Evolution in Electrical and Electronic Engineering Vol. 1 No. 1 (2020) 270 - 279

EEEE

Homepage: http://penerbit.uthm.edu.my/proceeding/index.php/eeee
e-ISSN : 2756-8458

Leg Flexibility Classification Using AutoML Tables

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DOI: https://doi.org/10.30880/eeee.2020.01.01.032
Received 3 August 2020; Accepted 06 September 2020; Available online 30 October 2020

Abstract: Silat performance covers many style of self-defence that requires hands and legs to perform punching and kicking. The aim of this project was to classify the leg flexibility by studying the correlation between flexibility index and kicking angle by means of classification using machine learning method. The main objectives were to develop an IoT based prototype utilizing flex sensor and Blynk platform, to measure the kicking angle and leg flexibility index on subjects and finally to conduct classification study on the measured data by using AutoML Table provided by Google Cloud. Twenty participant from two different backgrounds; silat athlete and non-silat athletes are selected as subjects in this study. In this project, the AutoML Tables was automatically built and deployed machine learning models based on the structured data. The .CSV file contained data of kicking angle and leg flexibility index are used to train the classification model. The prediction model successfully predicts the outcome (leg flexibility) when the two input features (flexibility index and kicking angle) are keyed-in during "Test and Use". In conclusion, the leg flexibility classification can be determined based on two parameters namely as flexibility index and kicking angle by using AutoML Tables. In the future, bigger sample size of data can be collected and trained using BigQuery.

Keywords: AutoML Tables, Blynk, Flexibility Index, Google Cloud Platform, Kicking

1. Introduction

Nowadays, martial arts are becoming one of the mainstream sport among youth all over the world and somehow their popularity is far-reaching. Martial arts are commonly viewed as both; educational and physical activities which involves any fighting style used to train and develop control of one-self. There are various types of martial arts including silat, taekwondo, karate and judo. All of these types of martial arts require different techniques of dynamic movement which one of them is kicking [1].

Biomechanics has been defined as the study of the movement of living things using the science of mechanics. Biomechanics is most useful in improving performance in sports or activities where

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technique is the dominant factor rather than physical structure or physiological capacity [2]. Through the understanding of coaches and trainers regarding the biomechanics, they can instantly examine and put the motion as a key element in sport for their athletes [3].

Google Cloud Platform (GCP) is one of a leading cloud computing platforms which available on the market today that provide users with infrastructure tools, and services to build on top of [4]. There are many services provided by GCP and one of them is AutoML Tables. AutoML Tables is a commercial platform that manages end-to-end AutoML from raw data to predictions [5].

Based on this project, several objectives have been formulated. The first objective is to develop an IoT based prototype utilizing flex sensor and Blynk Platform. Second objective is to measure the kicking angle and leg flexibility index on subjects and finally to conduct classification study on the measured data by using AutoML Tables provided by Google Cloud. The scopes of the study can be divided into three phases. The first phase involves the subject and experiment protocols. Twenty participants from two different backgrounds (silat and non-silat athletes) have been recruited and they are requested to perform front kicking as the standard kicking style for three times of trials. Second phase is the device development in which NodeMCU has been chosen to control and process the input and output and finally the third phase involves the employment of IoT in which the Blynk and Google cloud application have been chosen for receiving the data on the smartphone as well as for classification using AutoML Tables respectively.

2. Materials and Methods

The proposed functional block diagram was shown in Figure 1. The block diagram consists of three main stages; input, process and output. The input consists of flex sensor which used to measure the amount of deflection or bending of leg during kicking action. Next, the process stage involves the use of Arduino NodeMCU microcontroller (ESP8266) to process the data that have been collected and to send them to the Blynk interface of the smartphone through the Wifi module. Then, all the data of flexibility index and kicking angle will be trained by using AutoML Tables provided by Google Cloud for determination of leg flexibility classification.

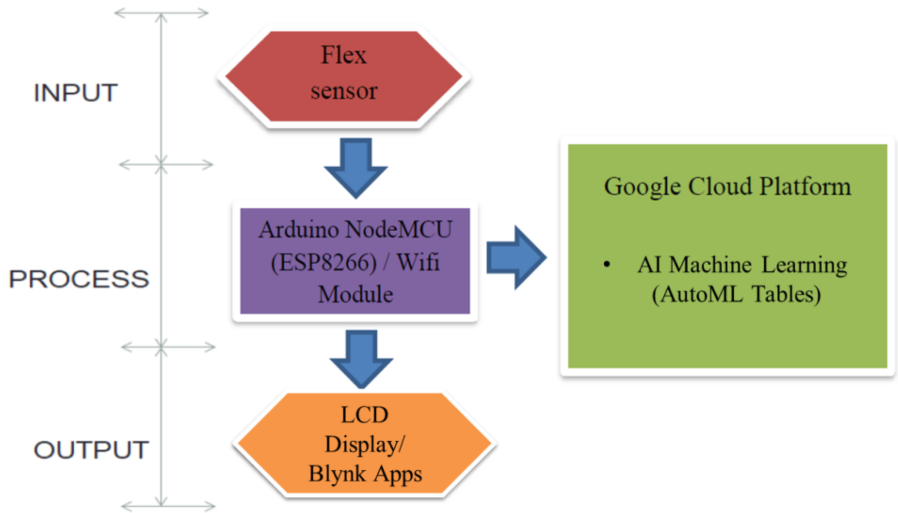

Figure 1 : Proposed functional block diagram

2.1 Establishment of measured angle during dynamic movement

Figure 2 shows the overview for subject's measured angle during dynamic movement of kicking. It shows the side view of the hip flexion that specifies the joint angle. The hip region between pelvis and upper thigh bone has been chosen for the placement of flex sensor. When the subject is performing their kicking, the bended flex sensor will determine its resistance. As the flex sensor is bent, the resistant will gradually increases. Further description on this assumption can be referred to [6]. Meanwhile, Figure 3 shows how the flexibility experiment is carried out during kicking action. The subject will be asked to wear the proposed device together with the placement of flex sensor that is attached on their hip. The placement of sensor can be changed based on subject's dominant leg (left or right leg). Then, they will be performing three trials of kicking. The value of kicking angle and resistance will be recorded and display in the LCD as well as on Blynk interface.

Flexibility index is dimensionless. It can be obtained by dividing the maximum range of kick with the body height of the subject [7]. However, in this case, we use subject's leg of length instead of body height to be more precise as shown in Eq. 1. The units of both parameters are measured in cm. This flexibility test is important as it used to measure the maximum range of kick which typically used during any type of matches such as karate, silat, taekwondo and judo.

$$Leg\ Flexibility\ Index = \frac{maximum\ range\ of\ kick\ (cm)}{length\ of\ leg\ (cm)} \qquad \text{Eq. 1}$$

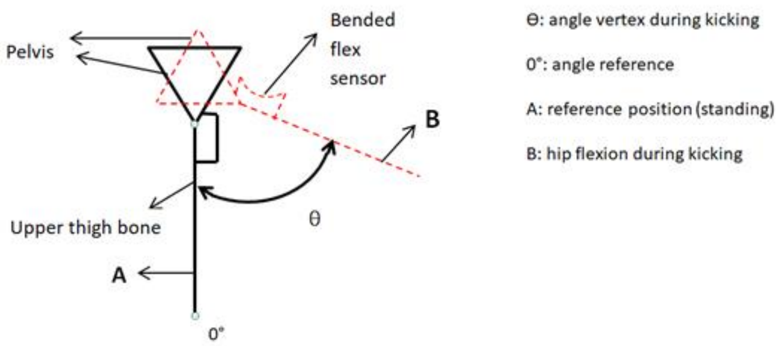

Figure 2 : Overview of subject's measured angle during kicking [6]

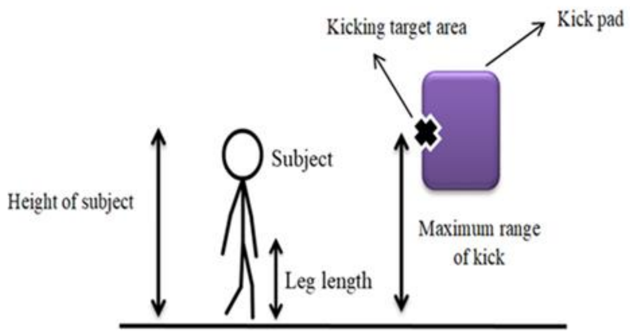

Figure 3 : Front kicking experiment set up

2.2 Leg flexibility prototype

In this project, the main components used are flex sensor, NodeMCU Microcontroller, and LCD Display. The flex sensor used in this project is a flexible sensor that has two output wires that change its output when bending. The flex sensor will be bended to a certain degree of angle. It can be said that, the greater the amount of bend applied, the higher will be its resistance [8].

2.3 Arduino IDE software and blynk platform

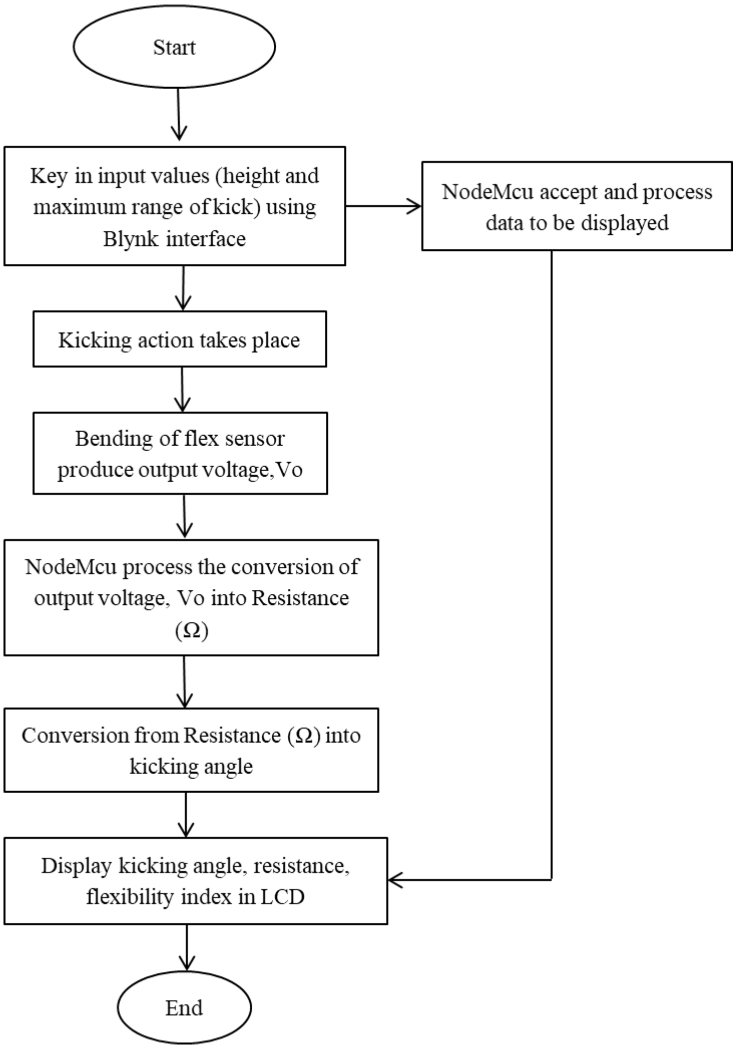

Figure 4 : Flowchart for arduino and blynk process

Figure 4 shows the flowchart for the process done in Blynk. It started with key in the input values, height and maximum range of kick using Blynk interface. Next, the kicking action will takes place which will be resulted in bending of flex sensor, producing the output voltage, Vo. The NodeMcu will process the conversion of kicking angle into resistance value and lastly, the output of flexibility index, resistance and kicking angle will be displayed in LCD.

2.4 AutoML tables

From the data of kicking angle and leg flexibility index that has been recorded, it is then need to be trained by using machine learning. There are a few examples of Artificial Intelligence products that are included in Google cloud services, but the one that will be used in this project is AutoML Tables. The process started by importing the dataset, followed by training the model [9].

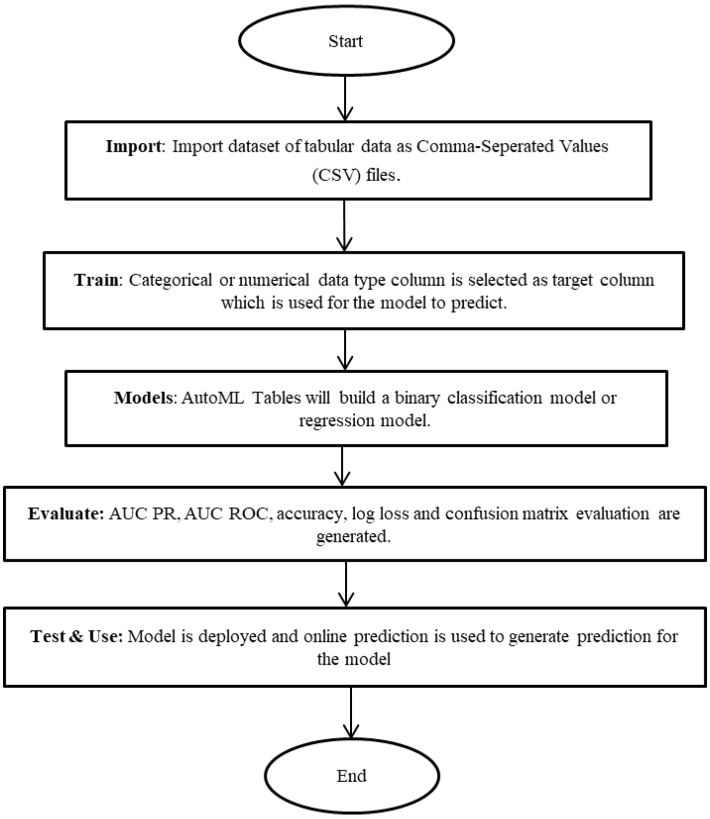

Figure 5 : Flowchart for the process of autoML tables

Figure 5 illustrates the process that takes place for the training of machine learning model by using AutoML Tables. The process begins with dataset being imported as CSV files. The targeted column which is selected from one of the column is used for prediction. The selected data could be categorical data or numerical data but in this research, it is a categorical data type. The AutoML will build classification model, which will predict the target from classes in the selected column. Next, the evaluation will determine the value for Area Under Curve (AUC PR), Receiver Operating Curve (ROC), accuracy and log loss. The final step is deployment of the model before using it for online predictions.

3. Results and Discussion

The main findings are presented in this section that cover the resulted circuit design and prototype, data collection on twenty subjects as well as the classification process using AutoML Tables.

3.1 Circuit design and prototype

Figure 6 shows the circuit diagram of the device that has been designed by using Fritzing Software. Meanwhile, Figure 7 demonstrates the hardware prototype as well as how the prototype is being placed on the subject's waist respectively and the implementation of IoT in retrieving the data obtained by using Blynk Apps. The circuit consists of NodeMCU (ESP8266) microcontroller that used to read the analog value of the flex sensor. This value will be printed on the serial monitor and will send to the Blynk by using WiFi module (ESP8266).

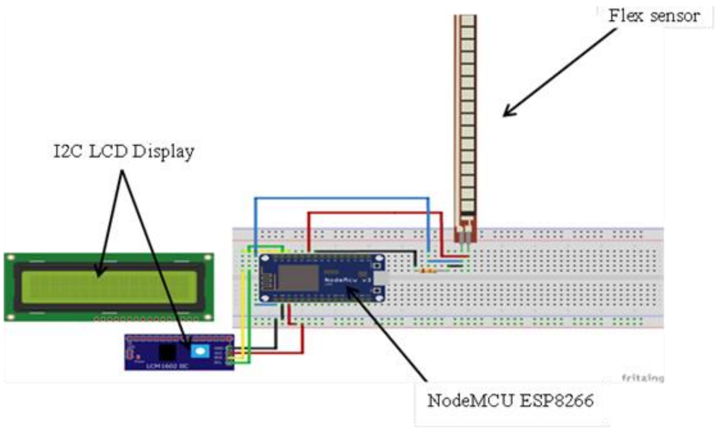

Figure 6 : Circuit diagram of hardware design

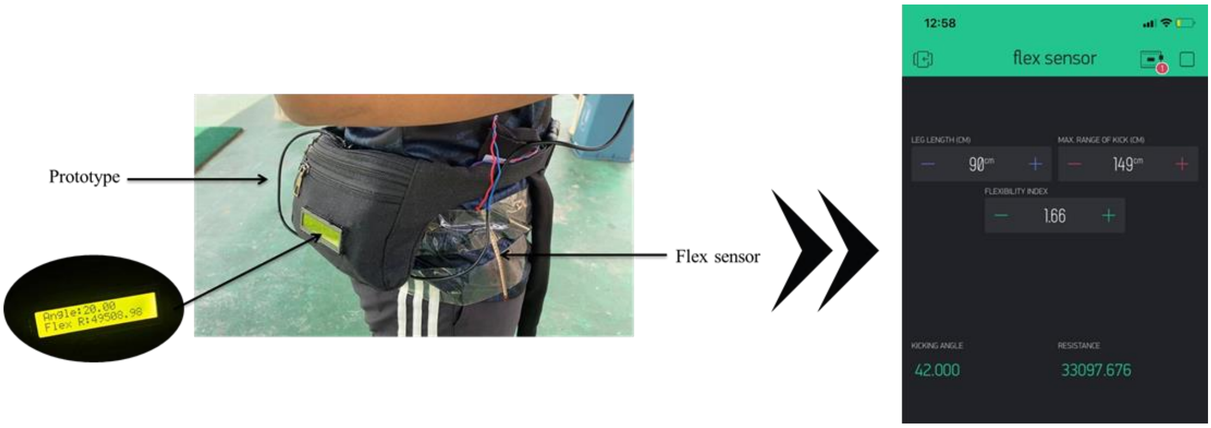

Figure 7 : Process of data obtained from hardware as well as monitoring them using blynk apps in mobile phone

3.2 Data collection (silat and non-silat athletes)

20 subjects comprised of 10 athletes and 10 non-athletes had been recruited to conduct front kicking experiment using developed device. Apart from that, the standard kicking style for all the participants in this study is focus on front kick which they need to do three trials in order to obtain the average and standard deviation. Two data was recorded namely as kicking angle and flexibility index of true leg. From the data collected, a prediction of relationship between flexibility index and kicking angle was carried out by using the AutoML Tables provided by Google Cloud.

3.3 Findings from AutoML Tables

The preparation of dataset starts with preparing the import source. This can be done in two ways but in this case, the use of comma-seperated values (CSV) files is considered. The data need to be prepared accordingly to the requirement of CSV file which includes the style of column names, header, number of rows and columns and also the size of the file. Table I shows the data that is used for the training. The data is consists of *Data_Split_Column*, *Outcome*, *Mean_Kicking_Angle*, *Flexibility_Index* and *Subject*. There are 1000 rows and 5 columns altogether.

Table 1: Tabular dataset in CSV file

Data_Split_Column	Outcome	Mean_Kicking_Angle	Flexibility_Index	Subject
train	non_flexible	41	1.56	Athlete
validate	non_flexible	49.33	1.59	Athlete
test	flex	60	1.63	Athlete
train	flex	80.33	1.65	Athlete
validate	flex	81.67	1.68	Athlete
test	non_flexible	54	1.62	Athlete
train	non_flexible	40.33	1.54	Athlete
validate	flex	59.33	1.63	Athlete
test	flex	70	1.66	Athlete
train	non_flexible	30.67	1.54	Athlete
validate	flex	72.33	1.66	Non-Athlete
test	non_flexible	53	1.55	Non-Athlete
train	non_flexible	40	1.52	Non-Athlete
validate	non_flexible	64.33	1.61	Non-Athlete
test	non_flexible	47.33	1.54	Non-Athlete
train	flex	68.33	1.63	Non-Athlete
validate	flex	71	1.64	Non-Athlete
test	non_flexible	38.33	1.45	Non-Athlete
train	non_flexible	44.67	1.52	Non-Athlete
validate	flex	71.67	1.64	Non-Athlete

The CSV file of the dataset is uploaded in the bucket storage as in Figure 8, where the bucket requirements are followed accordingly. This requirement includes the location type, location and storage class. In this project, we chose global (us-central1) for the location and region as the location type.

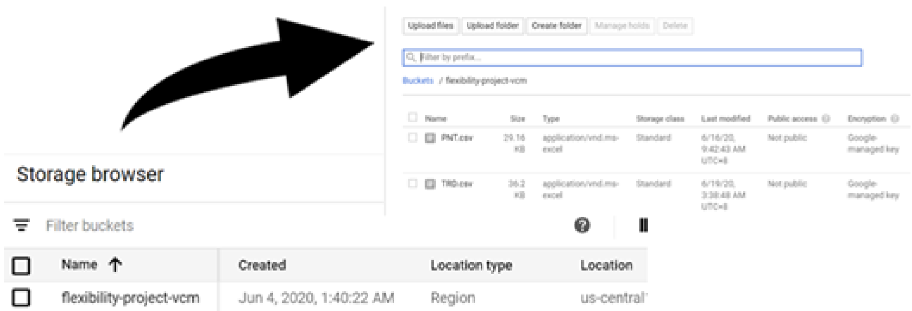

Figure 8 : Process of creating storage bucket and uploading dataset files

A bucket is created in the storage browser in order to store the data in CSV files. The bucket storage is a named file of Visual Components Model file (vcm). In this project, the file is named as flexibility-project-vcm. When the dataset is successfully uploaded, the process continues with data import, train, evaluate and test. In this project, Console is chosen as the method of training and evaluation of the model. The dataset takes a while to import and after it is done, it will show the summary of columns and rows.

i) Import

The data (CSV file) is uploaded from the Cloud Storage in the storage browser that has been created earlier. The dataset takes a while to import and when it meets success, the console will continue to the next step which is training of the data. Refer to Figure 9 (a).

ii) Train

In this part, a summary for column and rows will be displayed and it will also show the percentage of categorical and numerical data type by the column. The important part in this process is the selection of target column. Usually the target column is selected based on what element need to be predicted by the models. In this project, *Outcome* has been chosen as the target column. The model should be able to predict the result of *Outcome* as flexible or not flexible based on the *Flexibility_Index*. Flexibility index and mean kicking angle is selected as input feature as both of them are much influenced in this correlation. Refer to Figure 9 (b) and (c).

iii) Models

The model is the part where binary classification is generated. As the target column is chosen based on categorical data type, hence it will generate binary classification model. Otherwise, it will be generated as regression model. The metrics are generated based on the less common label being the positive class. Refer to Figure 9 (d).

iv) Evaluate

Evaluation of model is occurred in this step as it is the continuance from the binary classification that was generated earlier. The model is said to be optimized for AUC ROC, area under receiver operating characteristics curve. In this case, it is valued as 1 same as the AUC PR, area under precision-recall curve. Both range from 0 to 1 where higher value indicates higher-quality model. Besides, the confusion matrix and feature importance graph also presented as referred to Figure 9 (e). The confusion matrix presents the occurrence of misclassifications where which one of those classes got confused with each other. Each row is a predicted class and each column is an observed class. Meanwhile, the feature importance shows the score by how much the prediction varies when value of column changes. In this case, flexibility index shows the higher percentage as 80.063% where it indicates a greater importance to the model.

v) Test and Use

The last process is testing as shown in Figure 9 (f). In this part, online prediction is used. The model must have to deploy first before it can use to predict in real-time. The result of online prediction is shown in Table II.

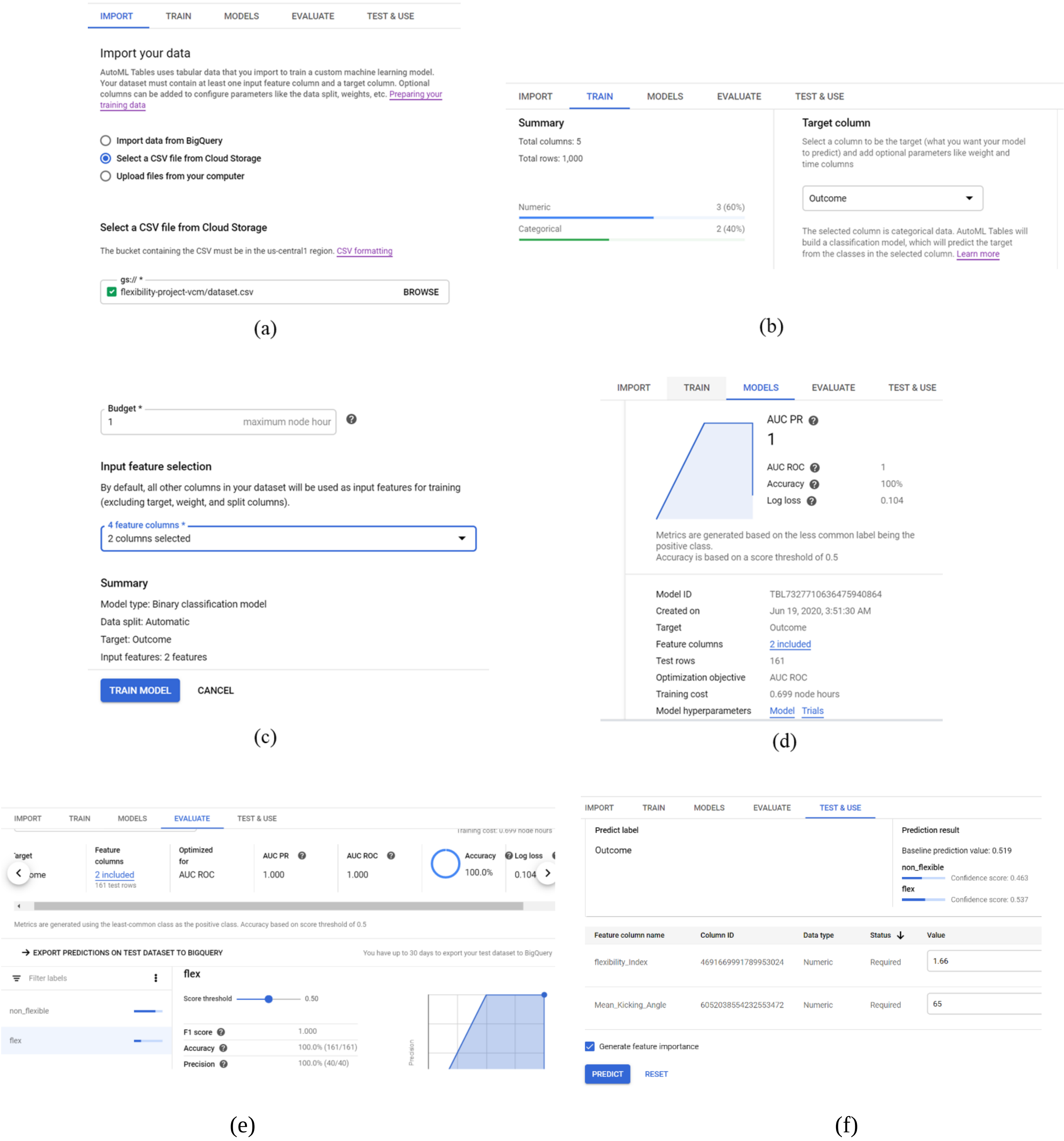

Figure 9 : a) Import data by selecting CSV file from cloud storage, b) training of data by selecting target column, c) input feature selection d) training of models, e) evaluation of models and (f) test and use

4. Conclusion

In conclusion, all objectives have been successfully achieved. The prototype is able to collect the data and implement the IoT platform using Blynk. The AutoML Tables manage to predict the relationship between kicking angle and flexibility index based on the specified outcome. In the future, Big Data such as BigQuery can be used for storing and querying large amount of datasets. As for recommendation, a bigger sample size of data can be collected to be fed into the AutoML Tables for better accuracy.

Acknowledgement

The authors would also like to extend sincere gratitude to RMC for providing additional funding under the TIER 1 grant (H226) and to Universiti Tun Hussein Onn Malaysia's Faculty of Electrical and Electronic Engineering for technical support as well as to Google Cloud Platform (GCP) for providing AutoML Tables service.

References

[1] S. Di Zio, “Future strategy for reducing violence against women: The Italian experience,” Foresight, vol. 12, no. 5, pp. 80–91, 2010

[2] G. Mustapha, et al., “Biomechanics research on martial arts– The importance of defensive study,” Arch. Budo, vol. 11, pp. 187–195, 2015

[3] D. Knudson, The Hill Muscle Model, Second Edi. Springer, 2004

[4] S. Tutorial, “Persistent Storage,” no. November, 2012

[5] N. Erickson, et al., “AutoGluon-Tabular: Robust and Accurate AutoML for Structured Data,” 2020

[6] J. Nur Anida, et al., "Development of wearable IoT-based front kicking's angle monitoring device." Malaysian Journal of Movement, Health & Exercise, [S.l.], v. 9, n. 1, jan. 2020. ISSN 2600-9404

[7] E. Franchini and S. Stanislaw, “Testing motor fitness in karate,” Arch. Budo, vol. 5, pp. 29–34, 2009

[8] A. Syed, et al., “Flex Sensor Based Robotic Arm Controller Using Micro Controller,” J. Softw. Eng. Appl., vol. 05, no. 05, pp. 364–366, 2012

[9] Google, “AutoML Tables,” Google Cloud, no. October, 2019