MASTER THESIS

Analyzing Cooking Behavior in the Kitchen

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Abstract

Cooking skill plays a vital role in maintaining a healthy diet and also greatly impacts the lifestyle of an individual. Culinary knife skill is one of the important skills when it comes to cooking, which enables you to work faster, making you much more efficient in the kitchen. In addition, it can help you to handle variety of ingredients in an organized way and also open up wider array of recipes to cook. This thesis work deals with cooking behavior analysis of cutting skills using pressure sensor on a cutting board. Classification of the culinary cutting technique is based on the features which are extracted from the time-series signals. Machine learning algorithms are explored for classifying the skill level of the participant and cutting technique. The results show that supervised learning using SVM classifier produced an accuracy of 45% in differentiating the cutting skill level and 72% in differentiating the cutting techniques. Unsupervised learning using K-means clustering technique produced an accuracy up to 96% in differentiating the cutting skill level and up to 84% in differentiating the cutting techniques. These results are very promising for practical activity recognition based applications in analyzing cooking skills.

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Contents

List of Figures

List of Tables

List of Abbreviations

HAR	Human Activity Recognition
HMM	Hidden Markov Model
RFID	Radio-Frequency Identification
WCSS	Within-Cluster Sum of Squares
PCA	Principal Component Analysis
T-SNE	T-Stochastic Neighbor Embedding
FSR	Force Sensitive Resistor
WHO	World Health Organization
ADL	Activities of Daily Living
AAL	Ambient Assisted Living

Chapter 1: Introduction

Having a healthy lifespan is mostly affected by the type and way in which we consume food [4, 6]. Culinary nutrition focused on producing sustainable healthy eating behavior through culinary confidence and nutrition alertness are a plausible proposition to improve lifestyle of individuals [4, 81]. Adhering to unhealthy diet can cause nutrition-related diseases, which in turn can decrease the quality of life. Life expectancy of individuals is rising all across the world. As per the reports of World Health Organization, it is estimated that there will be about 1.2 billion people in the age range of sixty years or older [1]. If we want to live these elderly years without the aggravation of any disease or disability, then we should adopt healthy eating habits. Obesity is one of the main botherations and is progressively becoming a worldwide epidemic. A solution to this is to maintain a healthy lifestyle. A healthy lifestyle is governed by several factors such as the interaction between genes, surroundings and lifestyle choices, especially diet and physical activity [2]. If we want to maintain a healthy lifestyle, then we should assess different techniques and identify all the steps to be taken for their implementation. Although genes are predetermined, factors such as diet and physical activity and their influence are alterable.

Physical fitness is generally achieved through proper nutrition, moderate physical activity and adequate rest. Proper nutrition offers one of the most effective and least costly ways to decrease the burden of many diseases and their associated risk factors, including obesity [2, 71]. Developing an unhealthy eating behavior can result in nutrition-related diseases and thereby decrease the quality of life [2, 70].

The process of improving both cooking knowledge and skills can significantly improve healthful nutrient intake [4]. Cooking is a valuable life skill which is often linked to improved diet quality [3]. There are a variety of barriers that prevent the habit of eating healthy food such as shortage of time or money to buy raw ingredients, lack of knowledge about cooking skills, availability and the ease of access to unhealthy food [6]. Therefore, there is an opportunity to assess and monitor cooking skills in the kitchen on a personal level to help intervene where necessary to promote the usage of these skills.

The kitchen is considered as the ‘heart of the home’ and is where most of the food is prepared with friends and families. It is a place where not only can you share the joy and experience of preparing a meal but also spread the spirit of togetherness, as a social affair to strengthen the bond with others through stories, experience and finding new recipes from each other. Since it is a place that witnesses a lot of activities, there is a lot of potential in knowing human behavior by installing sensors in the kitchen.

Cooking skills have been defined as a set of physical or mechanical skills used in the production of a meal. Knife skills are one of the many important skills in the kitchen as the first step before preparing any meal involves cutting the necessary ingredients. Existing measures for cooking and food skills developed have some limitations as they are mostly in the form of questionnaires/surveys. A key issue is that cooking skills tend to be encompassed in existing measures and skills such as knife skills are not considered as a stand-alone set of skills, but it could be argued whether good knife skills underlie cooking skills in general [66]. Other limitations of previous measures include: the use of certain food for the experiment which may not be transferable to all cultures, developed for specific intervention groups, and not having concise definitions of the skills being measured. Some of the measures also had issues with their validations including test-retest biased sample, using mainly female samples and self-selection bias. In recognition of these drawbacks, objective measurement could be a good approach to overcome these limitations [66]. In order to measure how good one is at cutting, it is important to determine the performance across different cutting techniques. We envision a system that monitors the cooking skill of the participants and that based on their knife skills could provide us with indicators for improving the wellbeing of an individual. For this to happen, the system should first be able to differentiate different cutting techniques.

Measuring cutting skill gives insights about knife grip, knife position, knife speed etc., and how these can be improved to make oneself more efficient in the kitchen. It can also be used to know the association between cutting skills and balanced food choices. Distinguishing cutting techniques provides useful information such as which activity a particular person should follow to complete some food preparation tasks in the kitchen.

It can be seen that culinary cutting skill or 'knife skill' is one of the foundations when it comes to cooking. In order to test the cooking skill of the participant, their cutting technique will be monitored objectively. Three basic knife cuts namely slicing, dicing and julienne will be tested out through a pressure sensor attached on a cutting board using an Arduino microcontroller and used to measure different parameters such as time taken, peak force, intervals between the cuts and number of cuts made in a time interval and analyze data through objective measurement of cutting skills.

To analyze this data and differentiate the cutting technique and the skill level, unsupervised learning can be applied. This unsupervised learning is a type of machine learning algorithm which is used to discover the unknown properties of the data. With the application of unsupervised learning on a participant's cutting technique, it is possible to classify the cutting technique as "skilled" or "novice". Clustering techniques such as hierarchical clustering and K-means will be used to see how closely the cutting style is related to one another. In the sources and literature reviewed during this thesis work, this method for classification has not been applied for cutting-technique classification and will be presented in this work.

1.1 Research Questions

We can see that there is no objective measurement available currently that reflects the cooking skill, whereas, there are several subjective methods in the form of questionnaires available for evaluating cooking skill. In this thesis work, an approach is taken towards designing an objective measurement. Machine learning algorithms can be used to classify whether a participant is skilled or novice. Cooking skills are in general attributed to a healthy lifestyle, however, far too little attention has been paid to objectively evaluate cooking skills, especially the culinary cutting skills.

This research work seeks to address the following questions:

(i) To what extent can you determine the cooking skill of an individual by measuring the cutting technique using a pressure sensor?

(ii) To what extent can you objectively distinguish different cutting techniques from each other in pressure sensor data?

1.2 Thesis Outline

In the last decade, the theme of 'cooking skills' has been the center of explorations and interventions in various countries. However, the notion of cooking skills still does not seem to be adequately discussed, beginning with definitions of the term cooking. Under most approaches, the definition of cooking would be confined to the application of heat to raw foods. Nevertheless, the term can constitute more complex definitions, when standpoints from different fields of knowledge are taken into consideration.

The scenario encourages to explore this topic, since there is neither a consensus on the definition of cooking skills nor a consistent way to measure it. Thus, a notable gap in the studies that assess cooking skills and their association with healthy eating deserve to be highlighted.

This thesis aims to review the concept of cooking skills and a possible way to measure it and contribute to the scientific debate. Chapter 2 provides the background for cooking skills, related work and the basic theory of the methods used. Chapter 3 explains the methods used, study procedure and the data analysis techniques. Chapter 4 presents the results of the methods and in the subsequent Chapter 5, these results are discussed in detail. Finally, Chapter 6 concludes the thesis and presents a section for the future work.

Chapter 2: Background

This chapter presents a review of prior research working the field of activity recognition and cooking skills estimation. After discussing the history of ubiquitous computing, we consider previous related work in the fields of wearable sensing, pervasive sensing, and activity recognition. We then proceed to consider previous applications of computer vision-based and audio-based approaches and why sensor-based approach is a good alternative to the problem of activity recognition.

One way to try and perform objective measurements of cooking and food skills is through simple sensors in the kitchen. Sensor network systems in the kitchen such as temperature sensors on the stove, mat sensors to detect pressure and cabinet door sensors can be used to detect meal preparation activities [8]. In order to understand the cooking and food skill of a person, it is important to interpret the data from the sensor. There are three terms which are essential in behavior recognition. They are "Activity Recognition", "Plan Recognition" and "Goal Recognition" [9]. Activity Recognition refers to predicting the user's current action based on sensor data. Goal Recognition refers to the goal the person is executing. Plan Recognition refers to a sequence of actions leading to the goal using observations. It can be considered as a combination of activity and goal recognition. All in all, behavior recognition comprises the overall process of activity, goal and plan recognition.

In the last 15 years, around 8 billion embedded microprocessors have been manufactured every year and this number has been on the rapid rise [24]. This has remarkably changed the way people interact with computers, indicating the surge in this field, the 'Ubiquitous Computing' era: one person operates many computers, and this data-processing power is increasingly implanted in today's world.

According to Mark Weiser's work [25], the term "ubiquitous computing" refers to a world in which computing devices "disappear" as they are woven into the fabric of our everyday surroundings. Context recognition is a major challenge in the field of ubiquitous computing. The term context itself a wide-ranging term and is usually used to include any information that distinguishes a particular situation from the rest. One of the essential components of many contexts in the field of ubiquitous computing is the activity that the user takes part in, the human activity. Human activity recognition contributes significantly in an extensive range of applications such as preventive health care systems and proactive service provision, yet the development of intelligently built and generally applicable approaches to the depiction of human activity recognition remains a principal challenge.

2.1 Human Activity Recognition (HAR)

Human activity recognition (HAR), is a wide-ranging field of study which involves recognizing the specific movement or action of a person based on sensor data. Here, we are going to discuss two main techniques involved in HAR, namely: (i) Wearable sensing activity recognition and (ii) Non-intrusive sensing activity recognition.

2.1.1 Wearable Sensing Activity Recognition

A great deal of work has tried to tackle the problem of Activity Recognition (AR) using accelerometers and other sensors put on different parts of a user's body. Most of these methods recognize low-level activities such as walking, running or cycling, and have produced accuracies of 80% and higher. A great number of these studies [26, 27, 28] involve wearing accelerometers and using machine learning methods such as supervised and unsupervised learning approaches across different domains. Hence, activity recognition through accelerometers can predict the current action of a person through the motion sensors worn on the body.

In one of the works by Ravi et al. [55], a 3-axis accelerometer was used on the subject's pelvis. They were asked to perform different activities ranging from walking, running to sit-ups and brushing teeth. Different classification algorithms were applied by computing the features using window methods. On one hand, subject-dependent tests revealed an accuracy of up to 90% while on the other hand, subject-independent tests reported low accuracy of 60%. Even though the results were favorable, the data collected were relatively elementary and involved an unnatural setting thereby not accounting for variations in a real world setting. Therefore, there is a need to carry out experiments in a naturalistic environment.

Contrary to the use of a single mode of sensing for activity recognition, Ward et al. [56] used a combination of sensors to detect skilled and semi-skilled activities. The experiment consisted of accelerometers and sound sensors that were affixed to the arm of the subject to recognize activities such as drilling, sanding and grinding. The results exhibited a good amount of recognition because of the fact that it involved the combination of two sensors. That being said, the environment in which the experiment was conducted was not completely naturalistic and was performed in a carefully controlled lab setting. Nonetheless, it is a positive stepping stone for activity recognition in a kitchen-based environment.

An additional heterogeneous approach by Maekawa et al [57], constituted a camera, microphone, accelerometer and a photometer to measure illumination. All these sensors were embedded into one device which was placed on the subject's wrist to detect activities one would normally perform at home such as listening to music, preparing juice, cooking pasta, etc. The variation in the activity described the need for a wide variety of sensors. Hidden Markov Model (HMM) classification algorithms were carried out to process the data that were collected in a semi-natural fashion. The subjects were asked to wear a laptop backpack which allowed the to-and-fro wired transfer of data between the sensor and the laptop. Although the set up was rather inconvenient, it allowed the subjects to perform activities based on their own desires. Therefore, intrusive sensors can cause inconvenience for the subjects and there is a need of unobtrusive sensors.

In a more thorough consideration in the field of wearable activity recognition, Tapia et al. [13] attempted to distinguish 52 activities with the help of 3 accelerometers on the hip, wrist and foot and a heart rate monitor. All in all, an activity recognition rate of 50.6% and 87.9% were obtained for subject independent and dependent assessment, respectively. Position and exercise activities could be precisely and reliably categorized. Additionally, the work exhibited that energy expenditure estimation could be enhanced using a combination of a heart rate monitor and activity dependent models rather than using accelerometer data alone.

On the whole, it can be observed that even though wearable sensing activity recognition provides good accuracy in sensing different activities, it is not a good fit for this experiment as it would cause inconvenience for the participants to chop, dice or julienne the vegetables in their natural cutting style and can hinder their performance.

2.1.2 Non-intrusive Sensing Activity Recognition

Wearable activity recognition approach have quite a number of obstacles based on their general implementation and these include: (a) their responsiveness and sensitivity to the positioning of the sensors and to adopt for this, automatic adaptation wearable sensors have made headway [29]; and (b) the requirement of annotated data sets to apply various machine learning algorithms such as unsupervised training, transfer learning and unsupervised learning [30]. Solving the problems pertaining to positioning and training data not only minimizes the computation time, cost and the overall error brought about by the sensor rearrangement, but can also enhance the efficiency of the activity recognition system [31]. Hence, wearable sensors even though they produce good results are not the best option for detecting activities in the kitchen.

A number of wearable activity recognition applications have been presented, and prototyped, mainly in the field of health and wellbeing. They involve diet monitoring [32], energy expenditure estimation [33], and behavior observation and assessment for autistic children [34]. Mostly, wearable computing activity recognition has been showing potential for the growth of pervasive computing applications. However, it has been observed that subjects are not often comfortable wearing on-body sensors. Wearable sensors often interfere with subjects to perform the activity in their natural state. In our own application of detecting activities in the kitchen relating to food preparation (i.e. slicing, dicing and julienne) on the kitchen instruments themselves (i.e. kitchen utensils such as cutting board) and these are rather different from the movement patterns of the user's body.

Chi et al. [63] developed a nutrition aware kitchen that gives feedback, during the actual preparation of a meal, as to its nutritional value. RFID sensors and scales placed in the kitchen counter detected and quantified ingredients. The system was able to make the participants calorie conscious, and helped in maintaining optimum calorie meal intake. Chang et al. [65] created a dining table using load cells, weight tracking algorithms and RFID technology to measure food intake. This was a significantly less obtrusive solution and involved sensors embedded in the user's environment. The experimental results have shown encouraging recognition accuracy around 80%. Kranz et al. [64] identified various ingredients using a combination of force sensors in the knife, microphones, and load cells in the chopping board. It was reported that the sensors were able to differentiate among six different ingredients.

Overall, we can see that non-intrusive sensors in the kitchen can provide good recognition accuracy and also allows a naturalistic setting in the kitchen environment. This is important for our research because it does not hamper the cutting style of the participant and he/she can perform the experiment in a natural manner.

2.2 Importance of Cooking Skills

In the 20th century, people had to suffer from bad health conditions because of poor food practices [37]. Today, it is accepted that a decrease in cooking skills is associated with bad diet quality and obesity [38]. An underlying issue and central problem in the analysis of cooking skills is the lack of a reliable, universally applicable cooking skill measurement [36].

Management of cooking skills were considered mandatory and taught in schools in the past century [36]. In one of the trials selected in the UK, 49% of women and 15% of men stated cookery classes in schools as a way for getting trained with the necessary cooking skills [39]. Today, mothers are considered as a significant source of learning about basic cooking skills right from young age [39]. Two fundamental problems are discussed as accountable for today's supposed inadequacy of cooking skills. First, there is a reduction in the multigenerational conveyance of basic cooking skills at home [40], and cooking classes in schools are no longer officially taught in the majority of the countries [41]. Secondly, because people's everyday lives are affected by a persistent feeling of time shortage, people tend to take on more time-saving actions even in connection to daily food consumption [42]. This is apparent in the present day speedy food preparations with little effort and in the reduced amount of time devoted for eating. Advancement in food technology has allowed the food industry to acknowledge people's demands with an improved availability of comfort and ready-to-eat food [43]. People regard time and effort when making decisions as to meal selection and adhere to convenience.

As a matter of consequence, cooking skills become infrequently carried out on a day-to-day basis as it is no longer needed to cook to acquire one's daily nutrition supply. The question comes to light if the accessibility of convenience food has led to the decline in cooking skills or if these elements have only coincided with each other. Arbitration studies that focus to promote healthy eating habits should have a rigid theoretical structure designed for enhancing understanding and positively influencing eating behavior. Self-efficacy is a central pillar used to determine the change in behavior. It refers to the confidence to beat the hurdle and successfully attain a particular behavior [44]. Culinary skill self-efficacy that is quantifiable may be successful at identifying productive changes in such behaviors [45]. It is important, however, to offer opportunities to use such learned practices as well as to impart positive reinforcement in order for learning to happen [46]. Practice is crucial to build up confidence to prepare a part of a meal using information and skills learned. The Nutrition and Culinary in the Kitchen (NCK) program was initiated in Brazil to handover knowledge about nutrition and culinary techniques [47]. The initiative allowed participants to improve their cooking skills so that they are able to feel confident and comfortable enough to make healthier food and to opt for nutritious ingredients. Participants cooking behaviors were tested such as: knife skills of slicing, dicing and cutting, elementary cooking techniques (i.e. roasting, sautéing, and pressure cooking), food preservation abilities, and nutrition labeling analysis to assist in the selection of healthy food [48].

The more one cooks for oneself, the healthier one lives. People who often cook dinner at home stay healthier and consume fewer calories than those who cook less [49]. Rather than learning individual recipes, it is necessary to learn techniques. By this manner, one can grasp and learn a few basic fundamentals and have the recipe for preparing all kinds of meals. Basic skills such as cutting vegetables into cubes or julienne strips, to fillet fish or to make simple soups, salads, and salad dressings are some of the important techniques to learn as the foremost thing you do when you start cooking almost any recipe is start cutting things. Having good knife skills can transfer its relationship to cooking, which in turn bridges their relationship to food, which helps maintain sustainable lifestyle changes.

A professional chef or cook knows the significance of mastering the technique of slicing and dicing vegetables. According to the reports of Michigan State University [50], maintaining a healthy diet involves a daily portion of vegetables and fruit, which may need some slicing and dicing. Considering the cutting techniques, slicing and dicing is one of the elementary skills used in the kitchen to prepare food. Along with knowing how to cut various vegetables into different shapes, knowing how to hold a knife and having a grip of the item you're cutting in a way that inhibits you from cutting yourself is equally important. Practicing and learning to grip the knife is a proper way that will not only aid in safety, but also allows you to perform tasks faster and more efficiently. Adequate knife skills also permits you to cut your food uniformly. Uniformity in the cuts is beneficial for two reasons [51]. First and foremost, pieces of food items that are cut in a uniform manner such that they have the same size, cook evenly. Considering cutting potatoes in order to make fries. If the potatoes are cut in an assorted manner, small pieces will cook much faster than the large ones such that when the small pieces are cooked, the large pieces will not be thoroughly cooked. By the time the larger pieces are cooked thoroughly, the smaller pieces will be overcooked creating an imbalance in the dish. Secondly, cutting food items into uniform pieces improves the overall presentation of the meal. Although presentation is not a major factor while cooking at home, the aesthetics can make the meal much more pleasing.

Studies have argued that changes in the way one prepares food can influence individuals' cooking skills and may be interconnected to the cooking knowledge between parents and their children in addition to skills taught at the school setting [52]. Such changes may be also associated with the possible adjustment in the way food is prepared at home, making use of technology (such as toaster, microwave) and of ready-to-eat food products to ease the preparation [52]. Lyon et al. inspected food practices followed by younger and older women in Scotland and recognized that dissimilarities in these practices are linked to current lifestyle. Hence, in this research, women had different levels of cooking knowledge, but they shared similarities in food practices in the kitchen [53]. In this regard, studies have strengthened the importance of positive intervention programs that focus to develop cooking skills, using changes in cooking knowledge, outlook, and behavior related to healthier eating habits and lifestyle [53].

Reicks et al. [54] dealt with the issue of health impact of home cooking on adults. The primary outcomes measured were dietary intake, skillset, cooking behavior, self-efficacy and health outcomes. The analysis of this dataset revealed that only half had a control group and the follow-up interval differed from one to forty-eight months. In this circumstance, the authors underline the wide methodological variability of studies, which involves the lack of methodological accuracy, as well as making use of non-validated instruments to assess cooking interventions. As a result, there is a need to assess such studies in the long term, so as to gather consistent evidence to correlate cooking skills with its effect in nutrition and health.

All in all, we can see that cooking skills can help people to fulfil nutrition recommendation in their daily nutrition supply. They let people opt for healthier food. It is, therefore, important to assess the cooking skills of individuals and see what factors can help them to develop their skills.

2.3 Machine Learning

Machine learning is defined as a field of computer science that developed from studying pattern recognition and computational learning theory in the domain of artificial intelligence. It involves learning and setting up of algorithms that can discover patterns and make predictions on data sets. These strategies work by construction of a model from sample inputs to make data-driven predictions or choices rather than sticking to firm static program instructions [72]. Machine learning algorithms seek to optimize the operation of a certain function by using examples and/or past experience. In general, machine learning can be categorized into two main groups, namely, supervised learning and unsupervised learning.

2.3.1 Supervised Learning

Over the last decade, supervised learning has become an area for a lot of research activity in the field of machine learning. Many of the supervised learning techniques have found application in processing and examining wide range of data. In supervised learning, algorithms adapt to fit a function that relates an input data to an output space. In other words, for a set of input variables ‘x’, the learning algorithm fits a function to predict the output variable ‘y’. The learning method in a basic machine learning model is split into two steps: training and testing. In training process, samples of training data are used as input in which features are gathered by learning algorithm to construct the learning model [73]. In the testing process, learning model uses the implementation engine to compute the prediction for the test or production data. Tagged data is the product of learning model which yields the final prediction or classified data.

2.3.1.1 Support Vector Machine

Support Vector Machine (SVM) is a kernel-based supervised learning algorithm, which is an amalgamation of machine learning theory, optimization algorithms and kernel methods from mathematical analysis. A fair generality of a classifier is accomplished when it reduces training error together with higher testing accuracy for a testing dataset. The training algorithm of SVM maximizes the distance between the training data and class boundary, eliminating unimportant data from the training dataset. Thus, the emerging decision function is dependent only on the training data called support vectors, that are nearest to the decision boundary. Hence, SVM maximizes the boundary by reducing the maximum loss and thereby produces good accuracy compared to classifiers which are formulated on minimizing the mean squared error [74].

SVM is a robust technique for building a classifier. Its objective is to produce a decision boundary between two classes that permits the prediction of labels from one or more feature vectors. This decision boundary, also called as the hyperplane, is aligned in such a way that it is as far as possible from the nearest data points from each of the classes [75]. In this study, we have used Support Vector Machines to differentiate the cutting techniques and the skill level.

2.3.2 Unsupervised Learning

Unsupervised learning is a type of machine learning algorithm where the data set consists of only inputs. This means that the inference is drawn from the data set that has no labels and classes. In supervised learning, the algorithm takes a known set of input dataset and its known responses to the data (output) to learn the regression/classification model. Therefore, the procedure taken to perform the tasks in unsupervised learning is very much distinct from that of supervised learning. Algorithms are made to work themselves to perform the task and uncover the patterns and structures in the data. Analytical measures should be taken to validate the tasks carried out by unsupervised learning algorithms.

Unsupervised learning can be broadly divided into two major types:

- Clustering - It is the process of finding similarities in the data patterns. There are various clustering algorithms, and utilization of these algorithms depends on the type of data.

- Association - Association allows discovering interesting relations within the database. For example, a group of people who prefer ordering food over cooking food at home.

In this research, we shall focus more on clustering as it involves grouping a set of objects in such a manner that objects in the same group are more similar than to those object belonging to other groups.

2.3.3 Clustering

Clustering is a process of gathering or grouping similar data points. The aim of this unsupervised machine learning technique is to find similarities in the data point and categorize similar data points together. Grouping similar data points together help characterize the attributes of different groups. In other words, this will give us an accurate and deep understanding of the underlying patterns of different groups. In this section, different clustering algorithms will be explored.

2.3.4 Dissimilarity Measures

In cluster analysis, to determine the similarity or associativity between two data points one has to specify a distance metric. This is called as dissimilarity measure.

Most commonly used distance measures are:

- Euclidean Distance - It is the measure of the distance between two points in two or three dimensional space.

$$d_{euc}(x, y) = \sqrt{\sum_{i=1}^{n} (x_i + y_i)^2} \qquad \textit{Eq. 2.1}$$

- Manhattan distance - In this method the distance is measured along the axes at right angles.

$$d_{man}(x, y) = \sqrt{\sum_{i=1}^{n} |(x_i - y_i)|} \qquad \textit{Eq. 2.2}$$

2.3.5 K-means Clustering

K-means clustering is one of the simplest and recognized unsupervised machine learning algorithms [58]. The algorithm to begin with, needs k as the number of clusters the data points have to be grouped into. The algorithm begins by assigning k centroids randomly. Next, individual data point is allocated to the cluster based on the least Euclidean distance between the point and the cluster. Let $X = x_1, x_2 \dots x_n$ be the set of data points that needs to be clustered into cluster sets $S = s_1, s_2 \dots s_k$. The data points have d dimensions. Subsequently, each data point can be denoted as:

$$argmin_{s_i \in S} \left(\sqrt{\sum_{i=0}^{d} (s_i - x_i)} \right) \qquad \textit{Eq. 2.3}$$

K-means is an immensely fast and less complicated algorithm compared to other clustering algorithms. However, its execution is usually not as ambitious as those of the other advanced clustering techniques because slight disparities in the data could lead to high variance.

2.3.6 Hierarchical Clustering

Hierarchical clustering is a type of clustering where homogenous data points are grouped together in a hierarchical fashion [59]. It is broadly divided into two types. They are Agglomerative and Divisive Clustering. These two classes of clustering methods are dependent on the distance metric and linkage criteria, which has to be calculated. Distance metric calculates the dissociation between two points, which implies that similar points are closer and the dissimilar points are farther from one another. Linkage criteria deduces the point from where the distance is measured between two clusters. For instance, when considering the mean distance between two clusters, the distance from the middle of one cluster to another is measured.

2.4 Cluster Evaluation Techniques

Assessment of the clusters is necessary to determine the quality that they display. If the entities in the cluster are similar, then the cluster quality is high. Low intercluster similarities and high intra-cluster similarities is a good depiction of the clusters created for the complete data set.

2.4.1 Silhouette Score

Silhouette score is an evaluation technique to measure how similar an object is to its own cluster compared to other clusters [60]. The silhouette score spans from -1 to $+1$, where a high value indicates that the object is similar to its own cluster and a low value indicates that it is poorly matched to neighboring clusters.

Mathematically it can be depicted as seen in Equation below. Let i be the data point that is associated with cluster a, and let $a(i)$ constitute the mean distance between i and other points in the same cluster, $b(i)$ represents the mean distance between i and the neighboring clusters. Thus, the silhouette score $s(i)$ is expressed as:

$$s(i) = \frac{b(i) - a(i)}{\max\left(a(i), b(i)\right)}$$

Eq. 2.4

2.4.2 Elbow method

In cluster analysis, the elbow method is a process used in calculating the number of clusters in a data set [61]. The criterion that estimates the elbow point is Within-Cluster Sum of Squares (WCSS). A cluster that is close-packed will have a smaller sum of squares, and a cluster that is wide-spread will have a higher value. Elbow point is situated where the WCSS reduces drastically from the previous observation. From Figure 2.1, it can be seen that the WCSS value falls as the number of clusters reaches 3. It can also be observed that WCSS drops notably when cluster number is 2. This makes it rather uncertain to use the elbow method. One has to verify it with other empirical methods and/or silhouette score technique to calculate the number of clusters.

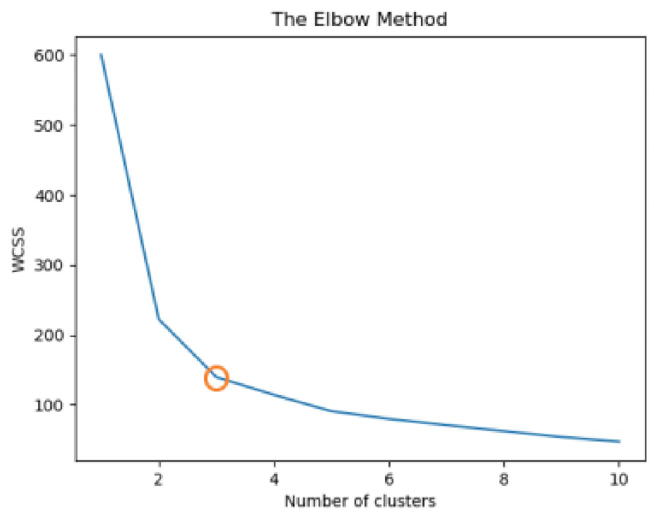


Figure 2.1: An example showing the elbow point where an increase in the number of clusters (x-axis) causes the WCSS value (y-axis) to decrease.

2.5 Dimensionality Reduction

When the number of features in the data set rises, it becomes laborious to elucidate or visualize the date in 2 or 3 dimensions. Dimensionality reduction techniques minimizes the number of features in a data set into principal components in such a way that these components hold most of the important information. The two major types of dimensionality reduction techniques are Principal Component Analysis (PCA) and T-Stochastic Neighbor Embedding (T-SNE). Principal Component Analysis (PCA) is dimensionality reduction technique where a set of possibly correlated variables are converted into a set of linearly uncorrelated variables called principal components [62]. T-Distributed Stochastic Neighbor Embedding (T-SNE) is a technique for dimensionality reduction that is especially applicable for the visualization of high-dimensional dataset.

2.6 Conclusion

A significant academic output exists that assess human activity recognition (HAR) and in particular the recognition of food preparation activities. The literature covers common approaches sensing configurations for HAR in wearable sensing and non-intrusive sensing. The principal drawback of previous work on wearable sensing for HAR is the obtrusive nature of the systems that users are required to wear, and in many studies users consistently express their skepticism as to the practicalities of wearing sensors solely for the purpose of recognizing their everyday activities. For these reasons, we deem that both wearable sensing is not suitable technology configurations for our approach.

To summarize, in this chapter, activity recognition and the sensors used in activity recognition were introduced. Followed by that, the importance of cooking skills and the factors that make up cooking skills are discussed. Moreover, related work on which this thesis is based on was presented. Lastly, concepts of machine learning used in this thesis were presented.

Chapter 3: Methodology

This chapter explains the description and discussion on the various techniques and procedures used in the study to collect and analyze the data, allowing readers to evaluate the reliability and validity of the research.

3.1 Study Materials

This section describes the various materials and equipment used in the experiment set-up.

3.1.1 FSR Pressure Sensor

With the idea of detecting low-level food cutting techniques and to differentiate a person who is skilled at cutting from a novice, a set of custom made cooking cutting board was created, which was embedded with an FSR (Force Sensitive Resistor) that allowed to measure physical pressure. This has an active area of 44x38 mm and a range of up to 1000 Pa [69]. An Arduino Uno microcontroller, which is able to convert analog readings to digital with the help of a variable resistance, is integrated with the sensor.

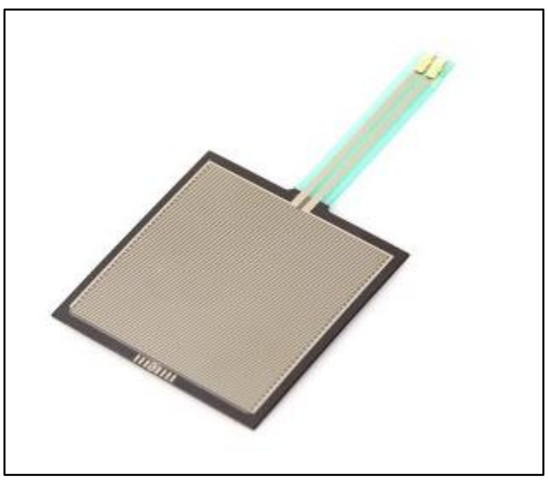


Figure 3.1: FSR 400 Pressure Sensor.

3.1.2 Arduino Uno Microcontroller

In order to control the working of the pressure sensor, Arduino Uno microcontroller was used. The Arduino Uno is an open-source microcontroller board that works on a Microchip ATmega328P microcontroller which is developed by Arduino.cc. The board comes with sets of digital and analog input/output (I/O) pins that can be used to connect and communicate with other circuits. The board is programmable with the Arduino IDE software, via a type B USB cable [68]. The straightforward way to set up the pressure sensor is to connect one end to Power and the other to ground through a pull-down resistor. Then the point between the fixed pulldown resistor and the variable FSR resistor is connected to one of the analog inputs of a microcontroller. The connection is as shown in the Figure 3.2.

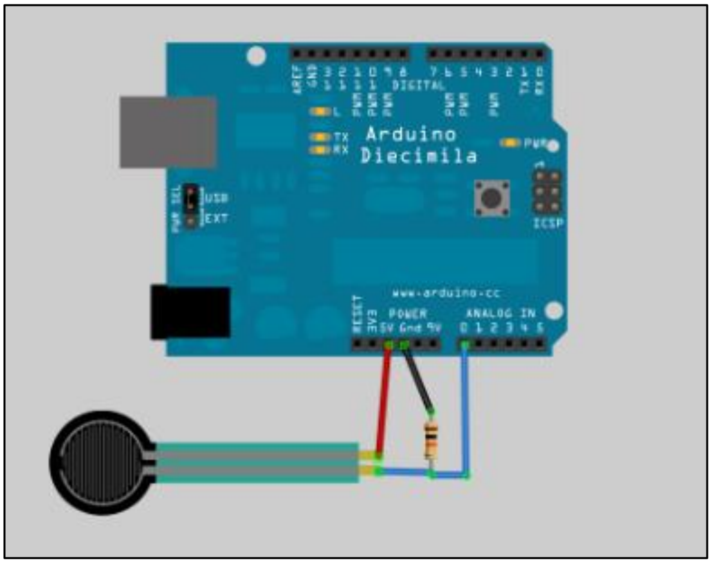


Figure 3.2: Arduino Microcontroller and its connection with the FSR Pressure sensor.

3.1.3 Cutting Board

The cutting board used is a 29*19 cm flexible polypropylene plastic non-slip type which is typical of the surface area of the chopping board in everyday use. The sensor is placed underneath the cutting board approximately at the center.

3.1.4 Kitchen Knife

A kitchen knife is any knife that serves its purpose to cut food items in food preparation. While much of this work can be carried out with a few general-purpose knives, there are numerous specialized knives that are developed for specific tasks. The knife used for the experiment is common for all the participants. It is a serrated utility knife of length 12 cm, which is longer than a paring knife, but shorter than a chef's knife. The utility knife is a reliable all-rounder in the kitchen. It is ideal for general culinary cuts such as slicing, dicing and julienne.

Figure 3.3: Serrated Utility knife

3.2 Recruitment and consent

The target population of the study was composed of university students. Sample recruitment and selection of participants for the cutting experiment was carried out taking into consideration some inclusion criteria: (1) being in the age range of 18 and above; (2) signing the Consent Form. Lead researcher of this study had sent an electronic (e-mail) invitation to the subjects that fit the criteria for inclusion to participate in the experiment.

3.3 Settings for the Kitchen Environment

The kitchen is organized much like any kitchen in a regular house. The chopping board along with the sensor and the knife sits on the work surface located between the stove and sink. To facilitate capture of cutting activities, a digital camera is installed. The overall layout of the kitchen is shown in Figure 3.4.

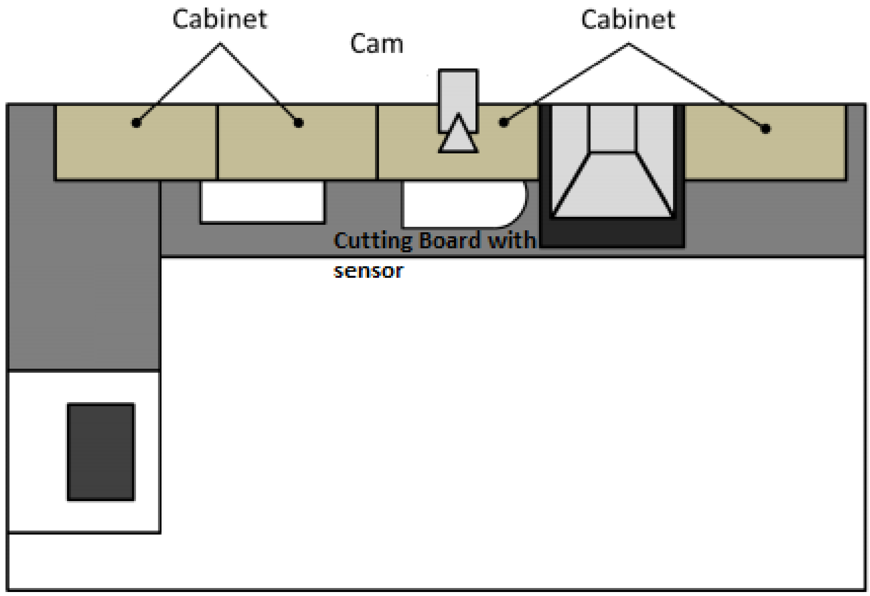


Figure 3.4: Layout of the kitchen which shows the cutting board and the digital cameras installed used for recording cutting activities.

3.4 Modifications due to Coronavirus

Special care was taken to make sure that the experiment was free from coronavirus risks. Initially 20 participants were supposed to perform the experiment in the university's smart kitchen. Due to coronavirus risk, the experiment was shifted to the student housing. The experiment was conducted only with participants living in the student housing and was restricted to 6 participants. Each participant had to perform 3 trials for slicing, dicing and julienne respectively. Surfaces and objects (e.g. knives, cutting board) were cleaned thoroughly before and after the experiment. At a time, only one person was allowed in the kitchen. The participant was verbally given all the necessary instructions to perform the experiment and the participant learnt about the cutting style through the help of a demo video before entering the kitchen. A distance of 1.5 meters was maintained between the instructor and the participant. Before the start of the cutting sessions, a questionnaire was administered to the subject. The questionnaire addressed questions relating to cooking skills and eating behavior of the subject.

3.5 Study Procedure

6 subjects were recruited through an email advertisement. To test the knife skills, healthy (without any visible defects) and uniform size potatoes of homogeneous physical structure were used. Weight of each potato was measured with the help of a weighing scale to make sure that they are of approximately the same weight. The potato to be cut was held on the active area of the sensor. The knife used for the experiment was a basic chef's knife as shown in the Figure 3.3. Pressure exerted on the test sample with knife travel during cutting was displayed on the laptop.

Overall each subject was required to cut the potato in three different styles (slicing, dicing and julienne). To start, a subject was introduced to the methods and procedure of the experiment, and asked to sign the consent forms. The subject was then given the instruction. An important element of the experimental design was that subjects needed to have a good understanding of all the steps prior to them performing the experiment. The subjects learnt about the cutting style through the help of a demo video.

The experiment session starts with a synchronization procedure. This was carried out by the experimenter who in plain view of a camera distinctively tapped the cutting board on a kitchen surface 5 times, thereby making appropriate peaks for pressure data synchronization. After the synchronization step, the subject was left alone to perform. During the cutting procedure, no time constraints and no instructions were provided to the subject.

All data was recorded on an Arduino microcontroller connected to a laptop near the wall of the kitchen. The pressure data was written into one excel file. Each sample was written with its timestamp. The camera recorded the video of all the trials and the video was named with the participant ID. Pressure data recorded from the session was processed by Matlab processing software. This signal had a power spectrum with high and low frequencies. Thus, a low pass filter with a cut off frequency of 150 Hz was designed. The power spectrum of the new signal was obtained such that the frequencies below 150 Hz were kept. This helps in the peak analysis of the signal.

3.6 Culinary Terms: Slicing, Dicing and Julienne

Slicing is cutting a food item into fairly broad, thin sections. Based on the food, slices can be crosswise or lengthwise.

Figure 3.5: An example of potato slices.

Dicing is a culinary knife cut technique in which the food product is cut into small chunks or dice. This is usually carried out for aesthetic purposes and also to produce evenly sized pieces to ensure uniform cooking. Dicing helps in the diffusion of flavor and texture in the dish, as well as a makes the cooking process faster. Dicing is usually used for vegetables but it can also be used in the preparation of meat or fish and fruit [67].

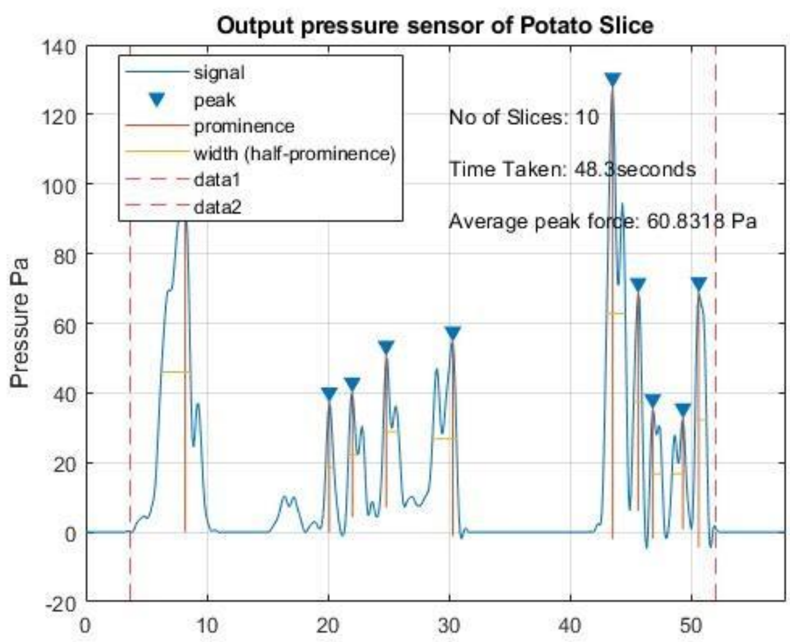
Figure 3.6: An example of potato dices.

The Julienne technique is used to cut foods into long, thin matchstick-like pieces. Hence they are also known as matchstick cuts. This is a cutting style that is usually used for vegetables like potatoes, zucchini, carrots, celery and capsicum.

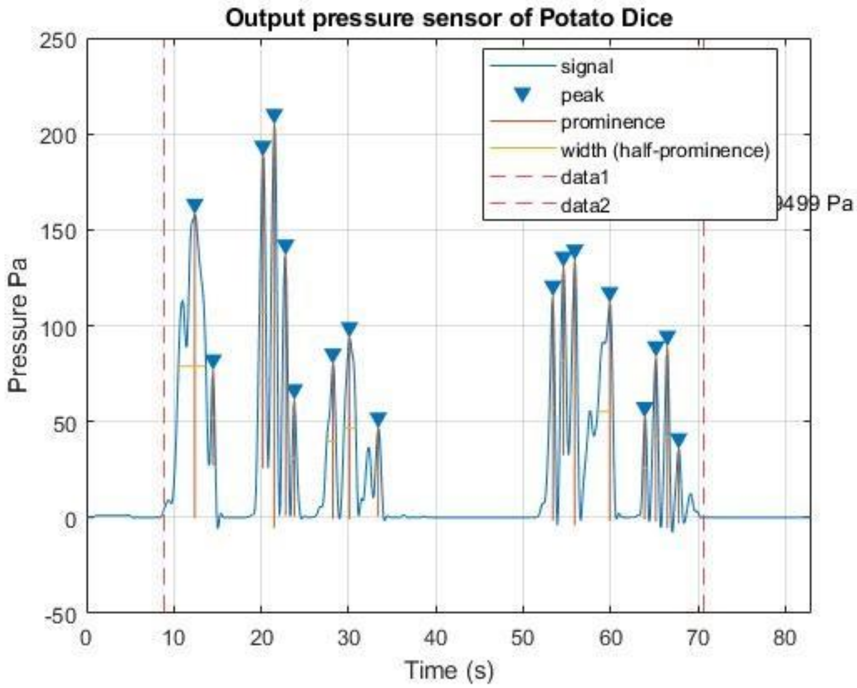
Figure 3.7: An example of potato julienne.

3.7 Data Annotation: Slicing, Dicing and Julienne

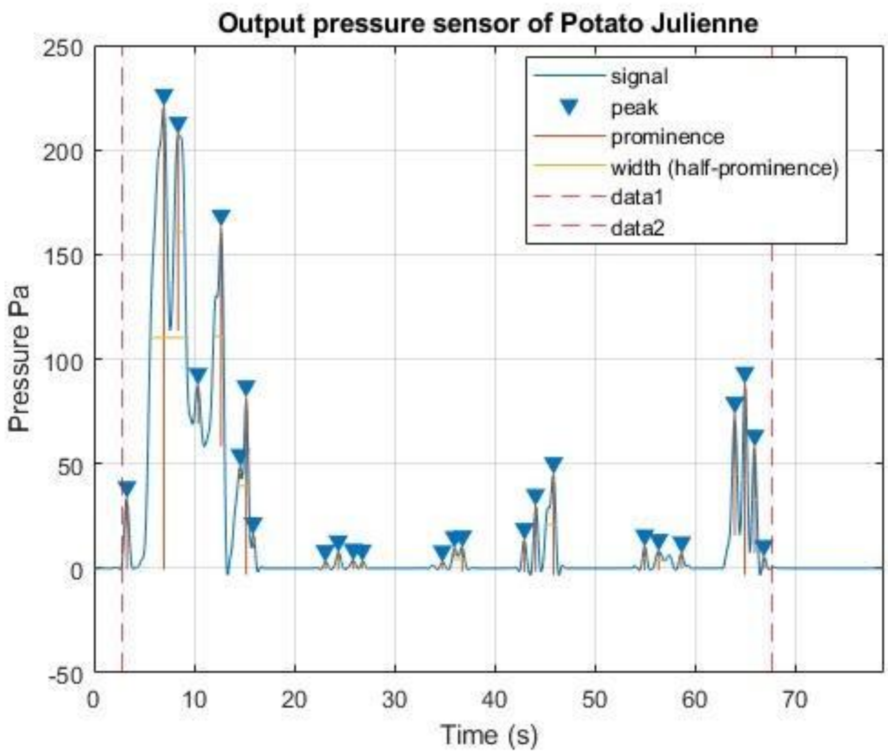
The illustrations of activity, and the pressure patterns for these activities, are shown in Figure 3.4. These pressure signals obtained are analyzed using Matlab processing software. Findpeaks function is used to returns a vector with the local maxima (peaks) of the input signal. These peaks represent the cutting activities. We therefore require our prototype to be capable of classifying each of these activities.



(a) Slicing



(b) Dicing



(c) Julienne

Figure 3.8: Pressure waveform of different cutting activities. Features are extracted from the cutting activities using the 'findpeaks' function in Matlab.

3.8 Pilot Study

To test our pressure sensor, a pilot study was conducted using potatoes. One subject was asked to slice, dice and julienne 10 potatoes. The recording session was carried out with the help of a camera that started when the subject started the activity. The data was collected using an Arduino microcontroller. After collection, the pressure data was segmented and used for testing.

3.9 Cooking Skills Assessment Questionnaire

Cooking skills questionnaire, consisting of 14 items which encompasses different techniques applied in cooking is used for the subjective analysis of the participant [66]. Participants are asked to rate how good they are at each skill, on a scale of 1–7, where 1 is very poor and 7 is very good. If a skill is not used, an option of ‘never/rarely do it’ is available for participants to tick. The cooking skill score is the average sum of the 1 to 7 ratings for all the skills that were stated as used.

1. ‘Chop, mix and stir foods, for example chopping vegetables, dicing an onion, cubing meat, mixing and stirring food together in a pot/ bowl’
2. ‘Blend foods to make them smooth, like soups or sauces’ (using a whisk/blender/food processor etc.)
3. Steam food (where the food doesn’t touch the water but gets cooked by the steam)
4. Boil or simmer food (cooking it in a pan of hot, boiling/bubbling water)
5. Stew food (cooking it for a long time (usually more than an hour) in a liquid or sauce at a medium heat, not boiling) e.g. beef stew
6. Roast food in the oven, for example raw meat/chicken, fish, vegetables etc.
7. Fry/stir-fry food in a frying pan/wok with oil or fat using the hob/ gas rings/hot plates
8. Microwave food (not drinks/liquid) including heating ready-meals
9. Bake goods such as cakes, buns, cupcakes, scones, bread etc., using basic/raw ingredients or mixes
10. Peel and chop vegetables (including potatoes, carrots, onions, broccoli)
11. Prepare and cook raw meat/poultry
12. Prepare and cook raw fish
13. Make sauces and gravy from scratch (no ready-made jars, pastes or granules)
14. Use herbs and spices to flavor dishes

Table 3.1: Cooking Skills Assessment Questionnaire devised from National Diet and Nutrition Survey (NDNS) [66]. Participants are asked to rate how good they are at each skill, on a scale of 1–7, where 1 is very poor and 7 is very good.

3.10 Experiment

A dataset which is collected under realistic conditions is more likely to be of importance to the development and estimation of dependable, robust machine learning algorithms for activity recognition, as it would capture much of the variation that actually occurs as a consequence of the naturalistic performance of kitchen activities. Such an analysis would be further strengthened if subjects that participate in such studies have different levels of skill set (i.e. skilled and novice). First we depict the design and collection of a dataset involving 6 subjects, in which each subject is involved in cutting the potato in three different styles in the naturalistic setting of the kitchen. These subjects will be given 3 potatoes, each for the respective style of cut and the knife and chopping board, which is attached to a pressure sensor. During the cutting session subjects will perform the activities at their own pace, and in their own natural style. Prior to the session, subjects will be given instructions through the help of a video that will show how the cuts should look for the respective style.

3.11 Pre-processing and Feature Extraction

The time-series data consists of raw information provided by the pressure sensor like cutting force, total time taken etc. This raw information is used along with built-in functions in Matlab to extract the features that characterize the participants' cutting technique and different cutting styles. In this section, these features along with the methods and calculations used to extract them are discussed.

Cutting force is linked to angle and sharpness of the knife blade, as well as the various cutting action mechanisms and blade movements and the relative movement of the object and cutting device which is dependent on the user [77]. Knife cutting speed and contact surface area of sample significantly influences magnitude of force required to cut [78]. This can be differentiated by calculating peak force. Knives cut crisp and faster when the blade is used in a back and forth motion and this allows the blade to move up and down at the same time. It also enables you cut more rhythmically, which enhances consistency and speed [76]. This can be distinguished by calculating the peak interval in the pressure signal. The goal of a chef is to make a good meal as fast and proficiently as possible, while reducing mess and later cleanup [79]. In general, novices take longer time to cook because of their poor cutting skills and lack of productivity. Hence, we can see that total time taken would be an important criteria to distinguish the skill level of the participants. Moreover, every professional chef knows that the shape and size of an ingredient is important for the overall taste of the dish. This is because ingredients that are cut into uniform pieces at an appropriate size not only cook more easily, but also improve the taste of the dish [80]. Hence, the symmetry and the uniformity is an important feature and can be tested by calculating the skewness and kurtosis of the peaks.

This section helps in establishing a relation between skilled and novice cutting style as well as the relation between slicing, dicing and julienne. The features are based on the pressure data obtained from the cutting board as the source of the data was a pressure sensor. These features are extracted using Matlab processing software as shown in Figure 3.8. The features that are used to classify the skill level and the cutting techniques are listed below:

- Average Peak Force
- Total Time Taken
- Number of Peaks
- Average Peak Interval
- Average Peak Width
- Skewness
- Kurtosis

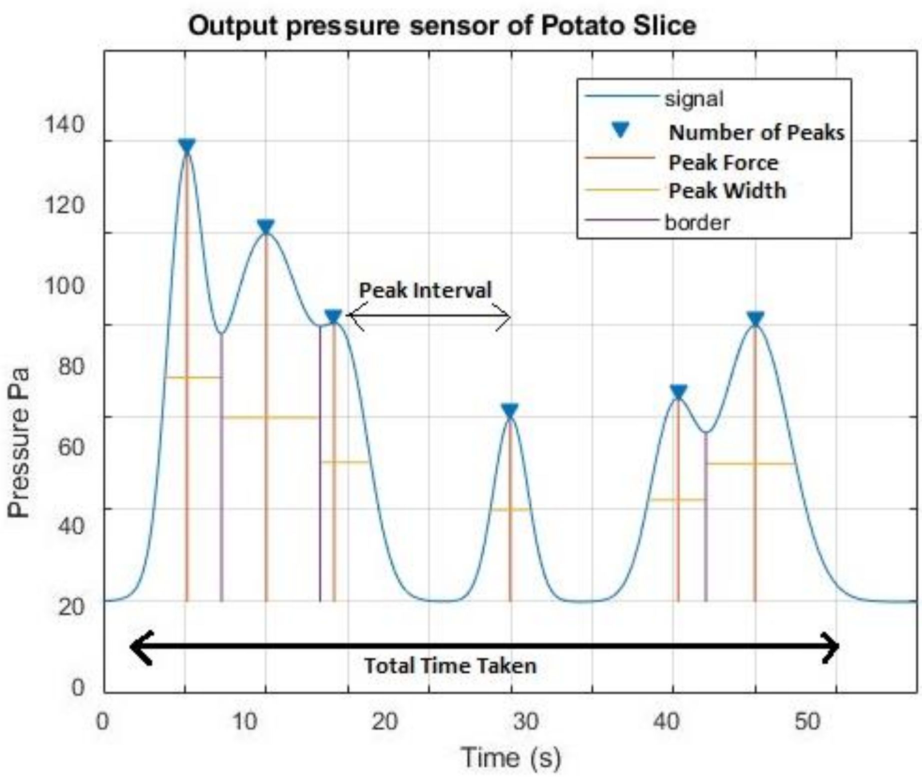


Figure 3.9: Example of feature extraction from the pressure data. These features are extracted using 'findpeaks' function in Matlab.

- Peak force refers to the amount of force applied by the participant while cutting. Cutting tool parameters such as knife sharpness, knife angle and speed of cut directly influence the shape of final samples and the required cutting force and energy for slicing or cutting operations. The maximum and minimum variation in the average peak cutting force varies for different vegetables. High speed (40 mm min−1), with a large knife-edge angle (25°) requires the highest force and specific energy to cut the vegetables, however, low speed (20 mm min−1), with a small knife-edge angle (15°) is preferred [78].

- Total Time denotes the start and the end of the cutting activity thereby giving how much time it takes for a participant to complete the task.

- The number of peaks denote the number of cuts made through the due course of the trial.

- Peak Interval denotes the time interval between two consecutive cuts. Slice or cut through the potato at nearly regular intervals results in a relatively uniform cut.

- Peak Width of a peak is the peak's full width at half maximum and denotes the time period for one cut.

- The skewness value can be positive or negative, or even undefined. If skewness is 0, the data is perfectly symmetrical, thereby depicting the symmetry in the cut. If skewness is less than -1 or greater than 1, the distribution is highly skewed.

- Kurtosis is a measure of the combined weight of a distribution's tails relative to the center of the distribution. The results can be tabulated for all the participants which can be used to differentiate between a skilled and novice user. Also, it can be used to compare with the results of the questionnaire.

Moreover, it was also found out using t-tests that there were no significant differences with features such as kurtosis, peak width and number of peaks among various cutting techniques. Hence, these features were not considered for further analysis.

3.12 Clustering: Unsupervised Learning

In this technique, no ground truth regarding the cutting technique is assumed and unsupervised learning is performed on the features extracted from the data sets.

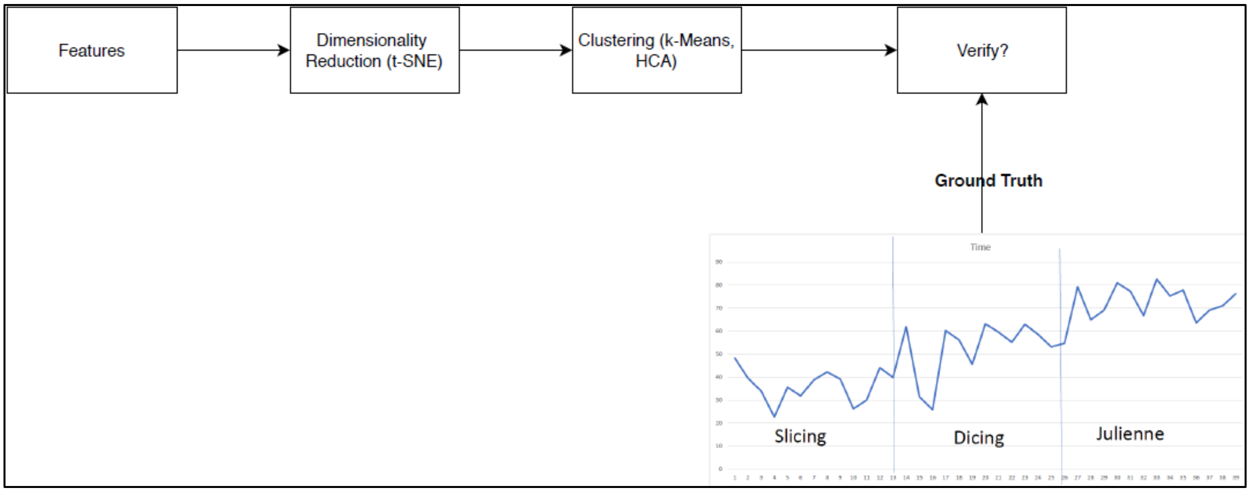


Figure 3.10: Flowchart for unsupervised learning. As seen, there is no supervision required, the model works on its own to discover information.

Typically unsupervised learning consists of clustering where a cluster is visualized in 2 or 3 dimensional space. The features extracted cannot be visualized in this limited dimensional space, so there is a need to reduce the dimensions keeping implied data intact. This is done making use of dimensionality reduction techniques. The process of clustering is presented in the Figure 3.10.

Using PCA and T-SNE, features are reduced to two dimensions. K-means clustering technique used to categorize the cutting styles. This leads to 2 dimensionality reduction technique in combination with a clustering algorithm. PCA and T-SNE reduce the dimensionality of the feature space by obtaining a set of principal features. In this way, we could eliminate redundant and irrelevant features without suffering much loss of data.

The clusters formed from these features will be compared will help conclude a relation between Slicing, Dicing and Julienne. T-SNE is a non-linear dimensionality reduction technique mostly used for visualization purposes. One of the advantages of using this technique is that it brings similar points in higher dimensional space closer when projected onto the lower dimensional space.

3.13 Support Vector Machine: Supervised Learning

Supervised learning methods are used such that all data is labeled and the algorithms learn to predict the output from the input data. One the main classification technique used is Support Vector Machine. Support vector machines (SVMs) are a set of supervised learning methods used for classification, regression and outliers' detection. Using support vector machines, cutting technique and skill level classification are considered. The different features in the dataset, consists of values for 54 (18*3) participants. A fetcher for the dataset is built into the Scikit-Learn package.

Principal component analysis is used to extract fundamental components to feed into our support vector machine classifier. For the sake of testing our classifier output, we will split the data into a training and testing set. The training and testing split used here is 43 and 11 respectively. Finally, grid search cross-validation is used to explore combinations of parameters. Here C (which controls the margin hardness) and gamma (which controls the size of the radial basis function kernel), are adjusted to determine the best model.

3.14 Ethical Considerations

This study has been approved by the Ethics Committee of the Faculty of Electrical Engineering, Mathematics and Computer Science (EEMCS) under the Biomedical Signals and Systems (BSS) discipline of the University of Twente. All participants in this study agreed with the informed consent form.

Chapter 4: Results

In this chapter the results of the study are presented with reference to the aim of the study, which is to differentiate the skill level of the participants and the cutting techniques. The results are presented using graphic representations of the cluster analysis and the questionnaire along with the numeric interpretation.

4.1 Overview of the Data Set

In this section, we will explain the data sets used to model and evaluate the clustering process illustrated earlier in Chapter 3. Six subjects had participated in the acquisition of this data set. To differentiate between 'skilled' and 'novice' cutting skill as well as the cutting techniques certain features are selected as described before and the a general overview of the features among the participants are show in Table 4.1 and Table 4.2 respectively. The experiment was performed during the month of May. The device used to collect the data is a PLX pressure sensor attached under the cutting board with the help of an Arduino microcontroller.

	Slicing		Dicing		Julienne	
	Average Time Taken (s)	Standard Deviation	Average Time Taken (s)	Standard Deviation	Average Time Taken (s)	Standard Deviation
Participant 1	33.57	5.01	43.87	1.93	70.60	0.9
Participant 2	38.93	3.05	48.10	2.55	75.93	1.52
Participant 3	44.97	0.41	58.67	2.95	82.43	2.03
Participant 4	30.07	3.62	37.53	2.77	61.07	2.25
Participant 5	35.47	1.20	51.93	1.65	78.43	3.39
Participant 6	36.02	4	53.17	2.33	78.37	3.2

Table 4.1: Descriptive statistics of all the participants for the cutting techniques as a function of Average Time Taken.

The data from six participants were measured at different time. Each participant was asked to perform each cutting activity 3 times, resulting in an overall data set of 54 readings. Thus, it created 18 instances of slicing, dicing and julienne respectively. From Table 4.1, we can see that, on average, participants took 36.5(±2.88), 48.8(±2.36) and 74.4(±2.21) seconds to slice, dice and julienne potatoes respectively. Table 4.2 shows the average force distribution among different participants in the three cutting techniques. It can be seen that the overall force used for slicing and dicing is higher compared to julienne. On average, participants applied 59.42(±10.44), 55.90(±9.45) and 32.95(±6.63) Newton of force to slice, dice and julienne potatoes respectively.

	Slicing		Dicing		Julienne	
	Average Force (N)	Standard Deviation	Average Force (N)	Standard Deviation	Average Force (N)	Standard Deviation
Participant 1	58.89	1.98	56.82	17.91	29.43	3.57
Participant 2	59.98	12.37	64.03	8.95	34.23	4.80
Participant 3	65.76	11.37	58.8	9.81	39.1	3.5
Participant 4	62.7	19.87	68.3	8.21	31.92	4.94
Participant 5	56.99	9.52	42.23	7.36	34.96	14.77
Participant 6	52.2	7.56	45.24	4.49	28.1	8.21

Table 4.2: Descriptive statistics of all the participants for the cutting techniques as a function of Average Force.

4.2 Results of the Questionnaire

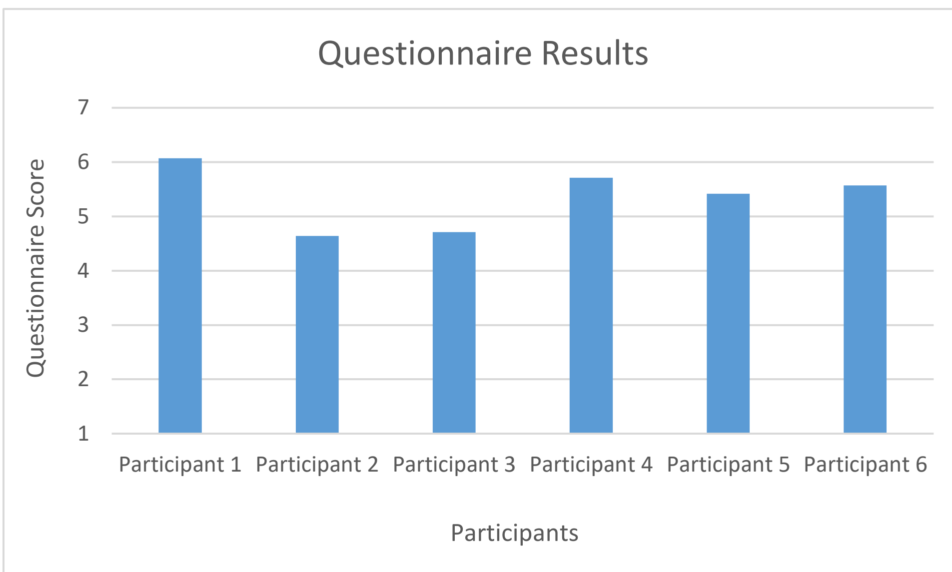


Figure 4.1: Results of the Cooking Skill Assessment Questionnaire

Participants' cooking skills were measured using the questionnaire consisting 14 items and their mean scores for each item was found. The questionnaire consisted of questions mainly related to different steps usually performed during cooking such as cutting vegetables, preparing sauces, baking cakes, frying meat etc. The mean scores of the participants are shown in Figure 4.10. All factor loadings were above the minimum criterion. 'Food preparation Novices' reported using

Chopping, Microwaving, Boiling, Roasting, and frying/stir-frying (100%) as top used skills in cooking. In comparison 'Experienced Food Preparers' reported using Peeling, Frying/stir-frying, Roasting, Boiling, Blending and chopping (100%) and Baking, preparing and cooking raw meat/poultry, and using herbs and spices (97.5%) as their top skills.

4.3 Clustering: Unsupervised Learning

The data set obtained is used to perform clustering to give visual indication of the cutting level and the cutting technique. First and foremost, the number of dimensions are decreased using dimensionality reduction techniques such as PCA and T-SNE. Then, we execute clustering using K-means and agglomerative methods. Later, we compare the different methods and deduce which method is more appropriate for this data set. The clusters obtained are evaluated with different clustering performance evaluation metrics.

4.3.1 Principal Component Analysis

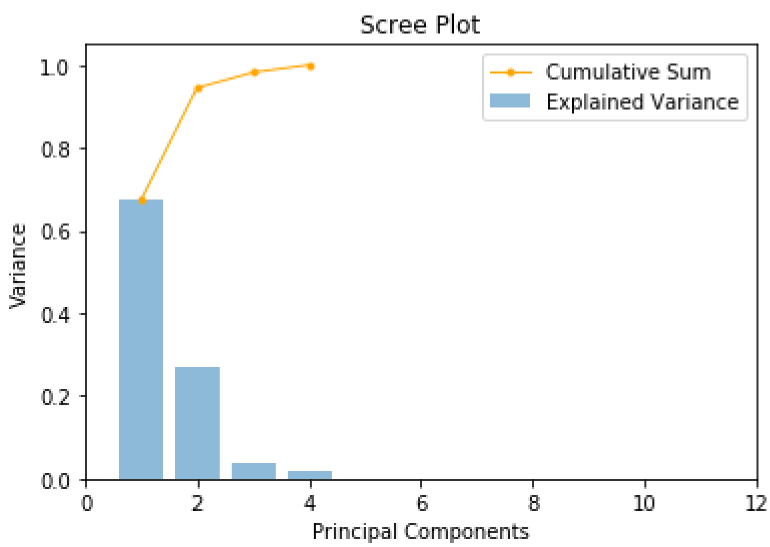


Figure 4.2: Scree plot showing the variance of principal components. It shows the cumulative variance explained by each principal component to make decision on the number of components to keep to adequately describe a dataset using ad-hoc rules such as components with a variance > 0.7.

By implementing PCA on the data set, the number of features are reduced to a few principal components and is visually represented in a scree plot. The scree plot as shown in Figure 4.1 is a line plot of the eigenvalues of factors or principal components in an analysis. In this evaluation, highly correlated features are converted into linearly uncorrelated features. As seen, it is clear that the resulting two principal components PC1 and PC2 constitute more than 85% of the variance. This implies that the four features can be depicted with these two principal components.

The overview of principal components of the data set are shown in Table 4.1. In PC1, total time taken, average peak force and average peak interval have the largest coefficients, whereas, in PC2, skewness has the largest coefficients. The coefficients with large magnitudes will determine the position of the skill level on a two dimensional projection.

Features	PC1	PC2
Total Time Taken	0.58	0.18
Average Peak Force	-0.56	0.23
Average Peak Interval	0.57	-0.05
Skewness	0.06	0.95

Table 4.3: Summary of the component loadings. They represent the correlation coefficients between the variables (rows) and factors (columns).

4.3.2 PCA Projection of K-means Clustering

First we perform K-means clustering with PCA reduced population, then we will experiment with T-SNE. For K-means clustering, the k value has to be determined. We use silhouette score and elbow method to arrive at this number.

From Figure 4.2 the elbow point is not very certain as it can be 2, 3 or 4. Therefore, the elbow method is not considered. In the Figure 4.3, from the silhouette method, the highest score is obtained when the number of clusters are 3. So, the optimal number of clusters from these plots are considered to be 3.

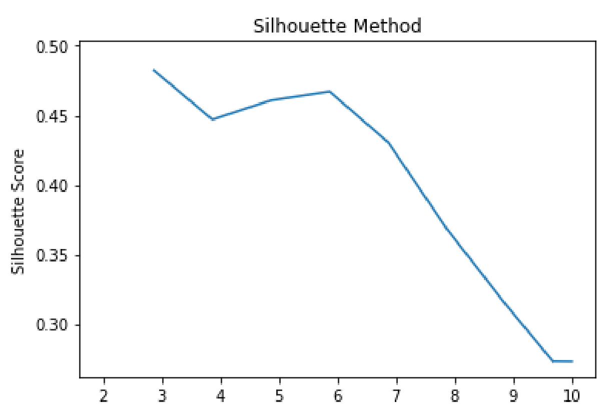


Figure 4.3: Within cluster sum of squares for PCA reduced population with K-means clustering.

Figure 4.4 shows the clusters obtained by reducing the dimensions through PCA. Among the three clusters obtained, cluster 1 represents the most efficient cutting technique by the participants and is labelled as ‘skilled’. Cluster 2 represents cuts that are not so efficient and is labelled as ‘novice’.

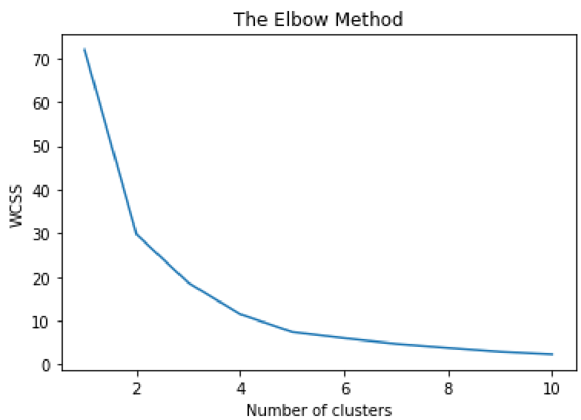


Figure 4.4: Silhouette scores for PCA reduced population with K-means clustering.

The labels to the clusters were voluntarily given as ‘skilled’ and ‘novice’ by observing the results of the questionnaire. These claims were further strengthened using video clips which were used a ground truth. These clips visually showed how some participants differed from others based on the skill level.

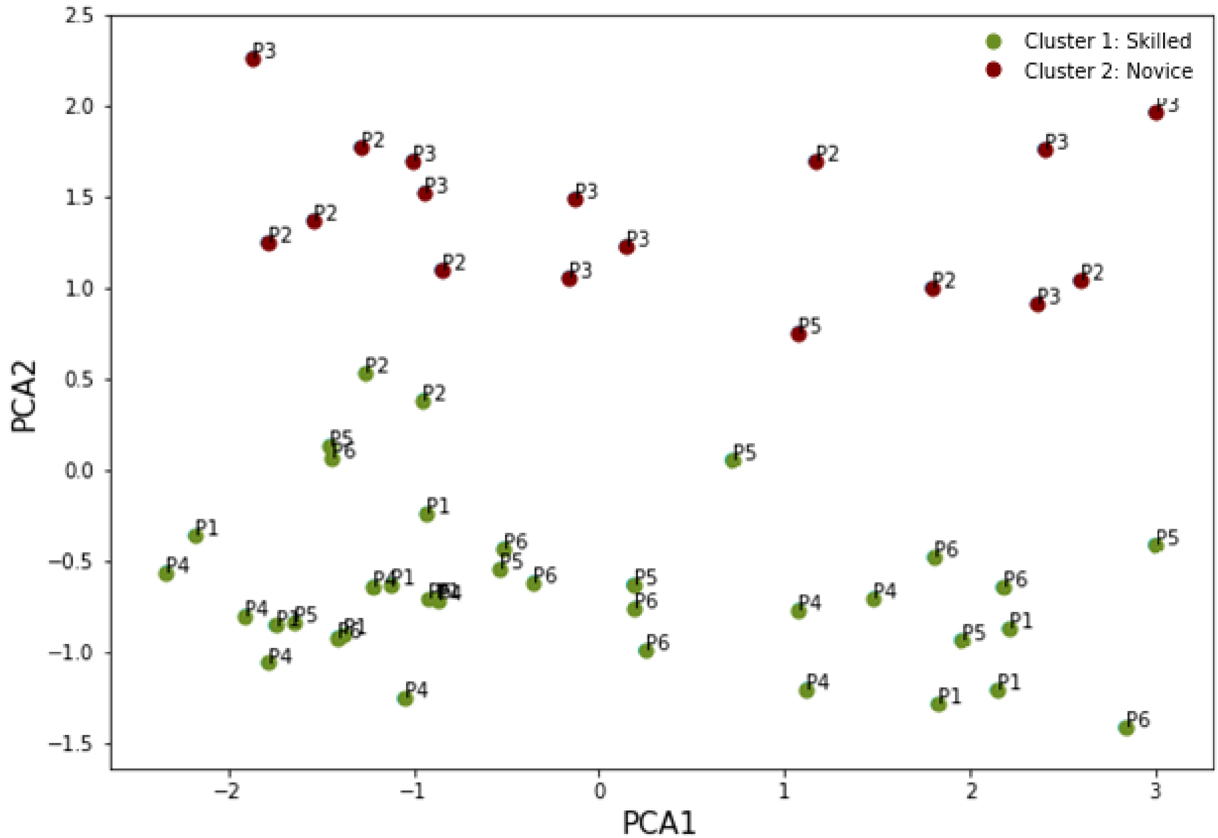


Figure 4.5: PCA projection of K-means clustering to show the difference between 'skilled' and 'novice' participants. X-axis represents an increasing axis for average time taken, average peak interval and a decreasing axis for average peak force. Y-axis represents an increasing axis for skewness.

We can see from Figure 4.4 that two points in cluster 1 representing 'skilled' cutting level has been misclassified, which corresponds to participant 2. In cluster 2, which represents 'novice' cutting level, one point has been misclassified which corresponds to participant 5. This results in a high overall accuracy of 94% for PCA based K-means clustering for differentiating the cutting skill level.

The labels to the clusters were voluntarily given as 'Slicing', 'Dicing' and 'Julienne' by observing the PCA axes. We can see that time taken by red cluster is highest and therefore represents 'Julienne'. The green cluster represents 'Slicing' as it has the shortest cutting activity. These claims were further strengthened using video clips which were used a ground truth. These clips visually showed how the cutting techniques differed from each other.

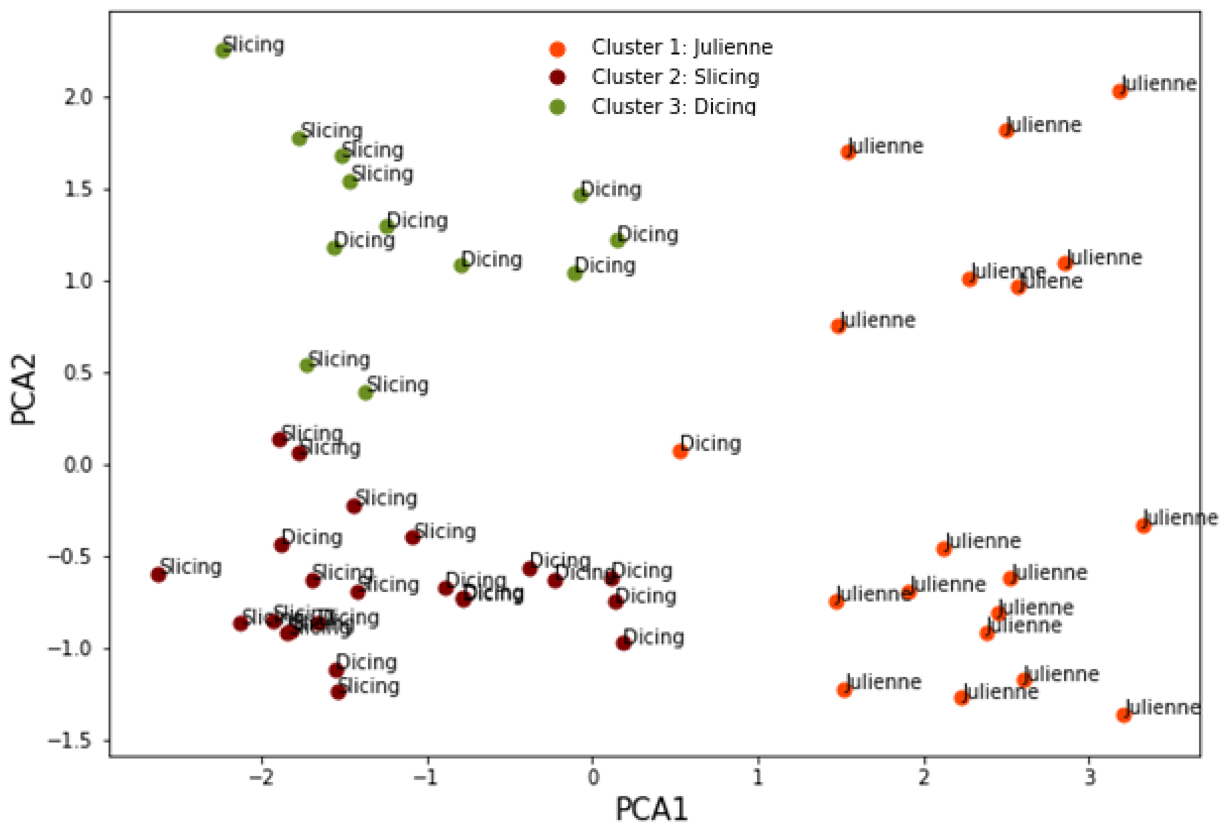


Figure 4.6: PCA projection of K-means clustering to show the difference between slicing, dicing and julienne techniques. X-axis represents an increasing axis for average time taken, average peak interval and a decreasing axis for average peak force. Y-axis represents an increasing axis for skewness

Figure 4.5 shows the clusters obtained by reducing the dimensions through PCA. Among the three clusters obtained, cluster 1 represents the slicing cutting technique by the participants. Cluster 2 portrays the dicing technique and cluster 3 is composed of julienne technique. We can see that all the points in cluster 3 representing julienne technique except one which corresponds to dicing has been correctly classified. 10 points in cluster 1 representing dicing technique has been misclassified as slicing and 6 points in cluster 2 representing slicing has been misclassified as dicing. This results in an overall accuracy of 69% for PCA based K-means clustering for differentiating the cutting techniques.

4.4 T-Stochastic Neighbor Embedding

T-SNE is a non-linear dimensionality reduction technique mainly used for visualization purposes. One of the benefits of using this technique is that it yields similar points in higher dimensional space closer when extrapolated onto the lower dimensional space. To carry out T-SNE one has to consider adjusting a few important variables. They are: number of components required, perplexity and number of iterations to converge. For this data set, the number of components is chosen to be 2, as we want to visualize data in two dimensions. Perplexity is adjusted to 14, and the number of iterations is set to 10000.

4.4.1 T-SNE Projection of K-means Clustering

We reduce the features using T-SNE and cluster with K-means. Figure 4.5 and 4.6 demonstrates the cluster evaluation methods. The elbow point descends when the number of clusters are 2 and 4, which makes it unclear. Silhouette score is highest when the cluster number is 2. Hence, the number of most appropriate clusters is considered to be 2.

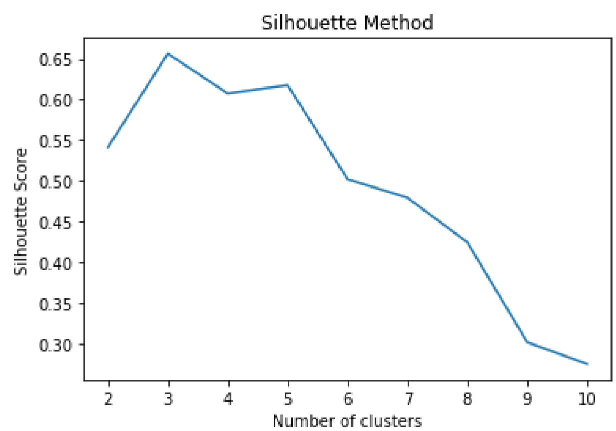


Figure 4.7: Within cluster sum of squares for T-SNE reduced population with K-means clustering.

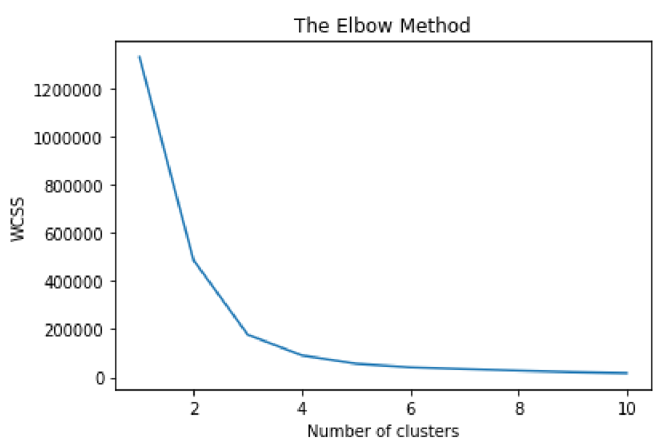


Figure 4.8: Silhouette scores for T-SNE reduced population with K-means clustering.

The clusters obtained from T-SNE projection of K-means is as shown in Figure 4.8. The obtained clusters clearly differentiate the cutting skill level. Among the two clusters obtained, cluster 1 represents the most efficient cutting technique by the participants and is labelled as 'skilled'. Cluster 2 represents cuts that are not so efficient and is labelled as 'novice'.

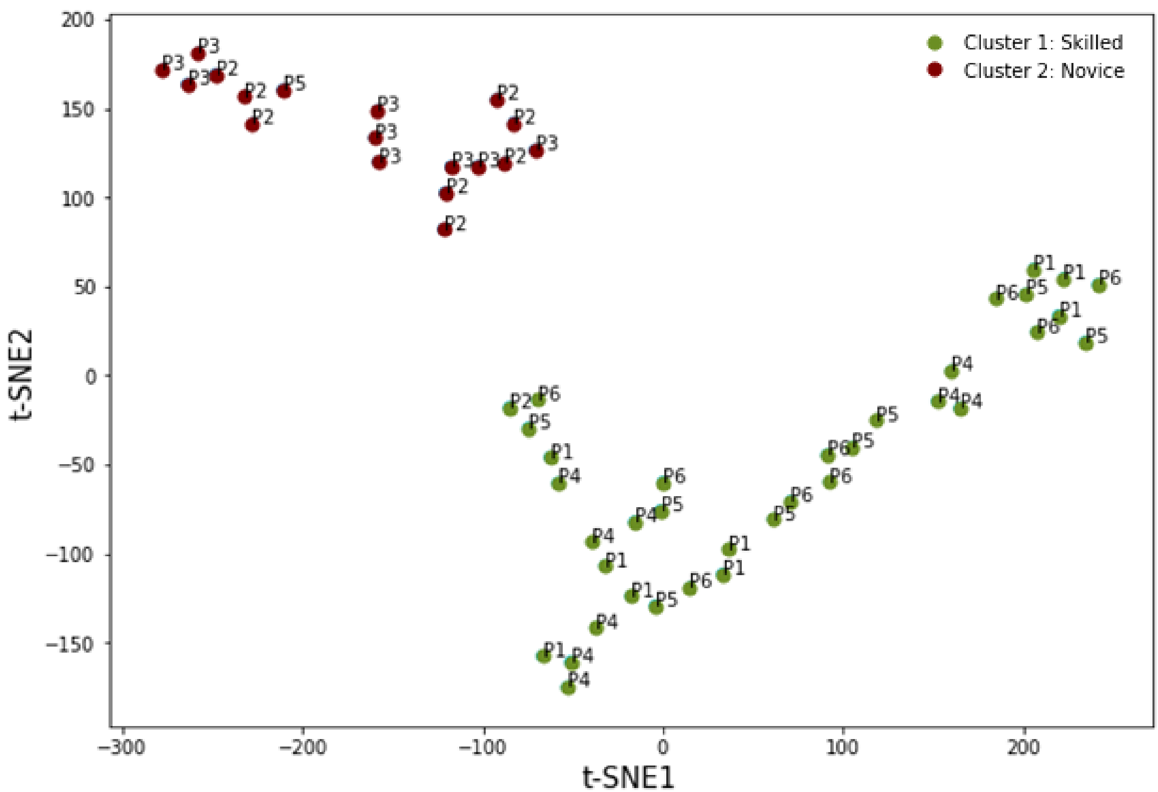


Figure 4.9: T-SNE projection of K-means clustering to show the difference between 'skilled' and novice' participants.

We can see that all the points in cluster 1 representing 'skilled' cutting level has been correctly classified except for one which corresponds to participant 2. In cluster 2, which represents 'novice' cutting level, one point has been misclassified which corresponds to participant 5. This results in a high overall accuracy of 96% for T-SNE based K-means clustering for differentiating the cutting skill level.

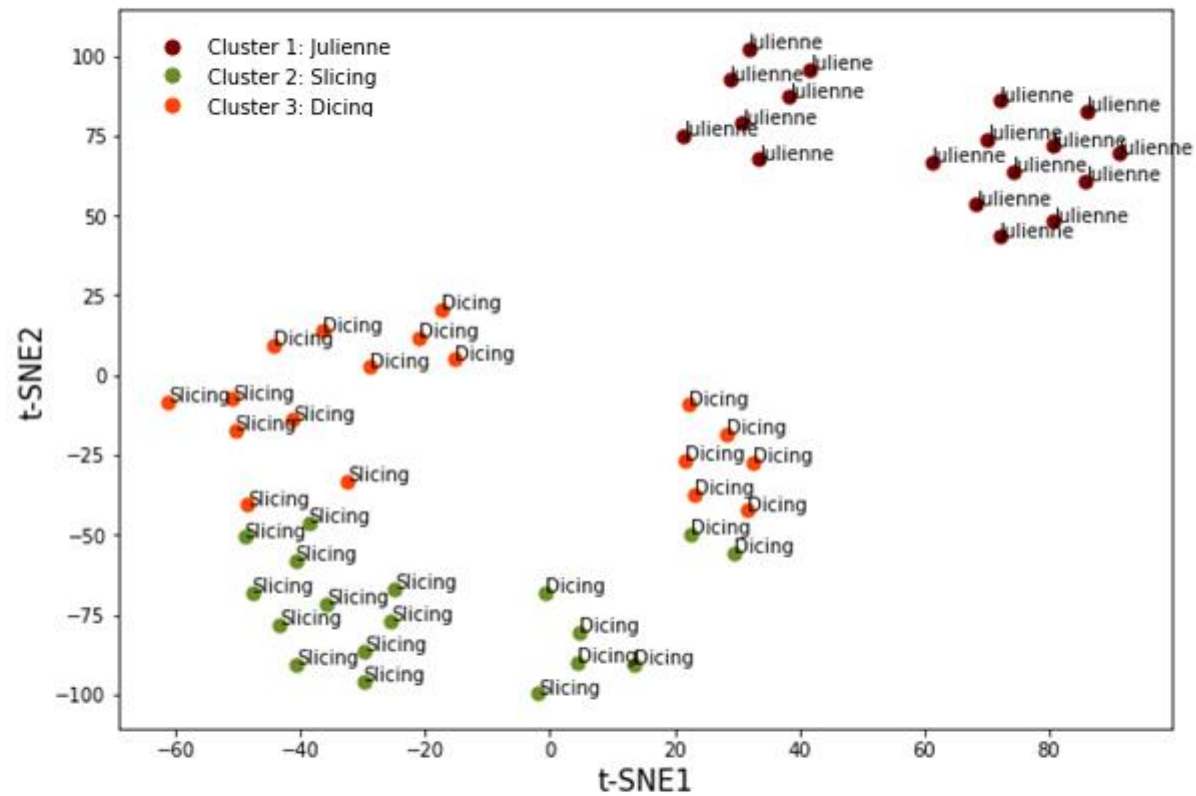


Figure 4.10: T-SNE projection of K-means clustering to show the difference between slicing, dicing and julienne techniques.

The clusters obtained from T-SNE projection of K-means is as shown in Figure 4.9. The obtained clusters clearly differentiate the cutting techniques. Among the three clusters obtained, cluster 1 represents the Julienne cutting technique by the participants. Cluster 2 represents the slicing technique and cluster 3 is composed of dicing technique. We can see that all the points in cluster 3 representing julienne technique has been correctly classified whereas 6 points in cluster 1 representing slicing technique has been misclassified as dicing and vice-versa. This results in an overall accuracy of 84% for T-SNE based K-means clustering for differentiating the cutting techniques.

4.5 Comparing PCA and T-SNE

Although we had very few cutting trials in our data set, PCA and T-SNE both were applicable to perform dimensionality reduction. PCA provides clear information about the number of components, their component loadings and separates correlated variables. Regarding T-SNE, it doesn't provide any information about its lower dimensional components. Hence, it has to be treated with extra attention because of its black-box nature. Having the ground truth in the form of videos helps making T-SNE interpretation simpler. There were no inputs that are required to be provided to the PCA algorithm for performing dimensionality reduction, but to get a good cluster representation using T-SNE, several hyper parameters have to be tuned. The hyper parameter tuning for T-SNE is more of a guess work. Comparing the clusters obtained visually, T-SNE clusters are compactly grouped compared to the PCA. This means, the local structure of the data points are well preserved using T-SNE.

4.6 Support Vector Machine: Supervised Learning

In SVM, each data set is split into two subsets: a training set of 80% (43) and a test set of 20% (11) of the total data (54) respectively. The RBF kernel is used for implementing SVM. The two parameters associated with the RBF kernel are C (which controls the margin hardness) and gamma (which controls the size of the radial basis function kernel). After conducting the grid-search for training data, the optimal value of C and gamma were found to be 5 and 0.5. After the optimal values were found, the complete training data was trained again to produce the final classifier. The classification confusion matrices are shown in Figure 4.11 and Figure 4.12 respectively.

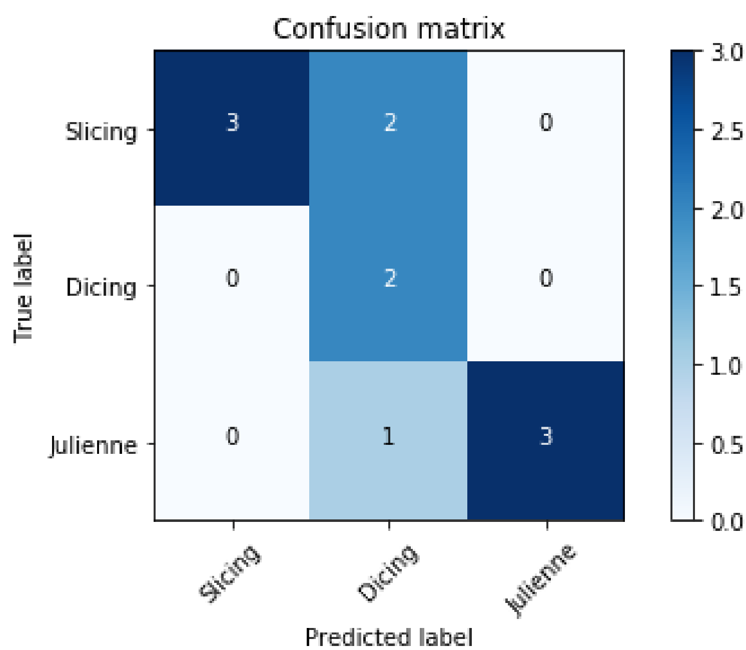


Figure 4.11: Confusion Matrix using SVM Classifier for cutting techniques.

Figure 4.11 shows the confusion matrix using SVM Classifier for the various cutting techniques. We can see that, for ‘Slicing’, out of the 5 test samples, 3 have been correctly classified and 2 has been misclassified as ‘Dicing’. For dicing, all the test samples have been correctly classified. However, as far as ‘Julienne’ is concerned, out of the 4 test samples only 1 has been misclassified. Thus, this results in an overall classification accuracy of 72%.

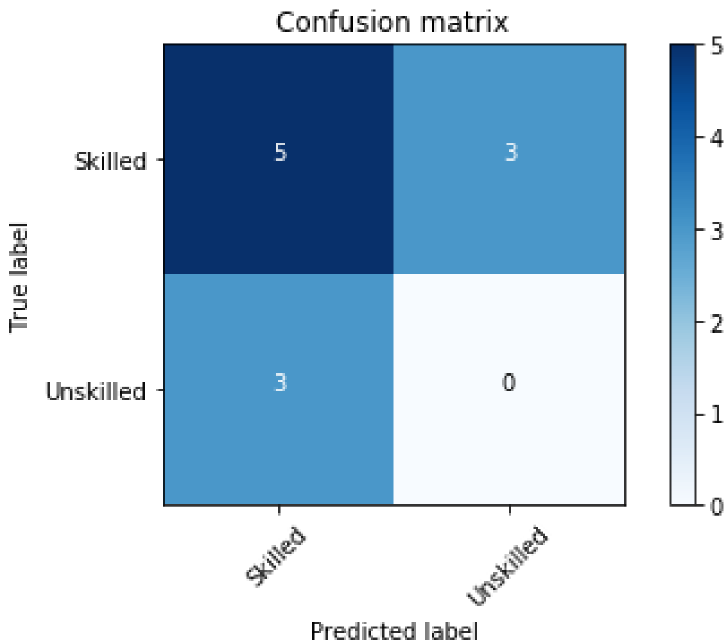


Figure 4.12: Confusion Matrix using SVM Classifier for cutting skill level.

Figure 4.12 shows the confusion matrix using SVM Classifier for the skill level of the participant. We can see that, for ‘Skilled’ cutting level, out of the 8 test samples, 55 have been correctly classified and 3 has been misclassified as ‘Unskilled’. For ‘Unskilled’, all the 3 test samples have been misclassified. Thus, this results in an overall classification accuracy of 45%.

Chapter 5: Discussion

In the method chapter, experiment set-up and study procedures were described and in the results, the outputs were shown that were generated using different clustering algorithms. In this chapter, intriguing outputs are discussed and a potential explanation for these results are described. This is done to further elucidate on the algorithms and their implementation.

In addition to discussing the results presented, this chapter also compares the non-intrusive activity recognition to the literature proposed in earlier research [25, 26, 27, 28] as described in section 2.1. In the following section of this chapter, important points are discussed on how an objective method using non-intrusive sensors can help in analyzing cooking skills of an individual. In the last section, limitations of the research are discussed.

The datasets were collected from six subjects who each performed a cutting technique three times in the kitchen. The kitchen setting for the experiment was a home-based kitchen and the subjects performed their cutting activities in a natural manner. The accuracy of activity recognition using different clustering algorithms were evaluated. Pressure sensor data were used for evaluating activity recognition. The analysis of culinary cutting skills using a chopping board has demonstrated the potential for the objective analysis of cooking skills. Generally, the classification results were also very promising.

By comparing the cluster labels of the true and the predicted class, accuracy of the clustering process was obtained. The PCA based k-means clustering technique produced accuracy of 94% in differentiating the cutting skill level and 69% in differentiating the cutting techniques. Alternatively, T-SNE based K-means clustering technique produced an accuracy of 96% in differentiating the cutting skill level and 84% in differentiating the cutting techniques. These results are very promising for practical AR-based applications. However, coming to the supervised learning algorithm, SVM classification technique produced a low classification accuracy of 45% for differentiating the cutting skill level and 72% in differentiating the cutting techniques. Thus, we can see that unsupervised learning algorithm performed better than supervised learning algorithm for this dataset.

In the background chapter, we have seen that [26, 27, 28], wearable sensors like accelerometers recognize low-level activities such as walking, running or cycling, and have produced accuracies of 80%. We have also noticed that Ward et al. [56] used a combination of on-body sensors to detect skilled and semi-skilled activities and produced accuracies up to 90%. However, it was found that it is not a good fit for this experiment as it would cause inconvenience as the sensors worn on the body would not allow the participants to perform naturally. Due to this reason, the motive of the thesis was to use simple non-intrusive sensors that is embedded in the device. We saw that Chang et al. [65] created a dining table using load cells, weight tracking algorithms and RFID technology to measure food intake. This was a significantly less obtrusive solution and involved sensors embedded in the user's environment. Kranz et al. [64] identified various ingredients using a combination of force sensors in the knife, microphones, and load cells in the chopping board and encouraging recognition accuracy around 80%. Our system was focused on recognizing the activities as well as objectively differentiate the skill level. As we have seen, our system was able to achieve a high accuracy of 96% in differentiating the skill level and an accuracy of 84% in differentiating the cutting technique.

However, with that said, let us focus on the techniques used to answer the research questions of this thesis: *'To what extent can you determine the cooking skill of an individual by measuring the cutting technique using a pressure sensor?'* and '*To what extent can you objectively distinguish different cutting techniques from each other in pressure sensor data?'* We used supervised learning algorithm such as SVM classifier and unsupervised learning methods such as clustering to find all kind of unknown patterns in data. This helped us understand how close or far the cutting techniques are from each other. It also helped to find features useful for categorization. PCA and T-SNE both were both applied to perform dimensionality reduction. It was also used to compare the best performing combination of the dimensionality reduction technique and clustering algorithm. It was observed that the clusters obtained from the combination of K-means and T-SNE had the highest accuracy. T-SNE is excellent for visualization, because similar items can be plotted next to each other and not on top of each other as opposed to PCA. From the clustering plots, it was seen that slicing and dicing are closely related to each other. This makes sense because of the operationalization in the methodological step. The participants were instructed such that the first half of dicing process was similar to slicing. Overall, the combination of clustering and dimensionality reduction techniques provided a good classification of cutting skill level and the cutting techniques from the reduced features. This also means that the feature vectors that were derived are a good representation of the skill level of the participant. This is also validated against the scores generated from the cooking skill assessment questionnaire. Moreover, SVM classifier produced a reasonably high accuracy for cutting technique classification but not so for skill level. This is because SVM works relatively well when there is clear margin of separation between classes. There are some cases in skill level classification where the two classes are close to each other. In other words, there are few instances where participants considered 'novice' have their performance comparable to 'skilled' participants. This creates disruption in the hyperplane which separates the data into classes thereby creating misclassification.

In addition, this study makes use of machine learning algorithms to make the most accurate predictions possible instead of traditional statistical models. The goal of the study is to see the extent of classification using the features. Therefore, accuracy is an important parameter. Statistical models are intended for finding out the relationships between variables. Many statistical models can produce promising predictions, but predictive accuracy is not their main strength. Clearly, unsupervised learning performed better than supervised learning. Since supervised learning works on training and testing set, it requires large amount of data to establish a pattern. In our case, this was not possible and understandingly the accuracy was low. Unsupervised machine learning was used to find all kind of unknown patterns in data and this was beneficial in finding features for categorization. Moreover, since the clustering takes place in real time, all the input data was analyzed and labeled in the presence of learners.

When we look at the clustering plots of the skill level (Figure 4.4 and Figure 4.8), we can clearly see that participant 2 & participant 3 stand out from the rest and they are voluntarily labeled as 'novice'. This objective result comes together and is supported by the subjective results from the questionnaire and the videos of the experiment, which is the ground truth. Accordingly, it is seen from the results of the questionnaire (Figure 4.10) that, participant 2 & participant 3 have comparatively lower scores of 4.64 and 4.71 respectively. The difference in scores among the participants is small and this is one of the drawback of subjective analysis that, it does not gives a proper interpretation of the skill level. This is addressed by the objective analysis of their cutting technique. Interestingly, it is seen from the questionnaire that the two 'novice' participants have scored themselves high when it comes to microwaving ready-made meals. This could be an intriguing factor as fixation to ready-made convenience meals could diminish one's cooking skill.

In addition, another interesting parameter to discuss is the placement of sensor underneath the cutting board. Selecting the best place to install the sensor allows to cover a larger area of contact. Since there was only one sensor used at the center of the cutting board, there could have been cases where the participants would have drifted away from the contact area. This might lead to blind spots and loss of data. Furthermore, the features used for classification have produced a reasonably high accuracy. It would be also interesting to see how the accuracy would improve by using other features such as peak area and knife angle.

All in all, we have seen that culinary cutting skills constitutes a major part in cooking skills. The features responsible for analyzing these cutting skills are also identified and tested. It is possible that people can develop an inclination to cooking by developing their knife skills and be more aware of their dietary intake. On a long run, this could help curb obesity and other diet related diseases.

5.1 Limitations

The results of our design, execution and experimental studies of activity recognition are confined by a number of limitations, some of which are workable topics for future development and research:

- The cutting board with a pressure sensor is a unique prototype for performing activity recognition. Although it gave a good indication of the force applied during cutting, only one sensor was used underneath the cutting board at the center. Participants, even after giving instructions, may have performed the cutting activity slightly away from the center sometimes, resulting in loss of reading. Cutting boards are usually washed between the preparations of ingredients and that participants did not attempt to do this is suggestive of the fact that they were not using it completely naturalistically.
- The experiment was originally planned for 20 participants. Due to Coronavirus, it was restricted to 6 participants such that each participant had to perform every cutting technique 3 times. Ideally, this is not a good way to perform the experiment as it can lead to participant bias.
- There were few things that were kept common for all the participants to reduce the number of variable parameters. The vegetable used for the experiment were potatoes only. To fully test the cutting skill, it is important to assess it using different vegetables and fruits. Moreover, only one type of knife was used for the experiment. Participants may not have been comfortable with the knife and that may have not allowed them to perform in their natural best form.
- The target group of the experiments were mainly college students and were divided beforehand into novice and skilled. In order to test the validity of the experiment, it is required to perform the experiment across a wide target group.
- The participants were mainly from the Asian sub-continent region. This can lead to prejudice bias as a result of training data that is influenced by cultural or other stereotypes.
- The recognition rates of cutting activities are still not high (i.e. between 65- 85% accuracy), very high accuracy seems difficult to be achievable using just clustering algorithms.

Chapter 6: Conclusion

In this final chapter, this thesis is wrapped up by looking back at the main research question. Next to that, recommendations for future research are given for further implementation in the project.

This thesis work presented a detailed description of the features which are obtained from the pressure sensor to classify the skill level and the cutting techniques. Feature extraction process along with the clustering model were also described in the earlier chapters. This clustering model helps in classification of cutting skill level as 'skilled' or 'novice'. As shown in the results, an accuracy up to 96% is achieved in classifying the cutting skill level and up to 84% in classifying the cutting techniques using unsupervised learning. On the other hand, supervised learning produced an accuracy of 45% in differentiating the cutting techniques and 72% in classifying skill level of the participants.

For most part, the key contribution of the thesis has been in the methodological field. This was achieved by the combination of subjective results of the cooking skill questionnaire and the objective results of the machine learning algorithms using pressure sensor data. This combination was further strengthened using video recordings as the ground truth. This method could be useful for other studies aiming to objectively calculate cooking skills of an individual.

During the literature survey, important factors that constitute the cooking skills were noted down. Based on these rules, six features were extracted from the time-series data collected from the sensor. On these extracted features, student t-tests were used which evaluates the importance of features for characterizing cutting technique. From this analysis, it was observed that total time taken, average peak force, average peak interval and skewness are the important features which best characterize the skill level and the cutting techniques. Also, there are some parameters like kurtosis which had very less correlation with the skill level, and thus do not contribute much to the cutting skill level classification.

To perform the quantitative evaluation of cutting skill level and the techniques, unsupervised machine learning concepts were used. Design space was explored for two dimensionality reduction techniques and K-means clustering algorithm. Based on this exploration, a combination of T-SNE (dimensionality reduction technique) and K-means (clustering technique) provided better results. These results were based on their silhouette score. From the results obtained, it can be concluded that the combination of dimensionality reduction techniques and clustering algorithm can distinguish the skill level and techniques clearly, which indicates that machine learning algorithms can be employed for cutting skill level classification.

6.1 Future Work and Recommendation

The results and conclusions presented in this thesis are based on the limited time frame available for this work. Due to this, there are a few tasks which were left unattended, and, few tasks which required more inputs in terms of data sets and time. Following points present future work and recommendations if this thesis work is carried out further:

- The goal of the thesis at a global level is to motivate people to improve their cooking skills and take nutrition into consideration. We have seen that we can objectively classify the cutting techniques and the skill level of the participants. It would be interesting to see if the features obtained can help in improving the cutting skills of the participant. A compelling research question would be: "Can you improve the cutting skill of an individual using objective analysis of cooking skills?". I think this is a fruitful and a valuable research question because we have seen the features responsible in determining the cutting skill of an individual. Participants can practice and learn where they went wrong and focus on working on their technique.
- Improving the recognition rates for activities and foods as well as reducing the number of misclassification errors are the key issues for the development of the recognition algorithms in cooking.
- Although the clustering model performed well on the activity recognition task, using the features associated with slicing, dicing and julienne, it is highly desirable that both the recognition rate and real-time performance is improved and tested across other cutting techniques like chopping, peeling etc. One alternative enhancement would be to address the use of audio sensor in combination with the pressure sensor.
- The experiment was limited to testing only certain cutting techniques. To realize its full scope it can be used in analyzing steps in preparing a recipe. One possibility is that the recipe is simply represented as a sequence of food preparation steps. For example, a simple pasta recipe can be split into 10 steps: boiling pasta, preparing sauce, cutting vegetables, cooking mix and serving. Each step might be a combination of several activities and food ingredients and can be operationalized. For example, the step "preparing sauce" would be collection of chef knife, peeler, peeling, chopping or/and slicing. In this presentation, a step is treated as a high-level activity and its components are utensils, food and low-level activities.

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Appendix I: Information Letter and Consent Form

UNIVERSITY OF TWENTE.

Information Letter to Participants
Name: Sujan Ponnappa
Email: s.ponnappa@student.utwente.nl

Title of the study: Analysis of culinary cutting skills in the kitchen using a cutting board embedded with pressure sensor.

Dear Participant,

To help you make an informed decision regarding your participation, this letter will explain what the study is about, the possible risks and benefits, and your rights as a research participant. If you do not understand something in the letter, please ask one of the investigators prior to consenting to the study. You will be provided with a copy of the information letter and consent form if you choose to participate in the study.

You are invited to participate in a research study for master thesis about analyzing the culinary cutting skills of an individual in the kitchen and using activity recognition to classify different cutting styles. Knife skills are one of the many important skills in the kitchen as the first step before preparing any meal involves cutting the necessary vegetables. In order to measure how good one is at cutting, it is important to determine the performance across different cutting techniques such as slicing, dicing and julienne.

The overall time duration for completion of the study will be about 30 minutes. First, you will be a given a short description about the experimental setup. You will be then asked to fill in a questionnaire with questions related to you cooking skills and rate them in the scale of 1-10. This will take about 5 minutes. You will be then shown a video demo describing the different cutting styles taking up another 5 minutes. This will be followed by the cutting experiment. The experiment will take about 15-20 minutes depending upon your style. It will consist of 3 sessions, each session dedicated to cutting uniformly sized potatoes in one of the 3 cutting styles namely: slicing, dicing and julienne.

In order to participate in the study you must (1) be in the age range of 18 or above; and (2) sign the Consent Form. Your participation in this study is voluntary. You may decide to leave the study at any time by communicating this to the researcher. You may also decline to answer any question(s) you prefer not to answer in the questionnaire. You will not receive payment for your participation in the study. Participation in the study may benefit you in knowing your cutting skill objectively. The study will benefit the academic community in understanding the link between cooking skills and healthy eating.

Safety instructions will be given prior to the start of the experiment and a first-aid kit will be available should there be any injuries. You can withdraw from the study at any time, without having to give a reason. Your participation in this study, and the data collected, is anonymous. The information you share will be kept confidential by assigning an ID code so that individual names are not associated with the data.

This study has been reviewed and received ethics clearance through a University of Twente EEMCS Research Ethics Committee.

UNIVERSITY OF TWENTE.

UNIVERSITY OF TWENTE.

Information Letter to Participants
Name: Sujan Ponnappa
Email: s.ponnappa@student.utwente.nl

If you have any questions regarding this study, or would like additional information to assist you in reaching a decision about participation, kindly contact any member of the research team listed below.

Contact information for the lead researcher

Initials: Sujan
Surname: Ponnappa
Education/Department (if applicable): M-BME
Student number: 2041618
Email address: s.ponnappa@student.utwente.nl
Telephone number (during the research project): 0645871908

Supervisors:

First Supervisor
Vries, R.A.J. de (EEMCS-BSS)
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Surname: Haarman
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Consent Form for *Analysis of Cooking Skills*

YOU WILL BE GIVEN A COPY OF THIS INFORMED CONSENT FORM

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated / /2020/, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	O	O
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	O	O
I understand that taking part in the study involves a survey questionnaire to be completed by the participant which involves rating his/her cooking skills and food skills on the scale of 1-10. It also involves video recordings of the participants which will capture their slicing activity of vegetables that will be used for analysis.	O	O
Risks associated with participating in the study		
I understand that taking part in the study involves the following risks: The participant can undergo physical discomfort such as getting minor cuts from the knife.	O	O
Use of the information in the study		
I understand that information I provide will be used for reports and publications.	O	O
I understand that personal information collected about me that can identify me will not be shared beyond the study team.	O	O
Consent to be Video Recorded *I agree to be video recorded.*	O	O
Future use and reuse of the information by others		
I give permission for the sensor readings that I provide to be archived in the University of Twente student repository so it can be used for future research and learning. The data will also have video recording and the deposited data will be anonymized to protect the identity of participants.	O	O

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I agree that my information may be shared with other researchers for future research studies that may be similar to this study or may be completely different. The information shared with other researchers will not include any information that can directly identify me. ○ ○

Signatures

______________________ ___________________ ________

Name of participant Signature Date

I have accurately read the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_________________________ _________________ ________

Researcher name Signature Date

Study contact details for further information: Name : Sujan Ponnappa
Email: s.ponnappa@utwente.nl

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact Dr.ir. Buitenweg, Ethics Committee member of the Biomedical Signal and Systems (BSS) group at the University of Twente by j.r.buitenweg@utwente.nl

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Appendix II: Ethics Form

Ethics Form: Faculty of Electrical Engineering, Mathematics and Computer Science

UNIVERSITY
OF TWENTE.

1. Title of the project: Analysis of Cutting Skills in the Kitchen using a pressure sensor embedded in a cutting board

2. Contact information for the lead researcher
Initials: Sujan
Surname: Ponnappa
Education/Department (if applicable): M-BME
Student number: 2041618
Email address: s.ponnappa@student.utwente.nl
Telephone number (during the research project): 0645871908

3. Supervisors:

First Supervisor
Vries, R.A.J. de (EEMCS-BSS)
Initials: R.A.J.
Surname: de Vries
Department: EEMCS-BSS
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Second Supervisor
Haarman, J.A.M. (EEMCS-HMI)
Initials: J.A.M.
Surname: Haarman
Department: EEMCS-HMI
.Email address:j.a.m.haarman@utwente.nl

4. Department responsible for the research: HMI and BSS

5. Location where research will be conducted: Macandra Student Housing, Emmastraat 210

6. Short description of the project (about 100 words):

The consumption of food prepared in the home environment has been related with an enhanced diet quality and better weight management. As obesity is progressively becoming a worldwide epidemic, any techniques that can help in the reduction must be assessed and all steps should be taken to help their implementation. Cooking is a valuable life skill which is often linked with improved diet quality, such as improving the uptake of fruit and vegetables and an increased recognition of healthier foods. Knife skills are one of the many important skills in the kitchen as the first step before preparing any meal involves cutting the necessary ingredients. Three basic knife cuts namely slicing, dicing and julienne will be tested out. Objective measurement is carried out, where a pressure sensor is attached to a cutting board using an Arduino microcontroller. The sensor is used to measure different parameters such as time taken, peak force, intervals between the cuts and number of cuts made in a time interval and analyze data through objective measurement of cutting skills. The first challenge is to be able to differentiate the cutting skills between skilled and novice participants in the target group of adults in the age range of 18 and above. The second challenge requires developing activity recognition that can segment and differentiate between different cutting activities such as slicing, dicing and julienne from sensor data. The scope of activity recognition entails the range of people who cook, giving information about daily life cooking activity.

7. Expected duration of the project and research period: 9 months

8. Number of experimental subjects: 20

9. EC member of the department (if available): Dr.ir. Buitenweg (BSS), Dr.ir. D, Reidsma (HMI)

2. Questions about fulfilled general requirements and conditions

1. Has this research or similar research by the department been previously submitted to the EC?

No

2. Is the research proposal to be considered as medical research (Also see Appendix 4)

No.
No medical equipment is used in the research.

3. Are adult, competent subjects selected? (§3.2)

Yes.
The subjects chosen are healthy, adults in the age range of 18 and above, who voluntarily participate in a trial. Participants sign the informed consent
Individually.

4. Are the subjects completely free to participate in the research, and to withdraw from participation whenever they wish and for whatever reason?

Yes. Subjects are not put under any pressure to participate. Subjects are informed that their participation is voluntary and they are allowed to decline or to withdraw from the research.

5. In the event that it may be necessary to screen experimental subjects in order to reduce the risks of adverse effects of the research: Will the subjects be screened? (§3.4)
Yes.
Subjects are screened insofar as it is with regard to having basic knife skills and avoid unnecessary cuts and bruises.

6. Does the method used allow for the possibility of making an accidental diagnostic finding which the experimental subject should be informed about?
No

7. Are subjects briefed before participation and do they sign an informed consent beforehand in Accordance with the general conditions?

Yes.

8. Are the requirements with regard to anonymity and privacy satisfied as stipulated in (§3.8)?

Yes.
Research data of persons is made anonymous at the earliest possible stage right up until the research report.

9. If any deception should take place, does the procedure comply with the general terms and conditions (no deception regarding risks, accurate debriefing) (§3.10)?

No, no deception takes place.

10. Is it possible that after the recruitment of experimental subjects, a substantial number will withdraw from participating because, for one reason or another, the research is unpleasant? (§3.5)

No.

3. Questions regarding specific types of standard research

11. Does the research fall entirely under one of the descriptions of standard research as set out in the described standard research of the department?

No.

12. If yes, what type of research is it? Give a more detailed specification of parts of the research which are not mentioned by name in this description (for example: What precisely are the stimuli? Or: What precisely is the task?)

It is a Laboratory Research.

20 subjects will be recruited to test their culinary cutting skills in the kitchen. Healthy (without any visible defects) and uniform size potatoes of homogeneous physical structure are used. Weight of each potato are measured with the help of a weighing scale to make sure that they are of approximately the same weight. The potato to be cut is held on the active area of the pressure sensor on the cutting board. The knife used for the experiment is a basic chef's knife. Pressure exerted on the test sample with knife travel during cutting will be displayed on the laptop. Overall each subject is required to cut the potato in three different styles (slicing, dicing and julienne).

Special care will be taken to make sure that the experiment is free from coronavirus risks. The experiment will be conducted only with participants living in the student housing. Surfaces and objects (e.g. knives, cutting board) will to be cleaned thoroughly before and after the experiment. At a time, only one person will be allowed in the kitchen. The participant will be verbally given all the necessary instructions to perform the experiment and the participant will learn about the cutting style through the help of a demo video before entering the kitchen. A distance of 1.5 meters will be maintained between the instructor and the participant. Before the start of the cutting sessions, a questionnaire will be administered to the subject. The questionnaire will address questions relating to cooking skills and eating behavior of the subject.

Appendix III: Cooking Skill Assessment Questionnaire

1. 'Chop, mix and stir foods, for example chopping vegetables, dicing an onion, cubing meat, mixing and stirring food together in a pot/ bowl'
2. 'Blend foods to make them smooth, like soups or sauces' (using a whisk/blender/food processor etc.)
3. Steam food (where the food doesn't touch the water but gets cooked by the steam)
4. Boil or simmer food (cooking it in a pan of hot, boiling/bubbling water)
5. Stew food (cooking it for a long time (usually more than an hour) in a liquid or sauce at a medium heat, not boiling) e.g. beef stew
6. Roast food in the oven, for example raw meat/chicken, fish, vegetables etc.
7. Fry/stir-fry food in a frying pan/wok with oil or fat using the hob/ gas rings/hot plates
8. Microwave food (not drinks/liquid) including heating ready-meals
9. Bake goods such as cakes, buns, cupcakes, scones, bread etc., using basic/raw ingredients or mixes
10. Peel and chop vegetables (including potatoes, carrots, onions, broccoli)
11. Prepare and cook raw meat/poultry
12. Prepare and cook raw fish
13. Make sauces and gravy from scratch (no ready-made jars, pastes or granules)
14. Use herbs and spices to flavor dishes