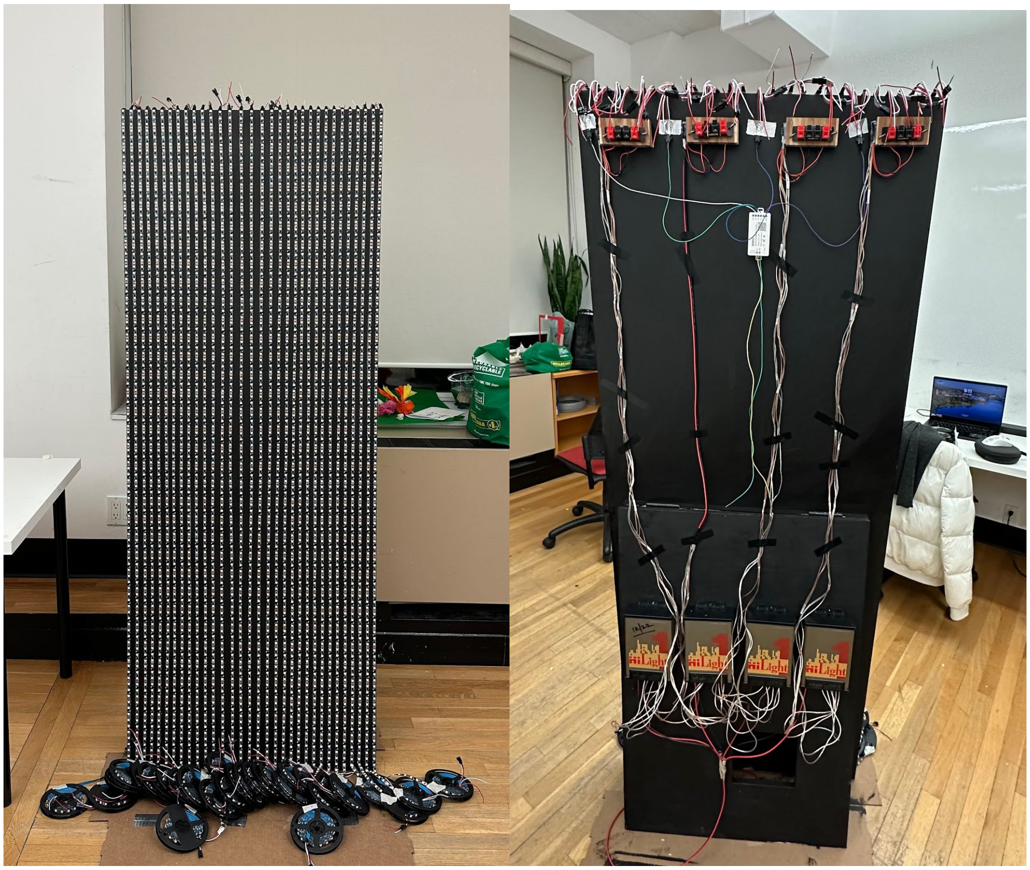

Figure 36: Photo of the final installation.

On the physical installation, the generative artwork is driven by averaging of the body joints data, segmentation, and motion prediction. As the output for the artefact is a LED array the size and the position of the body are crucial as standing too close to the installation will have a different output. A more accurate and detailed visualisation could be viewed from a farther distance which is a better experience for the audience. While the person engaging with the installation gets a unique experience, as the small queues that they are creating can be visualised in real-time to give feedback.

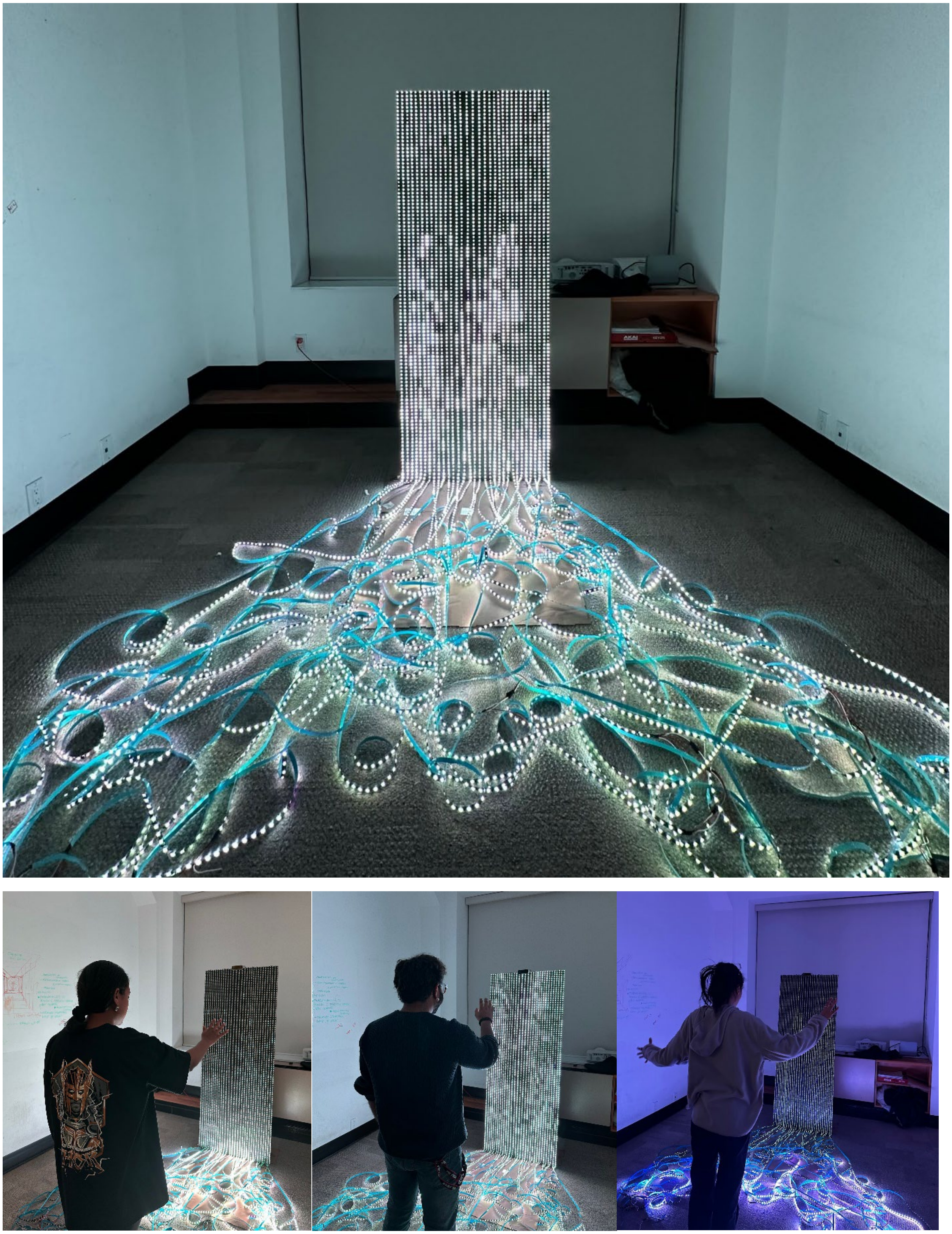

Figure 37: Photos of the installation with viewers engaging with it.

DISCUSSION ON INSTALLATION

I observed the ways that viewers interacted with the installation to gain insights into how the system worked and how the system responded to different viewer actions. This occurred during an installation of the first version of the artwork. I did not gather evaluation data through surveys.

There are two instances where the installation technology created an unexpected response to the user's presence. These instances could be applied to further research or development of the installation.

The first instance was one in which the user's interaction with the installation appeared as glitches and the data was not processed correctly. On the left side of the wall there was an area that was not in sync and threw a random generation of data (Fig 38). This was due to data drop over the network. Such a glitch could be incorporated into the installation in the future to show outlier data that does not fall in sync with the other data representation.

The second instance was one in which the system froze as two viewers decided to sit in the same place and both people were being captured in the same frame of the installation. This caused the system to freeze and hold the visualisation for a few seconds before the system recorded the information and processed it (Fig 38). This could be considered as a form of error that could occur in the model.

Figure 38: Photos of people engaging with the installation.

My most significant form of assessment was self-evaluation. I applied the following criteria:

- Interactivity: The installation was interactive in the sense that it was actively gathering data and representing that data to the user in a visual.
- Visuals: The visuals were built keeping the LED matrix in mind, so they are abstract representations of information in point data. It is an interesting and unique form of representation.
- Usability: The installation was designed to be simple, and you do not have to learn anything to interact with it.
- Responsiveness: The responsiveness of the installation is slowed down so that it can account for data gathering to be seen as with computer vision or tracking technologies it is a matter of seconds to compute the results.
- Functionality: I think the Installation does fulfil its intended purpose with room for improvement.
- Interface: The interface was not that well developed because having a LED matrix in mind was difficult for me to implement a good interface. That works out well for future work. Integrating the installation with some other interface.

- Durability: The hardware is durable enough to withstand rough handling and continuous use.
- Impact: I think the installation will have an impact on the user and how they perceive data and if that was not achieved, they will get artwork out of the experience.

Second Iteration:

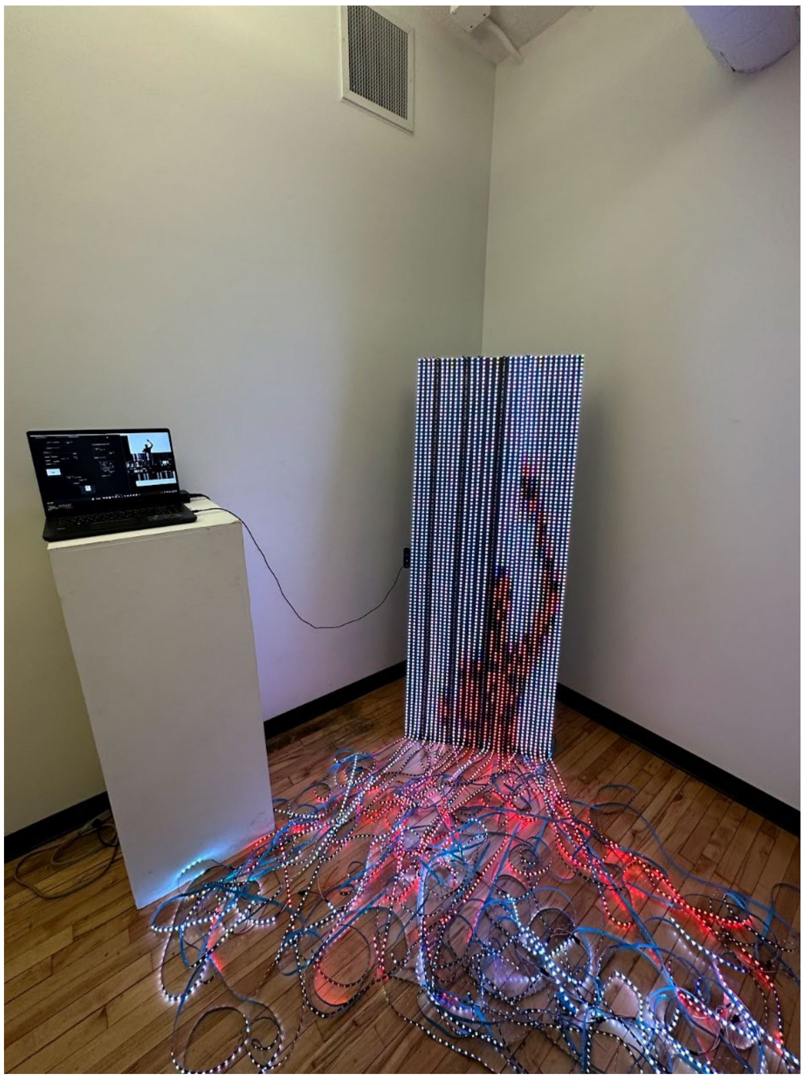

Figure 39: Second iteration of the installation

The installation was further developed for the Digital Futures Grad Show to further house more machine learning models to create an experience for the viewers to interact with. The interface was refined to be more informative and show the viewer the relationship between how the system collects the data and how the data is processed to show the visuals. The visuals were built keeping in mind the viewer may not have much prior knowledge about machine learning or coding. The engagement of viewers further contributed to the study through my observations of how they interacted with the installation and what they thought about the installation.

There were three key behaviours observed during the installation show:

- **Sparked Curiosity:** There were many viewers who looked at the installation, asked questions, and wanted to understand how the machine learning algorithms are collecting the data and the visuals are being generated. There was a common trend of viewers which was to look at the UI and then towards the LED matrix and then back to the UI on the laptop. This behaviour indicated the viewer wanted to understand what the laptop was doing and processing data.
- **Be Captured:** The system in place sometimes did not work as per the expectation of capturing the viewer because of various factors which included the hardware used and how the system was integrated. This resulted in more engagement of viewers as they wanted to be captured by the system which resulted in them understanding the system more and that the Machine Learning models that were in play. The other behaviour that the system created in viewers was to encourage them to return consecutive days with different attire to see if the system can identify them based on their clothing.
- **Understand from Distance:** There were many viewers who looked at the installation from a distance trying to understand the system and the algorithm in place but never engage with the system. This behaviour could be attributed to that the viewers understood about the data collection and the models being used but skipped the interaction to control their data and not share it with the system.

CHAPTER 7: CONCLUSION

This thesis builds upon the literature on how data has become an integral part of our lives and how we generate it. Understanding data and its implications has become crucial for individuals to make informed decisions in their daily lives as technologies have become more and more accessible. The Data Shed project was designed to encourage users to understand this data with the help of computer vision machine learning models and data visualization through in interactive installation. The aim of the installation was to encourage users to take control of their data and understand how the system in place is collecting that data. The viewers were encouraged to take control of their data by understanding the data that is being collected and the representation of it by clicking a picture of the artwork that they created while collaborating with the installation.

SUMMARY OF RESEARCH

This research aimed to create an interactive installation that would allow users to be able to better understand and interpret data to gain a deeper understanding of how data is gathered and used in the real world. The research explored these concepts by answering the secondary questions using a process of discovery and creation of standalone pieces that could be implemented in the full installation.

Development of the individual components that looked at the smaller scope of the bigger installation ultimately led to the contribution of answering the research questions. Through these small sprints and using different approaches to understand the question of data and its importance in society, discoveries were made that were further implemented into the installation to make it more useful to the user to understand the process. I believe that the main takeaway from this thesis is the possibility of using research-creation to build an artwork that can push the user to think about the data they use and how they can use it to gain a deeper understanding of the world around them.

The research also uncovered some interesting discoveries about how interactive artworks could be used to predict user behaviour and preferences and the implications this has for learning about the systems we create. These interactions with artworks can be used to analyse a novel approach to designing learning experiences that allow people to explore and gain a deeper understanding of things through interaction. This would require a more in-depth and thorough exploration which could be done in future works.

FUTURE WORK

The future stages of the installation could see development and research in the following areas:

1. Integrate more machine learning models and algorithms into the system. The aim for future developments would be to have the models respond to the interactions triggered by the users and not just the automatic collection of data. These would give the user the ability to learn about the models and algorithms that they want to learn about. For example, if the user wants to learn about the voice models the install should be able to trigger the specific voice model and present to the user the information.

2. Add more visuals and graphical representations of the data to help the user understand the data better and better integrate the system with other media like sound and video from a projector. The current installation design can only produce a pixelated representation of the data through the LED wall.

3. The inclusion of some computational heavy machine learning models to show the capabilities of the data that the big models can analyse and produce. The installation is currently showing only a small portion of the data and it is difficult for the user to interpret the data because of the limitation of the computation power available.

4. Theoretical research in Human Computer Interaction to better understand that ways that interactions as a framework combined with artworks and machine learning models represent a novel approach to design learning experiences that allow people to explore and gain a deeper understanding of data through interaction.

PRIVACY

To protect the audience's privacy the artefact under no condition uses any cloud-based solution to compute the audience data. All data that are captured are computed on the local device. The data are not stored anywhere and are only used to make the artworks that come up on the LED wall. If the audience does not want the artwork to be stored, they can opt out of the data sculpture and the artwork will not be stored. Storing the data sculpture does not mean that the data used to compute the artwork are also stored, that data is only used to generate the art and it is destroyed after the data sculpture is created.

The artefact in no condition or way discloses any private information. Nor does it use any such information to profile people in any way. The data points that are captured in the data sculpture are non-intrusive and do not profile faces or retain the data for longer than it is needed to generate the artwork.

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