

**MACHINE LEARNING-BASED FACIAL EXPRESSION  
RECOGNITION USING STRETCHABLE STRAIN  
SENSORS FOR REHABILITATION SYSTEM**

**BY**

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**A thesis submitted in fulfilment of the requirement for the  
degree of Master of Science (Mechatronics Engineering)**

**International Islamic University Malaysia**

**APRIL 2021**

## ABSTRACT

Facial expression recognition (FER) enables computers or machine to identify human emotions. The FER system is used in self-driving cars, healthcare and smart environments. Most of the facial expression systems are based on computer vision and image processing technologies. Computer vision technologies are quite expensive since they need massive memory and computation resources. It also depends on the environment changes. However, sensors technologies overcome all the limitations because it does not need a massive amount of memory, expensive computation resources, and not depend on environment changes. This study aims to develop FER systems based on stretchable strain sensors data using machine learning in driving a rehabilitation system. Two different stretchable strain sensors (commercial and developed) are used to recognize four facial expressions (neutral, happy, sad and disgust). This study mainly focuses on the developed stretchable strain sensor, but this sensor is still developed in the laboratory and is not stable. So, the commercial stretchable strain sensor is used for the analysis of the developed sensor performance. The stretchable strain sensors data is time-series data with noise and high dimensionality. The datasets are normalized and aggregated to remove noise and high dimensionality. It is processed as an input to the machine learning model, and then it is compiled and fitted by five machine learning models, which are K- Nearest Neighbour (KNN), Decision Tree (DT), Support Vector Machine (SVM), Logistic Regression (LR) and Random Forest (RF) models. The training and testing results show that the RF model achieves the highest accuracy than other machine learning models. The RF FER model is then implemented in the experimental hardware test of the facial expression-driven rehabilitation system. When facial expression neutral, happy, sad, and disgust emotion, the elbow rehabilitation system (ERS) motor speed is 60%,80%,0% and 30% of its full speed, respectively. The simulation results show that RF has achieved 96% and 90% accuracy, respectively, in recognizing the correct facial expression using the three commercial and four developed sensors, respectively. The offline hardware experimental test results show that the facial expression has driven rehabilitation system has successfully achieved 93% and 83% accuracy. The three commercial and four developed stretchable strain sensor data to drive the rehabilitation system's speed according to the facial expression displayed. In the real-time experimental test on five subjects, the system has achieved an accuracy of 75% in regulating the rehabilitation system's speed based on the actual users' facial expressions. The proposed study's limitation is that the stretchable strain sensors are uncomfortable for data collection and tests. However, the experimental results have proven that the proposed methods can drive the rehabilitation machine to move according to the recognized facial expression. The proposed system can enhance the rehabilitation system's comfort and safety according to the patients need. It will help the patients to recover better and faster and eventually improves their quality of life.

## خلاصة البحث

تعمل أنظمة التعرف على تعبيرات الوجه (FER) على تمكين أجهزة الكمبيوتر والآلات من تعلم المشاعر البشرية. يستخدم نظام التعرف على تعابير الوجه في السيارات ذاتية القيادة وفي الرعاية الصحية والبيئات الذكية. تعتمد معظم أنظمة تعبيرات الوجه السابقة على الرؤية الحاسوبية وتقنيات معالجة الصور. ولكن هذه التقنيات باهظة الثمن لأنها تحتاج إلى ذاكرة وموارد حاسوبية ضخمة. على الرغم من اعتماد الرؤية الحاسوبية على التغيرات البيئية، فإن تقنيات المستشعرات تتغلب على جميع القيود لأنها رخيصة الثمن وتستهلك القليل من الطاقة وتتميز بالاتصال اللاسلكي وتمتلك سعة وسرعة معالجة بيانات عاليتين. تهدف هذه الدراسة إلى تطوير أنظمة التعرف على تعبيرات الوجه وتصنيفها بناءً على بيانات المستشعرات المطاطية باستخدام تعلم الآلة لدفع نظام إعادة التأهيل. يتم استخدام مستشعرين مطاطيين مختلفين (تجاري ومطور) للتعرف على أربع تعبيرات للوجه (محايد وسعيد وحزين ومشمم). بيانات المستشعر المطاطي هي بيانات متسلسلة زمنياً مع ضوضاء وأبعاد بيانية مرتفعة، لذلك تتم تسوية مجموعات البيانات وتجميعها لإزالة الضوضاء والأبعاد المرتفعة، حيث تتم معالجتها كمدخلات في نموذج تعلم الآلة، ثم يتم تجميع النموذج وتركيبه بواسطة خمس خوارزميات، وهي: أقرب جار (KNN)، وشجرة القرار (DT)، وآلة متجه الدعم (SVM)، والانحدار اللوجستي (LR) وخوارزميات الغابة العشوائية (RF). تحقق أعلى دقة مقارنة بخوارزميات التعلم الآلي RF يُظهر التدريب واختبار النتائج أن خوارزميات هو بعد ذلك في اختبار الأجهزة التجريبية لنظام إعادة التأهيل القائم على تعبيرات RF الأخرى. نموذج تعبيرات الوجه الوجه. إذا تم التعرف على تعبير الوجه السعيد، فسيتم ضبط سرعة الماكينة على 80%. إذا تم الكشف عن تعبير وجه حزين، فلن تتحرك سرعة الماكينة 0%. إذا تم التعرف على تعبير الوجه المحايد، يتم ضبط سرعة الماكينة على 60%. إذا قد RF تم الكشف عن تعبير عن الاشمزاز، يتم تنظيم سرعة الماكينة إلى 30%. تظهر نتائج المحاكاة أن التعلم الآلي ل حقق دقة تصل إلى 96% و 90% على التوالي في التعرف على تعبيرات الوجه الصحيحة باستخدام المستشعرات التجارية والمتطورة، على التوالي. تُظهر نتائج الاختبار التجريبي للأجهزة غير المتصلة بالإنترنت أن تعبيرات الوجه دفعت نظام إعادة التأهيل إلى تحقيق دقة تصل إلى 93% و 83% بنجاح مع بيانات أجهزة الاستشعار التجارية والمطورة في دفع، سرعة نظام إعادة التأهيل وفقاً لتعابير الوجه المعروضة. في الاختبار التجريبي في الوقت الفعلي على خمسة مواضيع حقق النظام دقة تبلغ 75% في تنظيم سرعة نظام إعادة التأهيل بناءً على تعبيرات وجه المستخدمين الفعلية. أثبتت النتائج التجريبية أن الطرق المقترحة قد دفعت بنجاح آلة إعادة التأهيل للحرك وفقاً لتعابير الوجه المعترف بها. يعزز النظام المقترح من راحة وسلامة جهاز إعادة التأهيل وفقاً لاحتياجات المرضى. سيساعد هذا المرضى على التعافي بشكل أفضل وأسرع، وفي النهاية يحسن نوعية حياتهم.

## APPROVAL PAGE

I certify that I have supervised and read this study and that in my opinion, it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a thesis for the degree of Master of Science (Mechatronics Engineering).

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## DECLARATION

I hereby declare that this thesis is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted for any other degrees at IIUM or other institutions.

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## ACKNOWLEDGEMENTS

Firstly, it is my utmost pleasure to dedicate this work to my research team member and my family, who granted me the gift of their unwavering belief in my ability to accomplish this goal: thank you for your support and patience.

I wish to express my appreciation and thanks to those who provided their time, effort and support for this project. To the members of my dissertation committee, thank you for sticking with me.

I also thank the Asian Office of Aerospace Research and Development (AOARD) of the Air force office of Scientific Research (AFOSR) for sponsoring the machine learning part of the research under the grant number FA2386-18-1-4105 R&D 18IOA105.

Finally, a special thanks to Dr Norsinnira Zainul Azlan and Prof. Anis Nurashikin Nordin is continuous support, encouragement and leadership and for that, I will be forever grateful.



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## LIST OF ABBREVIATION

FER	Facial Expression Recognition
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
RL	Random Forest
KNN	K Nearest Neighbor
DT	Decision Tree
SVM	Support Vector Machine
LR	Logistic Regression
ACC	Accuracy
DOF	Degree of Freedom
PWM	Pulse Width Modulation
FE	Facial Expression
ERS	Elbow Rehabilitation System

## LIST OF SYMBOLS

$\sigma$	Defined parameter for standard deviation formula
$\mu$	the mean value of the dataset
$N$	The size of the facial expression dataset
$X_i$	Each data point
$D$	Defined the Minkowski distance formula.
$P$	Minkowski distance parameter
$E$	Entropy
$C$	Training set number
$P_i$	Probability
$B$	Bias
$f_b$	Train regression
$\hat{f}$	Prediction results

# **CHAPTER ONE**

## **INTRODUCTION**

### **1.1 BACKGROUND OF THE STUDY**

Ageing and stroke are two of the leading causes of impairment and disability in Malaysia (Ahmad et al., 2017). Malaysia is expected to become an old country in the next 15 years, with 15 per cent of its population projected to be 60 years of age or older. There are also six new stroke cases in an hour in Malaysia and more than 25,000 stroke patients are predicted to be admitted to hospitals every year over the next five years (Ma, Lin, & Wang, 2016). These people's capability is limited; hence, they are very dependent on their daily routine activities and rehabilitation therapy. Automatic rehabilitation therapy can be provided by robotic rehabilitation systems (Z. Wang, Chang, & Sui, 2017). Nowadays, many companies are making an automatic rehabilitation system. However, most automatic rehabilitation systems are unable to understand patients' feedback during the rehabilitation exercises. For this reason, some rehabilitation exercises become harmful and uncomfortable for the patients.

There are three traditional methods in controlling a rehabilitation robot: Electromyography (EMG) signal, computer vision or image processing and sensors technologies. The problem with controlling the rehabilitation robot using the EMG signal is that it is a complicated signal. The signal often varies between person to person and states of the same person. For example, a person's EMG signal may be different if they are relaxed and tired, even if they perform the same motion. It makes it challenging to recognize the pattern and distinguish the EMG signal when performing the desired function (Skov-Madsen, Rijkhoff, & Vistisen, 2008). Alternatively, to older and stroke patients with impaired ability, human facial expression can regulate different

movements and systems. Since it is more visible and requires minimal human interaction, the facial expression (FE) is more convenient to be measured than EMG signals.

Similarly, controlling a rehabilitation robot with computer vision or image processing also has some limitations. For example, computer vision/image processing needs a large amount of memory and needs computation resources such as GPU. Also, computer vision or image processing is affected by environmental changes. For example, when an image is of dark light, images or environments are dark and hard to classify using computer vision or image processing. However, sensors technologies overcome all the limitations because it does not need a massive amount of memory, expensive computation resources, and not depend on environment changes (Zhang et al., 2016).

One of the most famous wearable sensors is stretchable strain sensors for muscle movement detection(J. H. Lee, Yang, Kim, & Park, 2013). Stretchable strain sensors data are the time series data. Time series data built by the sampled data points are obtained from a continuous, real-valued process over time. The disadvantage of time series data is that it has high noise and dimensionality, and it does not confirm that there is sufficient information accessible to learn the process. However, the stretchable strain sensor's performance is better than the EMG and computer vision for muscle movement detection and classification (Din, Xu, Cheng, & Dirven, 2017). Stretchable strain sensors are used for different wearable biomedical applications, including human body observation, human body movement recognition and environment checking around the organic surface with the advancement of material and innovations and many other applications (Din et al., 2017).

In this study, the stretchable strain sensors are used for FE data collection. ML models are implemented to recognize the FE based on the sensors data. After that, the best ML FER model is used to drive an ERS. In the proposed FER model is driven rehabilitation system:

- If neutral FE is detected, the machine speed will be regulated to 60% of its full speed.
- If happy FE is detected, the machine speed will be regulated to 80% of its full speed.
- If sad FE is detected, the machine speed will be regulated to 0% or its stop.
- If disgust FE is detected, the machine speed will be regulated to 30% of its full speed.

## **1.2 PROBLEM STATEMENTS**

The following problems can be stated for this research.

In the modern world, many companies are making rehabilitation systems. Some of the systems are manual and some of the systems are automatic. Most of the automatic rehabilitation systems have one major limitation. That limitation is that it cannot accurately understand the patient's feedback when doing the rehabilitation exercise. For this reason, sometimes, the rehabilitation system becomes harmful and uncomfortable for the patients.

Computer vision/image processing-based FER system problems need a massive amount of memory and computation resource (GPUs) and it is costly. It depends on

environmental changes. For example, if the image is low light or dark, computer vision/image processing cannot accurately detect it.

Rehabilitation systems can be controlled using EMG signals. However, the EMG signal has some limitations, such as an EMG is one of the highly noisy signals, which shows different values at the same time for the same person. Therefore, it is difficult to drive a limb rehabilitation system using EMG.

### **1.3 RESEARCH OBJECTIVES**

The research aims to accomplish the following objectives:

1. To develop stretchable strain sensors-based FER system using a machine learning model.
2. To implement the facial expression recognition system to drive an elbow rehabilitation system.
3. To validate the proposed FER systems by simulation and hardware experimental tests.

### **1.4 RESEARCH METHODOLOGY**

The aim of the developed facial expressions driven rehabilitation system is to improve the rehabilitation system performance. Two different stretchable strain sensors (commercial and developed) are used for FER data collection and compared the performance between these sensors. The elbow rehabilitation system (ERS) mechanical design is taken from another research study (Alamoodi, 2015). This system has one degree of freedom (ODF) and is capable of flexion-extension motion. The rehabilitations machine's speed is adjusted based on the human facial expression, which

shows their emotion. It enhances the treatment and the patient's comfort while using the machine and helps patients to recover. As a result, the proposed system will improve the rehabilitation system and enhance treatment. Finally, it improves patients' quality of life.

This research starts with an in-depth literature review of machine learning, facial expression recognition and rehabilitation systems. The machine learning-based recognition system for facial expression is developed and this model is tested by a simulation platform (Colab). If the simulation performance is acceptable, the first objective is considered achieved after compared to the commercial and developed stretchable strain sensors performance. If the developed stretchable sensors performance is satisfactory, the first objective is completed. After that, designed EHS are integrated into the stretchable strain sensors based FER system (Alamoodi, 2015). The experimental ERS is used for experimenting with the subject. The rehabilitation system speed will be regulated according to facial expression and the system recorded the accuracy. If this experiment is successful, the second objective is considered to achieve. Finally, the whole system will be validated by simulation and hardware experiment test, the third objectives achieved and the research process ends. The flow chart of the research methodology is illustrated in Figure 1.1.

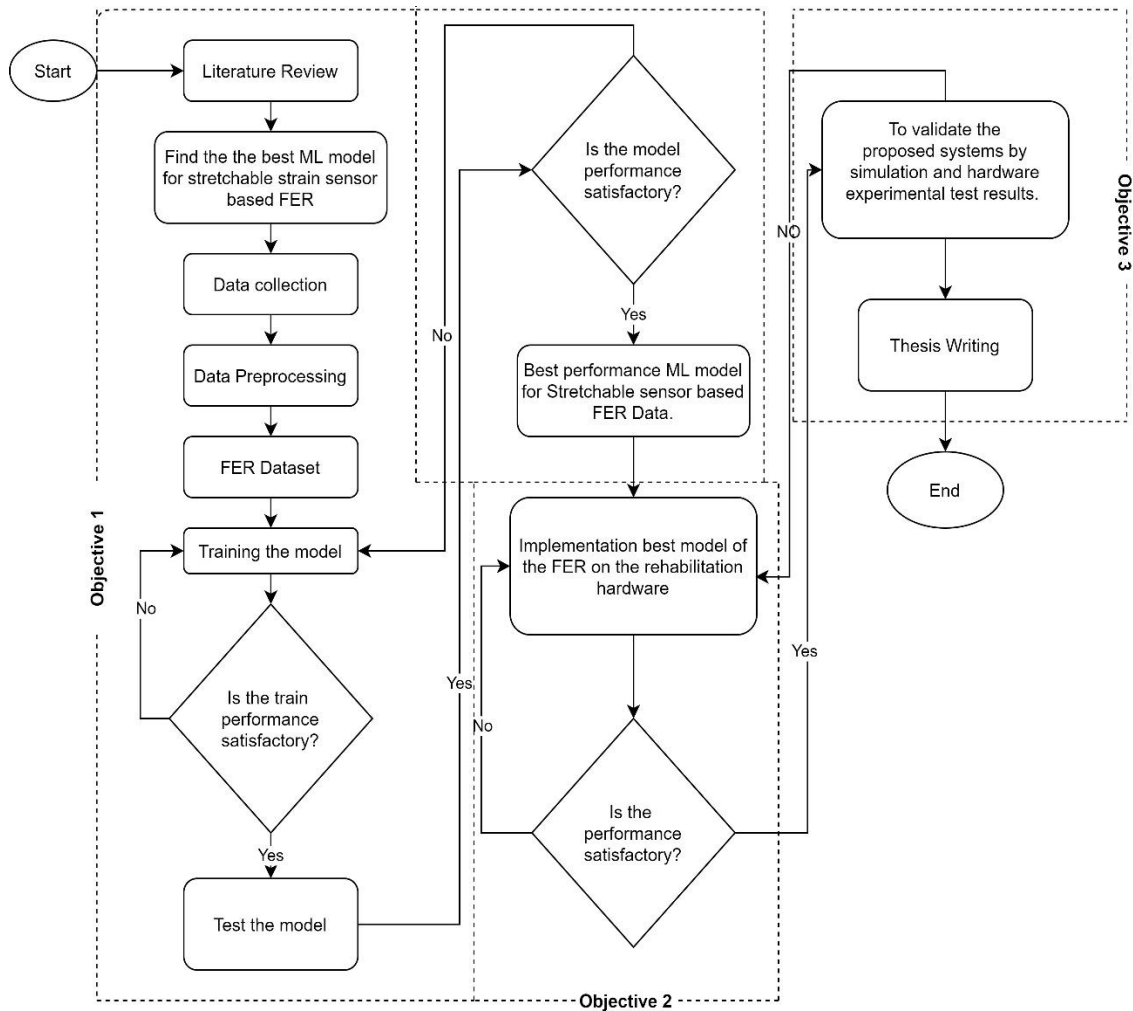


Figure 1.1: Research methodology

## 1.5 RESEARCH SCOPE

1. This research focuses on happy, sad, disgust and neutral facial expressions. For example, other facial expressions (angry, surprise and fear) are beyond this research's scope.
2. At this stage of the study, FE data was collected from 30 people ( 20 Male and 10 Female).
3. At this stage of the study, three commercial and four developed stretchable strain sensors used for FE data collection.