Project Title

Candidate Number: QMKR4 [1]

Programme: MSc Data Science and Machine Learning

Supervisors: Nadia Berthouze and Temitayo Olugbade

Submission date: 12 September 2022

[1]**Disclaimer:** This report is submitted as part requirement for the MSc Data Science and Machine Learning at UCL. It is substantially the result of my own work except where explicitly indicated in the text. *Either:* The report may be freely copied and distributed provided the source is explicitly acknowledged

The code for this project is included in the following public repository: `https://github.com/nswarawita/Final-Project`

Abstract

The abstract is a brief summary of the paper, which needs to be written extremely well. Try to address the following points in your abstract, with a single sentence per point. This will naturally keep the abstract compact:

1. Describe the task/problem the paper is going to address (high level)
2. Why is this an interesting/important problem?
3. How does one usually solve this?
4. How (and why) do we do it in this paper (key idea)? Highlight the novelty here.
5. Interpretation of the results (impact and importance)

Contents

Chapter 1

Introduction

Instructions for section: What is the problem and why is it interesting? State very clearly the problem that you are investigating. If your examiner cannot even understand the first few pages of your thesis, there is no chance that you will obtain a high mark.

1.1 Motivation

The fashion industry is one the most significant contributors to the current climate crisis. Fashion is responsible for approximately 10% of greenhouse gas emissions and roughly 20% of all wastewater worldwide. In addition to its disastrous environmental impact, the fast fashion industry has substantial implications on an individual's overall well-being and finances. The fashion industry has recently leveraged digital technology to create a more sustainable and circular economy. Instances such as virtual clothing try-ons and digital clothing for virtual presence aim to lessen a consumer's one-time use.

This project supports the digital initiative of creating a more sustainable and circular economy by building a novel machine learning model to infer affect from touch in the context of fabric handling. The data input to the model (EMG, accelerometer and quaternion) was collected from both hands (left and right) via wearable sensors. The model was built to achieve two research goals. The model should first detect the property an individual is assessing and then accurately predict the corresponding property rating. The novel machine learning method proposed in this project is the Property Rating Hierarchical Model (PRHM), a two-part model that predicts the assessed property and the corresponding property rating.

This project's findings significantly contribute to the end goal of building a smart chatbot that learns how people touch and engage with clothes. The chatbot aims to transform clothes shopping into a multi-sensory, reflective and recognition-based experience for the consumer, which will drive them to optimise their purchases and thereby reduce wasteful purchasing, resulting in a more circular and sustainable fashion industry.

1.1.1 The Importance of Touch when Purchasing Clothes

Multiple studies have discovered that consumers heavily rely on affective touch and tactile experience when purchasing clothes. Morrison defined affective touch as tactile processing with a hedonic or emotional component, i.e. the emotional aspect of touch [1].

Peck et al. discovered that touching an object may increase consumer confidence in product assessment and evaluation [2]. Other studies have also observed that tactile input is preferred over macro-spatial characteristics (shape and size) when assessing an item's physical properties (such as softness, smoothness, flexibility) unless there was no way to pass visual judgment [3, 4]. According to a study led by Holbrook [5], tactile cues were more important than visual cues in consumer perception and assessment of sweaters. Moreover, the principal effect of tactile cues may differ from one item to another [6]. For example, consumers will rely more on tactile inputs when assessing some objects (a coat with various properties such as weight, thickness and texture) than others (a standard AAA battery). Therefore, touch is a crucial criterion when assessing items that differ in their textual properties [7]. Consequently, it is plausible that conscious or unconscious tactile emotions (affective touch) play a leading role in consumer perception of clothing.

With the expansion of fast fashion and the development of the internet, online clothes shopping has become increasingly popular. However, online shopping mainly uses audio and visual channels to communicate product information with consumers and comes with the caveat that consumers cannot physically touch and engage with the clothes they purchase. Multiple studies on internet retail [8, 9] have confirmed that the main drawback of online shopping is the inability of the consumer to touch the products. Therefore, consumers find it challenging to develop a comprehensive evaluation of the product they are purchasing purely through online shopping. Studies have also discovered that some consumers feel frustrated or disappointed if they do not have the opportunity to touch and examine the products in real life; this is particularly true for consumers who have a higher need for touch (NFT) [2, 8].

The Property Ranking Hierarchical Model (PRHM) aims to infer the rating of several properties for each fabric. These ratings will inform the consumers roughly how smooth, thick, warm, flexible and soft the garment will be. Therefore, consumers can make more informed decisions when shopping online. Although the PRHM is not an identical substitute for physically touching a new item of clothing, it will give consumers a better understanding of the garment's textual and physical properties.

1.1.2 Crowdsourcing Tactile Perception

Although online shopping is very popular, consumers cannot physically touch the item of clothing they are purchasing. They can only gauge if the tactile sensation of the garment suits their needs based on the textual and visual (sometimes even video) description of the garment provided online. Therefore, recording and displaying the tactile information of an item of clothing may help the user get a better idea of its tactile experience [10]. Crowdsourcing how individuals touch a product and their tactile perception of the properties may act as a close substitute to someone physically touching the product before buying it.

Crowdsourcing is levered on as a feasible and low-cost method to present tactile experiences online [11]. Online product reviews provide information regarding an item's quality and how it feels to the touch. Such reviews are very common and help indecisive consumers decide whether to purchase the reviewed product [12]. Therefore, crowdsourcing tactile perception of an item of clothing may work as an alternative to physically touching the garment before buying it. Previous studies regarding crowdsourcing in the fashion/textile industry have mainly been in the form of text [11, 13]. An attempt to develop a system which crowdsources tactile experiences of clothes via sensors that track motion data from the user's hand is an exciting and innovative concept that can be explored in the future [10].

1.1.3 Fast Fashion and its Environmental Impact

'Fast fashion' refers to speedily and mass-produced, low-quality clothing that is quickly circulated through high street stores to satisfy the latest trends and maximise consumer demand [14]. Fast fashion garments are cheaply produced and priced and replicate the latest celebrity or catwalk styles [15, 16]. Fast fashion involves the rapid design, production, distribution, and marketing [15]. This allows retailers to obtain a larger quantity of assorted designs, and in turn, consumers are presented with a more extensive choice of inexpensive clothing [15].

As fast fashion relies on cheap and quick production, it promotes overproduction [16]. Fast fashion also encourages overconsumption because consumers are attracted to cheap and trendy clothing that copies current trends compared to relatively expensive, long-lasting items that fall out of style shortly [14, 16]. This toxic system of constantly buying clothing and almost immediately discarding them due to its low quality is the most significant pitfall of fast fashion [14, 16]. As a result, fast fashion massively harms the environment [16].

The environmental impact of fast fashion includes large-scale emission of greenhouse gases, the use of massive amounts of water and energy, and the depletion of non-renewable resources. Fast fashion is also one of the world's largest polluters.

According to the United Nations Environment Programme (UNEP), textile production accounts for up to 10% of total global carbon emissions (1.2 billion tonnes) [15, 17]. This figure is larger than the emissions from all international flights and maritime shipping combined. Further, according to the United Nations (UN) Framework Convention on Climate Change, global carbon emissions are estimated to skyrocket by more than 60% by 2030 [18].

The fashion industry is also the second largest consumer of the world's water supply [15, 19]. Approximately 700 gallons (3182.26 litres) of water is required to produce a single cotton shirt; this is enough water for an individual to drink at least eight cups per day for three-and-a-half years [15, 19]. Roughly 2 000 gallons (9092.18 litres) of water is used to produce a pair of jeans; this is more than enough for one person to drink eight cups per day for ten years. Further, the United Nations Environment Programme (UNEP) discovered that the fashion industry produces 20% of the world's wastewater and that fabric dyeing is the second largest water polluter because the water leftover from the dyeing process is dumped into rivers, streams, and other water bodies [20]. This severely affects marine life and the aquatic ecosystem.

Synthetic materials such as nylon, polyester and acrylic are created from fossil fuels and currently comprise over two-thirds of the materials used in the apparel industry [15, 21, 22]. Such materials take over hundreds of years to biodegrade [15]. A 2017 report from the International Union for the Conservation of Nature (IUCN) estimated that 35% of all microplastics in the ocean came from laundering synthetic textiles like polyester [15, 19, 22]. It is also estimated that microplastics cause up to 31% of plastic pollution in the ocean [19, 22].

There is also massive amounts of monetary and resource wastage resulting from fast fashion. According to Business Insider, 85% of textiles of all textiles go to the landfills each year – this is enough to annually fill the Sydney harbour [19, 23, 24]. Further, the equivalent of one garbage truck full of clothes is dumped in a landfill or burned every second [19, 25].

Consumers are drawn to fast fashion due to its affordability, accessibility and variety. Consumers impulsively buy fast fashion clothing and do not spend time engaging with and reflecting on the garment they are purchasing. The PRHM aims to contribute to the end goal of building a smart chatbot that learns how people touch and engage with clothes. The chatbot aims to create a reflective clothes shopping experience for the consumer by making consumers touch, reflect and critically think about the clothes they are about to purchase. This innovative tactile interaction with clothes may compel consumers to only purchase garments they will wear more than once and genuinely love, thereby slowing down fast fashion and its adverse impacts.

1.2 Objective

Past studies have discovered that consumers rely heavily on affective touch and tactile experience when purchasing clothes. Therefore, developing a method to comprehensively understand what individuals experience when touching a textile, how they feel after touching it, and how it influences their choice may help to reduce the impulsive buying habits of consumers. This study proposes a novel machine learning approach to estimate people's sensations and liking of the textile being touched.

The main objective of this project is to build a novel machine learning model to infer tactile affect in the context of fabric handling. The EMG and IMU data input to the model were collected from both hands (left and right) via wearable sensors. The two main research questions that this study aimed to answer were:

1. Can the model predict what property an individual is assessing based on the muscle and hand movement collected via the wearable sensors?

2. Can the model predict the property rating an individual gives each of the properties assessed for a specific garment, given the property?

The long-term aim of this project is to build a chatbot that helps reduce fast fashion's impact. The chatbot aims to transform clothes shopping into a multi-sensory, reflective and recognition-based experience. Firstly, the chatbot will ask individuals to touch new clothes, engage with the fabric, **reflect** on whether they like the garment and if they will wear it. Secondly, the chatbot will have stored information such as what clothes the individual has in their cupboards, what their favourite and most worn clothes are and what type of clothes they like. Based on this data, the chatbot will look at the cloth the individual is looking at and **recognise** if the individual likes it and will wear it.

1.3 Project Outline

This paper is organised as follows.

My comment - Include paragraph on paper organisation

Chapter 2

Background and Related Work

Describe here work that is connected to your thesis. This should include references to published work. There is no fixed rule, but I would expect a student to have read around 50 published research papers and reference them in a thesis.
Touch is the most advanced sensory function at birth and plays a vital role in emotional, social, cognitive, and cerebral development throughout infancy, and childhood [26, 27, 28, 29, 30]. Touch continues to play an essential role through adolescence and adulthood as it is used to express various emotions and manoeuvre various situations [29, 30, 31].

Touch is ranked as the second most important sensory modality in product evaluation, and the essential sensory modality involved in evaluating fashion goods [32]. Therefore, tactile input plays a crucial role in a consumer's clothes shopping experience.

2.1 Recognising Affect through Interpersonal Touch

Temi's comment - You have focused here on the context of human-human touch. You need to at least also include a few more relevant studies such as on human-object/computer touch. You should also at least mention the distinction between human-human/robot touch and human-object/computer touch. Does it matter when it comes to the ML or not (e.g. in the former where the intent may usually be communication or affect vs in the latter where the purpose of touch may be different such as simply functional)? And I think that rather than focusing on social sciences or HCI studies (alone), you need to cover ML studies especially those with settings and/or sensors most relevant to your work?

Temi's comment - People don't necessarily "change" muscle activity to signal emotion. Your framing assumes the context of emotion communication. I think you should instead reframe as emotion experience since that is more appropriate for the touch setting in your data. The participants are not touching the fabric in a way as to communicate an emotion. Rather, they are touching the fabric and this activity has associated with it an experience which may relate with how they touch the fabric (the way they touch the fabric can be captured using sensors such as muscle activity or movement sensors).

As humans, we use touch in our daily life for various reasons. We rely on touch to perform actions such as flirting (gently stroking face, hair, or arm), attracting attention (waving hands), offering congratulations (handshake or a pat on the back), and when thanking others (hugging and gently squeezing). We also express emotions such as love (embracing, hugging, and stroking), sympathy (embracing, stroking back), fear (squeezing hand) and anger (gently slapping) through touch.

Although touch plays an essential role in human life, it has received less attention in affective science than facial and vocal displays of emotion [30]. Initially, studies regarding touch as an affective modality claimed that it was mainly used to communicate the hedonic tone of emotions (positive and negative) [29, 33, 34, 35, 36] and increase the intensity of emotion-related communication [29, 36]. However, two consecutive studies by Hertenstein in 2006 and 2009 have argued that touch plays a much larger role in emotional communication.

The first study discovered that participants could identify several distinct emotions when they were touched on their forearm by their partner (a stranger), even though they could not communicate visually or verbally [29, 37]. This study observed that the tactile modality could distinguish between the emotions of love, gratitude, sympathy, fear, disgust and anger with accuracy rates between 48% and 83% [29]. The second study confirmed these results and observed that happiness and sadness could also be recognised with accuracy rates higher than chance [30, 37]. Therefore, the recognition performance attained with touch alone was comparable to those observed in studies of facial displays, and vocal communication [29, 37, 38, 39].

The second study investigated 23 types of tactile behaviour (ex: squeezing, stroking, pushing) and revealed systematic differences in how touch was used to communicate different emotions [30, 37]. For example, love was associated with stroking; gratitude was associated with shaking of the hand; sympathy was associated with stroking and patting; disgust was associated with a pushing motion; fear was associated with trembling, and anger was associated with hitting and squeezing [30]. However, as some types of tactile behaviour were used to communicate multiple emotions (for example, stroking was used to express both love and sympathy), the study concluded that tactile behaviour alone is insufficient to differentiate between different affective emotions [30, 37].

The second study by Hertenstein also discovered that emotions could be categorised according to differences in intensity and duration [30]. For example, love and sympathy were characterised by a moderate-intensity touch for a longer duration, whereas anger was characterised by a vigorous intensity of touch for a moderate duration [30].

2.2 Emotion Recognition based on Human-Computer Touch

Several studies have investigated the possibility of recognising affect based on how humans touch mobile devices. Gao et al. conducted a study to decode affective touch in the context of video games [37]. This study aimed to capture the emotional state of players in a real-world touch screen gameplay setting by using finger-stroking motions detected by an iPad [37]. Samurai Fruit is a modified version of Fruit Ninja (an iPhone game), and this game was used to evoke different emotions within participants and detect and store features related to their finger strokes, such as coordinates corresponding to the stroke and the duration of a stroke). Participants were asked to play twenty levels of the modified game and fill out a questionnaire regarding their emotional state (bored, frustrated, excited and relaxed) at the end of each level. The results revealed that the length and pressure of the strokes were important factors when classifying the hedonic tone of emotions (positive and negative). The speed and the direction of the stroke provided information regarding the player's level of arousal. This study discovered that tactile behaviour contains a wealth of information regarding users' affective states in touch screen gameplay. Another study conducted by Shah et al. used finger strokes to predict an individual's affective states in a more general touch screen usage setting [40]. Seven features related to finger strokes were used to build a regression model, and this model predicted the user's positive, negative and neutral affective states with an accuracy of 90.5%.

Multiple industries aim to leverage automatic emotion recognition technology for various reasons. The entertainment industry uses technology that automatically retrieves media (such as images and music) based on what an individual feels or wants to feel [41, 42, 43, 44]. The communication industry is attempting to use technology that automatically integrates text messages with the sender's emotions. The technology introduced in [45] allows the sender to add emotions to a text message by shaking their mobile phone differently. The new smartphone SAMSUNG [46] is creating a smartphone that can detect an individual's emotions based on how they tweet (number of spelling and grammatical errors, speed of typing, use of special symbols and emoticons). Further, [47] investigated how affective technology could help students better their emotional state to facilitate cognitive processing and stimulate motivation whilst e-learning [37].

2.3 Using Sensors to Recognise Affective Touch

2.3.1 Electromyography (EMG)

Electromyography (EMG) measures the muscle response or electric potential generated by the muscle [48, 49]. EMG is preferred over other sensor modalities used to capture hand gesture information because EMGs capture and evaluate the muscles' electrical activity; the physical phenomenon that results in hand gestures [50]. EMG data is recorded via both invasive and non-invasive methods [50]. Surface electromyography (sEMG) is a non-invasive technique that measures a muscle's action potential from the skin's surface [50]. This technique is preferred over other invasive methods that penetrate the skin to reach the muscle [50]. The acquisition of sEMG signals involves one or more sensors attached around the target muscle group [50].
Paragraph about the uses of EMG in gesture recognition

2.3.2 Accelerometer

A 3D accelerometer is used to measure kinematic information such as acceleration and velocity in a three-dimensional space [49].

Humayoun et al. conducted a study to define a set of gestures based on accelerometer data as accelerometers are embedded in most modern mobile devices [51]. Nine commonly used gestures related to mobile devices (tap, double-tap, left flick, right flick, press, drag, rotate, zoom-in, zoom-out) were transformed into appropriate accelerometer-based gestures [51]. Most participants found it easy to perform tasks using these 3D accelerometer-based gestures, thereby indicating the immense potential of accelerometers in facilitating gesture-controlled interaction [49, 51]. Further, as the accelerometer-based gestures are calculated according to the change in angle along the x, y and z axes, it can capture aspects of textile handling that EMG cannot [49].

2.3.3 Quaternions

An Inertial Measurement Unit (IMU) is an electronic device that can measure and report an object's distinct force, angular rate, and sometimes its orientation [52]. An IMU typically consists of accelerometers and gyroscopes and sometimes contains magnetometers [53, 52]. The two commonly used methods of representing IMU data are Euler angles and Quaternions. Both Euler Angles and Quaternions are used to represent a rotation in 3D space. Although quaternions are much less intuitive than Euler Angles, rotations defined by quaternions can be computed more efficiently and with more stability [54]. Quaternium representations are also less sensitive to gimbal lock problems than Euler Angles. Gimbal lock occurs when the axes of two gimbals in a three-gimbal device are driven into a parallel configuration, thereby losing a single degree of freedom and "locking" the system into rotation in two-dimensional space [55, 56]). Due to all these reasons, quaternions are more widely used to represent a 3D rotation.

Quaternions contain both real and imaginary components and can be written as $q = w + xi + yj + zk$ where $w, x, y, z \in \mathbb{R}$ and i,j and k represent the 3D imaginary component axes [54].
Paragraph about the uses of quaternions in gesture recognition

2.4 Recognising Affective Touch using Sensors in the context of Fabric Handling

Multiple studies have recently explored how muscle activity and hand movement data can be collected via wearable sensors to assess properties and property ratings of textiles in the context of fabric handling [49, 57, 10].

Wang explores the feasibility of incorporating EMG and accelerometer data to assess the tactile experience of fabrics [49]. In the first part of the study, participants were asked to freely explore four fabrics using their hands and then rate each fabric's softness, warmth, thickness, and smoothness [49]. The results from the discriminant analysis revealed that the EMG and accelerometer features could distinguish between the warmth, thickness and smoothness properties with a percentage accuracy of 55.1%. In the second part of the study, participants were asked to assess the enjoyment gained by caressing, scratching, squeezing, and rubbing the provided garment using varying speeds and strength. This part aimed to identify if changes in speed and strength would influence the enjoyment a participant feels during fabric handling. The discriminant analysis results revealed that classification accuracy was 75.4% when EMG, acceleration and speed features were used to discriminate between the four gestures used in textile handling. Therefore, the results from this study imply that sensor technology can be used to identify what individuals feel when touching textiles.

Gao explored the possibility of using motion sensors to investigate the automatic recognition of properties assessed in tactile interaction with textiles [57]. Participants were instructed to evaluate the textiles' smoothness, softness, warmth, thickness, and durability in both a lab and physical shopping environment. A wearable sensor was used to record kinematic data (EMG and IMU data) corresponding to the hand movements and gestures used when participants explored the textiles. The discriminant analysis results revealed that the classification model could accurately distinguish between the five properties with an average accuracy of 36.5% in a lab setting. The classification accuracies for all five properties were above the chance classification accuracy (20%). However, the classification model failed to distinguish between the properties using the data collected in the field environment. Further, the performance of the classification model increased when the field data was added to the experimental data, thus suggesting the importance of a large dataset for the model's accuracy. Although this project was only partially successful, it demonstrated the possibility of automatic recognition of textile properties and the feasibility of using sensors to record hand movement and gesture data. The results of Gao also confirm that individuals tend to use particular gestures when evaluating specific features of textiles, which is in line with the findings of Wang [49, 57].

Paragraph on Lili's experiment

This project builds on the findings of Lin [10].

2.5 Human Activity Recognition Using Machine Learning

2. How is this this knowledge used to inform ML techniques (automatic recognition, feature base etc) The machine learning community commonly uses the psychology behind affective touch and change in muscle activity to perform affective touch to inform the design of features used in machine learning models.

Refer [50]

Chapter 3

Extension of An Existing Textile Touch Dataset

The existing dataset contains EMG and IMU data collected via wearable sensors when exploring different properties and property ratings for various textiles. The dataset was collected in 2021 by Lin [10] as part of her MSc Final project. The author and two other researchers collected data to extend this existing dataset. The researchers had different motivations for collecting data, including developing a visualisation system for consumers. The author wanted to extend the existing dataset for two main reasons. Firstly, the author wanted to expand the current dataset so that the machine learning models would have more input data. Secondly, the author wanted to observe if a model built using the existing data could be generalised to a new type of garment that the model had never seen before.

The organisation of this chapter is as follows. Sections 3.1 and 3.2 provide an overview of the existing and new datasets. Section 3.3 explains the materials used in data collection, and Section 3.4 explains the experimental procedure followed when collecting the two datasets highlighting differences where necessary.

For this project, an 'instance' is defined as when a participant explores a single property of a cloth. For example, if participant two explores the 'softness' of the tenth item of clothing, this is an instance.

The study conducted to collect the existing dataset was approved by the UCL Research

Ethics Committee (Project ID Numbers: 5095/00167) to continue the research within the UKRI Textile Circularity Centre (TCC) [10]. The study to collect the new dataset was approved by the UCL Research Ethics Committee (Project ID Number: 4831).

3.1 Existing Dataset

Nine participants (eight females and one male) were recruited for the study that collected the existing dataset. [10]. Eight were students of the Human Computer Interaction department at University College London (UCL), while one was from another university [10]. These participants were all Chinese and righthanded [10]. Participants received an amazon voucher as a reward for their time [10].

Each participant was asked to select six different clothes from their wardrobe to explore their textile properties. The only limiting criterion was that they had to choose different types of clothes with different textile properties and tactile experiences [10]. For example, they could not choose six t-shirts as the t-shirts may have a similar tactile experience.

All nine participants in the study that collected the existing dataset recorded the data in their houses. Participants received two wearable sensors, a phone, chargers for the phone and armband and disinfecting wipes to carry out the experiment [10].

The existing dataset consisted of 324 (9 participants * 6 clothes * 6 properties) instances during round one of data collection. However, the data for a single participant had to be discarded because they collected it incorrectly.

3.2 New Dataset

Six (three females and three males) participants participated in the study that collected the new dataset. Five participants were PhD students at University College London, and one was a visiting researcher at University College London Interaction Centre (UCLIC). Five out of the six participants were right-handed, whereas the other was left-handed. Participants received an amazon voucher worth £15 as a token of appreciation for their participation.

All participants in this study touched the same six socks shown in Figure 1. No participant in the existing dataset opted to touch socks. Therefore, socks were selected to test the machine learning model's ability to generalise to new clothes.

Figure 1: Socks used in the subsequent study

The experiment carried out to collect the new dataset was conducted by the author and the two other researchers at UCLIC. The new dataset consisted of 216 (6 participants * 6 clothes * 6 properties) instances.

3.3 Material and Sensors

The same equipment and software were used to create the existing and new datasets.

1. **Armband with sensors**: Two OYMotion gForcePro+ EMG Armbands (refer Figure 2) were used to collect raw EMG and motion data from the participants' left and right hands (the armbands were labelled to differentiate between the left and the right). These armbands are examples of smart wearable human interface devices used for gesture recognition [58]. Each armband contains eight EMG sensors with differential dry electrodes, nine-axis IMU motion sensors and communicates using Bluetooth

BLE 4.2.[59, 10]. The armbands recognise gestures according to the sEMG signals of human forearms and calculate orientation data in quaternions or Euler Angles using its built-in nine-axis IMU sensors [58]. For this study, the armbands are used to collect raw EMG and IMU data.

Figure 2: OYMotion gForcePro+ EMG Armband [58, 59]

2. **Phone**: A Motorolla moto g^9 power phone (refer Figure 3) with both the GForce-TextileHand App [10] developed by Lin [10] and the gForceApp [59] developed by OYMotion installed were used to collect the data. This phone uses Android 10 with a Qualcomm® Snapdragon™ 662 processor and Bluetooth® 5.0 as its operating system [60, 10].

3. **Software**: The GforceTextileHand app was mainly used for data collection, whilst the gForceApp was also used. The user interface for the GforceTextileHand is given in Figure 4 [10]. The software used in this app employed SQLite to store experimental, EMG, Euler Angle and IMU (accelerometer, gyroscope, magnetometer, and quaternion) data [10]. SQLite is a C-language library that implements a fast and high-performance SQL database engine [10, 61]. This project only uses the EMG, accelerometer and quaternion data.

Figure 3: Motorolla moto g^9 power phone [60]

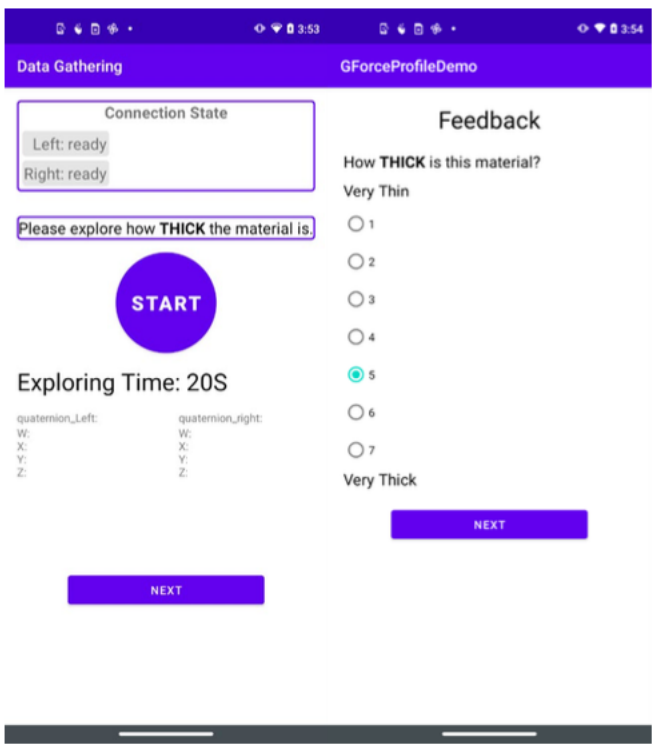

Figure 4: Sample User Interface of theGforceTextileHand App [10]

3.4 Experimental Procedure

Identical experimental procedures were followed when collecting the existing and new datasets. As mentioned before, the only difference was the experiment's location. For both experiments, the participants were sent an information sheet (included in the Appendix) by email and were asked to sign the consent form (included in the Appendix) via REDCap before the experiment started.

The data collection process consisted of two components. Firstly, we recorded the baseline readings. Then, participants were asked to assess six properties (five physical properties and enjoyment) for six items of clothing. The five physical properties evaluated were smoothness, thickness, warmth, flexibility and softness. Lin [10] selected these properties when creating the existing dataset based on the study done by Gao [10, 57]. However, Lin replaced durability with flexibility as Gao discovered that durability was challenging to identify using only touch [10, 57]. After evaluating a property, participants were asked to rate the property on a scale from 1 to 7. Ratings for each property were obtained using Likert scale questions with seven choices (for example, for the flexibility property, 1 was not at all flexible, and 7 was very flexible).

The procedure followed to collect the EMG and IMU data is as follows.

1. Before assessing the six properties for all clothes, participants received 10 seconds to touch the cloth freely, engage with it, and determine how they wanted to touch it to best assess the properties.

2. The participants touched their first item of clothing for a pre-determined time period and assessed a particular physical property. In the existing dataset, the pre-determined period was 20 seconds, as determined by previous studies [57, 49]. When extending the existing dataset, the time was shortened to 15 seconds for fear that the participants would get bored and not fully cooperate.

3. Then, the participants rated the property from 1 to 7 on a Likert scale.

4. Participants repeated steps 2 and 3 for the four remaining physical properties (for the first selected item of clothing).

5. Afterwards, the participants touched the cloth for a pre-determined period and explored how enjoyable it was to touch the cloth using their preferred gestures.

6. The enjoyment gained from touching the cloth was then rated on a Likert scale from 1 to 7.

7. The participants were then asked to reflect on their feelings when touching the cloth and comment on it. This included anything they enjoyed or disliked and whether the item of clothing had any characteristic features.

8. Participants repeated steps 1-7 for the remaining five clothing items.

The EMG, accelerometer and quaternion data were obtained using the armbands as mentioned previously. The armbands were worn as indicated in Figures 5 and 6. As shown, armbands on the left and right should be worn differently (the armband on the left should have the USB port facing the elbow, and the one on the right should have its USB port facing the wrist). This is so that when recording the data, the EMG channels are the same, but the IMU data signs are swapped.

There were two main reasons for obtaining the baseline readings [10]. The first reason was to check if the participants were wearing the armbands correctly. The position of the armbands (how high or low they sit on the forearm) varied depending on variables such as participants' gender and forearm circumference. This difference could also affect the data collected because if the participant had a smaller forearm circumference, the sensors on the armband might not have continuously had contact with the participant's skin. Therefore, the baseline readings were also used to normalise the collected data to account for personal idiosyncrasies in touching behaviour and strength differences between participants.

Participants had to perform two tasks when recording the baseline readings. Firstly, the participants had to lay both arms, relaxed on the table, palms facing upwards (as shown in Figure 5). This was to record the minimal contraction of a participant's muscles. Secondly, the participants had to clench their hands into a fist as tightly as possible (refer Figure 6) to record the maximum contraction of muscles.

After freely touching the cloth, participants would touch the cloth for a pre-determined time period to assess each property. When collecting the existing dataset, the order of assessing properties was fixed for each garment, and each participant [10]. This was because the participant conducted the experiment, and Lin wanted to keep the experimental procedure simple and uncomplicated [10]. However, the order of properties assessed for

Figure 5: Baseline 1 - Relaxed

Figure 6: Baseline 2 - Fist

each cloth and the order of clothes for a participant were randomised when extending the existing dataset. This order can be observed in Appendix A.3.

After touching the item of clothing for the pre-determined time to explore a property, participants were asked to rate the property on a Likert scale with values ranging from 1 to 7. For example, when assessing the property flexibility, 1 would signify that the cloth is not at all flexible (very stiff), and 7 represented a very flexible cloth.

It is important to note that the participants were not explicitly informed how to touch the cloth as we aimed to capture natural movements used in everyday life rather than prescribed gestures.

Chapter 4

Automatic Detection of Textile Touch Behaviour and Experience: Methods

4.1 Property-Rating Hierarchical Model (PRHM)

The Property-Rating Hierarchical Model (PRHM) was built to predict the property assessed and the corresponding rating. The PRHM is a two-part model that first predicts the assessed property based on the input EMG, accelerometer and quaternion data and then predicts the corresponding property rating. The first part of the PRHM is the PRHM property classification section, whereas the second part of the PRHM is the PRHM property classification section.

Different machine learning techniques were used to create three PRHMs to predict the assessed property and corresponding rating. Two variations of each PRHM were created. In the first variation, the property variable was not an input for the model that predicted rating. In the second variation, the property variable was one hot encoded and entered as input for the rating model. This variation of the PRHM assumed that all the properties were perfectly predicted when predicting the corresponding ratings. As expected, the second variation provided better predictions. Therefore, the second variation will be discussed in this report.

4.1.1 PRHM based on Random Forest

Bootstrapping is a sampling technique which randomly samples data with replacement from the main data set. Bagging (or bootstrap aggregating) is an ensemble algorithm that fits multiple models on different subsets of a training dataset and then combines the predictions from all models. In bagging, m decision trees are trained on m independent bootstrapped samples/training datasets (m is a hyperparameter that can be tuned). The final predicted value is the average of the decision trees.

A single decision tree has a high variance and tends to overfit. Bagging overcomes this problem by combining many weak learners to create a strong learner. Random forest is an extension of bagging and was used to create the first PRHM.

A nested Leave One Participant Out Cross Validation process was used in this PRHM model. The inner loop was used for hyperparameter tuning (finding the optimal number of trees in the forest), and the outer loop was used to test the model performance.

4.1.2 PRHM based on LSTM

4.1.3 Fully-connected PRHM

A fully connected neural network consists of a series of fully connected layers that connect every neuron in one layer to every neuron in the other layer. The major advantage of fully connected networks is that they are "structure agnostic", i.e. there are no special assumptions needed to be made about the input. n* is the batch size, features for properties = 180 and 185 for rating. Labels for properties=5 and labels for rating=3

4.2 Feature extraction

Use of low-level statistical features (remember to give a rationale for doing this and highlighting other methods that could have been used, possibly in the lit rev chapter, as you want the examiner to know that you understand available options) You can cover Data preparation here Data pre-processing Features

The existing datasets for EMG, accelerometer and quaternion consisted of 324 (9 participants * 6 clothes * 6 properties) instances, and the newly collected datasets consisted of

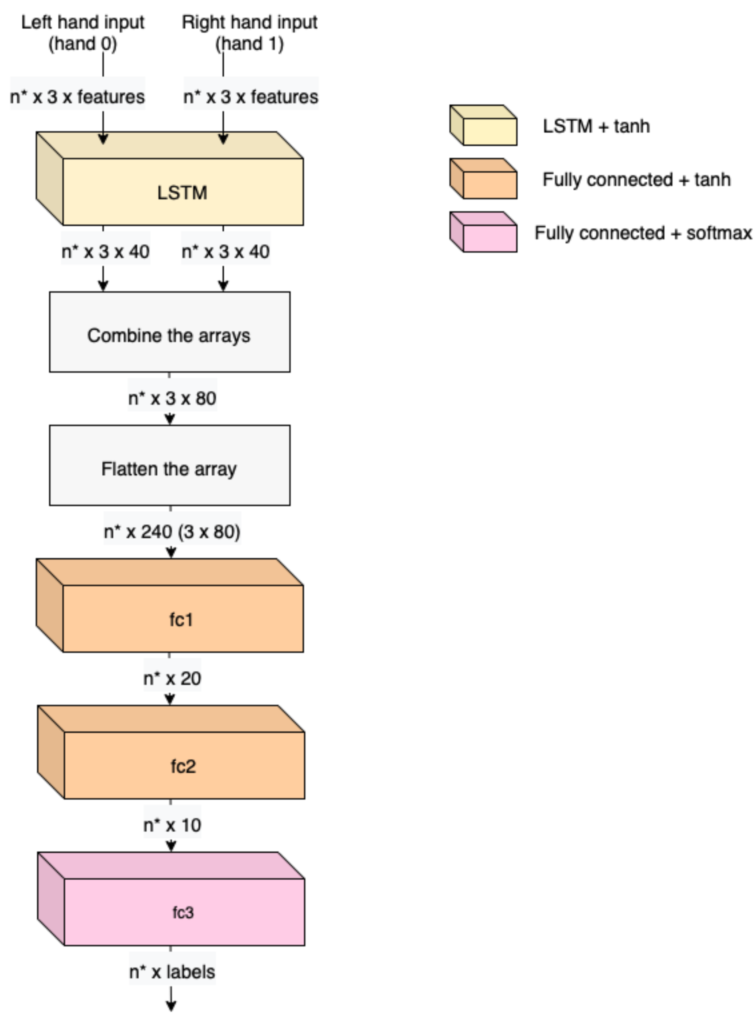

Figure 7: Architecture of the PRHM based on LSTM

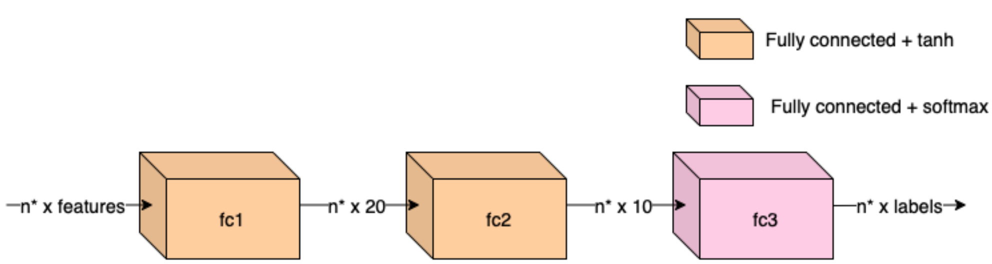

Figure 8: Architecture of the Fully-connected PRHM

216 (6 participants * 6 clothes * 6 properties) instances. The data for a single participant in the existing data set had to be discarded because they collected it incorrectly.

4.2.1 Sensor Data Preparation

As explained previously, this project uses the EMG and IMU (accelerometer and quaternion) data collected. The collected data needed to be pre-processed before it could be used in the machine learning models. The same pre-processing procedure was followed for both the existing and newly collected data to preserve uniformity.

Firstly, the baseline readings and free exploration data were removed from all three (EMG, accelerometer and quaternion) subsets of features. Then, the data regarding rating was attached to each of the three subsets of features.

As previously mentioned, an instance lasted twenty seconds when collecting data for the existing dataset and fifteen seconds when collecting the new dataset. Lin removed the first five seconds of data from each instance in the current dataset to account for human errors and slow reaction time [10].

EMG Data Preparation

The EMG data was collected via the eight channels of the armband. The preparation of EMG data consisted of rectification and normalisation. Raw EMG data consists of both positive and negative components. Rectification translates these components to a signal with a single polarity (usually positive) [62, 63]. This procedure is done so that the EMG signals do not average zero. The two commonly used rectification methods are half-wave rectification, and full-wave rectification [62]. Full-wave rectification was used in this project because it does not get rid of any data, whereas half-wave rectification removes some signals [62, 64]. Full wave rectification translates data below the baseline to data above the baseline so that all data is positive [62]. If the baseline is zero, this is equivalent to taking the absolute value of the signal [65]. The data for the existing and the newly collected datasets were centred around 120. Therefore, the EMG data was centred on zero before obtaining its absolute value. Normalisation was the second step of the EMG pre-processing process, and this refers to the conversion of the EMG signal to a relative scale by a reference value [66]. As EMG signals are inherently prone to variability, these signals require normalisation for physiologic interpretation and comparison between different participants [67]. The data was normalised by separating the data into left and right hands and then dividing the data in each channel by the maximum observed signal (in the channel).

Accelerometer Data Preparation

The accelerometer dataset included data regarding the linear acceleration along the x, y and z axes. The linear velocity and jerkiness along the x, y and z directions were computed from the provided data as follows.

$$a_t = \frac{v_t - v_{t-1}}{t_t - t_{t-1}} \iff v_t = v_{t-1} + a_t(t_t - t_{t-1}) \text{ (Note: } v_0 = 0, t_0 = 0) \tag{1}$$

$$j_t = \frac{a_t - a_{t-1}}{t_t - t_{t-1}} \tag{2}$$

Where $t \in \{0, ..., T\}$ (T=15 seconds), a_t is the linear acceleration at timestamp t, v_t is the linear velocity at timestamp t and j_t is the linear jerk at timestamp t.

Quaternion Data Preparation

The quaternion dataset contained data regarding the real and 3D imaginary components (w, x, y and z) of the raw quaternion. The angular velocity for the real and 3D imaginary components of the quaternions were computed using the quaternion library [68]. Then the angular acceleration and jerk for the quaternion's real and 3D imaginary components were computed using equations 1 and 2.

4.2.2 Extracting Low Level Features

Each instance was split into subwindows, and each subwindow was further divided into slices to extract meaningful low-level features from the data. Each instance was split into subwindows to create a larger number of sub-instances with a smaller time duration. These sub-instances were further divided into slices to differentiate the timesteps within a subwindow. This process of creating subwindows and slices was repeated using three different numbers of subwindows and slices. The three variations are as follows.

1. **3 window segmentation (Variation 1)**: Each instance was divided into three subwindows (subwindow duration = five seconds). The subwindows were not further

divided into slices. This was what Lin did in her project and was therefore included [10].

2. **15 window segmentation with 3 timesteps (Variation 2)**: Each instance was divided into fifteen subwindows (subwindow duration = one second), and each subwindow was divided into three slices (slice duration = a third of a second)

3. **15 window segmentation with 10 timesteps (Variation 3)**: Each instance was divided into fifteen subwindows (subwindow duration = one second), and each subwindow was divided into three slices (slice duration = 0.1 seconds)

The maximum, mean and standard deviation were calculated for each slice (of each sub-instance) for all the independent subsets of variables in the EMG, accelerometer and quaternion datasets. This process was done for both the left and right hands.

- **Maximum** $= max\ \{x_1, x_2, ..., x_n\}$

- **Mean** $= \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ where x_i is an observation in a slice and n is the total number of observations in the slice.

- **Standard Deviation** $= \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})$ where x_i is an observation in a slice, $\bar{x}$ is the mean of the observations in the slice and n is the total number of observations in the slice.

The EMG dataset contained eight independent variables corresponding to the data collected from the eight sensors of the armband. The accelerometer dataset contained nine independent variables (linear velocity, acceleration and jerk in the x, y and z directions - 3*3 variables). The quaternion dataset contained thirteen independent variables (the real and 3D imaginary components of the raw quaternion data (4 variables) and the angular velocity, angular acceleration, and angular jerk of the 3D imaginary components of the quaternions (3*3 variables)). Therefore, the EMG, accelerometer and quaternions contained 30 $(8 + 9 + 13)$ independent variables in total.

4.3 Primary Dataset

The first dataset was created by merging the EMG, accelerometer and quaternion data that Lin collected [10]. This data was pre-processed using the methodology explained in sections 4.2.1 and 4.2.2. The second dataset was created by merging the pre-processed newly collected EMG, accelerometer and quaternion data. Both the first and the second dataset consisted of 180 independent features (the maximum, mean and standard deviation were calculated for each of the 30 independent variables for both the left and right hands - 30*3*2)

The primary dataset for this project was then created by combining both these datasets. Three variations of the primary dataset were created based on how the subwindows and slices were created.

1. **Dataset 1 - 3 window segmentation**
2. **Dataset 2 - 15 window segmentation with 3 timesteps**
3. **Dataset 3 - 15 window segmentation with 10 timesteps**

These variations are summarised in Table 1.

	Subwindows per instance	**Subwindow duration (seconds)**	**Slices for each subwindow**	**Slice duration (seconds)**	**Frames per slice - EMG**	**Frames per slice - Accelerometer and Quaternion**
Dataset 1	3	5	-	-	-	-
Dataset 2	15	1	3	0.33	10	16
Dataset 3	15	1	10	0.1	30	48

Table 1: Variations of the primary dataset

4.4 Predicted Labels

4.4.1 Textile Properties

Participants had to assess six properties (five physical properties and enjoyment) for each clothing item. However, only the five physical properties were considered for this project. This was because of the time constraints involved and because enjoyment was very subjective. The five physical properties were represented by positive integers in the primary datasets.

- Smoothness (represented as 1)
- Thickness (represented as 2)
- Warmth (represented as 3)

- Flexibility (represented as 4)
- Softness (represented as 5)

4.4.2 Textile Property Ratings

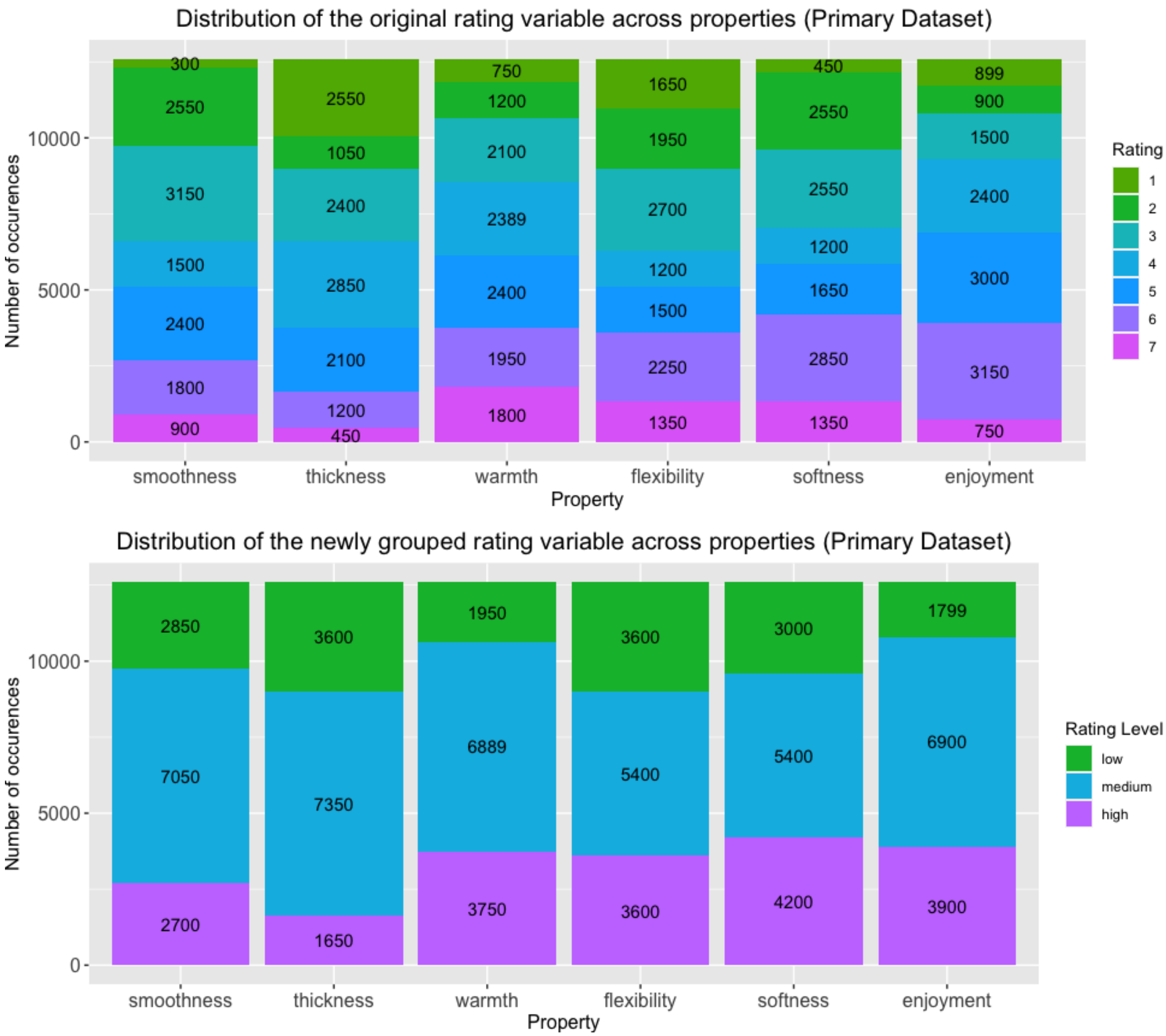

Figure 9: Distribution of the rating variable across properties for Dataset 3

The distribution of ratings by property for Dataset 3 (third variation of the primary dataset - 15 window segmentation with 10 timesteps) is shown in Figure 9 (top). This distribution is imbalanced, and the modal (most occurring) rating varies across the properties. Based on this distribution, the rating levels were grouped as follows: 1-2 into 'low', 3-5 into 'medium' and 6-7 into 'high'. Positive integers were used in the primary datasets to represent the newly grouped rating variable.

- Low (represented as 1)
- Medium (represented as 2)
- High (represented as 3)

The rating variable was grouped the same for all properties to maintain uniformity. As observed in Figure 9 (bottom), this grouping works very well for some properties, such as flexibility and softness but not so well for others. The rating variable was grouped for two main reasons [10]. Firstly, the rating was very subjective and could greatly vary across participants. Secondly, the dataset was relatively small and thus would present problems if all seven levels were used in granular modelling.

The distribution of the rating variable across properties for the existing and the newly collected datasets are provided in Appendix 3.

4.5 Evaluation methods

4.5.1 Cross-validation methods used

Usually, a machine learning model is trained (built) using the training dataset, and the model's performance is assessed using the test dataset [69]. A ratio of 80:20 is commonly used as a training-testing split (80% of the data is used as training data, and the remaining 20% is used as test data) [69]. However, splitting the dataset further into training and testing is not practical if the dataset is small. K-fold cross-validation is used to overcome this issue.

K-fold cross-validation is used to assess the performance of a machine learning model when predicting unseen data (data not used in the training of the model) [70]. K-fold cross-validation has a single hyperparameter (K), which determines the number of subsets a dataset is split into [70]. Once the dataset is split, each subset is used as the test set, whilst all the other subsets are combined and used as the training dataset [70].

Leave One Participant Out Cross Validation (LOPOCV) was used in this project. LOPOCV is a configuration of K-fold cross-validation where K is set to be the number of participants [70]. As an example, assume that a dataset has three participants. If LOPOCV is used to validate the model, three folds (iterations) would be completed [69]. In each iteration, the model would be trained using two people, and its performance would be assessed using the other participant [69]. This process is shown in Figure 10.

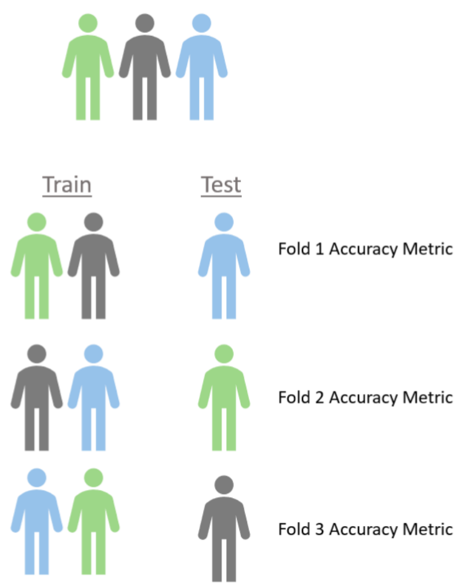

Figure 10: Leave One Participant Out Cross Validation [69]

4.5.2 Hyperparameters explored

A grid search was conducted to find the optimum number of trees (n_estimators in sklearn) for the PRHM based on Random Forest. The options for the number of trees were 100, 500, 1000 or 1500. Building random forests with a larger number of trees will create a more robust aggregate model with a lower variance. However, building a model with a large number of trees will take a long time to train.

The learning rate and the number of epochs were hyperparameters for the three neural network models. A grid search was conducted over the values 0.0001, 0.001, 0.005, and 0.01 to determine the optimal learning rate. The number of epochs was selected by analysing the graph containing training loss and validation loss against the number of epochs. The first 150 epochs were observed, and the optimal number of epochs was manually selected to avoid overfitting.

4.5.3 Loss functions and evaluation metrics used

Loss functions used

The cross-entropy loss was used as the loss function in all the models. Cross entropy is the default loss function used in multi-class classification problems [71]. Cross-entropy calculates a score that summarises the average difference between the actual and predicted probability distributions for all classes [71]. The formula used to calculate the multi-class cross-entropy loss is given in Equation 3.

$$L(\hat{y}, y) = \sum_{k}^{K} y^{(k)} \log \hat{y}^{(k)} \tag{3}$$

Where

- K is the total number of classes
- log denotes the natural logarithm
- $y^{(k)} \in \{0, 1\}$. $y^{(k)} = 1$ if the observation is predicted the correct class and $y^{(k)} = 0$ if the observation is predicted the wrong class
- $\hat{y}^{(k)}$ is the probability that the observation belongs to class k

Evaluation metrics used

The confusion matrix, F1 score and accuracy were the three main evaluation metrics used to assess the performance of the machine learning models. All these metrics were computed using sklearn [72].

1. **Confusion matrix**: A confusion matrix is a cross table that summarises the prediction results of a classification problem [73, 74]. The number of correct and incorrect predictions are summarised with count values and are broken down according to each class as shown in figure 12 [73]. Let $C_{i,j}$ be the value of the cell corresponding to

the i$^{\text{th}}$ row and j$^{\text{th}}$ column of a confusion matrix. $C_{i,j}$ is the number of observations expected to be in group i and predicted to be in group j [72]. In Figure 12, $C_{a,c} = 1$. If a model perfectly classifies the outcome variable, the confusion matrix will be a diagonal matrix (i.e. $C_{i,j} = 0$ if $i \neq j$).

		PREDICTED classification				
	Classes	a	b	c	d	Total
ACTUAL classification	a	6	0	1	2	9
	b	3	9	1	1	14
	c	1	0	10	2	13
	d	1	2	1	12	16
	Total	11	11	13	17	**52**

Figure 11: An example confusion matrix [74]

The F1 score and accuracy are calculated from the confusion matrix. True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN) are metrics that are calculated for each class based on the confusion matrix. Let $\mathrm{TP_i}$, $\mathrm{TN_i}$, $\mathrm{FP_i}$ and $\mathrm{FN_i}$ be the TP, TN, FP and FN for class i ($i \in a, b, c, d$) in Figure 12.

- $\mathrm{TP_i} = C_{i,i}$
- $\mathrm{TN_i} = \sum C_{j,k}$ where $i \neq j, k$ ($j, k \in a, b, c, d$)
- $\mathrm{FP_i} = \sum C_{j,i}$ where $i \neq j$ ($j \in a, b, c, d$)
- $\mathrm{FN_i} = \sum C_{i,j}$ where $i \neq j$ ($j \in a, b, c, d$)

2. **F1 score**: The F1 score is the harmonic mean of precision and recall and is calculated using Formula 4. The F1 score reaches its best value at 1, and worst score at 0 [74]. Precision measures the proportion of correct positive predictions. In contrast, recall measures the ratio of the number of correct positive predictions to the number of all the positive predictions that could have been made [75, 76]. Formulas 5 and 6 represent the precision and recall for a generic class, i.

$$\text{F1 score} = \frac{2}{\text{Precision}^{-1} + \text{Recall}^{-1}} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\mathrm{Precision_i} = \frac{\mathrm{TP_i}}{\mathrm{TP_i} + \mathrm{FP_i}} \tag{5}$$

$$\mathrm{Recall_i} = \frac{\mathrm{TP_i}}{\mathrm{TP_i} + \mathrm{FN_i}} \tag{6}$$

Several types of F1 scores are used in multi-class classification problems based on how the data is averaged. This project uses the micro F1 score, macro F1 score and weighted F1 score. The micro F1 score calculates the metric globally by counting the total number of TP, FN and FP [72]. The macro F1 score calculates the F1 score for each class and finds their unweighted mean [72]. This metric is commonly used when there is a similar number of observations for each class and was used to assess how well the PRHM model predicted properties. The weighted F1 score calculates the F1 score for each class and finds their average weighted by support (the number of true instances for each class) [72]. This metric changes the macro F1 score to account for label imbalance and was used to evaluate how well the PRHM model predicted rating.

3. **Accuracy**: Accuracy is a popular metric used in multi-class classification problems and measures the number of predictions the model correctly predicted [72].

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{7}$$

Chapter 5

Automatic Detection of Textile Touch Behaviour and Experience: Results and Discussion

5.1 PRHM Property Classification Results

Describe your method in detail and with great clarity, distinguishing it from other works (if it is indeed a novel idea). It is very important to clearly motivate your method. Describe the results of your method here in this chapter.

Overall, the PRHM Property model gave better results when all 180 features were used instead of only the 48 EMG features.

5.1.1 Using Dataset 1 (3 window segmentation)

The Random Forest PRHM property classification model that used all 180 features provided the best classification results when Dataset 1 was used. This model had an average macro F1 score of 0.32 and an average percentage classification accuracy of 37.2%. These values were almost double that of the chance level of 20%. The chance level is a model's average expected classification accuracy if it predicted properties at random. For example, if the properties were predicted randomly, the model would predict properties accurately 20% of the time (as there are five properties.

The LSTM PRHM property classification model had a performance worse than the chance accuracy level. This may be because Dataset 1 was very small, and a neural network typically performs better for larger datasets.

		PREDICTED Classification					
		Smoothness	**Thickness**	**Warmth**	**Flexibility**	**Softness**	**Total**
ACTUAL Classification	**Smoothness**	132 (52%)	40 (16%)	26 (10%)	43 (17%)	11 (4%)	252 (100%)
	Thickness	36 (14%)	107 (42%)	16 (6%)	55 (22%)	38 (15%)	252 (100%)
	Warmth	62 (25%)	26 (10%)	54 (21%)	66 (26%)	44 (17%)	252 (100%)
	Flexibility	33 (13%)	41 (16%)	18 (7%)	122 (48%)	38 (15%)	252 (100%)
	Softness	56 (22%)	62 (25%)	14 (6%)	66 (26%)	54 (21%)	252 (100%)
	Total						

Table 2: Confusion matrix - Random Forest PRHM using Dataset 1

5.1.2 Using Dataset 2 (15 window segmentation with 3 timesteps)

		PREDICTED Classification					
		Smoothness	**Thickness**	**Warmth**	**Flexibility**	**Softness**	**Total**
ACTUAL Classification	**Smoothness**	4144 (53%)	896 (11%)	968 (12%)	600 (8%)	1200 (15%)	7808 (100%)
	Thickness	1464 (20%)	2048 (27%)	824 (11%)	1720 (23%)	1448 (19%)	7504 (100%)
	Warmth	1640 (22%)	1304 (18%)	2184 (30%)	1056 (14%)	1200 (16%)	7384 (100%)
	Flexibility	808 (11%)	928 (13%)	592 (8%)	3568 (48%)	1504 (20%)	7400 (100%)
	Softness	1472 (19%)	976 (13%)	704 (9%)	1520 (20%)	2976 (39%)	7648 (100%)
	Total						

Table 3: Confusion matrix - Fully-Connected PRHM Property using Dataset 2

		PREDICTED Classification					
		Smoothness	**Thickness**	**Warmth**	**Flexibility**	**Softness**	**Total**
ACTUAL Classification	**Smoothness**	960 (38%)	408 (16%)	424 (17%)	392 (15%)	360 (14%)	2544 (100%)
	Thickness	264 (11%)	1008 (40%)	328 (13%)	384 (15%)	528 (21%)	2512 (100%)
	Warmth	320 (13%)	416 (17%)	1008 (41%)	496 (20%)	224 (9%)	2464 (100%)
	Flexibility	272 (11%)	264 (11%)	184 (8%)	1400 (58%)	312 (13%)	2432 (100%)
	Softness	232 (9%)	576 (22%)	296 (11%)	544 (21%)	944 (36%)	2592 (100%)
	Total						

Table 4: Confusion matrix - LSTM PRHM Property using Dataset 2

		PREDICTED Classification					
		Smoothness	Thickness	Warmth	Flexibility	Softness	Total
ACTUAL Classification	Smoothness	12328 (49%)	4640 (18%)	2000 (8%)	3936 (16%)	2456 (10%)	25360 (100%)
	Thickness	3488 (14%)	11904 (48%)	1120 (5%)	5424 (22%)	2864 (12%)	24800 (100%)
	Warmth	3704 (14%)	5184 (20%)	6240 (24%)	7216 (28%)	3280 (13%)	25624 (100%)
	Flexibility	2776 (11%)	3040 (12%)	592 (2%)	15920 (65%)	2304 (9%)	24632 (100%)
	Softness	3112 (12%)	4416 (17%)	1944 (8%)	5824 (23%)	10264 (40%)	25560 (100%)
	Total						

Table 5: Confusion matrix - Fully-Connected PRHM Property using Dataset 3

		PREDICTED Classification					
		Smoothness	Thickness	Warmth	Flexibility	Softness	Total
ACTUAL Classification	Smoothness	1136 (47%)	384 (16%)	480 (20%)	168 (7%)	248 (10%)	2416 (100%)
	Thickness	392 (15%)	728 (28%)	592 (23%)	528 (21%)	320 (12%)	2560 (100%)
	Warmth	600 (22%)	296 (11%)	1256 (45%)	384 (14%)	240 (9%)	2776 (100%)
	Flexibility	176 (8%)	192 (8%)	280 (12%)	1256 (54%)	416 (18%)	2320 (100%)
	Softness	344 (14%)	376 (15%)	352 (14%)	584 (24%)	816 (33%)	2472 (100%)
	Total						

Table 6: Confusion matrix - LSTM PRHM Property using Dataset 3

5.1.3 Using Dataset 3 (15 window segmentation with 10 timesteps)

5.2 PRHM Rating Classification Results

5.3 Results 2 - Classification model trained using the existing data and tested using the newly collected data

5.3.1 Using the Fully Connected PRHM

- Micro F1 score = 0.23
- Macro F1 score = 0.2

	Dataset 1		Dataset 2		Dataset 3	
	All 180 Features	Only EMG	All 180 Features	Only EMG	All 180 Features	Only EMG
PRHM based on Random Forest	**0.32**	0.27	0.3	0.25	0.27	0.24
PRHM based on LSTM	0.12	0.15	**0.39**	0.35	0.27	0.38
Fully-connected PRHM	0.26	0.17	0.33	0.37	**0.41**	0.31

Table 7: Average macro F1 scores when predicting properties

	Dataset 1		Dataset 2		Dataset 3	
	All 180 Features	Only EMG	All 180 Features	Only EMG	All 180 Features	Only EMG
PRHM based on Random Forest	**37.2%**	32.2%	34.4%	29.8%	32.2%	27.9%
PRHM based on LSTM	22.6%	23.3%	**42.4%**	38.8%	32.8%	41.4%
Fully-connected PRHM	33.1%	25.3%	38.6%	39.5%	**45.0%**	34.8%

Table 8: Average percentage classification accuracy when predicting properties

			PRHM RF	PRHM LSTM	FC PRHM
Dataset 1	**All 180 Features**	**Smoothness**	52.4%	43.5%	44.8%
		Thickness	42.5%	19.3%	34.9%
		Warmth	21.4%	27.3%	17.9%
		Flexibility	48.4%	51.2%	47.6%
		Softness	21.4%	19.5%	20.2%
	Only EMG	**Smoothness**	49.2%	17.9%	39.3%
		Thickness	23.0%	15.5%	9.9%
		Warmth	25.8%	19.0%	18.3%
		Flexibility	47.2%	41.7%	51.6%
		Softness	15.9%	41.7%	7.5%
Dataset 2	**All 180 Features**	**Smoothness**	49.0%	37.7%	49.5%
		Thickness	26.7%	40.1%	37.0%
		Warmth	27.4%	40.9%	27.5%
		Flexibility	50.1%	57.6%	49.6%
		Softness	19.0%	36.4%	29.3%
	Only EMG	**Smoothness**	46.3%	50.3%	53.1%
		Thickness	6.9%	21.9%	27.3%
		Warmth	32.2%	38.3%	29.6%
		Flexibility	45.3%	59.3%	48.2%
		Softness	18.1%	26.5%	38.9%
Dataset 3	**All 180 Features**	**Smoothness**	43.5%	37.4%	48.6%
		Thickness	19.3%	22.6%	48.0%
		Warmth	27.3%	19.5%	24.4%
		Flexibility	51.2%	57.2%	64.6%
		Softness	19.5%	27.8%	40.2%
	Only EMG	**Smoothness**	40.8%	47.0%	41.3%
		Thickness	5.3%	28.4%	35.6%
		Warmth	31.9%	45.2%	15.2%
		Flexibility	44.3%	54.1%	49.9%
		Softness	17.5%	33.0%	31.7%

Table 9: Average classification accuracy when predicting each property

	Dataset 1		Dataset 2		Dataset 3	
	All 180 Features + Properties	EMG + Properties	All 180 Features + Properties	EMG + Properties	All 180 Features + Properties	EMG + Properties
Random Forest PRHM	0.38	0.37	0.38	0.37	0.37	0.37
LSTM PRHM	0.72	0.73	0.67	0.62	0.59	0.62
Fully-connected PRHM	0.62	0.64	0.53	0.59	0.6	0.6

Table 10: Average weighted F1 scores when predicting property ratings

	Dataset 1		Dataset 2		Dataset 3	
	All Features	Only EMG	All Features	Only EMG	All Features	Only EMG
PRHM based on Random Forest	50.6%	49.3%	48.7%	49.1%	47.0%	47.9%
PRHM based on LSTM	76.5%	78.6%	71.6%	65.3%	62.2%	63.3%
Fully-connected PRHM	67.1%	70.6%	59.5%	64.2%	65.0%	64.6%

Table 11: Average percentage classification accuracy when predicting property ratings

- Percentage Classification accuracy = 22.7%

3741	1159	4885	477	88
2341	2134	5040	775	60
2889	2353	3921	1216	110
2619	2450	3415	1961	55
2384	2054	4902	1075	85

Table 12: Confusion matrix

- Percentage classification accuracy for smoothness: 36.1%
- Percentage classification accuracy for thickness: 20.6%
- Percentage classification accuracy for warmth: 37.4%
- Percentage classification accuracy for flexibility: 18.7%
- Percentage classification accuracy for softness: 0.8%

Chapter 6

Conclusion

It is unlikely that everything you tried worked well, so in this chapter you may wish to describe a modified version of your method and the associated results. Explain why you were motivated to try this extension and how you think it might help to address some of the shortcomings of the method is Chapter 3. Summarise what you have achieved and evaluate honestly if you feel the approach has been largely successful. Explain what could be improved still and perhaps why the method is not working well (if that is the case).

Bibliography

[1] India Morrison. "ALE meta-analysis reveals dissociable networks for affective and discriminative aspects of touch". In: *Human Brain Mapping* 37 (Feb. 2016). DOI: 10.1002/hbm.23103.

[2] Joann Peck and Terry Childers. "To Have and To Hold: The Influence of Haptic Information on Product Judgments". In: *Journal of Marketing - J MARKETING* 67 (Apr. 2003), pp. 35–48. DOI: 10.1509/jmkg.67.2.35.18612.

[3] Roberta L. Klatzky and Susan J. Lederman. "There's more to touch than meets the eye: The salience of object attributes for haptics with and without vision". In: *Journal of Experimental Psychology* 116.4 (1987), pp. 356–369. DOI: 10.1509/jmkg.67.2.35.18612.

[4] Susan J. Lederman, Georgie Thorne, and Bill Jones. "Perception of texture by vision and touch: multidimensionality and intersensory integration." In: *Journal of experimental psychology. Human perception and performance* 12.2 (1986), pp. 169–80.

[5] Morris B. Holbrook. "Aims, concepts, and methods for the representation of individual differences in esthetic responses to design features". In: *Journal of Consumer Research* 13 4 (1986), pp. 337–347. DOI: https://doi.org/10.1086/209073.

[6] Deborah Brown Mccabe and Stephen M. Nowlis. "The Effect of Examining Actual Products or Product Descriptions on Consumer Preference". In: *Journal of Consumer Psychology* 13 (2003), pp. 431–439.

[7] Bianca Grohmann, Eric R. Spangenberg, and David E. Sprott. "The Influence of tactile input on the evaluation of retail product offerings". In: *Journal of Retailing - J RETAIL* 83 (Apr. 2007), pp. 237–245. DOI: 10.1016/j.jretai.2006.09.001.

[8] Alka Varma Citrin et al. “Consumer need for tactile input: An internet retailing challenge”. In: *Journal of Business Research* 56.11 (2003). Strategy in e-marketing, pp. 915–922. ISSN: 0148-2963. DOI: https://doi.org/10.1016/S0148-2963(01)00278-8. URL: %5Curl%7Bhttps://www.sciencedirect.com/science/article/pii/S0148296301002788%7D.

[9] Deborah H. Lester, Andrew M. Forman, and Dolly Loyd. “Internet Shopping and Buying Behavior of College Students”. In: *Services Marketing Quarterly* 27 (2005), pp. 123–138.

[10] Lili Lin. “Inferring Fabric-Hand Perception from Wearable Sensors [Unpublished MSc dissertation]”. In: (2021).

[11] Lucy Hughes et al. “Crowdsourcing an Emotional Wardrobe”. In: *CHI ’12 Extended Abstracts on Human Factors in Computing Systems*. CHI EA ’12. Austin, Texas, USA: Association for Computing Machinery, 2012, pp. 231–240. ISBN: 9781450310161. DOI: 10.1145/2212776.2212801. URL: https://doi.org/10.1145/2212776.2212801.

[12] Chayapa Katawetawaraks and Cheng Lu Wang. “Online Shopper Behavior: Influences of Online Shopping Decision”. In: *eBusiness & eCommerce eJournal* (2013).

[13] Michele A. Burton et al. “Crowdsourcing subjective fashion advice using vizwiz: Challenges and opportunities”. English (US). In: *ASSETS’12 - Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility*. ASSETS’12 - Proceedings of the 14th International ACM SIGACCESS Conference on Computers and Accessibility. 14th International ACM SIGACCESS Conference on Computers and Accessibility, ASSETS 2012 ; Conference date: 22-10-2012 Through 24-10-2012. 2012, pp. 135–142. ISBN: 9781450313216. DOI: 10.1145/2384916.2384941.

[14] Olivia Lai. *What is Fast Fashion?* https://earth.org/what-is-fast-fashion/. (accessed: 07/08/2022). Nov. 2021.

[15] Rashmila Maiti. *Fast Fashion and Its Environmental Impact*. https://earth.org/fast-fashions-detrimental-effect-on-the-environment/. (accessed: 07/08/2022). June 2022.

[16] Solene Rauturier. *What Is Fast Fashion and Why Is It So Bad?* https://goodonyou.eco/what-is-fast-fashion/. (accessed: 07/08/2022). Apr. 2022.

[17] Rachael Dottle and Jackie Gu. *The Global Gut of clothing Is An Environmental Crisis*. https://www.bloomberg.com/graphics/2022-fashion-industry-environmental-impact/#xj4y7vzkg. (accessed: 09/08/2022). Feb. 2022.

[18] United Nations. *Fashion Industry, UN Pursue Climate Action for Sustainable Development*. https://unfccc.int/news/fashion-industry-un-pursue-climate-action-for-sustainable-development. (accessed: 09/08/2022). Jan. 2018.

[19] Morgan McFall-Johnsen. *The fashion industry emits more carbon than international flights and maritime shipping combined. Here are the biggest ways it impacts the planet.* https://www.businessinsider.com/fast-fashion-environmental-impact-pollution-emissions-waste-water-2019-10?r=US&IR=T. (accessed: 09/08/2022). Oct. 2019.

[20] Waste2Fresh. *Dye Pollution in the Textile Industry*. https://waste2fresh.eu/dye-pollution-in-the-textile-industry/. (accessed: 09/08/2022). June 2021.

[21] Gary Cook and Maya Rommwatt. *FASHION FORWARD: A Roadmap to Fossil Free Fashion*. https://www.stand.earth/sites/stand/files/standearth-fashionforward-roadmaptofossilfreefashion.pdf. (accessed: 09/08/2022).

[22] Julien Boucher and Damien Friot. *Primary Microplastics in the Oceans: A Global Evaluation of Sources*. Jan. 2017. ISBN: 978-2-8317-1827-9. DOI: 10.2305/IUCN.CH.2017.01.en.

[23] The United Nations Economic Commission for Europe. *Fashion and the SDGs: what role for the UN?* https://unece.org/fileadmin/DAM/RCM_Website/RFSD_2018_Side_event_sustainable_fashion.pdf. (accessed: 09/08/2022). Mar. 2018.

[24] Elizabeth Reichart and Deborah Drew. *By the Numbers: The Economic, Social and Environmental Impacts of "Fast Fashion"*. https://www.wri.org/insights/numbers-economic-social-and-environmental-impacts-fast-fashion. (accessed: 09/08/2022). Jan. 2019.

[25] United Nations Environment Programme. *Putting the brakes on fast fashion*. https://www.unep.org/news-and-stories/story/putting-brakes-fast-fashion. (accessed: 09/08/2022). Nov. 2018.

[26] Tiffany Field. *Touch*. 1st. MIT Press, 2001.

[27] Matthew J. Hertenstein. "Touch: Its communicative functions in infancy". In: (2002).

[28] Dale M. Stack. “The Salience of Touch and Physical Contact During Infancy: Unraveling Some of the Mysteries of the Somesthetic Sense”. In: 2007.

[29] Matthew J. Hertenstein et al. “Touch communicates distinct emotions.” In: *Emotion* 6.3 (2006), pp. 528–33.

[30] Matthew J. Hertenstein et al. “The communication of emotion via touch.” In: *Emotion* 9.4 (2009), pp. 566–73.

[31] Iren Eibl-Eibesfeldt. “Human Ethology”. In: 1989.

[32] Hendrik N. J. Schifferstein. “The perceived importance of sensory modalities in product usage: a study of self-reports.” In: *Acta psychologica* 121 1 (2006), pp. 41–64.

[33] Matthew J. Hertenstein. “Touch”. In: vol. 3. Sage Publications, 2005.

[34] Matthew Hertenstein and Joseph Campos. “Emotion Regulation Via Maternal Touch”. In: *Infancy* 2 (Sept. 2001), pp. 549–566. DOI: 10.1207/S15327078IN0204_09.

[35] Stanley E. Jones and A. Elaine Yarbrough. “A naturalistic study of the meanings of touch”. In: (1985).

[36] Mark L. Knapp and Judith A. Hall. *Nonverbal Communication in Human Interaction.* 1997.

[37] Yuan Gao, Nadia Bianchi-Berthouze, and Hongying Meng. “What Does Touch Tell Us about Emotions in Touchscreen-Based Gameplay?” In: *ACM Trans. Comput.-Hum. Interact.* 19.4 (Dec. 2012), 31:1–31:30. ISSN: 1073-0516. DOI: 10.1145/2395131.2395138. URL: %5Curl%7Bhttp://doi.acm.org/10.1145/2395131.2395138%7D.

[38] Hillary Elfenbein and Nalini Ambady. “On the Universality and Cultural Specificity of Emotion Recognition: A Meta-Analysis”. In: *Psychological bulletin* 128 (Apr. 2002), pp. 203–35. DOI: 10.1037/0033-2909.128.2.203.

[39] Klaus R. Scherer, Tom Johnstone, and Gundrun Klasmeyer. “Vocal expression of emotion”. In: Oxford University Press, 2003.

[40] Sachin Shah, J. Teja, and Samit Bhattacharya. “Towards affective touch interaction: predicting mobile user emotion from finger strokes”. In: *Journal of Interaction Science* 3 (Dec. 2015). DOI: 10.1186/s40166-015-0013-z.

[41] Lie Lu, Dan Liu, and Hong-Jiang Zhang. “Automatic mood detection and tracking of music audio signals”. In: *Audio, Speech, and Language Processing, IEEE Transactions on* 14 (Feb. 2006), pp. 5–18. DOI: 10.1109/TSA.2005.860344.

[42] KuanTing Liu and Roger Reimer. “Social playlist: enabling touch points and enriching ongoing relationships through collaborative mobile music listening”. In: Jan. 2008, pp. 403–406. DOI: 10.1145/1409240.1409299.

[43] Nadia Bianchi-Berthouze and Christine Lisetti. “Modeling Multimodal Expression of User’s Affective Subjective Experience”. In: *Bianchi-Berthouze, N. and Lisetti, C.L. (2002) Modeling Multimodal Expression of User’s Affective Subjective Experience. User Modeling and User-Adapted Interaction, 12 (1). pp. 49-84. ISSN 09241868* 12 (Feb. 2002). DOI: 10.1023/A:1013365332180.

[44] Michelle Thrasher et al. “Mood Recognition Based on Upper Body Posture and Movement Features”. In: Jan. 2011, pp. 377–386. ISBN: 978-3-642-24599-2. DOI: 10.1007/978-3-642-24600-5_41.

[45] Petra Sundström, Anna Ståhl, and Kristina Höök. “In situ informants exploring an emotional mobile messaging system in their everyday practice”. In: *International Journal of Human-Computer Studies* 65 (Apr. 2007), pp. 388–403. DOI: 10.1016/j.ijhcs.2006.11.013.

[46] Duncan Graham-Rowearchive page. *A Smart Phone that Knows You’re Angry*. https://www.technologyreview.com/2012/01/09/188503/a-smart-phone-that-knows-youre-angry/. (accessed: 07/08/2022). Jan. 2012.

[47] Sidney D’Mello and Art Graesser. “The half-life of cognitive-affective states during complex learning”. In: *Cognition & emotion* 25 (Sept. 2011), pp. 1299–308. DOI: 10.1080/02699931.2011.613668.

[48] John Hopkins Medicine. *Electromyography (EMG)*. https://www.hopkinsmedicine.org/health/treatment-tests-and-therapies/electromyography-emg. (accessed: 15/08/2022).

[49] Kejia Wang. “Using EMG and Accelerometer data to Capture the Tactile Experience with Fabrics [Unpublished MSc dissertation]”. In: (2017).

[50] Panagiotis Tsinganos et al. “Deep Learning in EMG-based Gesture Recognition”. In: Sept. 2018, pp. 107–114. DOI: 10.5220/0006960201070114.

[51] Shah Rukh Humayoun, Munir Ahmad, and Achim Ebert. “3D Accelerometer-based Gestures for Interacting with Mobile Devices”. In: *Proceedings of the 9th Nordic Conference on Human-Computer Interaction* (2016).

[52] VectorNav. *What is an Inertial Measurement Unit?* https://www.vectornav.com/resources/inertial-navigation-articles/what-is-an-inertial-measurement-unit-imu. (accessed: 15/08/2022).

[53] Jianyu Yang. "Chapter 4 - Bistatic SAR parameter estimation". In: *Bistatic Synthetic Aperture Radar*. Elsevier, 2022, pp. 185–215. ISBN: 978-0-12-822459-5. DOI: https://doi.org/10.1016/B978-0-12-822459-5.00004-9. URL: https://www.sciencedirect.com/science/article/pii/B9780128224595000049.

[54] Moti Ben-Ari. *A Tutorial on Euler Angles and Quaternions.* https://www.weizmann.ac.il/sci-tea/benari/sites/sci-tea.benari/files/uploads/softwareAndLearningMaterial quaternion-tutorial-2-0-1.pdf. (accessed: 15/08/2022).

[55] Jonathan Strickland. *What is a gimbal – and what does it have to do with NASA?* https://science.howstuffworks.com/gimbal.htm. (accessed: 15/08/2022).

[56] Adrian Popa. *What is meant by the term gimbal lock?* http://www.madsci.org/posts/archives/aug98/896993617.Eg.r.html. (accessed: 15/08/2022).

[57] Yuhan Gao. "Automatic Recognition of Properties Assessed in the Tactile Exploration of Textiles [Unpublished MSc dissertation]". In: (2019).

[58] OYMotion. *gForcePro/gForcePro+ Armband and gForceOct Module User Guide.* https://oymotion.github.io/gForcePro/gForcePro/. (accessed: 15/08/2022). Aug. 2020.

[59] OYMotion. *gForce EMG Armband User Guide*. https://oymotion.github.io/assets/downloads/gForce-EMG-ARMBAND-User-Guide-202108.pdf. (accessed: 15/08/2022).

[60] Motorolla. *Motorolla - motog^9 POWER.* https://www.motorola.co.uk/smartphones-moto-g-power-gen-9/p. (accessed: 15/08/2022).

[61] *SQLite Home Page.* https://www.sqlite.org/index.html. (accessed: 15/08/2022).

[62] M Raez, Md Hussain, and Faisal Mohd-Yasin. "Techniques of EMG signal analysis: Detection, processing, classification and applications". In: *Biological procedures online* 8 (Feb. 2006), pp. 11–35. DOI: 10.1251/bpo115.

[63] David M. Thompson. *Electromyography (EMG)*. https://ouhsc.edu/bserdac/dthompso/web/pk/emg/emg.htm. (accessed: 15/08/2022).

[64] Leandro R. Altimari et al. "Influence of Different Strategies of Treatment Muscle Contraction and Relaxation Phases on EMG Signal Processing and Analysis During Cyclic Exercise". In: 2012.

[65] William Rose. *Electromyogram analysis*. https://www1.udel.edu/biology/rosewc/kaap686/notes/EMG%20analysis.pdf. (accessed: 15/08/2022).

[66] Alexandre Chalard et al. "Impact of the EMG normalization method on muscle activation and the antagonist-agonist co-contraction index during active elbow extension: Practical implications for post-stroke subjects". In: *Journal of Electromyography and Kinesiology* 51 (2020), p. 102403. ISSN: 1050-6411. DOI: https://doi.org/10.1016/j.jelekin.2020.102403. URL: https://www.sciencedirect.com/science/article/pii/S1050641120300183.

[67] Gregory J. Lehman and Stuart M. McGill. "The importance of normalization in the interpretation of surface electromyography: A proof of principle". In: *Journal of Manipulative and Physiological Therapeutics* 22.7 (1999), pp. 444–446. ISSN: 0161-4754. DOI: https://doi.org/10.1016/S0161-4754(99)70032-1. URL: https://www.sciencedirect.com/science/article/pii/S0161475499700321.

[68] Martin Ling. *Quaternions in numpy*. https://quaternion.readthedocs.io/en/latest/. (accessed: 07/08/2022).

[69] Brinnae Bent. *Step-by-Step Guide to leave-one-person-out Cross Validation with Random Forests in Python*. https://medium.com/analytics-vidhya/step-by-step-guide-to-leave-one-person-out-cross-validation-with-random-forests-in-python-34b2eaefb628. (accessed: 15/08/2022). June 2020.

[70] Jason Brownlee. *LOOCV for Evaluating Machine Learning Algorithms*. https://machinelearningmastery.com/loocv-for-evaluating-machine-learning-algorithms/. (accessed: 15/08/2022). July 2020.

[71] Jason Brownlee. *How to Choose Loss Functions When Training Deep Learning Neural Networks*. https://machinelearningmastery.com/how-to-choose-loss-functions-when-training-deep-learning-neural-networks/. (accessed: 15/08/2022). Aug. 2020.

[72] Fabian Pedregosa et al. "Scikit-learn: Machine Learning in Python". In: *Journal of Machine Learning Research* 12 (2011), pp. 2825–2830.

[73] Jason Brownlee. *What is a Confusion Matrix in Machine Learning*. `https://machinelearningmastery.com/confusion-matrix-machine-learning/`. (accessed: 15/08/2022). Nov. 2016.

[74] Margherita Grandini, Enrico Bagli, and Giorgio Visani. "Metrics for Multi-Class Classification: an Overview". In: *ArXiv* abs/2008.05756 (2020).

[75] Jason Brownlee. *How to Calculate Precision, Recall, and F-Measure for Imbalanced Classification*. `https://machinelearningmastery.com/precision-recall-and-f-measure-for-imbalanced-classification/`. (accessed: 15/08/2022). Jan. 2020.

[76] Purva Huilgol. *Precision vs. Recall – An Intuitive Guide for Every Machine Learning Person*. `https://www.analyticsvidhya.com/blog/2020/09/precision-recall-machine-learning/`. (accessed: 15/08/2022). Nov. 2016.

Appendix A: Documents related to the newly collected dataset

A.1 Information Sheet

UCL INTERACTION CENTRE
RESEARCH•CONSULTANCY•SEMINARS•COURSES

UCL Interaction Centre
2nd floor, 66 – 72 Gower St
London WC1E 6EA

INFORMATION SHEET FOR PARTICIPANT

Project Title: TCC: Affective sensing technology: **The affective tactile language in clothing attachment**

Department: University College London Interaction Centre

Researcher: Yuanze Gan yuanze.gan.20@ucl.ac.uk, Alice Sansoni, a.sansoni@ucl.ac.uk, Nihara Warawita nihara.warawita.21@ucl.ac.uk,

Principal Researcher: Prof Nadia Berthouze, nadia.berthouze@ucl.ac.uk

Data Protection Email: data-protection@ucl.ac.uk

This study has been approved by the UCLIC Research Ethics Committee: UCLIC_2021_018_Berthouze_PE

1. Invitation Paragraph

You are being invited to take part in a research project. Before you decide whether to take part, it is important for you to understand why the research is being done and what participation will involve. Please take time to read the following information carefully and discuss it with others if you wish. Ask us if there is anything that is not clear or if you would like more information. Take time to decide whether or not you wish to take part.

2. What is the project's purpose?

This project is part of the Textile Circularity Centre (TCC) funded by UK Research & Innovation, to understand important factors in sustainable fashion consumption and facilitate the development of a textile circular economy.

In this project, we explore the role of touch when buying clothes, or its role in building and expressing attachment. Specifically, we want to understand how gestures and movements with items correspond to different material properties and how much the cloth represents that property by using sensing technology. The extracted data could be visualised help material understanding. Our findings will inform the design of technology which encourages consumers to connect with and reflect upon their clothing items, to facilitate sustainable and circular textile consumption.

Information about the larger Textile Circularity Centre project can be found at: https://www.rca.ac.uk/research-innovation/research-centres/materials-science-research-centre/textiles-circularity-centre/.

3. Why have I been chosen?

We are asking people caring about the sense of touch when interacting with clothes, living in London and are at least 20 years-old to take part in our study.

4. Do I have to take part?

It is up to you to decide whether or not to take part in this study. If you do decide to take part, you will be given this information sheet to keep and be asked to sign a consent form. You can withdraw from the study at any time and without giving a reason. You will not in any way be penalised for withdrawing from the study.

You can additionally withdraw data collected during the study up till 2 days after your study session, without giving a reason. To withdraw from the study or withdraw your data, you should contact the researcher, using the contact details at the top of this information sheet. We will no longer use data that you withdraw if it is withdrawn no more than 2 days after the last data we collected from you. If you choose to withdraw from the study, you will be asked to revoke your original consent by signing a consent change form.

5. What will happen to me if I take part?

You will be asked to wear two Armbands [GForcePro+] (http://www.oymotion.com/en/product32/149). This armband measures the muscle activity in your arm and your arm movement. They do not harm your skin or hurt you in anyway. We use these devices to measure the muscle activity and movement of your arm while touching the six sample clothes you will be asked to engage with during the experiment. You will be asked to freely touch 6 items assessing different properties (e.g., its softness) of the fabrics. A mobile app will guide you in the use of the sensors and allow you to complete a questionnaire during the experience. The questionnaire will ask you to rate the properties of the clothes material after touching it. We will take a video of you while touching the fabrics, trying to avoid including your face, keeping only your hands and arms. The goal of this study is to use EMG data to build a AI-system that can infer your perception of the fabric qualities. The study will last 1h 15min.

The study will follow COVID-19 safety measures (see at the end of this information sheet for covid-safety procedure)

DEVICES:

- All of our study devices (smartphone, EMG band) are cleaned and disinfected after each participant.
- The researchers will use gloves to give you the devices

6. Will I be recorded and how will the recorded media be used?

NO ONE outside of our research team will be allowed access to any written or verbal information which can be used to personally identify you that you have provided in your communication with us or when giving your consent unless you have given us permission to do so (e.g., showing your video).

Your Responses - What we will record:

a. The gathered movement and physiological (e.g., muscle activity) data from sensors, video/image, audio, and questionnaire and diary recordings of your activities, as described above, will be used for our analysis. We would further use examples from the sensor recordings of your activities and your responses to our questions, neither of which can be used to personally identify you, in scientific publications (including academic theses) and presentations.

b. Questionnaires data - Your responses to our questionnaires will be recorded in digital format either as online forms or other electronic documents, e.g. pdf forms.

c. Video/Audio data – We will video record the study to capture yours hand and arms movement. We will try to avoid to capture your face.

How we will use what we record:

- The data we record (letter, sensor data, questionnaire ratings and transcribed interview) will be used for analysis. Anonymized data will be shared with our collaborators UKRI Textile Circularity Centre (https://www.rca.ac.uk/research-innovation/research-centres/materials-science-research-centre/textiles-circularity-centre/) and related project (e.g. CX) (https://www.rca.ac.uk/research-innovation/research-centres/materials-science-research-centre/textiles-circularity-centre/) that the principal researcher Nadia Berthouze is part of.

- ADDITIONAL USE OF DATA THAT CAN BE USED TO IDENTIFY YOU: We will never disclose your name or contact details with the data gathered. We will not share the video or the audio outside our UCL research group unless you have given us written permission to do so.

- ADDITIONAL USE OF DATA THAT CANNOT BE USED TO IDENTIFY YOU If you give us permission, we will share anonymised data (sensor data, questionnaires responses), which CANNOT be used to identify you, with the wider research community, without your names or contact details included. This will further support advance in better understanding of movement and the design of related AI-technology.

7. What are the possible benefits of taking part?

As a thank you for your time, you will receive £15 as payment. There are no immediate benefits for those people participating in the project. It is hoped that this work will shape future research on movement and touch sensing technology and technology to automatically detect affective experiences from movement and touch. We also hope our research will contribute to design technology that foster wellbeing and create a more sustainable and circular economy.

8. What if something goes wrong?

Extreme care will be taken in this research. However, if you wish to complain or have any concerns that are not addressed by the researcher, you should contact Prof Nadia Berthouze (nadia.berthouze@ucl.ac.uk) who is the Principal Researcher on the project. If you further feel that your complaint has not been handled to your satisfaction, you can contact the Chair of the UCL Research Ethics Committee (ethics@ucl.ac.uk).

9. Will my taking part in this project be kept confidential?

Your name and contact details will be kept strictly confidential. We would further only share DE-IDENTIFIED questionnaire, transcripts and sensor data with other researchers, and only if you give us permission to.

10. Limits to confidentiality

Confidentiality will be respected unless there are compelling and legitimate reasons for this to be breached. If this happens, we will inform you of any decisions that might limit your confidentiality.

11. What will happen to the results of the research project?

The findings of our analysis of the data collected from the participants of the research project will be published in reports and articles and presented at public engagement and research talk venues. You will be able to access academic publications of these findings on the project website: https://uclic.ucl.ac.uk/people/nadia-berthouze. You will not be identifiable in these publications and presentations. Your name and contact details will never be included in publications and presentations.

The questionnaire and sensor data we collect from you, which CANNOT be used to identify you, will be made open for use by other researchers, for the benefit of scientific and technology development; but only if you give us permission to do so in the consent form.

12. Local Data Protection Privacy Notice

Notice: The controller for this project will be University College London (UCL). The UCL Data Protection Officer provides oversight of UCL activities involving the processing of personal data, and can be contacted at data-protection@ucl.ac.uk

This 'local' privacy notice sets out the information that applies to this particular study. Further information on how UCL uses participant information can be found in our 'general privacy notice: https://www.ucl.ac.uk/legal-services/privacy/ucl-general-research-participant-privacy-notice

The categories of personal data used will be as follows:

- Name, Age, Gender, contact details
- Muscle and movement activity
- Video

The lawful basis that would be used to process your personal data will be performance of a task in the public interest. The lawful basis used to process special category personal data will be for scientific and historical research or statistical purposes.

Your personal data will be processed so long as it is required for the research project. If we are able to anonymise or pseudonymise the personal data you provide we will undertake this and will endeavour to minimise the processing of personal data wherever possible. If you give us permission to make open the data to the wider research community or use it in other research projects we are involved in, processing of the personal data will continue beyond the end of the research project.

If you are concerned about how your personal data is being processed, or if you would like to contact us about your rights, please contact UCL in the first instance at data-protection@ucl.ac.uk.

Thank you for reading this information sheet and for considering taking part in this research study.

A.2 Consent Form

Information and Consent

A A A

INFORMATION SHEET

Thank you for your interest in our research project.
Please carefully read the Information Sheet attached below,
then proceed to complete the Consent Form below.

Attachment: Information Sheet.pdf (0.14 MB)

CONSENT FORM

Project Title: TCC: Affective sensing technology: The affective tactile language in clothing attachment

Department: University College London Interaction Centre

Researcher: Yuanze Gan yuanze.gan.20@ucl.ac.uk, Alice Sansoni, a.sansoni@ucl.ac.uk, Nihara Warawita nihara.warawita.21@ucl.ac.uk,

Principal Researcher: Prof Nadia Berthouze, nadia.berthouze@ucl.ac.uk

Data Protection Email: data-protection@ucl.ac.uk

This study has been approved by the UCL Interaction Centre Research Ethics Committee: UCLIC_2021_018_Berthouze_PE

Thank you for considering taking part in this research. If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time. Before the study starts, you will be able to ask further information during a video conference call and you will still have the option to opt out. Please note that if you answer No to some of the questions you may not be elegible for this study.

1) **I confirm that I have read and understood the Information Sheet for the above study. I have had an opportunity to consider the information and what will be expected of me. I have also had the opportunity to ask questions which have been answered to my satisfaction.**

* must provide value

- Yes
- No

2) **I confirm that I understand the recruiting criteria and I also confirm to be at least 20 years old.**

* must provide value

- Yes
- No

3) **I consent to participate in the study. I understand that my personal information, if applicable, (name, age, address) will be used to contact me, send me any materials, or used for the purpose explained to me in the Information Sheet.**

* must provide value

- Yes
- No

4) **I understand that I will be audio and video recorded to enable accurate analysis of the data. I understand that my personal information, survey data (text question responses, think aloud), sensors data (physiological data and movement data), interview transcript, audio recordings will be**

used for the purposes explained to me. I understand that according to data protection legislation, 'public task' will be the lawful basis for processing for my personal data and the lawful basis used to process any special category personal data will be for scientific and historical research or statistical purposes.

* must provide value

- Yes
- No

5) **I understand that my participation is voluntary and that I am free to withdraw from the study at any time. I understand that if I decide to withdraw from the study, I can revoke my consent by signing a consent change form. I understand that I can also withdraw data I have provided, up till the 2nd day after the experiment session I took part in is completed, without giving a reason. If I choose to also withdraw my data, the data will no longer be used.**

* must provide value

- Yes
- No

6) **I am aware of who I should contact if I wish to lodge a complaint.**

* must provide value

- Yes
- No

7) **I understand that identifiable information collected will remain confidential and that all efforts will be made to ensure that I cannot be identified except where explicit consent is given below.**

* must provide value

- Yes
- No

8) **FURTHER USE OF MY DATA (Tick the boxes to indicate you agree with the related use of your data)**

- [ ] I agree for my sensors data [body/hand movement or related physiological data], text question responses, interview transcriptions, which CANNOT be used to identify me, to be made open to other researchers and for future research or secondary analysis, to facilitate research and innovation.
- [ ] I agree for PHOTOS recorded from me (e.g., during the study) to be included in written publications used to disseminate the project findings. I understand that I could be recognised from such images and the audience may make copies of the image(s) and that the researcher will not have control over such copies.
- [ ] I agree for PHOTOS/VIDEOS/AUDIO recorded from me to be used in presentations used to disseminate the project findings. I understand that I could be recognised from such photos/videos/audio and the audience may record the presentation and that the researcher will not have control over such recordings.
- [ ] I agree for my non personal information (sensors data, text question responses, interview transcript, diary) to be used for secondary analysis in other studies that the researchers of this study are involved in, to facilitate research and innovation.
- [ ] I agree to be contacted to participate in follow up studies to this project, or in future studies of a similar nature. I understand that my name and contact details will not be shared with anyone who is not a member of this research team.
- [ ] I agree for PHOTOS/VIDEOS/AUDIO recorded from me to be shared with Alice Sansoni (University of Milano, Italy) and used in her thesis and related presentations.

9) **Preferred Contact Details (email):**

* must provide value

10) Full Name of Participant
* must provide value

11) Date
* must provide value

12) Signature
* must provide value

Submit

A.3 Order of properties and socks

Participant 1: PARTICIPANT ID 19

Cloth 3:

1st prop: Softness

2nd prop: Flexibility

3rd prop: Smoothness

4th prop: Thickness

5th prop: Warmth

Enjoyment

Cloth 2:

1st prop: Warmth

2nd prop: Thickness

3rd prop: Softness

4th prop: Smoothness

5th prop: Flexibility

Enjoyment

Cloth 4:

1st prop: Smoothness

2nd prop: Thickness

3rd prop: Flexibility

4th prop: Softness

5th prop: Warmth

Enjoyment

Cloth 6:

1st prop: Softness

2nd prop: Thickness

3rd prop: Flexibility

4th prop: Smoothness

5th prop: Warmth

Enjoyment

Cloth 5:

1st prop: Warmth

2nd prop: Softness

3rd prop: Smoothness

4th prop: Flexibility

5th prop: Thickness

Enjoyment

Cloth 1:

1st prop: Thickness

2nd prop: Flexibility

3rd prop: Warmth

4th prop: Smoothness

5th prop: Softness

Enjoyment

Participant 2: PARTICIPANT ID 22

Cloth 1:

1st prop: Softness

2nd prop: Warmth

3rd prop: Flexibility

4th prop: Thickness

5th prop: Smoothness

Enjoyment

Cloth 6:

1st prop: Softness

2nd prop: Warmth

3rd prop: Smoothness

4th prop: Flexibility

5th prop: Thickness

Enjoyment

Cloth 5:

1st prop: Softness

2nd prop: Smothness

3rd prop: Warmth

4th prop: Flexibility

5th prop: Thickness

Enjoyment

Cloth 2:

1st prop: Smoothness

2nd prop: Thickness

3rd prop: Smoothness

4th prop: Warmth

5th prop: Flexibility

Enjoyment

Cloth 4:

1st prop: Softness

2nd prop: Flexibility

3rd prop: Thickness

4th prop: Smoothness

5th prop: Warmth

Enjoyment

Cloth 3:

1st prop: Softness

2nd prop: Thickness

3rd prop: Flexibility

4th prop: Warmth

5th prop: Smoothness

Enjoyment

Participant 3: PARTICIPANT ID 23

Cloth 1:

1st prop: Thickness

2nd prop: Flexibility

3rd prop: Smoothness

4th prop: Warmth

5th prop: Softness

Enjoyment

Cloth 6:

1st prop: Softness

2nd prop: Flexibility

3rd prop: Smoothness

4th prop: Thickness

5th prop: Warmth

Enjoyment

Cloth 4:

1st prop: Thickness

2nd prop: Softness

3rd prop: Flexibility

4th prop: Warmth

5th prop: Smoothness

Enjoyment

Cloth 2:

1st prop: Warmth

2nd prop: Softness

3rd prop: Thickness

4th prop: Flexibility

5th prop: Smoothness

Enjoyment

Cloth 3:

1st prop: Warmth

2nd prop: Thickness

3rd prop: Softness

4th prop: Flexibility

5th prop: Smoothness

Enjoyment

Cloth 5:

1st prop: Flexibility

2nd prop: Smoothness

3rd prop: Softness

4th prop: Warmth

5th prop: Thickness

Enjoyment

Participant 4: PARTICIPANT ID 21

Cloth 4:

1st prop: Warmth

2nd prop: Softness

3rd prop: Thickness

4th prop: Smoothness

5th prop: Flexibility

Enjoyment

Cloth 6:

1st prop: Flexibility

2nd prop: Warmth

3rd prop: Softness

4th prop: Thickness

5th prop: Smoothness

Enjoyment

Cloth 1:

1st prop: Warmth

2nd prop: Smoothness

3rd prop: Flexibility

4th prop: Thickness

5th prop: Softness

Enjoyment

Cloth 5:

1st prop: Softness

2nd prop: Warmth

3rd prop: Thickness

4th prop: Flexibility

5th prop: Smoothness

Enjoyment

Cloth 3:

1st prop: Thickness

2nd prop: Warmth

3rd prop: Softness

4th prop: Smoothness

5th prop: Flexibility

Enjoyment

Cloth 2:

1st prop: Thickness

2nd prop: Flexibility

3rd prop: Smoothness

4th prop: Softness

5th prop: Warmth

Enjoyment

Participant 5: PARTICIPANT ID 25

Cloth 4:

1^{st} prop: Thickness

2^{nd} prop: Warmth

3^{rd} prop: Flexibility

4^{th} prop: Smoothness

5^{th} prop: Softness

Enjoyment

Cloth 3:

1^{st} prop: Smoothness

2^{nd} prop: Warmth

3^{rd} prop: Thickness

4^{th} prop: Flexibility

5^{th} prop: Softness

Enjoyment

Cloth 5:

1^{st} prop: Softness

2^{nd} prop: Flexibility

3^{rd} prop: Thickness

4^{th} prop: Smoothness

5^{th} prop: Warmth

Enjoyment

Cloth 2:

1^{st} prop: Flexibility

2^{nd} prop: Softness

3^{rd} prop: Smoothness

4^{th} prop: Thickness

5^{th} prop: Warmth

Enjoyment

Cloth 1:

1^{st} prop: Flexibility

2^{nd} prop: Warmth

3^{rd} prop: Thickness

4^{th} prop: Smoothness

5^{th} prop: Softness

Enjoyment

Cloth 6:

1^{st} prop: Smoothness

2^{nd} prop: Warmth

3^{rd} prop: Softness

4^{th} prop: Flexibility

5^{th} prop: Thickness

Enjoyment

Participant 6: PARTICIPANT ID 24

Cloth 5:

1st prop: Smoothness

2nd prop: Thickness

3rd prop: Flexibility

4th prop: Warmth

5th prop: Softness

Enjoyment

Cloth 2:

1st prop: Smoothness

2nd prop: Thickness

3rd prop: Softness

4th prop: Warmth

5th prop: Flexibility

Enjoyment

Cloth 6:

1st prop: Flexibility

2nd prop: Smoothness

3rd prop: Warmth

4th prop: Thickness

5th prop: Softness

Enjoyment

Cloth 4:

1st prop: Softness

2nd prop: Smoothness

3rd prop: Thickness

4th prop: Flexibility

5th prop: Warmth

Enjoyment

Cloth 1:

1st prop: Flexibility

2nd prop: Softness

3rd prop: Warmth

4th prop: Thickness

5th prop: Smoothness

Enjoyment

Cloth 3:

1st prop: Smoothness

2nd prop: Softness

3rd prop: Warmth

4th prop: Thickness

5th prop: Flexibility

Enjoyment

Appendix B: Distribution of the rating variable across properties

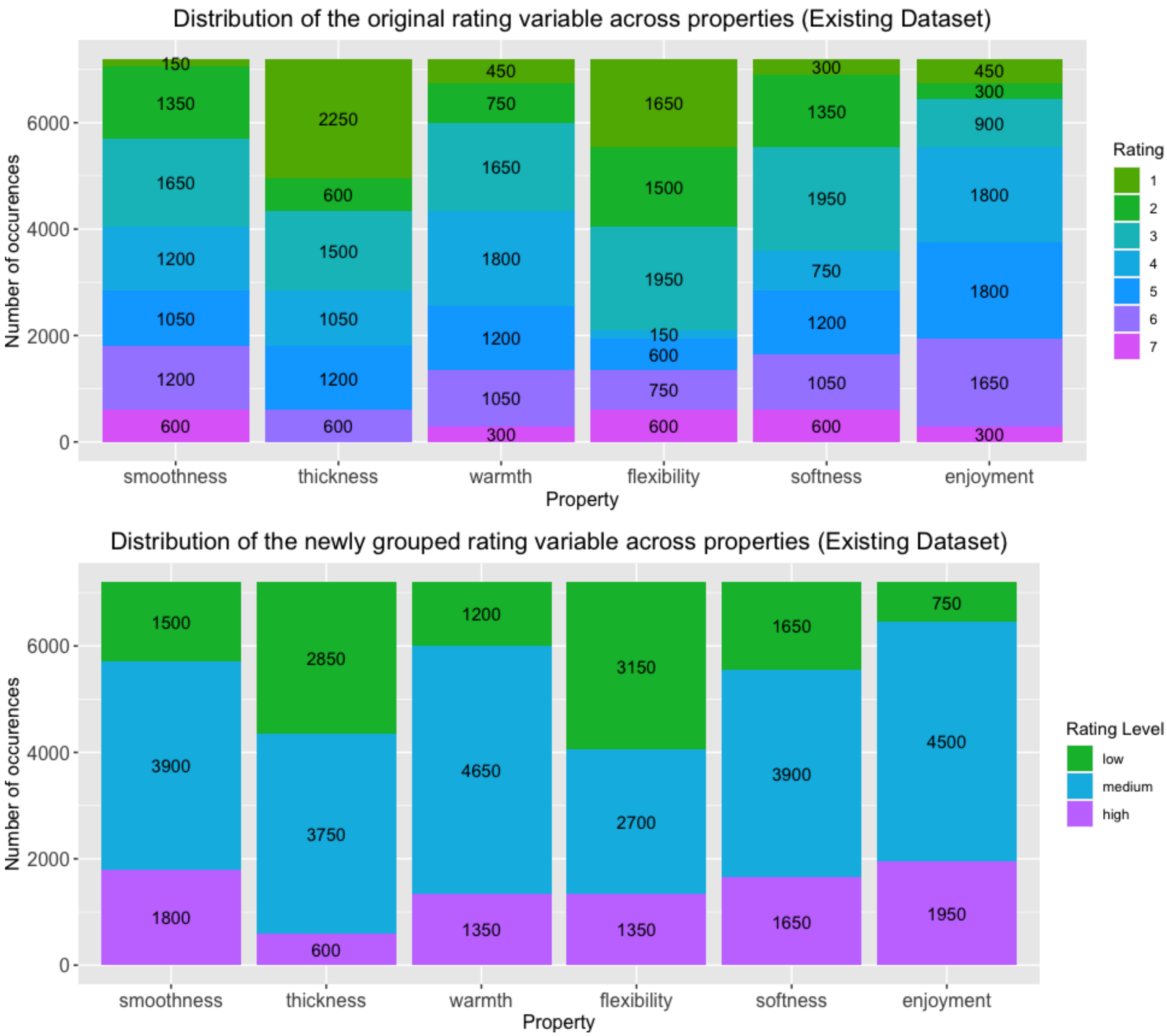

Figure 12: Distribution of the rating variable across properties for the existing dataset

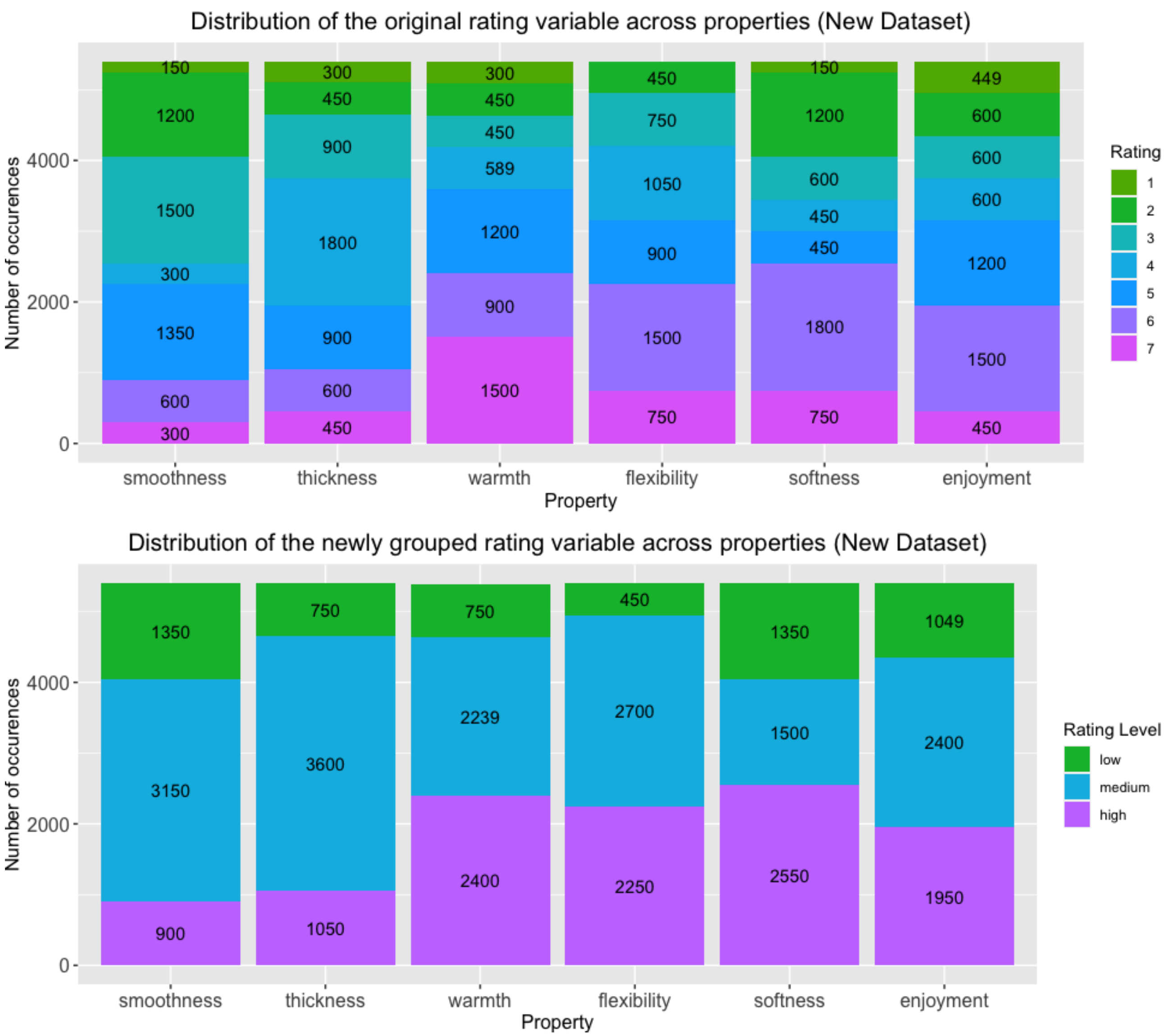

Figure 13: Distribution of the rating variable across properties for the newly collected dataset

Appendix C: Additional Results

C.1 PRHM Property Classification Results

	Dataset 1		Dataset 2		Dataset 3	
	All 180 Features	**Only EMG**	**All 180 Features**	**Only EMG**	**All 180 Features**	**Only EMG**
PRHM based on Random Forest	0.37	0.33	0.34	0.3	0.33	0.28
PRHM based on LSTM	0.23	0.23	0.42	0.39	0.33	0.41
Fully-connected PRHM	0.33	0.25	0.39	0.4	0.45	0.35

Table 13: Average micro F1 scores when predicting properties

C.2 PRHM Rating Classification Results

	Dataset 1		Dataset 2		Dataset 3	
	All Features	**Only EMG**	**All Features**	**Only EMG**	**All Features**	**Only EMG**
PRHM based on Random Forest	0.51	0.49	0.49	0.49	0.47	0.48
PRHM based on LSTM	0.77	0.79	0.72	0.65	0.62	0.63
Fully-connected PRHM	0.67	0.71	0.6	0.64	0.65	0.65

Table 14: Average micro F1 scores when predicting property ratings