Validating ‘Chope’ Seats

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1. INTRODUCTION

A. Problem statement

Figure 1. Singapore “Chope” Culture (source: visitsingapore.com)

It is common to see free seating eateries in Singapore, such as hawker centres and food courts. When eating in such places, there exists a culture to first find an empty table, ‘chope’ it by placing an item, then going off to the stalls to order food. The term ‘chope’ refers to reserving a table and marking it as one’s own using any item, such as a bottle, an umbrella, or the most infamous one, a packet of tissue paper. For the purpose of this report, the term ‘chope’ is equivalent to the term ‘reserve’.

The downside to such a culture is that these reserved tables are inefficiently used, they remain empty despite being ‘occupied’. As such, the effective number of tables being used for food consumption reduces. The following are some situations which may occur.

During peak periods like lunch or dinner, there would be a large number of patrons in these free seating eateries. With long queues at food stalls, a reserved table might remain unused for a long time. This becomes a problem to other patrons as they would face difficulty in finding an empty table, especially for those who do not follow the culture and buys their food first before looking for an empty table.

Large groups of patrons would also face difficulties in finding multiple tables which are close enough to each other in order to accommodate everyone. As such, most of these large groups of patrons would usually break into smaller groups to find any empty tables instead.

There are some cases, although few, where patrons accidentally leave an item on the table after finishing their food, thus other patrons see it as a reserved table when it actually is not, further reducing the number of available tables.

2. APPLICATION DESCRIPTION

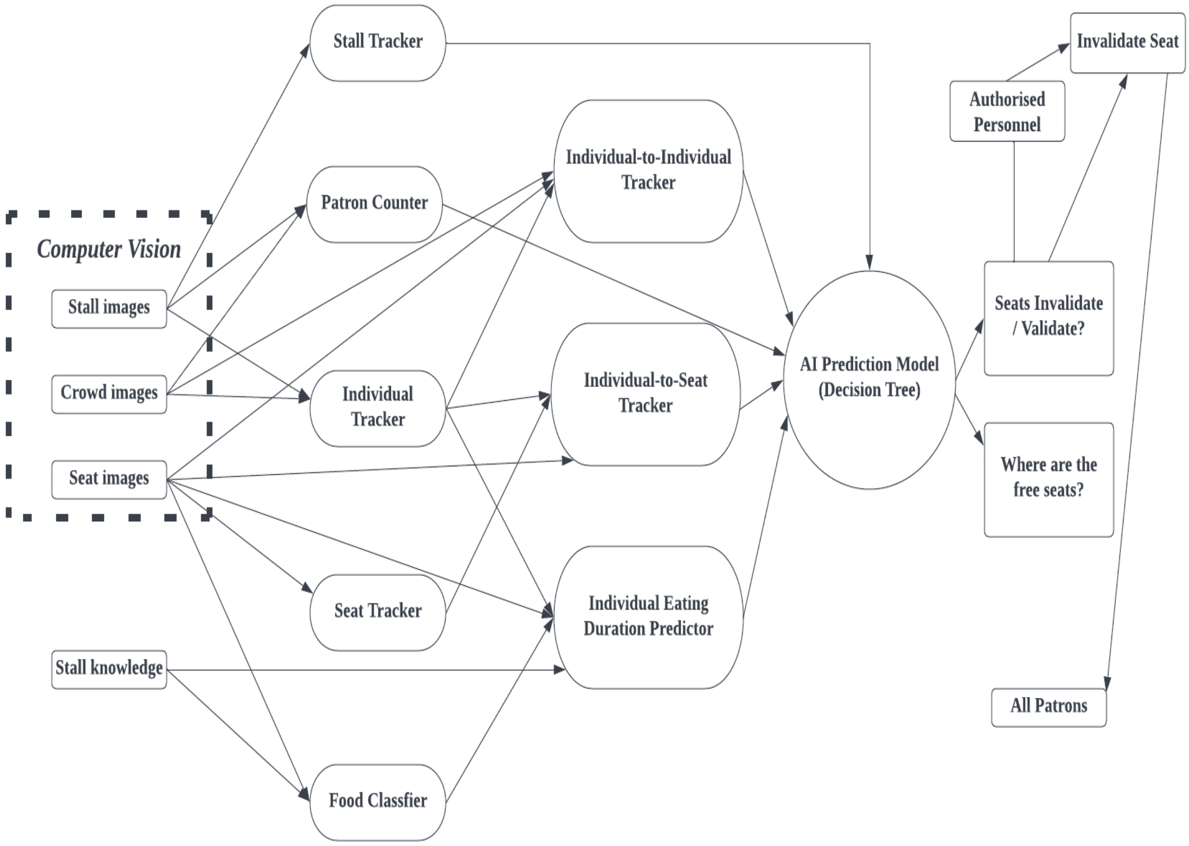

Figure 2. Flow Diagram of Proposed System

The 'chope' culture will be unfair to some patrons and make the eatery underutilized. Our solution is to design a system to predict whether a seat should be invalidated fairly. In order to make a fair a decision, our main idea is to track total duration of every seat assigned to a patron according to several factors such as type of patron and serving rate of different stalls. The system will automatically mark a seat for invalidation if it goes beyond allowable reserved duration. We will discuss these factors and the algorithm in detail in Section 4B.

Basic inputs of the systems are surveillance footage within the eatery where several cameras pointing towards the stalls, crowds, and seating areas. You can see them in the left part of Figure 2. The other parts of Figure 2 will be introduced in detail in Section 3 and 4. The cameras pointing towards the stalls would produce images containing information such as patrons in the queue for each stall. The cameras pointing towards the crowd provides information of the patrons who are finding seats or waiting for their food. Cameras pointing towards the seating areas would produce images containing information of the patrons sitting in their seats, together with the seat state, such as occupied or empty. If the eatery is large, more cameras would be required to be placed around the eatery to cover all the areas of interest.

We set a unique ID to every seat so that output of the system should be the ids of the seats to be invalidated. After a seat is invalidated, it will mark as free seat. In order to help patrons find the free seats more easily, we use a TV screen to show the information of the current free seats. Furthermore, the system will help authorized personnel identify seats to be invalidated. If a seat is occupied by a patron, the system will update the seat state on the screen. As a result, it is convenient for patrons to locate free seats and for authorized personnel to identify invalid seats and take necessary actions. They only need to notice the information displayed on the screen.

The system would also have a knowledge database of stalls and their selling food items, as well as the average time to prepare and consume the food, which are defined by the stall owners themselves.

3. USE OF AI TECHNOLOGIES

A. Patron Counter / Stall Tracker

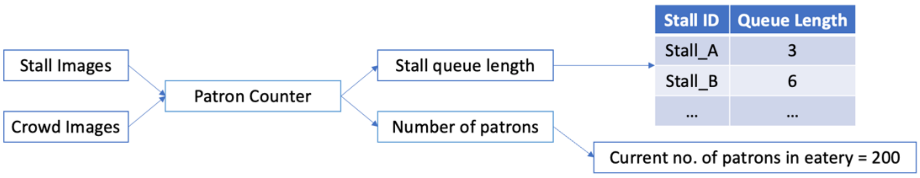

Figure 3. Patron Counter Model

The patron counter is a person detection algorithm, specifically to detect individual patron and count the number of patrons. The algorithm takes in images from cameras of the stall and the crowd within the eatery, and will produce two outputs, first being the number of patrons in each stall queue and second, the total number of patrons in the eatery.

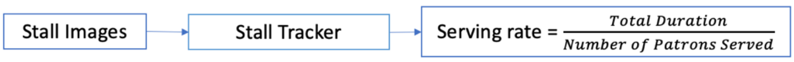

Figure 4. Stall Tracker Model

As the output of the patron counter algorithm are dynamic values, there would also be a tracker for each stall queue length. This would allow us to compute the serving rate of each stall, which is simply the average time taken to get one patron served (the duration of one served patron refers to the time when the patron enters the queue up to the time which he receives his food).

B. Individual Tracker

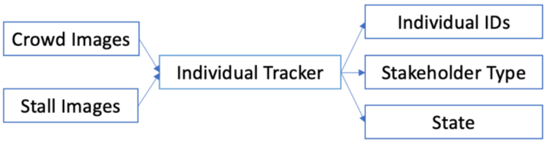

Figure 5. Individual Tracker Model

The individual tracker is a person identification and tracking algorithm. It is designed to identify all patrons and assign an ID number to that patron, as well as to classify that patron in two categories, the state of patron and the stakeholder type.

The state of the patron would refer to what the patron is doing. It can be queuing at a stall, searching for a seat, eating, not eating at all, etc. If the patron is queuing at a stall, the position in the queue would also be provided for that individual patron.

The stakeholder type refers to whether the patron is from a protected or unprotected type. A protected type refers to young children, elderly, and persons with special needs, while unprotected refers to adults, young adults, etc. The algorithm must therefore be trained to be able to differentiate one type from another, which can be based on features such as walking pattern, hair colour, presence of walking stick and wheelchair, etc.

C. Seat Tracker

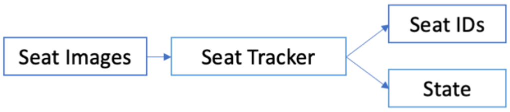

Figure 6. Seat Tracker Model

With prior knowledge of the seats and their respective IDs, the seat tracker takes images of the seats to classify that seat's state, which can be free (or unoccupied), reserved, or occupied.

D. Individual-to-individual Tracker

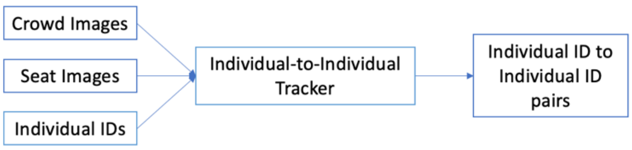

Figure 7. Individual-to-Individual Tracker Model

The individual-to-individual tracker is a person-to-person matching algorithm. It takes in the images of the crowd and seats, as well as the individual IDs produced from the individual tracker, in order to identify patrons who come as a group and then outputs pairings of their individual IDs.

E. Individual-to-Seat Tracker

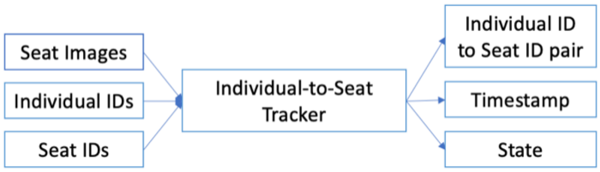

Figure 8. Individual-to-Seat Tracker Model

The individual-to-seat tracker takes the seat images, individual IDs produced from the individual tracker, and seat IDs produced from the seat tracker in order to produce the pairings of the individual to a respective seat. It also produces a timestamp from which the pairing is produced, as well as the state of the individual.

The outputs from the individual tracker, seat tracker, individual-to-individual tracker and individual-to-seat tracker would look something like the information shown in Table I.

Table I. Example Output of Models

Individual ID	Stakeholder Type	Stall ID	Paired IDs	Seat ID	State	Queue Position
x_1	Protected	Stall_A	x_2, x_3	Seat_123	Queuing	2
x_2	Unprotected	Stall_C	x_1, x_3	Seat_124	Queuing	5
x_3	Protected	Stall_D	x_1, x_2	Seat_125	Eating	-
x_4	Unprotected	-	-	-	Searching for seat	-
x_5	Unprotected	-	x_6	Seat_45	Seated	-
x_6	Unprotected	Stall B	x_5	Seat_46	Queuing	0
…	…	…	…	…	…	…

F. Food Classifier

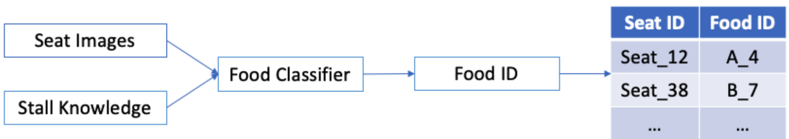

Figure 9. Food Classifier Model

The food classifier is an object detection and classification algorithm. It takes images of the seats as its input. The algorithm will first detect whether there is food in the images, if any food is detected, it will classify the food type and assign the unique food ID, according to the stall knowledge (the stall’s menu), to each seat ID where food is detected.

G. Individual Eating Duration Predictor

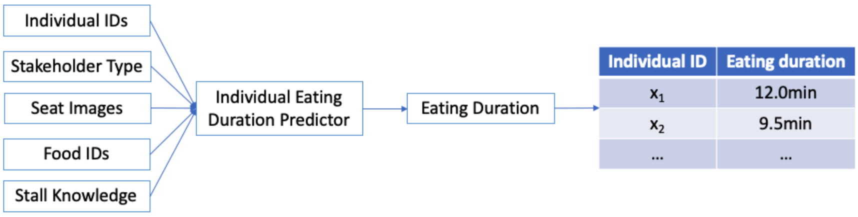

Figure 10. Individual Eating Duration Predictor Model

The individual eating duration predictor takes the individual IDs the corresponding stakeholder type produced from the individual tracker, the seat images, the corresponding food ID produced from the food classifier, and the stall knowledge as the inputs to make a prediction of the individual eating duration. This eating duration will be an important factor for our system to decide whether a seat should be invalidated.

H. Overcrowding predictor

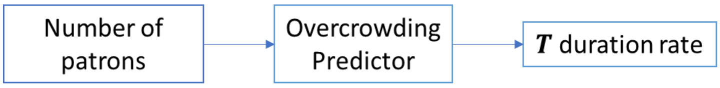

Figure 11. Overcrowding Predictor Model

The overcrowding predictor is an algorithm which determines if the eatery is overcrowded or not and predicts the allowable duration T for a seat to be reserved. It will recognize whether the eatery is in a peaked period or not and output the duration T where T is a hyper-parameter depending on period of the day (peaked / non-peaked period). Here we have three options to estimate allowable duration T.

The first option uses a human-defined rule to directly decide allowable duration T. For example, T will be 15 mins if the eatery is in a peaked period and be 30 mins if the eatery is in a non-peaked period. This option is simple but may be not so suitable for every situation because the level of peaked or non-peaked period may also differ. Therefore, two more options are proposed which calculates the T based on many observations of the period and learns from it.

Option 2 approximate T by how fast (average duration rate) the eatery will become overcrowded. The formula is

$$T = \max\left(\frac{\sum_{i=1}^{N} duration_{under\_to\_over}}{N},\ \min\left(\sum_{i=1}^{N} duration_{reserved}\right)\right)$$

where $\text{duration}_{\text{under\_to\_over}}$ is the duration from under-crowded period to over-crowded period and N is the total number of observations in peak or non-peak periods.

Option 3 calculates T by finding the average of the 90-percentile individual duration in peak or non-peak periods. The formula is

$$T = \max\left(\frac{\sum_{i=1}^{N} duration(x_i)}{N},\ \min\left(\sum_{i=1}^{N} duration_{reserved}\right)\right)$$

where $\min(\sum_{i=1}^{N} duration_{reserved}) \geq avg\_queueing\_duration$

4. RESPONSIBLE AI PRACTICES ADDRESSED

A. EXPLAINABILITY

We designed a decision tree using outputs from all AI modules (see Section 3) to predict if a seat should invalidate or not. Any seat not reserved will be regarded as a free seat. For reserved or occupied seats, if the eatery is predicted to be undercrowded (see Section 3H), all seats will consider as valid meaning that no invalidation is required. Also, any seat occupied by an eating patron or whose individual patron duration is under a considerable time limit $\boldsymbol{T}$ will be considered as valid. Otherwise, seats who has exceeded the time limit $\boldsymbol{T}$ will be marked for invalidation.

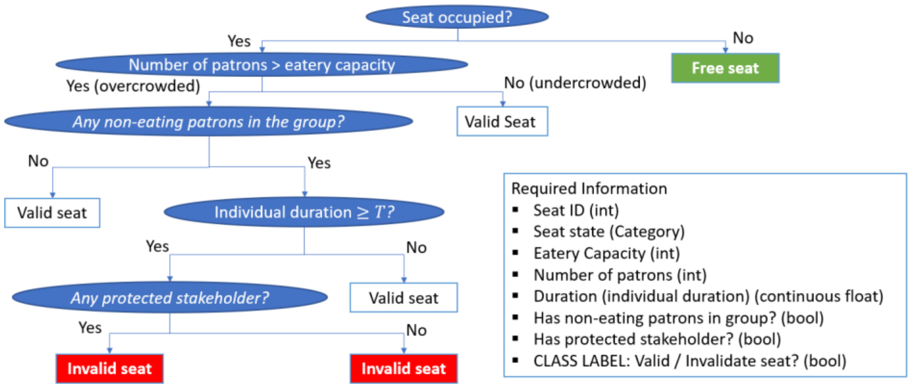

Figure 12. Decision Tree to Classify Seats as Free, Valid or Invalid

With this design, we can establish explainability AI [2] in various ways. First, free seats are marked by the seat tracker (see Section 3C) and displayed to the public so that patrons who are looking for seats can swiftly find seats.

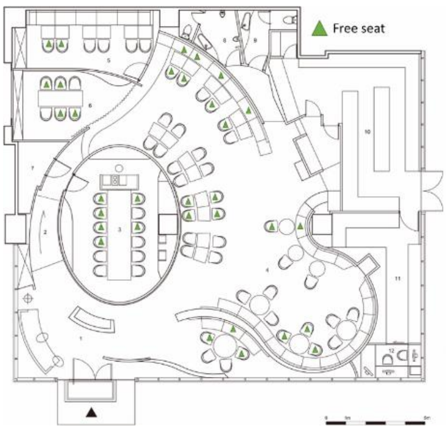

Figure 13. Free seat indicator (source: Very Space International)

Seats marked for invalidation will be highlighted and display to authorised personnel. The human expert can then examine each seat state by going through the individual patron duration, seat images, food images and images of associated individual patron or group that reserved the seat. When an authorised personnel is satisfied with the presented information, he or she can then decide and take action to invalidate the seat or not.

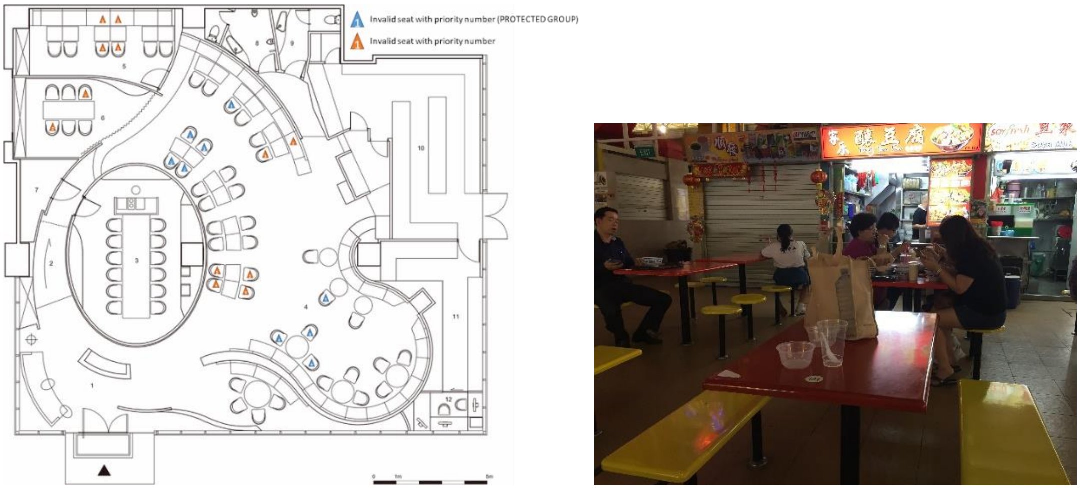

Figure 14. Invalid Seats Indicator (source: Very Space International) and image evidence of invalidate seats presented to authorised personnel (source: Jordyn Khoo's blog)

If the authorised found cases (as illustrated in Figure 15) that are misclassified after examining the presented evidence, authorised personnel can provide feedback to the system by updating the prediction with correct labels. The correct labels can then be used to re-train the relevant AI modules.

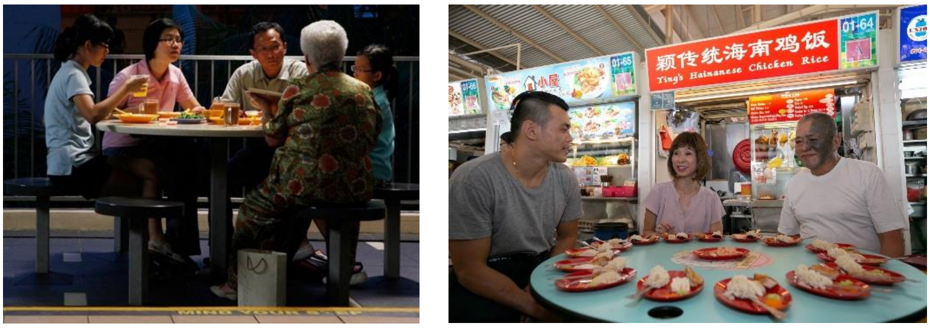

Figure 15. Misclassified Invalid Seats (source: pride.kindness.sg, theindependent.sg)

B. FAIRNESS

In order to ensure that the reserved seats are marked for invalidation in a fair way, we have to consider different customer group's needs. Patrons such as young children, elderly, and those with special needs will usually take longer time to complete their meals. Besides this, due to varying stall serving rate, some patrons may take longer time to order and pick-up their meals. Also, different types of food have different eating duration. As such, we took into consideration these legitimate factors and stakeholder groups in our system design.

Patrons who usually take longer time to complete their meals are categorized as the protected group (see Section 3B) and we will use their eating duration as one of the key considerations in deciding whether to invalidate their seats or not. We therefore designed the individual tracker AI model (see Section 3B) to classify the patrons either as protected or unprotected. We adopted fairness through awareness notion [1] in this classifier to ensure two patrons who possess similar properties, such as age and physical ability or behaviour, should receive similar classification.

Using this classified stakeholder types, we adopt conditional statistical parity fairness notion [1] to ensure that patrons in protected and unprotected groups with similar legitimate factors, such as eating habits and food preferences, have similar eating duration.

With the patron's eating duration estimated (see Section 3G), we designed an algorithm that updates the individual duration of patrons who visited the eatery in a group such that all patrons in the same group will share a common eating and queue durations based on the group member who has the longest eating or queuing duration.

<u>Algorithm: Update individual duration in a group</u>

Inputs:

- $N =$ *number of patrons in a group,* $N > 1$
- $G = \{x_1, x_2, \ldots., x_N\}$ *contains individuals (or patrons) in a group*
- queuing duration = serving rate * queue position
- total seat occupied duration = time since timestamp from individual-to-seats tracker (see Section 3F)
- $duration(x_i)$ = total seat occupied duration – eating duration – queuing duration

For i in range(N):

For j in range (N):

if $i \neq j$:

$$individual\ duration_i = \max\left(duration(x_j), duration(x_i)\right)$$

Seats predicted to be invalidated are first categorised into protected and unprotected based on group containing any protected stakeholder or not and, in each category, ranked by descending number of non-eating patrons in the group and individual duration in each protected group and unprotected group (see Figure 12 and Figure 14). Using this algorithm, reserved seats by patrons who are not queuing or having a meal will have longer duration than those who are queuing or having meal. Hence, will be prioritized for invalidation.

REFERENCES

[1] Makhlouf, Karima, Sami Zhioua, and Catuscia Palamidessi. "Machine learning fairness notions: Bridging the gap with real-world applications." *Information Processing & Management* 58, no. 5 (2021): 102642.

[2] Arrieta, Alejandro Barredo, Natalia Díaz-Rodríguez, Javier Del Ser, Adrien Bennetot, Siham Tabik, Alberto Barbado, Salvador García et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." Information fusion 58 (2020): 82-115.