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Intelligent Automatic Door System based on Supervised Learning

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Abstract— The widespread adoption of automatic sliding doors in both commercial and non-commercial environment globally has necessitated the need to improve their efficiency, safety and mode of operation. Automatic door gives access to go into or outside a building by sensing the approaching individual using sensors. However, it does not have the intuition to understand when a person is not authorized to go outside based on their age limit, for example, children. To address this problem, researchers have proposed solutions ranging from the use of fuzzy logic to rule-based approaches to make automatic doors better than the previous ones. In this study, an AI-based automatic door system is proposed, which uses a supervised machine learning approach to train classifiers using human body measurement. Our evaluation of different classifiers indicates that SVM is capable of classifying the instances correctly while achieving about 88.9% F-score. Thus, the proposed approach is expected to improve the safety of automatic doors, thereby making them smarter and more intelligent.

Keywords— *Automatic door, Body measurement, Machine Learning, Supervised Learning.*

I. INTRODUCTION

Automatic doors have been in existence for many centuries, and they are widely used in both commercial and non-commercial environment for entering and exiting buildings. They are designed to automatically detect proximity of a person or object approaching, using powerful sensors and other components. Since its invention, the technology keeps changing every year to conform to the current technology requirement. The technology behind an automatic door comprises different sensor technologies such as infrared, ultrasonic and other wireless sensors like weblink sensors, which detect objects within a specified range and indicate to the microcontroller to open or close [1]. Even though these techniques are effective and successful in determining and detecting objects, yet they fail to intuitively understand their environment [2].

As they get more intelligent and advanced, the need to incorporate decision making arises when experts discovered that automatic doors could pose some challenges to human beings. The first challenge is that an automatic door cannot decide whether it should open or not when there is an intruder. The second challenge is whether it should open and allow a 4-year-old child who is under the supervision of a parent to exit a building or not. Another challenge is based on how the doors respond to input request, especially if there is

speed involved [3]. These imply that the door system should be able to make a distinction between a person who is old enough to access the doors and a child who should not. Likewise, it should accurately synchronize its request speed with the speed of the person or object approaching. Furthermore, automatic door should be able to understand the intention of the object in proximity.

In order to make automatic doors smarter, researchers must incorporate advanced technologies such as artificial intelligence (AI). AI gives machine or system the ability to perform tasks and make decision by learning from the immediate environment. This includes training of the system to distinguish different task scenario such as whom to open the door or not. This, in a nutshell, gives the door system the ability to act like humans by following a pedagogical process known as machine learning. In this paper, we demonstrate that by utilizing machine learning techniques on automatic door systems, automatic doors will be able to make rational decisions and become fully automated. In this attempt, we propose an AI-based automatic door system using supervised machine learning. The proposed system is trained on a dataset which includes different body measurements from different individuals. The system is designed to learn the different body measurements based on features such as age, height, shoulder-length, arm's length, belly size, head size, etc. By learning these features, the system should be able to distinguish between a 4-year-old child and an adult who is old enough to access the door. The contributions of this paper are as follows:

- We present an AI-based automatic door system based on supervised learning to classify individuals according to their body measure dimensions.
- We present a new set of datasets that can be utilized on a wide range of computational problems in various domains.

The structure of this paper is as follows: in section 2, we discuss the methods and techniques used in this study. We also discuss the steps taken in the experiment. In section 3, we discuss previous works and the state of the art of the current domain. In section 4, we discuss the proposed system, its component and system design. In section 5, we discuss the

results of our experiment. And in section 6, we provide concluding remarks and suggest some future focus.

II. AUTOMATIC DOOR

Automatic doors could be traced back to ancient Egypt when tombs were barricaded with such doors to protect the tombs from unauthorized access. Decades later, automatic doors were recorded in the early Greek civilization. Since then, homes and buildings began to install them in order to separate the main building from outdoors [4]. However, the modern automatic door was invented in 1931 by Horace Raymond and Sheldon Roby [5]. The first of its kind was installed in restaurants in the United States [6] to allow waiters to enter or exit the restaurant without having to open or close the doors. Modern automatic doors are designed to use sensors to detect movement. These sensors could be ultrasonic, infrared, or wireless sensors. A sensor can use active or passive approach for operation. The active process draws infrared waves from the main controller. It captures the beamed signals to determine whether an object is close. This approach is considered accurate in identifying the position of an object and the speed at which the object is approaching. On the other hand, passive approach uses infrared waves carried by people to determine the next action. They are considered simple, low cost and effective. Another example is that of ultrasonic approach which emits radio signals to scan the immediate environment to determine the next action.

There are different types of automatic doors based on their mode of operations. Some automatic doors work by sliding along a rode track into or behind the wall. Some work by rolling or revolving around an axis panel, while some swing as an object comes within range of detection [4]. Modern automatic doors are much advanced; therefore, they have more sophisticated architecture and components that support their operation. The following components constitute an automatic door:

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A. Door operator

The door operator comprises of a collection of controllers and motor gears that help the door to open or close depending on the situation

B. Sensors

Sensors are an integral component of automatic doors. They are devices designed to detect events (such as proximity) and send signals to the door operator to take further action. Automatic doors have various types of sensors for different tasks. Activation sensor is one type of sensor that works with the door transom to activate automatic doors when it detects objects or people approaching. Safety sensors, also known as threshold sensors, are another type of sensor designed to prevent the door panels from trapping individuals by providing safety and failover in case of failure.

C. Transom

Transom is an additional advanced safety feature that ensures safe passage. It can be mounted on the ceiling, on the floor or in between door panel to detect incoming and outgoing movements. Some transoms are placed on the

ground to be walked on as this allows the sensors to detect the presence of individuals.

D. Door Panel

The door panels are entry points made from tempered glass, stainless steels or aluminum materials. The panels can operate by rolling, sliding, or rotating.

E. Access Controller

Automatic door access controller is a system that handles the request from other door components such as lock system, sensors, transom and motor. In a high configuration environment, access controller serves as an authentication and verification system, at times even works as an emergency handler. It can also be used to restrict access into a building or even set time and triggers.

F. Lock System

The lock system allows the door controller to lock the door from inside or outside. Lock system comes in various forms – double-bolt lock is a type of lock that creates a double layer of protection. Smart locks are electronic locks which come with biometric access or key panel to enable extra security through verification and authentication.

III. METHOD

In this study, we experimented using a new set of data that is characterized by a combination of different body measurement and dimensions taken from a diversified population of people. We hypothesized that some selected features from human body measurement such as height, shoulders, arms, waist, legs could be used to train a model that is capable of classifying and distinguishing door users from underage with no permission to access the door to adults with full permission to access the door. In the process, we utilized a supervised learning approach to machine learning by selecting six different classifiers. Fig. 1 demonstrates the step by step process taken in this study:

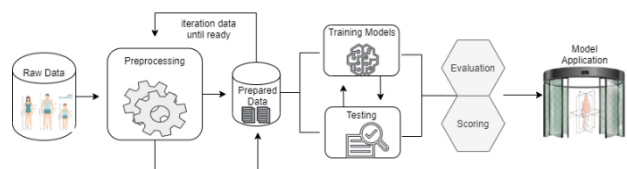


Fig. 1: Step by step process of building the system

A. Datasets

The researchers collected the training data by taking body measurements of various individuals from a diversified population, namely Africans and Asians. The measurements were taken from 716 individuals out of which 391 were men, and 325 were women. The individuals were primarily children between the age of 1 to 12, teenagers between 13 to 19 and adults aged 20 to 65. Standard body measurements such as height, shoulders, arms, head, belly, waist etcetera were taken, and they were measured using inch measurement scale. The dataset has 716 observations and 13 variables (instances) with a class label notated by 'open and close'. The following table provides a summary of the dataset features:

Table 1: Summary of dataset features

Item	Variable	Description	Instances
1	Gender	Denoted by M=1 & F=2	391 Males & 325 Females
2	Age	Age of subject	716
3	Head	Head circumference	716
4	Shoulder	Shoulder width	716
5	Chest	Chest width	716
6	Belly	Belly size	716
7	Waist	Waist width	716
8	Hips	Hips width	716
9	Arm	Arm length	716
10	Shoulder to waist	Length of subject from shoulder to waist	716
11	Waist to knee	Length of subject from waist to kneecap	716
12	Leg	Length of leg from waist down to toe	716
13	Height	Height of subject from head to toe	716

B. Feature Engineering

To train a model efficiently, the features used play a very important role in determining the accuracy of the trained model. In this study, we used 13 features extracted from different body dimensions. The features are listed in table 1. We selected these features based on previous studies, including [7] and [8]. The reader should note that this experiment employed a linear support vector machine (L-SVM). This is because L-SVM provides information relative distribution as well as contribution of each feature in the experiment. Besides that, feature ranking was employed based on the weight obtained through linear SVM. This process helped us gain insight into the dataset and eliminate features with less impact or less contribution to the development of the model. The ranking of the features was obtained by sorting the features based on the absolute values of the relative weight as depicted by the linear SVM algorithm, as suggested by a similar study [9]. The algorithm works like this (1).

Algorithm 1: Feature ranking with L-SVM [10]

Input: Training sets $(x_i, y_i), i = 1, \dots, l$ (1)

Output: Sorted features ranking list

- Make use of grid search to find the most relevant parameter C
- Train a L2-loss linear SVM model using the best C
- Sort the features according to the absolute values of weights in the model

C. Classification

Classification in machine learning is a supervised technique of learning in which a model is trained to accurately identify a category of observations or a target class from labeled data. This study involves a classification problem in which an automatic door system is trained to predict whether the user of the door is permitted to access the door or not. In this study, we conducted our experiment using Weka. Weka, which means Waikato Environment for Knowledge Analysis, is a free tool for data mining and a training environment for machine learning algorithms by the

University of Waikato in New Zealand. To train and evaluate our model, we utilized different machine learning algorithms including Naïve Bayes, SVM, Decision tree, AdaBoost and JRIP. In this experiment, we divided our datasets into training sets and testing sets. Training sets constituted about 80% of our data, while testing sets constituted the remaining 20%. For the evaluation of models, we used different evaluation metrics, including precision, recall and F-measure.

IV. RELATED WORKS

This section focuses on the research efforts that precede this research work. However, this includes studies dedicated to the application of artificial intelligence in developing automatic door systems. It is worth noting that not many researches have attempted to address the problems mentioned above using artificial intelligence techniques. Notwithstanding, researchers have proposed several automatic door systems.

An attempt has been made by [11] to develop an intelligent automatic door system which uses infrared sensors to capture human body signals. The signals are then stored into the microcontroller signal processor. Along the line, the microprocessor controller controlled the stepper motor rotation which enables the door to open and close. However, this system is not fully automated, as it requires manual switch when the door sensors failed. The overall design does not have a decision-making system, it relies on rules programmed to operate.

The next study [2] proposed an automatic door access system based on face detection and recognition. The Principal Component (PCA) Analysis method was used to extract relevant features of facial images and send to the microcontroller for authentication. Matlab program was a detection and recognition system; its output is sent to the microcontroller for further action. Although PCA is efficient in reducing the dimensionalities of the extracted features. Notwithstanding, convolutional neural network (CNN) can do a better job since facial images must be converted to grayscale images.

Another study by [3] proposed an automatic door controller based on fuzzy logic. Fuzzy logic was used to improve the door opening speed and distance. According to the study, a fuzzy logic controller is developed based on 25 rules that operate the system controller in a heuristic manner. However, the use of fuzzy logic here does not make the system smart, since the system is designed based on "if A then B format". The system cannot make a rational decision before carrying out a task.

[1] proposed an automatic door system based on human detection and intention analysis. This study aims to reduce the false actions taken by the door system while introducing a behavior analysis system which improves tasks accuracy. The researchers use contour detection to detect whether an object is a person, and then use trajectory tracking and statistical analysis to determine the intention of the person. The system achieved low false rate (near 0%), short response time of about 2 seconds from the time of detection and confirmation of intention, and a high correct activating rate of about 99%.

It is worth noting that none of the above studies have tried to use classification techniques with machine learning to

address the above-mentioned problems, hence the need to fill this gap and contribute to the body of knowledge.

V. RPROPOSED SYSTEM

In this section, we briefly introduce the proposed AI-based Automatic Door System and its essential components. The purpose of the system is to make predictions based on body measurement. The system is designed to leverage a supervised type of machine learning which allows the system to detect any incoming and outgoing movement and make predictions based on the features of the subject. If the person is between 1 year to 5 years, it means he or she is not authorized to gain access through the door except under supervision by an adult. The prediction is determined by features such as the height, body size, length of arms and legs and so on. If the body build up matches the requirements, then access is giving.

A. Overall System Design

The proposed system uses an activation sensor to detect the presence of an object or person when they are within range. Laser scanners are used to scan and measure the body dimension using the standard inch scale. The output of the scan is forwarded to an artificial intelligence system to determine whether to send a request to open or not. The microcontroller, upon receiving the instruction, triggers the motor driver if necessary. Fig. 2 illustrates the entire system architecture. The architecture comprised of sensors, microcontroller, display modules, memory module, access control module, auto-door core module, driver motor, access control panel, laser scanner, USB to RS232 converter, AI system/Database and sockets.

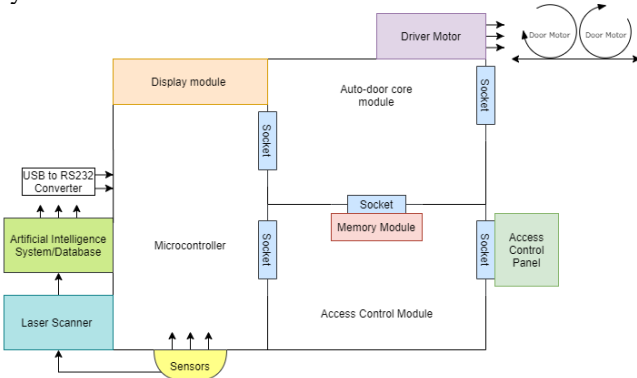


Fig. 2: AI-based automatic door system architecture

VI. EVALUATION AND DISCUSSION

One of our aims is to ensure that the proposed system does well in terms of accuracy and performance. Hence, we evaluated our models using 10-fold cross-validation. When using 10-fold cross-validation, the original dataset was randomly divided into ten (10) equal-sized samples. One sample was kept aside for testing while the remaining nine (9) samples were utilized for training of the model. The reason for selecting this approach is that all samples could be used once only for validation. Moreover, the evaluation metrics used for the evaluation of the models include precision, F-measure and recall. Also note that classified item can be true positive (TP), false positive (FP), false negative (FN) and true negative (TN).

TP is used to measure the outcome of the actual positives that were correctly predicted. FP is used to measure the proportion of negative outcomes that were predicted incorrectly. FN is used to measure the outcomes of the model wrongly classified as positive class. And lastly, TN is used to measure outcomes that the model correctly classified as positive class [12].

Considering the number of TP and FN, recall is computed as follows:

$$\text{Recall} = \frac{TP}{(TP+FN)} \quad (2)$$

Considering the number of TP and FP classified items, precision is computed as follows:

$$\text{Precision} = \frac{TP}{(TP+FP)} \quad (3)$$

When we combine precision and recall, we have our F-measures, given as:

$$F = \frac{(1+\beta^2) \times \text{Recall} \times \text{Precision}}{\beta^2 \times (\text{Precision} + \text{Recall})} \quad (4)$$

Where β^2 denotes the relative value of precision. The value of $\beta = 1$ denotes the equal value of precision and recall. The lower value indicates that importance is given to precision; therefore, a higher value indicates a larger emphasis on the recall [12].

Table 2. Evaluation results of classification using different models

Algorithms	Precision	Recall	F-score
Logistic regression	0.832	0.832	0.832
Random Forest	0.881	0.876	0.878
JRip	0.834	0.829	0.831
SVM	0.889	0.889	0.889
Naïve Bayes	0.757	0.757	0.757
Decision Tree	0.826	0.826	0.826

A. Evaluation of Classification

In this section, we illustrate how we evaluated our models and the results of the classification. As observed from Table 2, we have applied six supervised classification approaches or models, namely: Logistic Regression, Random Forest, Repeated Incremental Pruning, Support vector machine, Naïve Bayes and Decision Tree. As observed above, SVM with sequential minimal optimization offers the best performance with an F-measure score of 0.889. SVM successfully and correctly classified 87.9% of the instances in 10-fold cross-validation. If compared with others in terms of speed, SVM took only 0.04 seconds to train the model. Likewise, the instances were classified faster, making it suitable for application in the automatic door system.

It is worth noting that naïve Bayes has the least performance with an f-score of 75.7%. This could be linked to the lack of enough datasets used in this study. Naïve Bayes usually demands larger datasets if compared with Support Vector Machine to train the algorithm with a higher accuracy and performance. Nevertheless, the evaluation shows that SVM algorithm has performed better than Naïve Bayes, JRip and Logistic regression on t-test with a confidence interval of 0.04. Yet, SVM has not proven to be any significantly better than Random forest and Decision trees.

VII. CONCLUSION AND FURTHER RESEARCH

In this study, we present an AI-based automatic door system based on supervised machine learning. The use of ML allows the automatic door system to detect certain features in an individual to determine whether it should open or not. Our approach is new if we compare it to the existing approaches which utilize fuzzy logic [3] and rule-based [11] to automate the door system. Also, our approach allows the door system to intuitively make decisions independently even if the situation is dynamic. We also demonstrated that our system is capable of classifying the body measurements with 88.9% accuracy using SVM. This approach has some limitations. The first limitation is the lack of enough datasets to train our classifiers and achieve high performance. This is because body measurement datasets are not available on public repository, which is why as part of our contribution we take the liberty to share our dataset with research communities. The second limitation is that this study did not focus its attention on feature engineering. Thus, with effective feature engineering techniques, high accuracy and performance can be achieved through the selection of the best feature candidates.

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