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MACHINE LEARNING AND BORDER SECURITY

Harjeet Kaur
Research Scholar, Punjabi University, Patiala

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ABSTRACT

Border security has been a significant issue of concern since decades, not only for India but for the whole world. Conventional border surveillance and protection systems include video surveillance systems, border patrol vehicles, permanent and mobile observation posts and control centers which engage high deployment and operational expense. Moreover, the hostile nature of borders makes deployment of the surveillance systems trickier. Conventional border surveillance and protection systems are not competent to ensure complete security, so an improved surveillance and protection system is needed. This research examines numerous intrusion detection techniques, border surveillance methods and a variety of algorithms for tracking moving objects.

Keywords: *Border Surveillance, Weapon Detection, Patrolling, WSN, Machine Learning.*

INTRODUCTION

Border security and surveillance is an everlasting operation that cannot afford time off or periods of reduced readiness. Border security has been a significant issue of concern since decades, not only for India but for the whole world. Securing against smuggling, illegal immigration and terrorism needs dependable long-range threat detection and detection of potential threats positively all day, all night and in all circumstances. Conventional border surveillance and protection systems include video surveillance systems, border patrol vehicles, permanent and mobile observation posts and control centers which engage high deployment and operational expense. Moreover, the hostile nature of borders makes deployment of the surveillance systems trickier. Conventional border surveillance and protection systems are not competent to ensure complete security, so an improved surveillance and protection system is needed.

Presently, the majority of the countries are facing the problem of enlarged cross border terrorism, ex-filtration, and infiltration of armed rebellions and illegal migration. Supervising the border for these threats has turned out to be the most critical problem for almost all the countries. This research examines numerous intrusion detection techniques, border surveillance methods and a variety of algorithms for tracking moving objects.

Challenges of Border Surveillance

- **Energy Efficiency**

Surveillance operations generally last for a prolonged period of time. The criticality of the mission makes manual replacement of batteries impractical or impossible. Therefore, an energy-aware and optimized technique must be considered in drafting such applications, which can improve the lifetime of sensor devices and the network.

- **Stealthiest system and Security**

It is essential that a border security system should have least probability of being detected, which in turn will affect the success probability of the operation. In addition, any transmitted and stored information should be encrypted and secured against interruption from rival communication devices. There is a basic tradeoff between energy consumption and security level. Besides, certain techniques to enhance stealthy network might recommend reducing bandwidth and communication energy. The significance of ensuring integrity and security check for the border surveillance network has been initially introduced in [1].

- **Wide area coverage**

Border surveillance generally comprises monitoring of a broad area throughout the border to locate the trespassers. The border security and protection system must be able of detecting the wide area comprising rivers, hill sides, mountains and rural areas enclosed by wildlife.

- **Accuracy**

Bogus alarms will furnish the surveillance task into failure. Therefore, the precision of tracking, detection and classification of intruding objects is very significant. Thus, techniques of aggregate alarms and in-network processing can be applied to reduce false alarms. In addition, as discussed before, the integrity of the network is very significant in minimizing the fake alarms and improving the accuracy of the entire system.

- **Quality of Service**

Timeliness and dependability of detecting the invasion is one more important element of the successful surveillance tasks. Quality of Service provisioning on communication should be enforced when an invasion alarm is issued [2].

- **Quality of Coverage**

Providing the complete coverage of a surveillance field is a very significant factor of the success of the surveillance operation. Providing the complete coverage while reducing the cost has been a dynamic area of research in the operational research field.

- **Robust**

Any country's border area must be guarded against the impostors and illegal actions at any cost. The Border surveillance systems must be robust which can bear ruthless environments in the isolated locations.

NEED OF BORDER SECURITY:

The increasing number of crimes on border each year arouses the need to study all the present systems or algorithms or techniques designed for encouraging border protection so that it may direct the way to a new system. Inclusion of machine learning based techniques using wireless sensor networks can be a possible solution to address this problem.

MACHINE LEARNING:

Machine learning is an application of artificial intelligence (AI) which offers the system an ability to learn automatically and refine from experience without being programmed explicitly. Machine learning emphases on the evolution of computer programs which can access data and use it to learn from them.

The method of learning begins with data or observations, such as direct experiences, illustrations or instructions, in order to find patterns in data and make improved decisions in the future grounded on the examples that we furnish. The principle aim is to permit the computers to learn automatically in the absence of human intervention and regulate actions appropriately.

MACHINE LEARNING METHODS

- **Supervised machine learning:** These algorithms implement what has been learned previously to the new data by making use of labeled examples to forecast future events. Starting from the examination of a recognized training dataset, the learning algorithm generates an assumed function to make guesses about the resultant values. The system is capable of providing targets for any new input after adequate training. The learning algorithm can also evaluate its output with the accurate, intended output and locate errors in order to adapt the model accordingly.
- **Unsupervised machine learning:** These algorithms are applied when the information which is used to train is neither labeled nor classified. Unsupervised learning enquires how systems

can deduce a function to illustrate a latent structure from unlabeled data. The system does not figure out the correct output, but it investigates the data and can draw conclusion from datasets to explain latent structures from unlabeled data.

- **Semi-supervised machine learning:** These algorithms falls in between supervised and unsupervised learning as they use both unlabeled and labeled data for training - usually a small number of labeled data and a large number of unlabeled data. The systems which use this technique are able to considerably enhance learning accuracy. Generally, semi-supervised learning is used when the acquired labeled data needs skilled and related resources to train it or learn from it. Or else, capturing unlabeled data usually do not require additional resources.
- **Reinforcement machine learning:** These algorithms are the learning method that communicates with its environment by generating actions and finds faults or rewards. Trial and fault search and deferred reward are the most appropriate features of reinforcement learning. This technique permits machines and software agents to identify the ideal behavior automatically within a certain context for the purpose of maximizing its performance. Simple reward feedback is needed for the agent to learn which action is the finest; this is called the reinforcement signal.

Machine learning permits examination of huge quantities of data. While it usually delivers faster, more precise results for the purpose of identifying profitable opportunities or the dangerous risks, it may also need extra time and resources to train it properly. Merging machine learning with Artificial Intelligence and cognitive skills can make it even more efficient in processing immense volumes of information.

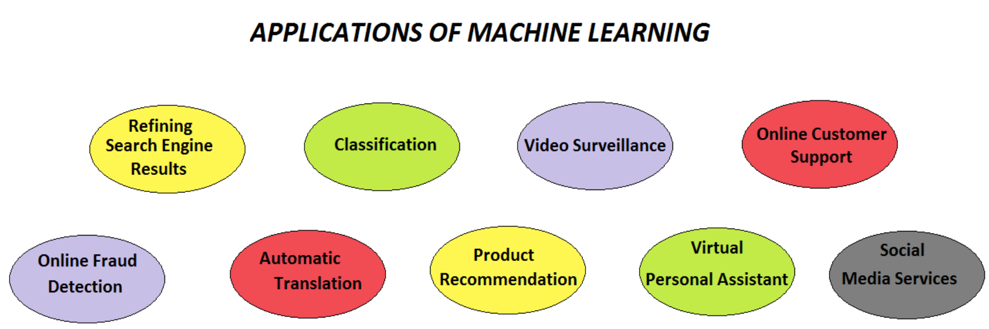

Fig 1: Applications of Machine Learning

PROBLEM OF BORDER SURVEILLANCE

Border security pertains to safeguarding the boundaries of the country against illegal movement of drugs, humans, goods and weapons. It is the key element in sustaining trade and travelling lawfully along with ensuring protection against terrorism across the world. This assists in sustaining a nation’s safety, freedom and economy. Border surveillance systems are the systems engaged in monitoring the activities taking place across the border lines and identifying if any suspicious behavior is going on. This system must comprise the following characteristics:

1. The system must detect the objects in real time.
2. The system must be able to trace the intruders (human and objects) across the border.
3. The system must be connected wirelessly to exchange the information among the border surveillance system and the base station.
4. The system must be capable of taking the necessary actions whenever needed.

LITERATURE SURVEY

Border Patrol Techniques:

Border patrol widely relies on the involvement of humans. The relative cost to raise the personnel count and the declining precision of human-only supervision necessitate the involvement of high-tech strategies in border patrol. The use of Unmanned Aerial Vehicles (UAVs) for aerial surveillance detects and tracks the illegal border trespassing automatically [3-5]. The involvement of humans is highly reduced due to the UAVs as they cover wide range of area and has high mobility. The valuable human resources can thus be allocated for taking actions based on the data received from these devices. Though, like the typical border patrol methods, UAVs solely cannot provide complete coverage to the whole area at a particular time. At some point of time, few areas of the border may remain unsupervised.

Moreover, the UAVs have significantly higher costs and accident rates than those of manned aircrafts and require large human footprint to control their activities. In addition, inclement weather conditions can also impinge on the surveillance capability of UAVs. To complement the UAV activities, recently, Fiber Optic Sensors (FOSs) [6] are introduced. Seismic sensors are equipped with FOSs so that they can measure pressure waves in the earth caused by intruders. However, FOS communication depends on a single wire along the border. As a consequence, any single point-of-failure can affect very long distances. Due to the harsh environmental conditions along a border, wired sensor systems are not robust.

Moreover, deployment costs of wired sensors surpass existing costs in long borders limiting their practical application. Compared to the wired sensors, Unattended Ground Sensors (UGSs) [7, 8,9] provide higher system robustness. UGSs have been intensively used for military Intelligence Surveillance and Reconnaissance (ISR) applications. UGSs can detect vibration/seismic activity or magnetic anomaly, which indicate that people or vehicles are crossing the border. Moreover, UGSs can pick up moving heavy vehicles (such as tanks) from a distance of 500 m and walking humans from 50 m [9]. However, the information provided by the UGSs can be limited and inaccurate. Therefore, based on the limited information acquired by current ground sensors, it is difficult to distinguish actual intrusion alarms from false positives, i.e., nuisance warnings caused by environment elements (insects, weather, animals, etc). According to the US department of homeland security, 90% of the alerts are caused by animals or environment impacts instead of illegal immigrants and this result in a significant amount of wasted time for the deployment of agents to check on the provided information [10]. In addition, it has been reported that the existing sensors are often damaged by insects or moisture and hence, are not robust to external impacts [10].

While scalar sensors such as vibration sensors are important to detect an intrusion, these sensors provide limited information to classify the intruder. To this end, surveillance towers equipped with video monitors and night vision scopes provide high accuracy in human detection and keep false alarms to a minimum [11]. The monitoring range is also much larger than the ground sensors. These systems, however, typically require human interaction to determine the type of intrusion. Moreover, the video monitors require the target within the line of sight. If the monitoring area consists of obstacles such as rocks, brushwood, or trees, the miss rate increases.

The existing techniques for border patrol, which include surveillance towers, ground sensors, or unmanned aerial vehicles, are deployed completely aboveground. In certain areas, aboveground components are vulnerable to the effects of the environment, vehicles or large animals. Visible devices may also be easily found, damaged, or avoided by intruders. For instance, for a system with surveillance towers, the intruders will look for areas and times not properly covered by adjacent towers. In addition to these major challenges, the existing solutions for border patrol systems lack a coherent system that coordinate various technologies to improve the system accuracy.

INTRUDER DETECTION TECHNIQUES

Manish Khare [12] applied Haar like features to prepare the image set. This system was used to identify the persons and particle filter was used to locate them. This system permitted identifying a human in bad lighting situations, different sizes and shapes etc. This system can also detect various human objects in a video. A machine learning technique is used for Object detection which is relied on Haar-like features. As training, the human detector binary adaptive boosting is used to accelerate the process. For training the detector, 2000 positive images containing human and 2700 negative images without human are collected. After collecting the samples, the Haar-like feature extraction is done from the samples. This system has the ability to characterize a non-linear object tracking system where non-Gaussian nature of noise is present. Two techniques are used to track various objects, first by creating several particle filters for each and every track and second one is by using one particle filter for all tracks. The newly detected human object is represented using a Color Histogram. Probability of the particles is calculated using this histogram in the future frames.

Nizar Zarka [13] formed a system which can detect humans in both the environments i.e. indoor and outdoor. Initially a robust adaptive background model is designed which can handle varied lighting circumstances and object occlusions. A background subtraction technique is used to obtain the foreground pixels. Once the foreground pixels are obtained, the human objects are detected by applying a noise cleaning and object detection method.

Neha Gaba [14] applied an advanced technique that is used on videos for detecting motion objects. Using this system, complete moving object detection is done which is vigorous although the brightness varies continuously; adjacent environments and noises vary dynamically. To build the model, a pixel dependent approach is used which is linked with the initial frame of the video. After capturing the subsequent frame, the foreground is detected which is applied to represent various detected objects and then it’s background. Unique tracking techniques are then used to identify and remove the ghost objects. Faults in currently developed methods were overcome by applying a single set of variables.

Chun-Ming Li [15] suggested an algorithm which is applied for detecting the humans and is based on the data that is obtained from the human shape and movement. A moving object is detected by applying the Eigen object that is calculated from the first video frame. The shape of the human body is used to distinguish it from other objects. Constant multiple frames are applied to verify whether there is occlusion among the objects. Eliminating shadows associated with objects reduces their effect on the human body.

Hyukmin Eum [16] established a technique to identify human action at nighttime. An infrared thermal camera was used that works on heat signatures released by the body as a substitute of normal visual traits. This camera was preferred as it made detection of human movement easier at night.

Xiaoshi Zheng [17] projected that the detection of moving object is one of the most significant steps in video surveillance. These applications are accomplished by using frame difference algorithms. Initially, the moving pixels of frames are obtained in the video by applying an automatic threshold calculation algorithm. Then a morphological operation is used for the configuration of moving areas. At last, the shortest distance among two areas was computed and was used in the region combination. This surveillance application is completely automatic and efficient.

Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) are used to process the sequential multimedia data. A very good result is given by RNN and LSTM by processing this type of data. These networks were applied in identifying the speech, digital signal processing, processing of the video and analyzing the text data. Amin Ullah [18] suggested a technique by using Deep Bidirectional LSTM and Convolutional Neural Network (CNN) on the video frames for action recognition. For reducing the duplicity, every sixth frame of the incoming video is used for the extraction of deep features. For discovering the sequential information from the frame features and for increasing the depth, various layers are applied which are combined in both forward as well as the backward pass of DB-LSTM. This technique is applied in learning long term sequences and in processing of large videos by evaluating its features for a set time interval. Action recognition is enhanced largely by using this technique.

WEAPON DETECTION TECHNIQUES

One way to reduce violence is interception by initial detection so that the security guards or policemen can act. Particularly, an innovative solution to this issue is to provide surveillance or control cameras with a precise automatic handgun detection alert system. Associated studies discuss the recognition of guns but only on milli-metric wave images or X-ray images and by only applying usual machine learning techniques [19, 20, 21, 22, 23]. During the five years, Convolutional Neural Networks (CNNs) in particular and deep learning in general have gained superior outcomes to all the traditional machine learning techniques in image classification, segmentation and detection in various applications [24, 25, 26, 27, 28, 29]. Traditional techniques need manual intervention, while the deep CNNs models detect increasingly higher level features from data automatically [30, 31].

The detection of hidden handguns in milli-metric wave images or X-ray images is used mostly in luggage control at airports. The current techniques receive high accuracies by applying various combinations of feature extractors and detectors, applying border detection and pattern matching [20], simple density descriptors [19] or by applying more complex techniques like cascade classifiers with boosting [21]. The efficiency of these techniques made them crucial in some particular areas. Though, they have various limitations. As these systems are metal detection systems, they cannot recognize non metallic guns. They are expensive to be used in many regions as they need to be shared with Conveyor belts and X-ray scanners. They are not accurate because they respond to all the metallic objects.

The gun detection by applying traditional techniques is also done in RGB images. Some existent papers essentially use methods such as RIFT (Rotation-Invariant Feature Transform), SIFT (Scale-Invariant Feature Transform), together with the Harris interest point detector or FREAK (Fast Retina Key point) [22, 23, 32]. For instance, the authors in [22, 23] proposed a precise software for detecting pistol in RGB images. Though, their technique is not able to detect various pistols in the same area. The used method starts initially by removing non-related objects to a pistol from the segmented image by applying K-mean clustering algorithm and then SURF (Speeded Up Robust Features) method is applied for detection points of interest. Likewise, the authors in [32] revealed that BoWSS (Bag of Words Surveillance System) algorithm has a high potential in detecting the guns. In this system, initially SIFT was used to extract features; K-Means clustering was applied for clustering the achieved functions and SVM (Support Vector Machine) was used for training. The authors in [33] proposed riffle detection in RGB images by applying SVM (Support Vector Machine).

The idea of automated image understanding from videos for public security applications is well explored and well known in various domains. For instance, Jang and Turk suggested a vehicle recognition system which is based on the SURF feature detection algorithm [34]. The idea of automated CCTV analysis of image and detection of dangerous situations has been suggested and analyzed in numerous studies. Marbach et al. suggested an automated fire detection system based on temporal variation of fire intensity [35]. Such solutions exploit an identical research direction, while dealing with a less complicated problem. Same is the case for systems designed for deduction and surveillance based on human shape detection and pose estimation. A good overview of shape representation is suggested by Chen et al. in [36]. Such a technique is used in crowd density management system suggested by Velastin et al. [37] and the congestion detection system suggested by Lo et al. [38]. A system for automated robbery identification based on actors' pose estimation was proposed by Dever et al. [39].

An automatic threat level detection and alert warning system in Remote Video Surveillance (RVS) Systems for border patrol and border security is presented in [40], where the threat levels are based on the type of target intrusions at the border. Machine Learning algorithms were employed to detect the targets, to classify the threat levels and to display the alerts in the warning system. For weapons detection, the algorithm is trained for handgun detection only. A novel automatic pistol detection system in videos appropriate for both, surveillance and control purposes is proposed in [41]. This detection system focuses on the problem of minimizing false positives and solve it by building the key training data-set guided by the results of a VGG-16 based classifier, then assessing the best classification model under two approaches, the sliding window approach and region proposal approach.

The primary idea of automated gun crime detection was suggested by Darker et al. as a part of United Kingdom-based MEDUSA project [42]. This team also worked on recognizing the cues that might indicate that a person is carrying a hidden firearm [43]. The initial trials made by the similar team for using CCTV as an automated sensor for firearm recognition emerged next [44]. An example of a latest technique is FISVER, a structure for smart public safety in video-surveyed vehicles, which has the capacity of universal object recognition including substances, such as firearms [45]. Additionally, Arslan et al. designed a threat assessment solution making the use of visual hierarchy and conceptual firearms ontology [46]. The current progress in automated CCTV surveillance systems is offered by Dee and Velastin in [47]. Moreover, it is worth noting that there are various promising techniques for detecting dangerous objects in identical scenarios. It is explained by Yong et al. that the detection of metal objects such as guns and knives is possible by using microwave swept-frequency radar [48]. X-ray imaging can also be used to detect objects as presented by Mery et al. [49]. Health hazards and economic cost are the factors that affect the application of these techniques practically. Moreover, the video-based detection of firearm is a precautionary approach regarding acoustic gunshot detection and both can be coupled [50, 51]. Detection of dangerous objects can be carried out using methods such as principal components analysis (PCA) as stated in [52].

CONCLUSION

As a developing country, India faces many problems regarding border security. India's border is very diverse as it covers rivers, land, high lands, mountains etc. Safeguarding the country's border is the most important issue of concern in this period of globalization. The issues faced on border include illegal migration of immigrants, human trafficking, drug trafficking, trade of arms and weapons, intruder detection etc. this paper reviews various border patrol techniques, intruder detection techniques and weapon detection techniques. It is also found during research that use of machine learning techniques for border surveillance can be a possible and efficient solution to the problem of border security.

REFERENCES

1. P. Rothenpieler, D. Kruger, D. Pfisterer, S. Fischer, D. Dudek, C. Haas, A. Kuntz and M. Zitterbart, "Flegsens: Secure Area Monitoring Using Wireless Sensor Net-works," Proceedings of the 4th Safety and Security Systems in Europe, 2009.
2. E. Felemban, C. Gun and E. Ekici, "MMSPEED: Multi-path Multi-SPEED Protocol for QoS Guarantee of Reli-ability and Timeliness in Wireless Sensor Networks," IEEE Transactions on Mobile Computing, Vol. 5, No. 6, 2006.
3. C.C. Haddal, J. Gertler, Homeland security: unmanned aerial vehicles and border surveillance, CRS Report for Congress, July 2008..
4. A.R. Girard, A.S. Howell, J.K. Hedrick, Border patrol and surveillance missions using multiple unmanned air vehicles, in: Proc. IEEE CDC'04, Atlantis, Paradise Island, Bahamas, December 2004.
5. A. Marino, L.E. Parker, G. Antonelli, F. Caccavale, Behavioral control for multi-robot perimeter patrol: a finite state automata approach, in: Proc. ICRA '09, May 2009.
6. G. Loney, Border intrusion detection: thinking outside the perimeter, in: Proc. IEEE International Carnahan Conference on Security Technology, 2007.
7. Trident Systems Incorporated, Unattended Ground Sensors, <http://www.tridsys.com>.
8. Crane Wireless, Micro Observer Unattached Ground Sensor System, <http://www.cranewms.com>.
9. Elta Systems, Unattended ground sensors network (USGN), <http://defenseupdate.com/newscast/0608/news/news1506_ugs.htm>.
10. M. Riley, Building a border, the denver post, March 12, 2007, <http://www.denverpost.com/fortressamerica/ci_5356695>.
11. A. Patrascu, Optimizing distributed sensor placement for border patrol interdiction using Microsoft excel, Thesis, Department of the Air Force, Air University, Air Force Institute of Technology, April 2007.
12. Maneesh Khare, Rajnesh Kumar Srivstav and Ashish Khare, Automatic Multiple Human Detection and Tracking for Visual Surveilance Sys- tem, IEEE/OSAIIAPR International Conference on Informatics, Electron- ICS Vision.
13. Nizar Zarka, Ziad Alhalaha and Rada Deeb, Real-Time Human Motion Detection and Tracking, 3rd International Conference on Information and Communication Technologies: From Theory to Applications, 2008.
14. Neha Gabal, Neelam Barak and Shipra Aggarwal, Motion Detection, Tracking and Classification for Automated Video Surveillance, 1st IEEE International Conference on Power Electronics. Intelligent Control and Energy Systems (ICPEICES- 2016).

15. Chun-Ming Li, Yu-Shan Li, Shu-Hai Wang, And Xiu-Qing Zhang Moving human body detection in video sequences, Proceedings of the Sixth International Conference on Machine Learning and Cybrnetics, Hong Kong, 22 August 2007.
16. Hyukmin Eum, Jeisung Lee, Changyng Yon and Mignoon Parke Human Action Recogntion for Night Vision Using Temparal Templtes with In- frared Thermal Camera, 10th International Conference on Ubiquitus Rabots and Ambient Intelligence (URAI), 2013.
17. Xiashi Zeng, Yaling Zhaao, Na lee, Huimean Woo An Autamatic Mov- ing Objct Dtection Algorithm for Video Surveilance Aplications, International Conferences on Embedded Software and Systems 2009 International, 2009.
18. AMIN ULAH, JAMIL AHMAD Action Recognition in Video Sequences using Deep Bi-Directional LSTM With CNN Features, Digital Object Identifier 10.1109/ACCESS.2017.2778011.
19. Greg Flitton, Toby P Breckon, and Najla Megherbi. A comparison of 3d interest point descriptors with application to airport baggage object detection in complex ct imagery. Pattern Recognition, 2013, 46(9):2420–2436.
20. Richard Gesick, Caner Saritac, and Chih-Cheng Hung. Automatic image analysis process for the detection of concealed weapons. In Proceedings of the 5th Annual Workshop on Cyber Security and Information Intelligence Research: Cyber Security and Information Intelligence Challenges and Strategies, ACM, 2009, page 20.
21. Zelong Xiao, Xuan Lu, Jiangjiang Yan, Li Wu, and Luyao Ren, Automatic detection of concealed pistols using passive millimeter wave imaging, In 2015 IEEE International Conference on Imaging Systems and Techniques (IST), IEEE, 2015, pp. 1–4.
22. Rohit Kumar Tiwari and Gyanendra K Verma, A computer vision based framework for visual gun detection using harris interest point detector, Procedia Computer Science, 2015, pp:703–712.
23. Rohit Kumar Tiwari and Gyanendra K Verma. A computer vision based framework for visual gun detection using surf, In Electrical, Electronics, Signals, Communication and Optimization (EESCO), 2015 International Conference on, IEEE, 2015, pp. 1–5.
24. Quoc V. Le, Building high-level features using large scale unsupervised learning, In 2013 IEEE Int. Conf. Acoust. Speech Signal Process, 2013, pp. 8595–8598.
25. Geoffrey Hinton, Li Deng, Dong Yu, George Dahl, Abdel-rahman Mohamed, Navdeep Jaitly, Andrew Senior, Vincent Vanhoucke, Patrick Nguyen, Tara Sainath, and Brian Kingsbury. Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups. IEEE Signal Process. Mag., , 2012, 29(6):82–97.
26. Tara N. Sainath, Abdel-rahman Mohamed, Brian Kingsbury, and Bhuvana Ramabhadran. Deep convolutional neural networks for LVCSR, In 2013 IEEE Int. Conf. Acoust. Speech Signal Process., 2013, pp. 8614–8618.
27. Mostafa Mehdipour Ghazi, Berrin Yanikoglu, and Erchan Aptoula, Plant identification using deep neural networks via optimization of transfer learning parameters. Neurocomputing, 2017, in press.
28. Wei Yu, Kuiyuan Yang, Hongxun Yao, Xiaoshuai Sun, and Pengfei Xu, Exploiting the complementary strengths of multi-layer cnn features for image retrieval, Neurocomputing, vol 237, 2017, pp. 235–241.
29. Xiangbo Shu, Yunfei Cai, Liu Yang, Liyan Zhang, and Jinhui Tang, Computational face reader based on facial attribute estimation. Neurocomputing, Vol 236, 2017, pp.153–163.
30. Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton, Imagenet classification with deep convolutional neural network, In Advances in neural information processing systems, 2012, pp. 1097–1105.
31. Yanming Guo, Yu Liu, Ard Oerlemans, Songyang Lao, Song Wu, and Michael S Lew, Deep learning for visual understanding: A review. Neurocomputing, vol 187, 2016, pp.27–48.
32. Nadhir Ben Halima and Osama Hosam. Bag of words based surveillance system using support vector machines, International Journal of Security and Its Applications, vol 10(4), 2016, pp.331–346.
33. Osama Hosam and Abdulaziz Alraddadi, K-means clustering and support vector machines approach for detecting fire weapons in cluttered scenes, Life Science Journal, vol 11(9), 2014.
34. Jang, D.; Turk, M. Car-Rec: A real time car recognition system. In Proceedings of the IEEE sWorkshop on Applications of Computer Vision (WACV), Kona, HI, USA, 5–7 January 2011; pp. 599–605.
35. Marbach, G.; Loepfe, M.; Brupbacher, T. An image processing technique for fire detection in video images. Fire Saf. J. 2006, 41, pp. 285–289.
36. Chen, C.; Zhuang, Y.; Xiao, J. Silhouette representation and matching for 3D pose discrimination—A comparative study. Image Vis. Comput. 2010, 28, pp. 654–667.

37. Velastin, S.; Yin, J.; Davies, A.; Vicencio-Silva, M.; Allsop, R.; Penn, A. Automated measurement of crowd density and motion using image processing. In Proceedings of the Seventh International Conference on Road Traffic Monitoring and Control, London, UK, 26–28 April 1994; pp. 127–132.
38. Lo, B.; Velastin, S. Automatic congestion detection system for underground platforms. In Proceedings of the 2001 International Symposium on Intelligent Multimedia, Video and Speech Processing, Hong Kong, China, 2–4 May 2001; pp. 158–161.
39. Dever, J.; da Vitoria Lobo, N.; Shah, M. Automatic visual recognition of armed robbery. In Proceedings of the 16th International Conference on Pattern Recognition, Montreal, QC, Canada, 11–15 August 2002; pp. 451–455.
40. Ayush Goyal, Shreedevi Bugudanahalli Anandamurthy, Pritam Dash, Swati Acharya, Disha Bathla, David Hicks, Anupama Bhan and Priya Ranjan, Automatic Border Surveillance Using
41. Machine Learning in Remote Video Surveillance Systems,Springer 2020, pp. 751-760.
Roberto Olmos, Siham Tabik, Francisco Herrera, Automatic Handgun Detection Alarm in Videos Using Deep Learning, Elsevier 2017, vol 275, pp. 66-72.
42. Darker, I.; Gale, A.; Ward, L.; Blechko, A. Can CCTV Reliably Detect Gun Crime? In Proceedings of the 41st Annual IEEE International Carnahan Conference on Security Technology, Ottawa, ON, USA, 8–11 October 2007; pp. 264–271.
43. Blechko, A.; Darker, I.; Gale, A. Skills in detecting gun carrying from CCTV. In Proceedings of the 42nd Annual IEEE International Carnahan Conference on Security Technology, Prague, Czech Republic, 13–16 October 2008; pp. 265–271.
44. Darker, I.T.; Gale, A.G.; Blechko, A. CCTV as an automated sensor for firearms detection: Human-derived performance as a precursor to automatic recognition, In Proceedings of the International Society for Optical Engineering, 15 September 2008; pp. 11–12.
45. Barros, H.; Neto, A. FISVER: A Framework for Smart Public Safety in Video-Surveilled Vehicles. In Proceedings of the 3rd Internation Workshop on ADVANCEs in ICT Infrastructures and Services, Miami, FL, USA, 24 August 2014; pp. 221–225.
46. Arslan, A.N.; Hempelmann, C.F.; Attardo, S.; Blount, G.P.; Sirakov, N.M. Threat assessment using visual hierarchy and conceptual firearms ontology. Opt. Eng. 2015, 54, pp. 105–109.
47. Dee, H.; Velastin, S. How close are we to solving the problem of automated visual surveillance? Mach. Vis. Appl. 2008, 19, pp. 329–343.
48. Li, Y.; Tian, G.Y.; Bowring, N.; Rezgui, N, A microwave measurement system for metallic object detection using swept-frequency radar, In Proceedings of the Millimetre Wave and Terahertz Sensors and Technology, Cardiff, UK, September 15 2008; pp. 13–16.
49. Mery, D.; Riffo, V.; Zuccar, I.; Pieringer, C, Automated X-Ray Object Recognition Using an Efficient Search Algorithm in Multiple Views. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, Portland, OR, USA, 23–28 June 2013; pp. 368–374.
50. Maher, R. Modeling and Signal Processing of Acoustic Gunshot Recordings. In Proceedings of the Digital Signal Processing Workshop, 12th—Signal Processing Education Workshop, Teton National Park, WY, USA, 24–27 September 2006; pp. 257–261.
51. Chacon-Rodriguez, A.; Julian, P.; Castro, L.; Alvarado, P.; Hernandez, N. Evaluation of Gunshot Detection Algorithms, IEEE Trans. Circuits Syst. I Regul. Pap. 2011, 58, pp. 363–373.
52. Malagón-Borja, L.; Fuentes, O. Object detection using image reconstruction with PCA. Image Vis. Comput. 2009, 27, pp. 2–9.