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Mini-review of Street Crime Prediction and Classification Methods

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ABSTRACT

Crime rates are one of the biggest problems in today's modern society, especially in urban cities. Various techniques on crime prediction and detection have been developed by previous researchers in reducing the crime rates that keep increasing throughout the year as well as to assist the government authorities in combating crimes. These include studies on forecasting crime activities based on both primary and secondary data that include numerical data, statistics, video, and images related to various categories of crimes. Thus, in this study, a mini-review is conducted related to the database used as well as methods that have been developed by previous researches related to crime classification, crime analysis and forecasting of crime or crime prediction. Further, a new technique will be proposed in the detection of crime activities. The proposed technique involves evaluation and validation of several Deep Learning (DL) specifically the Convolutional Neural Network (CNN) along with the type of database to be used specifically for street crime detection that focuses on snatch theft.

Keywords: Crime Prediction; crime classification; snatch theft; street crime; deep learning

INTRODUCTION

Crime around the world manifests in various forms, including murder, shooting, drug trafficking, concealment, fraud, black marketing, and many more. The general trends of the different types of crimes that occur in any country are indeed vital to be analysed to better understand the most prevalent crimes and the reason crime rates are high in certain areas. This is one of the research areas that can be explored related to crime prediction and detection in urban cities. In addition, crime is not random; it is either planned or opportunistic. Crimes usually occur if the activity space of the offender intersects with the activity space of the victim (Rachel Boba 2006). Note that a person's activity space consists of locations' such as workplace or office, school, home, shopping mall, or entertainment areas. For instance, the offenders are lurking in the area and the victim might be someone walking home, thus the offender sees this as an opportunity to commit a crime. Victims usually feel at ease due to familiarisation of their housing area and sometimes they are unaware of the abnormality of the surroundings or presence of offenders. This is one of the ways of crime occurrence.

Conversely, criminal that occur in public areas like street crimes include mugging, pick-pocketing and snatch theft (Truntsevsky et al. 2018) . Although the authorities have conducted many action plans in reducing these crime rates and raising awareness about street crimes, the crime index still increases throughout the year. As we know, pick-pocketing is a criminal act by stealing from the victims' pockets. It usually works in teams with one of the team members distracts their target victim and the other will steal by purposely bumping into their victims as a distraction. Pickpocket tends to occur in crowded areas.

On the other hand, mugging or robbery is an act of criminal by threatening victims and by taking any valuable belongings of the victims. As for snatch theft, that will be the scope in this study, is a criminal act that forcefully takes a pedestrians' personal belonging that includes necklace, mobile phone, and handbag. This crime is performed either by running and robs tactics. Nowadays, one of the most regular street crimes is snatch theft (Latimaha et al. 2019) as illustrated in Figure 1 with two men involved, one handles the motorcycle and the other conducts the crime or stealing (Md Sakip & Moihd Salleh 2018). This is one of the worrisome problem among pedestrians since it can cause injury to the victims and further lead to anxiety, trauma, and fear (Snatch Theft Victim Still Unconscious in ICU_ Malaysian Talk n.d.). Sometimes, pedestrians are insensitive of their belonging which could further create opportunities for offenders to conduct crimes.

Until today, snatch theft is one of the highest crimes

FIGURE 1. Illustration of snatch crime

in Malaysia that needs to be combated (*Department of Statistics Malaysia Official* Portal n.d.), (Laporan Jawatankuasa Kira-kira Wang Negara Parlimen Ketiga Belas 2017). Even though the awareness of street crimes has been broadcasted to all citizens, this particular crime rate still increases throughout the year. Many predictions and forecasting methods such as hotspot mapping and image detection have been proposed to assist authorities and also in strategising the deployment of officers. Therefore, as mentioned earlier, this study will conduct a mini-review of all previous researches that are related to the prediction and classification of crimes that include the datasets, prediction techniques, classification methods followed by identifying the research gaps. Future studies and research directions of this area will be proposed as well.

LITERATURE IDENTIFICATION AND SELECTION

A systematic literature search was conducted to determine all the related previous researches related to street crime predictions and identifications. The search quries are criminal images and street crime and the search is conducted in the IEEE Explore, Web of Science, Science Direct, and Scopus databases. Detailed search is further defined as image classification or image prediction or street crime. The targeted articles are from 2015 to 2020 namely the last five years duration. Table 1 tabulated the selection criteria in this mini-review.

TABLE 1. Search Query and Inclusive Term

Search query	Inclusive
Criminal images	Prediction
	Classification
	Analysis

RESULTS AND DISCUSSION

This section will discuss in detail each of the articles under the selection criteria mentioned earlier.

TYPES OF CRIME DATA

Firstly, the types of data that have been utilised by previous researches in crime detection will be elaborated. Generally, there are two types of data used namely as the primary data that is collected by government authorities that include statistical data, video surveillance, and closed-circuit television (CCTV). Here, researchers put in a request for usage of these data for research purposes. Next is the data from the authorities' online database, online sources like YouTube or Google platform that can be accessed publicly and this is known as secondary data. In addition, another example of secondary data is the data that was once a primary data collected by other researchers and further made it available to be used by others as well. Next, for both primary and secondary data, specifically in numerical form, it can be categorised as geographical, categorical, or numerical data. If the data is in raw or crude form, it is known as primary data whilst secondary data occurred once refined and simplified, and normally made available to the public.

Table 2 summarised the available datasets used by previous researches versus the type of crimes. As reported by (Md Sakip & Moihd Salleh 2018; Jin et al. 2020; Feng et al. 2020; Zhuang et al. 2017; Yadav et al. 2017; Bharati & Rak 2018; A, Mary Shermila; Bellarmine 2018), secondary data of crime datasets that are in the form of numerical data with specified duration are used. These data were obtained from the authorities and police departments. Firstly, (Jin et al. 2020) collected a violent crime dataset within San Francisco City from 2003 until 2018. The author sorted the data and analysis according to the timestamp, longitude, and latitude. Furthermore, this data was used to predict the new number of cases in upcoming months or years. Next, (Feng et al. 2020) utilised the criminal database from three cities in the US, namely San Francisco, Chicago, and Philadelphia, that are publicly made available. The database contains the number of criminal cases, crime type, location, coordinate, date of crime occurrence as well as the number of perpetrators arrested. Subsequently, these data are tabulated according to the timestamp and further used as time series forecasting. Moreover, (Lee et al. 2019) acquired data for the whole year of 2019 from the District Police Station in Seoul that comprised of data related to crime location and the date as well as type of crime. The data were sorted according to the timestamp in analysing the number of cases that further acted as the input data in their study. Furthermore, (Md Sakip & Moihd Salleh 2018) obtained the snatch theft statistics data from Polis Di Raja Malaysia (PDRM) from 2010 until 2015, focused on four states namely Selangor, Kuala Lumpur, Penang, and Johor. The data were sorted and analysed according to each state. The state with the highest cases was identified and chosen as the primary state. This is followed by categorisation according to the district and the highest index amongst these states was identified. Furthermore, (Bharati & Rak 2018) extracted crime data specifically drug-related and theft-related crimes between the years of 2013 to 2018 that was obtained from the Chicago Police official website. Data were sorted according to timestamp, location coordinates and the number of incidents. Besides that, (A, Mary Shermila; Bellarmine 2018) focused on crimes that occurred in Alaska and Alabama. The data analysed was based on the data collected from the FBI's Supplementary Homicide Report between the years of 2000 until 2014. These data that comprised of date, crime type, perpetrator as well as victim's gender and type of weapon used were pre-processed and sorted according to the perpetrator's gender and crime type. On the other hand, databases in the form of videos and images that were used by previous researches are as tabulated in Table 2. These include data from video surveillance and CCTV cameras. In addition, YouTube or Google is also a good platform for data acquisition of videos or images. For instance, (Zhuang et al. 2017) collected theft crime data from the Oregon Police Bureau for five years from 2012 until 2016. The type of crime to be analysed was burglary, street crime, and auto theft. The parameters related to the crime being extracted are longitude, latitude, and timestamp. Based on these data, the geographical map was identified in analysing past crime hotspot areas. Next, (Yadav et al. 2017) collected data from 2001 until 2014 from the India online portal, National Crime Records Bureau Website. Here, the parameters extracted were the state, type of crime, perpetrator gender, and age as well. Besides that, the type of offenses extracted from the online portal includes rape, murder, kidnapping, and abduction. Furthermore, (Butt et al. 2020) obtained 21 videos related to snatch crimes. Likewise, (Kaya et al. 2019) collected 2 500 images of weapons. The purpose was for detection of weapons existence in the crime scene followed by classification as a safe location or vice versa. Additionally, (Han et al. 2019) obtained 71 clips of fire events and non-fire events along with 156 clips of non-fire almost to fire event. Moreover, (Roy & C. 2018) managed to collect 35 videos of street crime around Hyderabad, India for their study. Likewise, (Navalgund & Priyadharshini 2018) gathered a total of 224 for both videos and still images specifically crimes related to using strictly prohibited weapon(s) in the banks or ATMs vicinity. The data was further classified as crime or non-crime. Furthermore, (Karim et al. 2018) also acquired 76 videos and images associated with the usage of weapons in committing crimes. For instance, if the CCTV caught a glimpse of a gun or firearm, this was classified as a crime scene. In addition, (Nieto et al. 2016) collected 37 videos of crimes specifically fighting scenes.

TABLE 2. Summary of Data and Types of Crimes by Previous Researches

No	References	Data Category	Type of crime
1	Jin GuangYin et al. (2020)	Numerical data (2003-2018)	Violent crime
2	Mingchen Feng et al. (2020)	Numerical data (2006-2017)	Theft and violent crime
3	Umair Muneer Butt et al. (2020)	21 Videos	Snatch crime
4	Mustapha Kaya et al. (2019)	2 500 Images	Crime involving weapon
5	Han Jiseong et al. (2019)	298 Videos	Crime involving fire
6	InHye Lee et al. (2019)	Numerical data (the year 2019)	Street crime
7	Siti Rasidah Md Sakip et al. (2018)	Numerical data (2010-2015)	Snatch theft
8	Alkesh Bharati et al. (2018)	Numerical data (2013-2018)	Drugs, theft
9	Mary Shermila A et al. (2018)	Numerical data (2000-2014)	Homicide

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10	Debaditya Roy et al. (2018)	35 Videos	Street crime
11	Umadevi Navalgund et al. (2018)	224 Images	Crime involving weapon
12	Shahid Karim et al. (2018)	76 Videos	Crime involving weapon
13	Yong Zhuang et al. (2017)	Numerical data (2012-2016)	Burglary, street crime, and auto theft
14	Sunil Yadav et al. (2017)	Numerical data (2001-2014)	Murder, kidnapping, and abduction
15	M. Neito et al. (2016)	37 Videos	Crime involving fighting
16	Rupesh Mandal et al. (2016)	20 Videos	ATM theft
17	Xia YiZhiang et al. (2016)	5 000 Images	ATM theft
18	M. A. Rashidan et al. (2015)	200 Videos	Street crime
19	Nor Surayahani et al. (2014)	80 Videos	Snatch crime
20	Norazlin Ibrahim et al. (2010)	260 Videos	Snatch crime
21	Koichiro Goya et al. (2009)	20 Videos	Snatch crime

Also, (Mandal & Choudhury 2016) acquired 20 videos of crimes related to ATM theft. The authors then converted each video into frames of sequence images and classified these frames as normal or abnormal. Moreover, (Xia et al. 2016) collected 5 000 images of face occlusion for behaviour detection of a person in ATM vicinity. Additionally, (Rashidan et al. 2015) acquired 200 videos of snatch-related events that were used for the classification of an event either as a snatch or otherwise. Besides that, (Suriani et al. 2014) collected 80 videos and (Ibrahim et al. 2010) gathered 260 videos of snatch crime of theft in one single viewpoint. This can be a disadvantage as the angle of crime occurrence may not be able to be identified. Also, (Goya et al. 2009) collected 20 videos of crime related to snatch theft as well.

CRIME PREDICTION AND CLASSIFICATION

Next, the prediction and classification techniques used by earlier researches will be discussed specifically for preventing, reducing and forecasting future crimes. It is already known that crime prediction could be used to assist by locating future crime as prior and vital information for the security departments and officers to plan ahead their patrol routines. On the other hand, the Geographical Information System (GIS) as shown in Figure 2 was proven capable of capturing and analysing spatial and geographical data. This acted as another tool that can be used for crime prediction. Here, GIS allows users to create interactive queries, analyse the spatial information output along with data editing within the map followed by visually sharing the output or results. Additionally, GIS can record data through the date and time series of an event along with its longitude and latitude. Therefore, GIS is apt to be used upon obtaining the crime data from the police or security departments and mapping it accordingly for identifying the crime hotspot.

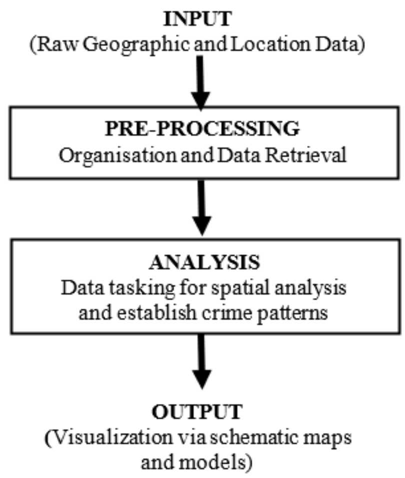

FIGURE 2. Overall Process in Geographical Information System (GIS)

Moreover, GIS can also be used for the detection of criminal activities in this hotspot area. This could further control the crime occurrence by sharing the hotspot analysis with the authorities and the public as well. Furthermore, (Khalidi et al. 2012) used the ArcGIS 10 software to analyse the crime data and identified crime hotspots. Meanwhile, (Lee et al. 2019) used Quantum GIS 2.6.1 for this purpose too. On the other hand, (Mansor et al. 2019) utilised ERDAS 2011 to obtain satellite imagery followed by GIS analysis tools to create the hotspot and analysed the crime patterns and trends. With Classification by Aggregating Emerging Pattern (CAEP), (Takizawa et al. 2018) were able to enhance the classification accuracy using GIS. Here, the data acquired were used to establish hotspot maps to highlight the occurrence of criminal cases according to specific months and years. This information could significantly assist the authorities in crime prevention.

Another classification approach for the prediction of crime was via the convolutional neural network (CNN), specifically one of the Deep Learning algorithms that accepts images as input data by assigning its weight and biases (Zhu et al. 2017). CNN is best used in predicting and classifying images as well as for recognition purposes (Navalgund & Priyadharshini 2018; Xia et al. 2016; Rasanayagam et al. 2018). Figure 3 shows the basic structure of CNN that consists of a convolutional layer, pooling layer, and fully connected layer.

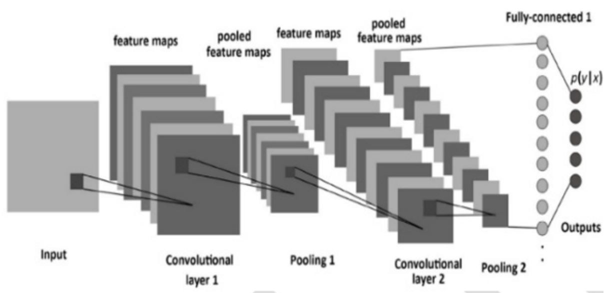

FIGURE 3. Convolutional Neural Network Architecture

Some of the previous work related to CNN on crime classifications includes (Xia et al. 2016) that used pre-train multitask CNN for recognition of front and both sides of the face in detecting face occlusion in ATM vicinity. In this study, new face datasets were created that include images of subjects wearing sunglasses, helmets, hats or face masks for perpetrator identification related to committing a crime in ATM surrounding area. In addition, (Rasanayagam et al. 2018) employed LeNet architecture to identify suspicious person by classifying the person's face expression namely anger, happiness, sadness, surprise, disgust, fear, neutral, and stress during money withdrawal activities in ATM vicinity. The architecture consists of two sets of convolutional and pooling layers with two fully connected layers used as face recognition in detecting facial expressions related to committing a crime in ATM environment.

Conversely, (Rasanayagam et al. 2018) implemented a feature-based method that processed input images to identify and extract feature characteristics such as eyes, nose, and mouth. Also, Caffe model framework was implemented along with the CNN to improve the classification accuracy. As for (Nakib et al. 2018) biases were used in the CNN model that includes the use of 0.1 noises for the weight to avoid zero gradients. In addition, ReLu was employed to prevent dead neurons with an insignificantly small amount of biases during initialisation process. The developed CNN is further used for detecting the presence of blood, knife, revolver, machine gun, shotgun, or gun. (Dinama et al. 2019) also used ReLu as an activation layer since the convolutional layer consists of a linear filter and non-activation layer that could detect the presence of humans versus the person's walking trajectory. This is further used for predicting the potential running direction by the person upon committing the crime for instance after pick-pocketing, snatch, or hit and run offense. Besides that, CNN usually has an over-fitting problem since the network could be too vulnerable during data training. This could lead to low recognition accuracy in the testing phase, although the training data attained high accuracy. To overcome this limitation, (Kim et al. 2018) used a dropout method by inserting a 50% of the dropout probability between the first and second fully connected layers to randomly disconnect the connection. Another method is the recurrent neural network (RNN) as depicted in Figure 4. CNN is indeed one of the best classifiers for images but not for non-sequential data and temporal domain. Therefore, (Han et al. 2019) RNN to analyse the temporal domain in the middle of sequential information. Here, training and testing data were done through a fully connected layer of CNN followed by RNN as video feature extraction in generating the new training set for RNN for better accuracy of the CNN upon collaborating with the RNN.

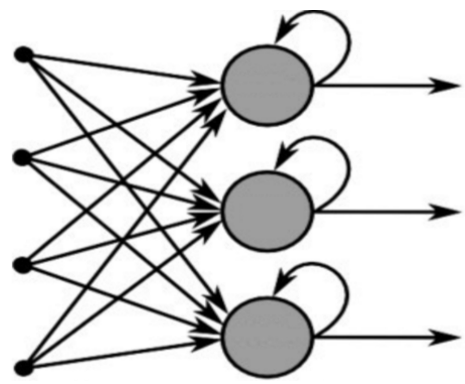

FIGURE 4. Recurrent Neural Network architecture

Moreover, the Long Short-Term Memory (LSTM) is another type of artificial RNN architecture. LSTM has a feedback connection, unlike others that have a feed-forward neural network. LSTM processes the entire sequence of data such as statistical data, images, and videos along with classifying, processing, and predicting based on time series. Furthermore, LSTM can overcome the vanishing gradient problem during the training phase (Choi et al. 2019; Shi et al. 2019). The common unit that can be used in building the LSTM is as depicted in Figure 5. Conversely (Choi et al. 2019) proposed a two-stack LSTM structure to cipher motion information of each passer-by as a character vector to predict the direction the passer-by chose. This can be used to track the location of the person's walking in a crowd and further predict the criminal next move upon committing the crime. By stacking the LSTM, each LSTM layer with numerous memory cells has made the model deeper to achieve better definite prediction. LSTM and MLP are further implemented to detect the direction and velocity of pedestrian walking using location features by encoding the coordinates of pedestrians and adding the encoded vector over time. However, one of the limitations of LSTM is sequencing since it predicts the next value either in real value sequence or formats. Therefore (Shi et al. 2019) employed an Encoder-Decoder LSTM. One acted as input sequence and encoding these inputs into a fixed-length vector and the other was for decoding the fixed-length vector at the output section for sequence prediction. In this study, each pedestrian's historical trajectory, specifically pedestrian scale information along with a layer of LSTM is used for detection of possible direction the perpetrator of snatch theft escaped.

(Wawrzyniak et al. 2019) utilised LSTM with 32 nodes that were further connected to another LSTM using 256 nodes for the first input. As for the second input, the data is connected to the LSTM dense layer with one node. Furthermore, both layers merged as dense layers with 256 nodes through the normalisation layer and the ReLu activation produced an output layer that consisted of three nodes. In this study, since LSTM has a memory block linked through layers, a conditional gate was introduced. This LSTM architecture was used for crime predictions that include robbery, burglary, misdeed, or violence upon data assorted according to the timestamp. The LSTM was also used for forecasting the number of cases that might occur in the next month or even the next day.

Furthermore, (Wang & Yuan 2019) collected crime data or information in the United States from 2009 until 2019 that contain the type of crime, date, longitude, and latitude. Here, LSTM is used for predicting the next number of crimes that occurred in Atlanta. The author stated that to achieve good prediction results, the spatial cell size needs to be exact or perfect since large cell size resulted in low resolution of predicted results. However, if the cell size is too small, certain crime situations will be missed that leads to the waste of computer resources. Conversely, Visual Geometry Group (VGG) 19 is another type of deep learning (DL) CNN that can also be used for image classification. VGG19 consists of 19 layers specifically 16 convolutional layers, three fully connected layers, five max-pooling layers, and one softmax layer. (Navalgund & Priyadharshini 2018; Butt et al. 2020) used VGG19 for the prediction and detection of snatch theft events. Image classification is used for categorisation of events such as snatch or non-snatch events using a fixed size of 224 by 224 RGB images as inputs. VGG19 is indeed suitable since it has good classification architecture and widely used in facial recognition task. Meanwhile, VGG16 consists of 13 convolutional layers and three fully connected layers. (Kim et al. 2018) used facial recognition for detection of any abnormality in facial expression to determine crime committing potential via surveillance cameras.

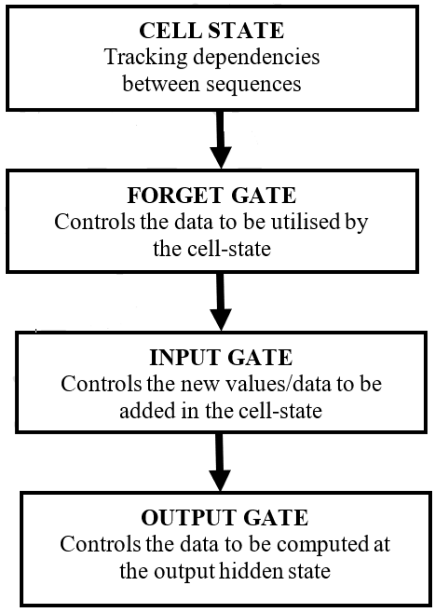

FIGURE 5. Basic Unit in Long Short-Term Memory

This section will focus on snatch theft, specifically the criminal act of stealing pedestrians' belonging forcefully. It is well known that street crime is a criminal act that took place in open public spaces. Some examples of street crimes are as shown in Figure 6 that includes mugging, pick-pocketing, and snatch theft. Rob and run tactics are involved and typically committed by two people, one drove the motorcycle and the other conducted the stealing activities.

Firstly, Butt et al. (2020) used VGG19 CNN to recognise a large scale image or video of snatch theft crime and achieved 81% of accuracy in detecting snatch theft using 21 videos as a database. Next is Lee et al. (2019) that acquired snatch theft data from District Police Station in Seoul. The logistic regression method is used to derive the crime prediction equation and embedded this equation with GIS. The detection of crime occurrence is set at every 20 m radius as in the GIS and an 80.65% prediction rate is attained. Furthermore, (Roy & C. 2018) used another approach for detection of snatch theft using the Gaussian Mixture Model (GWM) along with Universal Attribute Model (UAM) to train human behaviour during snatch theft incidents. Due to the super vector effect on the basic UAM along with Maximum Aposteriori (MAP) that has high dimensional and contains numerous attributes, low dimensional factors were used instead that was known as action.

FIGURE 6: Some examples of Snatch theft event

Additionally, (Md Sakip & Moihd Salleh 2018) developed hotspot maps via GIS based on snatch theft data attained from PDRM. Moreover, (Takizawa et al. 2018) used a basic GIS for mapping the hotspot similar to the method developed as reported in (Roy & C. 2018) that was within a 20 m radius but here, Classification by Aggregating Emerging Patterns (CAEP) was used instead in classifying criminal.

The initial findings showed that the occurrence of theft was higher in open areas or spaces. On the other hand, (Suriani et al. 2014) conducted video recording as the database for their research on snatch theft detection. The recorded videos focused on one angle solely. Here, extractions algorithms features were developed based on the videos that were further converted into image sequences with 80% accuracy in classifying snatch theft events. (Khalidi et al. 2012) also used kernel density and incorporated with GIS in enhancing crime hotspot detection. The CompStat model for network analysis was also added in assisting the authorities during patrolling by re-routing arrival via the shortest route. This method was able to reduce the crime rate in the area to 42.47% from years 2012 to 2013. Findings from this study revealed that crimes occurred during day time specifically in massively populated areas.

TABLE 3. Summary of Methods Used by Other Researchers for Street Snatch Theft

References	Dataset	Methods Developed	Strength	Limitation
Umair Muneer et al. (2020)	Video/Image from CCTV	VGG19 CNN	Enhancement in computational or processing time during detection.	Not suitable for crowded moving pedestrians environs.
InHye Lee et al. (2019)	Statistics dataset	Geographical Information System (GIS)	Suitable for predicting areas with similar building structures.	Inapt at the residential area with various building space or areas under development or construction.
Debaditya Roy et al. (2018)	CCTV Video surveillance	Gaussian Mixture Model (GMM) & Universal Attribute Model (UAM)	Performed well for information extraction using in producing better.	Unsuitable for street crime due to dimensional vector and redundant attributes.
Siti Rasidah et al. (2018)	Statistics dataset	Geographical Information System (GIS)	Ease of locating street patterns and layout.	Difficulties in mapping the street patterns for narrow access roads.
Atsushi Takizawa et al. (2018)	Statistics dataset	Geographical Information System (GIS)	Excellent classification accuracy for small areas of the vicinity.	Inaccurate mapping for a street patterns with guarded areas that include opening between fences or hedges.
Umadevi et al. (2018)	Video/image from Google & YouTube	VGG19 with Faster RCNN	Effective categorization of weapons achieved.	The classification task was unable to detect a person holding the weapon as a criminal or vice versa since the classifier categorised all subjects carrying a weapon(s) as the perpetrator.

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Kazumasa Hanaoka et al. (2018)	LandScan Global Population Database	Logistic regression model and kernel density map	High accuracy in classification of crime occurrence based on the density of population in every hour.	Computed populations were based on both populations inside and outside of the building. Population inside should be excluded for detection of snatch theft since this has affected the probability of crime occurrence.
M. Neito et al. (2016)	CCTV dataset	Video Content Description (VCD) and Rule manager	Flexibility in the rule manager structure that can adapt differences in scenarios or locations.	VCD was not suitable for complex events of the semantic layer.
Nor Surayahani et al. (2014)	Video sequences	Multi Agent Event Recognition (MAER) & Motion Vector Flow (MVF) & Directional Motion Histogram (DMH) & KNN classifier	Capable for snatch theft detection based on the interaction of two people in the scene being analysed.	
	Scene detection can only be done based on CCTV focus angles.			
Shoaib Khalidi et al. (2012)	Statistics dataset from police	Geographical Information System (GIS)	Suitable for locating hotspot areas of the crime event.	GIS analysis was only suitable based on the shortest route during patrolling.
Juan Lu et al. (2011)	Statistics dataset from police	Geographical Weighted Regression (GWR)	Suitable for spatial distribution analysis.	Population density of the area was dynamic and unsuitable for mapping hotspots based on population.
Norazlin Ibrahim et al. (2010)	Video sequences	Low-level feature & Kalman filter & Support Vector Machine (SVM)	Capable to avoid complicated segments of human behaviour and abnormality detection based on the interaction of two persons moving towards each other.	Video databases utilised were based on one angle only.
Koichiro Goya et al. (2009)	Video surveillance	Public System Safety (PSS)	Capable of distinguishing scenes with several different walking directions.	Video databases utilised were based on one angle only.

On the other hand, (Lu & Tang 2011) used Geographical Weighted Regression (GWR) for analysing the spatial distribution of theft crime rate and to determine the correlation between theft crime rate with regards to population, road network, police intensity, and average land. Results obtained showed that the population density of these areas was dynamic and the developed method for mapping and establishment of hotspot based on population was inappropriate for these areas. Furthermore, since the optical flow is suitable for human motion detection

(Ibrahim et al. 2010) implemented optical flow along with Kalman Filter and low-level features for snatch theft scene analysis and detection. The accuracy attained was at 90% using support vector machine (SVM) as the classifier. Besides that, (Goya et al. 2009) implemented Public System Safety, specifically a video surveillance system that consists of four sequential blocks, namely data acquisition, object detection, feature extraction, and scene classification. In this study, tracking was done based on human motion using optical flow along with background subtraction followed by computing the velocity of the subjects in the scene of interest.

PROPOSED METHOD

As discussed earlier, the type of database utilised and methods developed by previous researchers faced some challenges and difficulties that lead to imperfect prediction accuracy. Hence, in this section, the proposed approach for the street crime prediction will be discussed as depicted in Figure 7.

DATA ACQUISITION AND PRE-PROCESSING

Collection of datasets will be done via an online platform that includes YouTube and Google. The data will be divided into two datasets specifically anomaly or normal events. Note that anomaly event will be based on the occurrence of snatch theft whilst normal event includes average motorcycle rider passes through the passerby. The next stage is pre-processing. The video sequence will be pre-processed and normalised followed by categorisation as either anomaly or normal datasets. The total target database is approximately 7 000 images for each category.

CLASSIFICATION STAGE

The capabilities of deep learning for crime prediction and detection in urban cities will be tested based on image processing and deep learning analysis techniques. The proposed CNN model that will be used in determining the most optimum model of snatch theft detection, and prediction includes AlexNet, GoogleNet, ResNet, and InceptionV3. To the extent of our knowledge, these CNN have not been fully utilised by other researchers. Performance measures will be used to evaluate the effectiveness of the proposed model that includes prediction accuracy, specificity, sensitivity and establishment of a confusion matrix for each category.

EVALUATION AND VALIDATION

Upon determining the most optimum CNN architecture model, this proposed method will be evaluated, validated, and tested in a real-time scenario to confirm the model works well in real-time in terms of its accuracy for snatch theft prediction and detection.

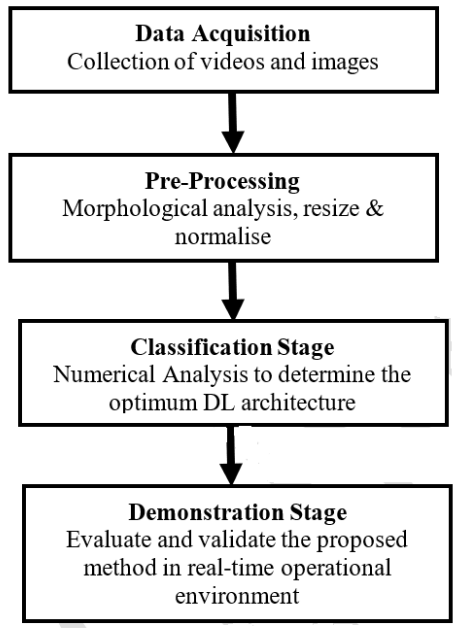

FIGURE 7. Overall proposed method for snatch theft prediction and detection

In conclusion, a mini-review of the crime analysis that focused on street crime scenes specifically on snatch theft is conducted. It was found that developing the most optimum classifier is indeed vital in predicting and classifying this category of crime. Previous researches have utilised CNN as the classifier. However, the prediction accuracy could be further enhanced. One of the reasons that limited higher accuracy attained was due to the complexity of human or persons' behaviour during committing crimes. The next step of work is to implement the proposed method using all potential DL neural networks that have not been explored followed by evaluation and validation of the proposed classification model in real-time scenario.

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DECLARATION OF COMPETING INTEREST

None

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