Visual Social Signals for Shoplifting Prediction

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***Abstract*—Retail shoplifting is one of the most prevalent forms of theft, estimated to cost UK retailers over £1 billion in 2018. One security measure used to discourage shoplifting is surveillance cameras. However, evidence shows that unless these cameras are constantly monitored, they are ineffective. Automated approaches for detecting suspicious behaviour have proven effective but lack the transparency to enable them to be used ethically in real life scenarios. One way to overcome these problems is through the use of social signals. These are observable behaviours which can be used to predict an individual's future behaviour. To this end we have developed a set of 15 visual attributes which can be used for shoplifting prediction. We then demonstrate the effectiveness of these attributes by deriving a new dataset of visual social signals attributes by manually annotating videos from the University of central Florida Crimes dataset.**

Keywords—Social signal processing; Ethical AI; Activity recognition; Behaviour recognition; Data analytics.

I. Introduction

In 2018, retail shoplifting accounted for over £1 billion in losses for retailers in the United Kingdom [1]. In order to reduce these losses, many retailers are applying increased security measures, such as hiring security staff and using security tags on their more expensive items. The use of surveillance cameras is one method which has proven effective at deterring potential thieves. However, in order to be fully effective, these cameras need to be carefully monitored at all times [2]. Furthermore, evidence has shown that serial shoplifters have developed methods to evade security cameras, such as concealing the goods while in surveillance blind spots. This can make it very difficult for a human observer to catch all incidences of shoplifting [3].

Recently there have been attempts to automate the detection of individuals who are likely to shoplift through the use of computer vision techniques [4]. While these approaches have shown great accuracy, they are often based on black box learning techniques. This makes it impossible to justify why an individual has been classified as a potential shoplifter and raises ethical questions about how these methods come to their decision [5]. The Committee of Experts on Internet Intermediaries (MSI-NET) at the council of Europe has already outlined concerns around the admissibility of black box algorithms in criminal justice, and there are ongoing questions about the potential human rights violations of using evidence from these systems in a court of law [6].

Psychological and criminology literature has shown that individuals who are likely to shoplift exhibit a number of observable behaviours beforehand. These behaviours can be categorised as social signals and include looking around for staff, pacing back and forth, and avoiding other customers [7]. By detecting one's social signals, it is possible to make predictions about one's future behaviour [8]. Thus, an automated approach to doing so could provide transparency, enabling us to determine how an algorithm makes a decision.

In this paper we have derived a set of 15 social signal attributes which can be used for detecting shoplifting, based on previous findings [7], [9]–[11] and our own observations. Furthermore, we have evaluated the effectiveness of these attributes for shoplifting detection by developing a novel dataset using real surveillance footage of shoplifters and genuine shoppers. The remainder of the paper is outlined as follows: in Section II we discuss the literature and the current methods; in Section III we will outline the set of attributes and the justifications for selection. Section IV outlines our experimental setup and our dataset and in Section V we will discuss these results. Finally, Section VI will conclude the paper.

II. Background

According to official police statistics, shoplifting remains one of the most common forms of theft [12]. To combat this, retailers are spending increasing amounts on time and money on security. According to the British Retail Consortium, retailers in the United Kingdom spent over £1 billion on crime prevention in 2018; almost four times as much as was spent in 2014. Despite this, customer theft is on the rise, accounting for £663 million in losses over the same period [1].

The installation of closed-circuit television cameras (CCTV) is one commonly used security method which is often employed by retailers to deter criminals. However, research has shown that unless footage is actively monitored, surveillance cameras will prove ineffective at preventing crime [2]. Furthermore, the research conducted in [13] showed that thieves use several techniques in order to avoid detection. These included using their body to conceal theft, becoming immersed within a crowd, and wearing a disguise such as a cap or a hoodie. Without the proper training it can be difficult for those monitoring the footage to detect these behaviours and prevent theft. This is compounded by the fact that those monitoring the footage will quickly become fatigued and may miss important

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indicators if they have to monitor several video cameras for prolonged periods [14].

The work in [4] aimed to detect suspicious behaviour by training a 3D-Convolutional neural network (3D-CNN) model. To do this, they proposed a new model for processing surveillance footage by segmenting each video into three distinct sections:

- **Strict crime movement -** The segment of the video where the individual commits the crime.
- **Comprehensive crime movement -** The precise moment when an ordinary person can detect the suspects intentions.
- **Pre-crime behaviour -** The individual's behaviour from the time they enter the store until the comprehensive crime movement begins.

They then trained their computer vision model using video footage of pre-crime behaviour in order to detect potential shoplifters. Building on this work, [15] expanded the definition of suspicious behaviour to include actions preceding other crimes, such as arson or abuse, and managed to improve the accuracy of the approach. They found that trying to find suspicious behaviour of a particular type was difficult due to the high visual similarity between suspicious and non-suspicious behaviours. Their key finding was that a binary classification approach for a generalised suspicious behaviour achieved higher accuracy than using a multi-class approach.

Both [4] and [11] use deep neural networks, trained using raw video footage taken of individuals before they shoplift. Previous research has shown that the use of these types of black box machine learning methods for this type of application can be problematic. The most obvious issue is the fact that it is very difficult to determine whether the algorithm is learning to classify potential shoplifters based on their pre-crime behaviours, or if it is learning to classify shoplifters based on some other aspect such as potential biases within the dataset [16]. The work of [17] outlines the need for transparent, interpretable machine learning approaches for high stakes learning problems such as this.

Human action recognition tasks such as shoplifting prediction can be achieved through the detection of social signals. First identified by [18], social signals are defined as "the observable behaviours displayed by an individual". Social signals can be used to infer an individual's intentions and to make predictions about their future behaviour. For example, the work of [19] used a number of vocal based social signals to determine the level of conflict within political radio debates. Social signals are generally defined in terms of five key modalities: physical appearance, vocal features, posture and gestures, facial features and interpersonal distance (Proximetrics) [8]. The automatic extraction of social signals from each of these modalities encompass a wide range of open problems within the field of pattern recognition.

In order to implement a social signal processing approach for shoplifting prediction, it is necessary to first determine a set of social signals which can accurately predict the behaviour. To this end we present a set of fifteen social signal attributes for the task of shoplifting prediction, based on the current literature, and verified through the use of a manually annotated dataset of social signal attribute taken from real shoplifting videos. This will facilitate the development of automated computer vision approaches that are interpretable (i. e. , where we can see why the model came to its decision), as well as helping to provide some clarity around the effectiveness of these attributes for the task of social signal processing. These are outlined in Section III.

III. Attribute Selection

To develop a set of social signal visual attributes for shoplifting prediction, we first examined the psychology and criminology literature in order to create an initial set of approximately 60 potential attributes. We then reduced that number by combining similar attributes and removing those which would be impossible to detect using computer vision techniques. This process results in a compact set of 15 social signal attributes as outlined below.

A. *How many individuals are with them?*

According to [20], most organised retail crime is committed by a group of two or more individuals. Therefore, observing whether an individual is alone or with a group can help determine if they are a potential shoplifter.

B. *Are their staff members visible within the video?*

According to [7], shoplifters are less likely to attempt to take items when there is a member of staff nearby, as they perceive that there is a higher risk of getting caught. Further, it has been shown that placing desirable items closer to the registers or security guards reduces the incidences of theft of those items [9].

C. *What gender is the individual?*

This attribute was important to determine as certain behaviours may or may not be suspicious depending on the individual's gender [21].

D. *What gender is their accomplice?*

Similar to C, this attribute was important to determine as certain behaviours may or may not be suspicious depending on the individual's gender.

E. *Duration of time spent in the video*

According to [7], individuals who are shoplifting are constantly on the lookout for security and customers or staff watching them. As a result, they may take longer to perform certain actions than a normal customer. This attribute was measured in seconds and is calculated based on the amount of time the individual is observed in the video. However, this does not necessarily correlate to the total time spent in the store; only when the individual entered and left the cameras view.

F. *Are they watching staff or other customers?*

The work in [7] found that individuals who are planning on shoplifting are often on the lookout for staff or other customers. Due to the difficulty in determining where an individual is looking, we defined this attribute to be true if they exhibited two or more of the following observing behaviours:

I. Do they clearly look around for other customers or staff before picking up an item?
II. Do they pick up an item while looking towards a member of staff?
III. Does their accomplice look out for staff or other customers while they are picking up an item?
IV. Do they frequently look towards shop staff?
V. Do they appear to be interested in the shopkeeper's interactions with other customers?

G. Do they exhibit avoidance behaviours?

In order to prevent being detected, shoplifters will often try to avoid security staff or other customers and to prevent them from seeing what they are doing. Therefore, if an individual appears to be exhibiting avoidance behaviours, such as waiting for individuals to move away from them and pacing back and forth to the same area of the shop, this may be because they are waiting for an opportunity to steal a targeted item [7]. To determine whether or not the individual was exhibiting avoidance behaviours, we used a weighted metric where one point was added for each of the following four behaviours which indicate avoidance:

I. Do they deliberately go to an area of the shop where they are not visible to the shopkeeper or security staff and stop and stay there for more than 5 seconds?
II. Do they pick up an item while the shopkeeper's back is turned to them?
III. Do they wait until other customers move away from them before picking up an item?
IV. Do they pace back and forth to a specific location before picking up an item?

Additionally, a point was subtracted if any of the following behaviours which indicate non-avoidance were observed:

I. Do they pick up an item while visible to the shopkeeper?
II. Do they pick up an item while visible to other shoppers?

If the final score for the metric was found to be one or higher, the individual was deemed to have exhibited avoidance behaviours.

H. Is the shopkeeper distracted while they pick up an item?

If an individual is contemplating shoplifting, they will wait for the shopkeeper to be distracted before attempting to hide the item. This is particularly problematic with professional thieves, where often one individual will be charged with distracting the shopkeeper while the other steal the items [20]. We defined this attribute as true if the shopkeeper was distracted while an individual picked up an item, or if either they or one of their accomplices distracted the shopkeeper (e. g. , by asking for something on a shelf behind the shopkeeper), and then picked up an item.

I. Do they appear to hide what they are doing?

If individuals are planning to steal, they may attempt to hide what they are doing from the store staff or security cameras by using either their body or an object, such as a blanket or an umbrella [9]. Therefore, it is worth noting if an individual appears to be attempting to hide themselves in this way as it may indicate that they are attempting to shoplift.

J. Do they place an item out of view either into their bag or into their pocket or else give an item to their accomplice?

Individuals who are shoplifting will all often conceal a stolen item either in a bag or in a coat before leaving. Therefore, it is important to detect if they have placed an item out of view in this way [7], [13].

K. Potential difficulty to steal the item

According to [7], one method which can be used to reduce shoplifting incidences is to place high value items closer to tills or behind the counter in order to make them more difficult to steal. Therefore, items in these locations may be more likely to be targeted by organised criminals as opposed to impulsive actors. We classified the difficulty to steal a given item on a scale of 1 to 3, where a score of 1 means the item has very little security and 3 means that the item was well guarded. This score was determined depending on whether the item was kept behind the counter, how far the item was from the entrance/exit to the store, and how likely the item was to have a security tag.

L. Are they wearing a hood baseball cap or some other clothing items that hide their appearance?

Individuals who are planning to shoplift may attempt to disguise their appearance by wearing clothing that makes it difficult to identify them from surveillance videos [13]. This may include hoodies, baseball caps, etc.

M. Are they wearing baggy clothing or carrying a bag that could potentially conceal an item?

As well as wearing clothing that may conceal their appearance, individuals may wear baggy clothing that would make it easier to conceal a stolen item, such as large coats, baggy trousers, etc. [13]. Therefore, it is worth detecting if an individual appears to be wearing this type of clothing as it may indicate that they are a potential risk.

N. Do they pick up an item and appear to be interested in it?

If an individual picks up an item and appears to examine it, this may be a sign that they are waiting for staff or other customers to move away from them before they conceal the item. Additionally, they may be examining an item for security tags [10].

O. Does the video show them interacting with staff before leaving?

According to [7], individuals who have shoplifted are likely to exit the shop quickly and try to avoid interacting with staff in case they are caught. Therefore, if individuals interact with staff before leaving this may indicate that they are not trying to avoid staff.

IV. EXPERIMENTS

A. Dataset

In order to evaluate the effectiveness of these social signal attributes for the problem of shoplifting prediction, it was

TABLE I. OPTIMISED HYPER PARAMATERS FOUND USING A GRID SEARCH

Optimised Hyper parameters	
Model	Parameters
SVM	C=1, Gamma=0. 01, Kernel=Linear
KNN	Distance Metric = Manhattan, Neighbours=4, weights= Distance
Decision Tree	Criteria=Entropy, Max depth=5, Max features=log2, Minimum samples split=6, splitter=random
Random Forest	Criterion= gini, max depth=6, max features=log2, minimum samples split = 2, number of estimators=30
MLP	Activation Function= Identity, Hidden layers=2, layer sizes =(250,350) Solver=lbfgs

necessary to develop a novel dataset. This was done by using videos from the University of Central Florida Crimes dataset (UCF-Crimes). This dataset contains video clips for a large number of different criminal behaviours, such as arson and assault, as well as control videos. However, for these experiments we were only interested on the videos relating to shoplifting. For each video, a human observer manually annotated whether or not they observed a particular attribute as listed above. For the control group, we used the videos from the UCF-crimes dataset which were based in a retail setting and where the individual being observed made a legitimate purchase.

Attribute A was recorded as an integer denoting the number of other people with the shopper or shoplifter. Attributes C and D were encoded using one hot encoding in order to prevent the model from inferring some ordered relationship. Therefore, for attribute C there was two values "Gender is Male" and "Gender is Female," and for attribute D there was two attributes "Accomplice is Male," and "Accomplice is Female." If there was more than one accomplice, the gender was encoded as the majority of the group. Attribute E was recorded as an integer denoting the amount of time the individual was observed in seconds. Attribute K was recorded as an integer value between 1 and 3 as detailed in section III. The remaining attributes were all recorded as either true or false. This resulting dataset contained a total of 93 records, with 48 shoplifting records and 45 control records.

B. Experimental design

In order to evaluate the effectiveness of these attributes, we used them to train a diverse set of supervised learning models and evaluated them in terms of accuracy, precision, and recall. These models were as follows: Support vector classifier (SVM) [22], K-Nearest neighbours (KNN) [23], Classification and regression decision tree (CART) [24], Random Forest [25] and multi-layer perceptron (MLP) [26]. Each model was evaluated using five-fold cross validation and the hyper parameters were optimised using a grid search.

For the support vector classifier, we used a grid search to find the optimal kernel, and the optimal values for C and Gamma. The kernels used in the grid search were linear, radial basis function, polynomial and sigmoid. The values for the regularization parameter C used in the grid search were: 1,10,100 and 1000. Finally, the values used for gamma in the grid search were: 10^2, 10^3 10^4.

For the KNN classifier, we used a grid search to find the optimal distance function, optimal number of neighbours, and if the weights of the neighbours were uniform or weighted based on distance. The distance metrics used in the grid search were Euclidian distance, Manhattan distance, Chebyshev distance, and Minkowski distance. For K we tested the range of values between 1 and 16.

For the decision tree classifier, we used a grid search to determine: the optimal criterion used to measure the quality of the split, either using gini impurity or entropy; the optimal strategy used to split each node, either using the feature with the highest importance or using a random feature, with the random distribution weighted by importance; the max tree depth, between None up to 8; the minimum samples needed to split a node again from None up to 8, and finally, the number of features to consider when looking for the best split, either the square root of the number of features, $\log_2$ of the number of features, or just using the entire set of features.

For the random forest classifier, we used a grid search to determine the optimal values for the criterion, max depth, minimum number of samples needed to split a node, and the number of features to consider when looking for the best split. We also optimised for the number of trees used in the forest in multiples of 5 from 25 up to 100.

Finally, for the MLP model, we used a grid search to find: the optimal activation function, either using an identity function (where $F(x) = x$), a logistic activation function, a hyperbolic tan activation function or a rectified linear activation function; the optimiser, either stochastic gradient decent, an Adam optimiser or the LM-BFGS optimiser; and the optimal number of neurons for each of the two hidden layers, in increments of 50 from 50 up to 400. The optimised parameters for each of these models are presented in Table I.

V. RESULTS

We evaluated the performance of each of our learning models in terms of accuracy, precision, and recall, where accuracy is calculated as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

Precision is calculated as:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

And recall is calculated as:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

where TP is the number of true positive predictions, FP is the number of false positive predictions, TN is the number of true

TABLE II. RESULTS FROM MACHINE LEARNING METHODS

Method	Accuracy	Precision	Recall
SVM	92.40%	93.05%	92.44%
KNN	80.64%	82.09%	81.00%
Decision Tree	83.92%	84.36%	86.78%
Random forest	94.50%	93.75%	91.33%
MLP	92.40%	91.85%	92.44%

negative predictions and FN is the number of false negative predictions. The results for each approach are presented above.

As can be seen in Table II, the Random Forest approach was found to be the most accurate on our dataset, with an accuracy of 94. 5%. This was followed by the SVM approach, the MLP approach the decision tree approach and the KNN approach. This was the same for the precision metric. However, for the recall metric, both the SVM and MLP approach slightly outperformed the random forest approach. This is important as the recall metric determines how many of the individuals who were genuinely shoplifters were detected as such. However, if the system fails to highlight a suspicious individual who does go on to shoplift, then that individual may evade detection.

These results indicate that there are clear and measurable differences between the social signals exhibited by shoplifters and those exhibited by regular shoppers.

Figure 1 shows the feature importance generated by the random forest model [27]. The results here indicate that the most significant attribute was: “Do they exhibit avoidance behaviours.” This was followed by: “Do they interact with staff before leaving,” “potential difficulty to steal the item,” “Do they place the item out of view,” and “Do they appear to hide what they are doing.” These attributes almost all relate to the individual performing (or not performing) a given action, which may indicate that an individual’s behaviour gives a more reliable indicator of their intention than environmental factors, such as their clothing. Conversely, the least important features were “Gender,” “Gender of accomplice,” “Are they wearing clothing items that could hide their appearance,” and “Are their staff members visible withing the shot.” Again, this makes sense, as these are all environmental attributes which don’t give an indication about how an individual is behaving.

As well as generating the feature importance, we also performed sensitivity analysis on each of the attributes. This was done by removing each attribute individually and then evaluating the change in performance. As can be seen from the

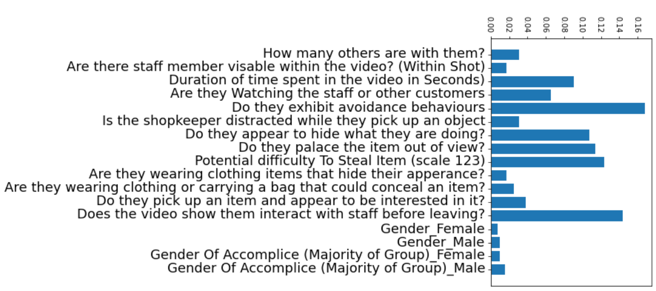

Figure 1. Feature importance from the random forest model.

TABLE III. RESULTS FROM SENSITIVITY ANALYSIS

Attribute	Accuracy	Precision	Recall
A	-1.05%	-1.00%	-1.00%
B	-2.11%	-1.91%	-2.11%
C	-2.05%	-1.31%	-2.33%
D	0.06%	0.03%	0.11%
E	-1.11%	-0.82%	-1.11%
F	-3.22%	-3.02%	-3.22%
G	-4.27%	-3.93%	-4.33%
H	-2.11%	-1.91%	-2.11%
I	-3.16%	-1.96%	-3.33%
J	-2.11%	-1.91%	-2.11%
K	-1.05%	-1.00%	-1.00%
L	-2.05%	-1.59%	-2.11%
M	-2.16%	-1.82%	-2.11%
N	1.11%	1.00%	1.11%
O	-5.26%	-5.13%	-5.33%

results in Table III, the most important attributes are: F *“are they watching staff or other customers,”* G *“Are they exhibiting avoidance behaviours,”* I *“Do they appear to hide what they are doing,”* and O *“Do they interact with staff before leaving*.”

This is consistent with the results found by calculating the feature importance. As discussed above, these attributes all relate to the individual performing a specific action, which may be why they are stronger features for predicting shoplifting. It is interesting to note that removing attribute N “*Do they pick up an item and appear interested in it”* caused the model to improve in accuracy. This may indicate that this attribute is a poor indicator of potential shoplifting or that it may appear too frequently in both groups to be useful. All of the other attributes showed some decrease in classification accuracy when removed.

VI. CONCLUSION

In this paper we have outlined the need for a transparent interpretable model for the problem of suspicious behaviour detection. To this end we developed a set of 15 social signal visual attributes which have been used to predict if an individual is likely to shoplift. We demonstrated the effectiveness of these attributes for the problem of shoplifting detection by manually annotating a subset of videos from the UCF-crimes dataset. We evaluated the effectiveness of each attribute by calculating the feature importance and through the use of sensitivity analysis. These results showed that detection of attributes which show individuals performing actions, such as interacting with staff and exhibiting avoidance behaviours, were the strongest indicators of whether or not an individual was a potential shoplifter.

For future work, these results will be validated using a larger dataset of shoplifting videos. Currently, the UCF-Crimes dataset [28] is the largest open-source dataset for this problem.

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However, this dataset only contains 50 videos of shoplifting; a number of which are cut short and don't provide enough footage to definitively determine the social signals exhibited before a shoplifting attempt. Furthermore, the videos in this dataset come from a number of different retail environments. A single dataset of retail shoplifting from a single store with multiple cameras and which contains both genuine customers and thieves, and where each customers entire history, from the moment they enter the store to the moment they leave, would enable us to determine more definitively which social signals are suspicious, and the frequency at which they occur.

Secondly, we suggest that there may be other social signals that indicate that an individual is likely to shoplift which we may have missed, or which may not be present in the current literature. Further to this, it has already been noted that individuals who are shoplifting have developed techniques to attempt to evade security measured. It is inevitable then that once these methods are implemented individuals will develop new techniques in order to evade them.

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