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Comprehensive Survey on Object Detection and Anomaly Detection Techniques for Ensuring Pedestrian Safety in Walkways

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Ensuring pedestrian safety in walkways gains more significance in urban surroundings. Anomaly detection (AD) approaches had a crucial role in assuring pedestrian safety in pathways, where abnormal events or behaviours can give rise to potential risks. To attain this, potential AD and object detection approaches are essential to identify abnormal behaviours and potential hazards in real-time. This survey presents a complete overview of AD and object detection algorithms particularly devised for pedestrian walkways. The survey starts by discussing the importance of pedestrian safety and the difficulties related to identifying anomalies and objects in walkway settings. Then it delivers a comprehensive analysis of different object detection algorithms that includes existing deep learning methods and classical computer vision (CV) based methods. The applications, strengths, and limitations of all methods are inspected, emphasizing their potentiality in pedestrian tracking and detection. Moreover, the survey explored AD approach that intends to determine abnormal events or behaviours in walkways. Such methods have machine learning-based methods, statistical modeling, and AD methods designed for pedestrian-centric situations. The survey inspects their respective pros, cons, and real-time applications. The survey concluded by discussing future directions and emerging trends in object detection and AD for pedestrian safety in walkways.

Keywords: Pedestrian walkways; Object detection; Anomalies; Deep learning; Machine learning.

1. Introduction

With the extensive usage of surveillance cameras in public places, computer vision (CV) related scene understanding has obtained more popularity among CV researchers [1]. Visual data has rich data associated to other data sources namely radar signals, GPS, mobile location, and many more. Hence, it can serve a crucial role in forecasting or finding congestion, accident and another anomaly other than gathering statistical data regarding the status of road traffic [2]. Different CV-related studies were carried out concentrating on activity learning, data acquisition, scene learning, behavioural understanding, feature extraction, etc. Such studies mainly discuss on aspects like vehicle detection and tracking, scene analysis, anomaly detection methods, traffic monitoring, multi camera-based methods and difficulties, video processing techniques, activity recognition, human behaviour analysis, event recognition, emergency management, etc [3]. Anomaly detection (AD) in pedestrian walkways is a sub-domain of behaviour understanding from surveillance scenes. Certain samples of anomalies are Jaywalking, vehicle presence on walkways, an abrupt dispersion of persons within a crowd, U-turn of automobiles during red signals, an individual falling abruptly while walking, and signal bypassing at a traffic junction [4]. Anomaly detection structures commonly use semi-supervised or unsupervised learning. In this study, the author explores AD methods utilized in road traffic scenarios concentrating on entities like environment, vehicles, pedestrian, and their communications [5].

Several CV hinges on works devised by focusing on tasks like behavioural learning, data acquisition, scene learning, activity learning, feature extraction, etc [6]. Generally, anomaly predictive methods implement semi-supervised and unsupervised learning. A significant goal of this study is to find the anomaly prediction methods implemented in road traffic cases and focuses on utility such as atmosphere, vehicles, communication, and trespassers [7]. The scope of this has to encircle the nature of input dataset in addition to the ability of the system in application contents, representations, anomaly predictive outcomes, likelihood of supervised learning, class of abnormalities, and termination criteria [8]. The anomaly predictive system can be functioned by understanding the typical data patterns to develop public profiles. If the usual patterns were described, anomalies can be forecasted with the new approaches developed. Later, the simulation of the method can be label that forecasts that the data is healthy or abnormal [9]. Eventually, Deep Learning (DL) depend on anomaly prediction approaches were deployed. Primarily, Convolution Neural Networks (CNNs) are used and classified the presence of objects. It has faced some problems such as huge spatial locations along with aspect ratios of objects from images [10]. To overcome such issues, many regions should be chosen and lead to processing complexity. Therefore, YOLO and region-based CNN (R-CNN) were accomplished for identifying the incidence at robust rates.

This survey presents a complete overview of AD and object detection algorithms particularly devised for pedestrian walkways. The survey starts by discussing the importance of pedestrian safety and the difficulties related to identifying anomalies and objects in walkway settings. Then it delivers a comprehensive analysis of different object detection algorithms that includes existing deep learning methods and classical computer vision (CV) based methods. The applications, strengths, and limitations of all methods are inspected, emphasizing their potentiality in pedestrian tracking and detection. Moreover, the survey explored AD approach that intends to determine abnormal events or behaviours in walkways.

2. Background Information: Types and Challenges

2.1. Types of Anomalies in Pedestrian Walkways

Anomalies in pedestrian pathways denote the events, behaviours, or situations that get deviated from the anticipated or usual patterning perceived in the pedestrian motion. These deviations can cause security worries or possible dangers and are crucial to perceive and solve to make sure pedestrian security.

2.1. Anomaly types in Pedestrian Pathways

Below are few prevalent kinds of discrepancies that can happen in pedestrian pathways:

Jaywalking: Jaywalking denotes to pedestrians who cross a pathway or a road in improper or illegal places, ignoring traffic signs or appropriate crossings. Detection of jaywalking anomalies can assist in recognizing possibly hazardous circumstances and reduce the accident risk.

Crowd Anomalies: Crowd anomaly happen if there exists unfamiliar patterning or activity in a group of pedestrians. This can comprise rushes, congestion, abrupt shifts in direction or movement, or unpredicted crowd dispersion. Crowd anomaly detection is significant for handling crowd security and averting events in congested pathway circumstances.

Unusual Activities: Unusual events include actions that are uncharacteristic or doubtful inside a pedestrian pathway background. These encompasses uncommon mannerisms or stances, strolling, wreckage, or other actions that elevates safety worries. Inspecting and detecting such uncommon actions can assist in averting possible hazards or criminal activities toward pedestrian security.

Object Abandonment: Object abandonment anomaly happen when objects are left deserted in pathways, possibly instigating security or hindrance risks. Identifying neglected objects can assist recognize possible hazards like unnoticed objects or baggage and help prompt interference or retort.

Falls or Accidents: Anomaly in pedestrian pathways can also comprise casualty or mishap, in which a person lapse, misstep, or undergo wound because of irregular surface, impedes, or other circumstantial aspects. Identifying like occurrences can sharply allow instance aid or medical care, developing comprehensive pedestrian security.

Identifying and attending anomaly in pedestrian pathways need excellent scrutiny schemes, comprising sensors, audio-visual cameras, and intellectual procedures. These structures influence machine learning, computer vision, and anomaly recognition methods to investigate pedestrian action, recognize diversions from usual patterning, and initiate proper interferences or warnings. By identifying anomaly in real-time, pedestrian security can be improved, possible hazards can be reduced, and proper steps can be utilized to preserve a safe pathway atmosphere.

2.2. Challenges involved

Few of the severe threats on recording-based anomaly recognition are:

- Illumination: Though various anomaly identification techniques are previously recommended, the number of techniques that can handle illumination discrepancies, is restricted. This is because of the inabilities of illuminations sceptic feature extraction from the recordings. The techniques or standard employed under diverse illumination circumstances can be diverse for real-life functioning.

• Pose and Perspective: Mostly camera slants concentrating on observation area can have significant influence on the presentation of anomaly recognition as the arrival of automobile may vary relying on its distance from the cameras. Although the precision of the object recognition has improved propagation by employing deep neural network-based techniques, there still exist threats in tracking trivial objects. While people can identify objects at diverse stances effortlessly, machine learning may encounter problems in tracking and identifying similar objects under stance discrepancies.

• Heterogeneous object handling: Anomaly identification systems are widely depended on designing the scene and its entity. Nevertheless, designing mixed objects in scene or learning the mixed objects motion in a scene can be tough sometimes.

• Sparse vs. Dense: The techniques implemented for identifying anomaly in dense or sparse circumstances are diverse. However, few techniques are good in positioning anomaly in sparse circumstances, dense scene-related techniques can produce several fake negatives.

• Curtailed tracks: As various anomaly recognitions are depended on automobile tracking, primary tracking methods are likely to accomplish with precision. Although precision of the tracking has improved in the past decade, several current tracking methods will not function under diverse situations. Tracking under obstruction is one other threat though people can effortlessly track those visually.

• Lack of real-life dataset: There exists a requirement for real-life dataset to perceive the efficiency of anomaly recognition methods. There are plenty needs and opportunities for anomaly recognition study depending on the gaps debated priory. With the progression in machine learning methods and inexpensive hardware, CV-based action evaluation, anomaly anticipation and recognition can advance in future. DL-based fusion frameworks are capable of handling varied traffic strategies. This also can assist in building complete automated traffic investigation frameworks that are able to report actions of interest to the investors.

3. Overview of Machine Learning and Deep Learning

Machine learning (ML) and deep learning (DL) approaches play a vital part for training the computer network as skilled personnel which is utilized for decision making and prediction. ML gives computer the capability of learning without clearly being programmed. DL is a kind of ML that authorize system to obtain fact and understand the world based on the pecking order of idea. This field brings intelligence to computers that could derive the pattern based on particular information and later processes for automated reasoning. Digital image processing provides considerable impact on making decision depend on certain predictions. It provides best feature extraction and precision. The process of functioning evaluation is complex and comprises different properties. The digital image processing method is implanted in various computer systems. The validation of image processing methodologies can be indispensable that provides an application of particular procedure that offers impact on the performance. Then, it brings about decision and action depending on the methods in imaging. This delivers several visualization tools and refined and rudimentary image analysis. Artificial intelligence (AI) is the most important field and ML and DL. AI is the main domain to exhibit human intelligence in machines; ML was utilized to accomplish AI, while DL is a method utilized to apply ML.

The different steps were executed on processing images beforehand for the identification of output. At first, the image was given as inputs to the DL and ML approaches. Then, the image was classified into various segment to zoom the interested region. Next, the feature was mined from this segment via data retrieval technique. The desired feature was chosen and the noise is detached. Lastly, the classifier is utilized for classifying the extracted data and making prediction according to these classifications. This step was utilized in all the experiments of ML. Active learning, supervised, semi-supervised, unsupervised and reinforcement approaches are the major classes of ML. Furthermore, the DL approaches are essentially advanced stage of ML approaches that classifying data and predicting more precisely using NN.

Supervised learning

It provides training sets of samples with proper objective to computer systems. Take this training set mechanism provides response precisely on provides potential input. Regression and classification are the classes of Supervised Learning.

· The input is dispersed into dissimilar classes utilizing classification method, and trained model should produce action that allocates hidden input to this classes. This can be named multi-labeling procedure. The spam purifying refers to the case of classification, where emails were categorized into “spam” and, “not spam”.

· The regression can be a supervised method where the outcome is continuous instead of discrete. The regression prediction is estimated by the root mean squared error (RMSE), different from classification prediction where precision was utilized as performance measures.

Unsupervised learning

The method decides by itself instead train based on certain datasets. No labeling can be provided to the mechanism that is utilized for prediction. Unsupervised learning is utilized for retrieving the hidden pattern through feature learning of the provided dataset.

The clustering refers to an unsupervised learning method that can be utilized for dividing the input into cluster. This cluster is not recognized earlier. It constructs group based on resemblance.

Semi-supervised learning

In Semi-supervised learning, the system was considered to be partial training dataset. This kind of training was utilized with few trained dataset that could target few missed outcomes. This kind of method can be utilized on untagged dataset for training. This presented learning method trained on labelled and unlabelled dataset and this learning shows the feature both the supervised and unsupervised-learning methods.

Active learning

In Active learning, the systems get training tag for a limited set of incidences. It can be utilized for enhancing its optimality of substance for gaining tags. This is budgets function in an entity.

Reinforcement learning

In Reinforcement learning (RL) the trained dataset can be offered as a reply to the activity of a program in self-motivated condition to drive the vehicle or playing video games.

Evolutionary Learning

It is primarily utilized in the biological domain for learning biological organism and to forecast the existence rate and the casual of offsprings. Then, these models through knowledge of fitness, to forecast how accurate the outcome is.

Deep learning

This can be the advanced stage of ML that mostly exploits NN for the prediction and learning of data. It is a group of dissimilar approaches. These are utilized for designing complicated generalize mechanism that could take any kind of difficulties and provides prediction. It exploits the deep graph including several processing layer, composed of linear and non-linear conversion. The improvement of these information is vital to process and mine this reports efficiently and elegantly. There are dissimilar kinds of ML approaches are presented that are used for using particular classifier for the data distribution based on the features.

4. Review of Anomaly Detection Techniques on Pedestrian Walkways

This section discusses a comprehensive set of existing anomaly detection techniques in the pedestrian walkways as given in Table 1. In [11], a new approach to localize and find anomalous objects automatically amongst multi-pedestrian masses through conditional random field and DL was presented. Primarily, essential preprocessing was effectuated on abstracted frames and with enhanced watershed transform, super-pixels are made, the objects are segmented by means of conditional random field. A DL-FPN is applied to categorize and detect the objects in all regions and lastly, the anomalous object is ascertained with the use of Jaccard similarity. Choi et al. [12] suggest predicting displacement between neighbouring frames for all pedestrians sequentially. The author leveraged an LSTM model motion data for every pedestrian and leverage an MLP for mapping position of all pedestrians to high dimension feature space in which the inner products among features was exploited as a measurement for positional relation among dual pedestrians. Afterwards, the author weight the pedestrian’s motion features depends on their positional relation for location displacement prediction.

Kalatian and Farooq [13] presents DeepWait, a new structure to predict waiting time of pedestrian at unsignalized mid-block crosswalk in mixed traffic condition. The author use the strengths of DL in seizing the nonlinearity in data and developed a cox proportional hazard method with DNN as the log-risk function. An embedded feature selection method for enhancing the network interpretability and reducing data dimensionality is designed. Anderson et al. [14] described a new scheme with the use of a stochastic sampling-related simulation for training DNN for pedestrian trajectory forecast with social communication. The new simulation approach can produce massive quantities of automatically annotated, real, and naturalistic synthetic pedestrian trajectory related to smaller quantities of real annotation. The author used these synthetic trajectories fir training an off-the-shelf existing DL method Social GAN to achieve pedestrian trajectory estimation.

Deshpande and Spalanzani [15] suggest using a DRL related approach to resolve this issue of navigation. A Deep Q-Network related agent was trained in simulators for common intersection crossing system among pedestrians. The author devises a grid-based representation as state space inputs to learning agents. Zhang et al. [16] modelled a CircleNet, new feature learning method for attaining feature adaptation by imitating the process humans looking at low resolution and occluded objects: concentrating on it again, at finer scales, if object could not be detected obviously for initial time. The presented was applied as set of feature pyramid and utilizes weight sharing path augmentation for superior feature fusion.

Mustapha et al. [17] present potential methods to predict crowd flow and load on pedestrian bridge with the use of advanced ML approaches with sensor dataset abstracted from both wearable devices and structural sensors. A key originality of the methods is the use of sensor fusion at the feature and input level in ML approaches utilized. The ML methods are SVM and CNN; they are implemented on each of the sensing source, IMUs, and FOSs, individually and extended for multi-modal data fusion at feature and input levels. Dow et al. [18] introduce a realtime pedestrian recognition mechanism that ensured high accuracy through a DL method and zebra-crossing detection approaches. The presented mechanism was devised for enhancing pedestrian safety and minimize accident at intersections. Environmental feature vector is exploited to identify zebra crossing and to ascertain crossing regions. A dual camera system was utilized for maintaining detection accuracy and enhance system fault tolerance. Eventually, the YOLO method has been leveraged for recognizing pedestrian at intersections.

In [19], a DRL related decision-making method for high-level driving performance was modelled for urban settings in the occurrence of pedestrian. So, the utility of Deep Recurrent Q-Network (DRQN) was explored; a technique integrating existing Deep Q-Network (DQN) includes a LSTM layer assisting the agent gains memory of the setting. To train the agent to learn a suitable behavior policy in a realtime, a 3-D state representation was devised as the input integrated with defined reward function. Li et al. [20] devised a new learning-related human-machine cooperative driving method (L-HMC) with active collision avoidance capability with the use of DRL. Initially, an DQN approach was devised for learning the best driving policy for pedestrian collision avoidances. In the enhanced DQN approach, two replay buffered with non-uniform examples were modelled for shortening the learning procedure of the best driving policy.

In [21], executed four experiments like realtime comprehensive pedestrian activity identification, pedestrian motion mode recognition, pedestrian navigation, and smartphone posture identification. In the process of detection, the author devised and trained DL methods with the use of CNN and LSTM networks related to Tensorflow structure. Xue et al. [22] devise categorizing pedestrian trajectory into amount of route classes (RC) and utilizing them to describing the pedestrian movement pattern. Depending on the RCs, the forecast of pedestrian paths by LSTM (PoPPL), forecasts the destiny using a bidirectional LSTM classification ssytem in the initial phase and produces trajectory respective to the forecast destiny using one of the three LSTM-related structure in the second phase.

Zhao et al. [23] devise a P-LPN (pedestrian location perception network). The presented method can produce realtime semantic segmentation while concurrently offering location inference for all pedestrians in semantic maps. This enabled autonomous driving mechanism for classifying pedestrians into diverse safety levels. In [24], recommend utilizing multichannel tensors for denoting the ecological data of pedestrians. In the meantime, the spatiotemporal communications between the pedestrian were denoted by convolution operation of tensors. After, an end wise fully convolution LSTM encoder–decoder was modelled, tested, and trained. Eventually, the method is compared with present LSTM-related approaches with the use of 5 crowded video series with public data.

Li et al. [25] present a recurrent attention and interaction (RAI) method for forecasting pedestrian trajectory. The presented method has a randomness-modeling module, temporal attention module, and spatial pooling module. Pustokhina et al. [26] developed an automatic DL related AD approach in pedestrian walkways (DLADT-PW) for vulnerable road user's safety. The aim of the presented method was to categorize and find the different anomalies that present in the pedestrian walkways like jeeps, cars, skating, etc. The presented method includes pre-processing as the primary step that can be adapted to exterminate the noise and rise the image quality. As well, for the detection, mask region CNN (Mask-RCNN) includes DenseNet method was used.

Jeong et al. [27] utilizes DL methods to solve the limits of the present smartphone-related PDR method. A CNN method was utilized for categorizing the smartphone positions; then, applicable sensor dataset are adjusted and selected. The LSTM approach was utilized for predicting user step length. Though the PDR performance can be boosted with the use of the DL approach, accumulated error was inevitable as the method traced the relative position in terms of the original place. Everett et al. [28] developed a method that studies collision avoidance among various heterogeneous, non-communicating, dynamic agent without assuming they follow any specific behavior rules. It extended the preceding work by presenting a method through LSTM that enabled the method to exploit observations of a random number of other agents, in its place of a small, fixed number of neighbours.

Sun et al. [29] developed a novel method named reciprocal twin network, for human trajectory learning and prediction. The author designed two network, forward predictive network for predicting future trajectory from a backward prediction and previous observations that implements the trajectory prediction backward in time. The backward prediction system acts as an inverse function of forward prediction system, which forms the reciprocal constraints. In [30], the problem is resolved by means of GAN and a GAT based on spatiotemporal information regarding the pedestrian. The study, STI-GAN, depends on the end wise GAN module which simulates the pedestrian distribution for generating more reasonable future trajectories and capturing the uncertainty of the predicted path. The complex interaction between peoples is modelled by the GAT, and spatiotemporal information was leveraged for improving the performances of predicting trajectories.

Table 1 Review of Anomaly Detection Techniques on Pedestrian Walkways

Reference	**Year of Publication**	**Aim**	**Methodology**	**Dataset**	**Metrics**
Abdullah and Jalal [11]	2023	DL-based Multi-Pedestrians Anomaly Detection	CRF	UCSD Ped 1 and Ped 2 datasets	$Accu_y$ of 94.2% and 95.4%
Choi et al. [12]	2019	DL-based Pedestrian Trajectory Prediction	LSTM	Grand Central (GC) dataset	ADE of 0.016
Kalatian and Farooq [13]	2019	Pedestrian Wait Time Estimation	DeepWait	Support, METABRIC, and Rotterdam & GBSG	C-index of 0.64
Anderson et al. [14]	2019	Pedestrian Trajectory Prediction	GAN	ETH and UCY datasets	-
Deshpande and Spalanzani [15]	2019	Vehicle Navigation amongst pedestrians	DQN		-
Zhang et al. [16]	2019	Reciprocating Feature Adaptation for Robust Pedestrian Detection	CircleNet	Caltech and CityPersons	-
Mustapha et al. [17]	2020	Estimation of crowd flow and load on pedestrian bridges	CNN and SVM	-	$Accu_y$ for single class 98% and multiclass 91%
Dow et al. [18]	2020	A crosswalk pedestrian recognition system utilizing DL	zebra-crossing recognition and YOLO	COCO dataset	TPR of 100% and FPR 7.84%
Deshpande et al. [19]	2020	autonomous driving in presence of pedestrians	DQN and LSTM	-	Average speed 6.09 and travelled distance is 123.1
Li et al. [20]	2020	Pedestrian Collision Avoidance and Human-Machine Cooperative Driving	DQN	-	-
Ye et al. [21]	2020	Human Activity Real-Time Recognition for Pedestrian Navigation	LSTM and CNN	UCI dataset	$Accu_y$ of 89.39%
Xue et al. [22]	2020	Pedestrian Trajectory Prediction With Automatic Route Class Clustering	BiLSTM	-	-
Zhao et al. [23]	2020	Real Time Pedestrian Location Perception	InCNet and RPN	CityScapes	speed at ~22 fps
Chen et al. [24]	2020	Pedestrian behavior prediction model	LSTM	ETH and UCY	-

Li et al. [25]	2020	predict pedestrian trajectories using DL	RAI	ETH and UCY	-
Pustokhina et al. [26]	2021	anomaly detection in pedestrian walkways	Mask-RCNN and DenseNet	UCSD Anomaly Detection Dataset	$Accu_y$ for Test004 of 0.982 and Test007 of 0.896
Jeong et al. [27]	2021	Indoor Positioning Using Deep-Learning-Based Pedestrian	CNN and LSTM	-	-
Everett et al. [28]	2021	Collision Avoidance in Pedestrian-Rich Environments	LSTM	-	-
Sun et al. [29]	2021	Pedestrian Motion Learning and Future Path Prediction	GAN and LSTM	ETH and UCY	-
Huang et al. [30]	2021	Multimodal Pedestrian Trajectory Prediction	GAT, GAN, and LSTM	ETH and UCY	ADE of 21.9% and FDE of 23.8%
Zhang et al. [31]	2021	Multispectral Pedestrian Detection	GAFF	KAIST and FLIR ADAS	Runtime of 9.34ms
Li and Ma [32]	2022	Street tree planning based on pedestrian volume	LightGBM and KMSSL	-	R2 = 0.8360, RMSE = 0.2304
Harrou et al. [33]	2022	Forecasting of Bicycle and Pedestrian Traffic	VAE and LSTM	bicycle traffic flow	RMSE of 37.37, MAE of 28.30, and R2 of 0.91
Liu et al. [34]	2022	Ground Pedestrian and Vehicle Detections Using Imaging Environment	MSCN and SVM	-	MAP of ~80% and ~94%
Alia et al. [35]	2022	Visualization Framework for Pushing Behavior Detection	EfficientNet-B0	MIM dataset	$Accu_y$ of 86%
Jain et al. [36]	2023	Robust Multi-modal Pedestrian Detection	SimAM-EfficientNet, NLSTM, DBN, ELM	UCSD pedestrian dataset	Running time of Ped1 is 2.24s and Ped2 is

Zhang et al. [31] presented an attentive multispectral feature fusion method. In the guidance of inter- and intra-modality attention models, the DL structure learn to dynamically weigh and combine multispectral features. Li and Ma [32] developed a LightGBM model with K-fold Max variance Semi Supervised Learning and DeepLab v3+ (LKMSSL-DL). This method integrates ML and CV approaches for estimating pedestrian volumes with unlabelled dataset from high dimension urban feature, and extracts tree crown from satellite images. Harrou et al. [33] presents a new mechanism with the fully guided-attention module for improving bicycles and pedestrians’ traffic flow prediction. Particularly, the presented method expands modelling ability of the VAE by combining the LSTM with VAE decoder and with the use of a self-attention mechanism at multi-phase of the VAE models (viz., before data resampling and decoder).

In [34], a strong ground pedestrian and vehicle detection technique for UAV application was introduced. Firstly, the evaluation of entropy-related imaging luminance descriptors are effectuated ; later image dataset are converted from RGB to Lab color space, the MSCN values abbreviated as mean-subtracted and contrast-normalized are computed for all elements in Lab color space, and later data entropy was evaluated by the MSCN values. Next, environment perception was implemented. Alia et al. [35] introduced a hybrid DL and visualization architecture which focuses on assisting the research workers to automatically identify pushing behaviors in the video. The presented method includes two major elements: (i) the fusion of EfficientNet-B0-related classifiers and a false reduction technique to detect pushing behaviors at the video patch level. (ii) wheel visualization and Deep optical flow; for generating the motion data map. Jain et al. [36] introduced a Robust Multi-modal Pedestrian Detection utilizing a DCNN with an Ensemble Learning (RMPD-DCNNEL) approach to solve Pedestrian challenges. This method uses ensemble learning and CV to attain precise pedestrian recognition.

5. Discussion

This section provides a detailed result analysis of various anomaly detection techniques. Table 1 and Fig. 1 presents the accuracy analysis of the different models on datasets 1 and 2. The results indicate that the DLADT-PW technique and RS-CNN technique attain improved results. On dataset 1, the DLADT-PW technique and RS-CNN technique offer increased accu_y of 98.20% and 97.50% respectively. On the contrary, the Fast R-CNN, MDT, MPPCA, and SF methods reach reduced accu_yof 85.10%, 81.10%, 74.60%, and 56.40% respectively. Also, on dataset 2, the DLADT-PW method and RS-CNN algorithm offer increased accu_y of 89.60% and 86.70% correspondingly. In contrast, the Fast R-CNN, MDT, MPPCA, and SF methods reach reduced accu_y of 82.10%, 77.80%, 71.80%, and 69% respectively.

Table 1 Accu_y analysis of various anomaly detection approach on two databases

Accuracy (%)		
Methods	**Dataset-1 (Test004)**	**Dataset-2 (Test007)**
DLADT-PW	98.20	89.60
RS- CNN	97.50	86.70
Fast R- CNN	85.10	82.10
MDT	81.10	77.80
MPPCA	74.60	71.80
Social Force	56.40	69.00

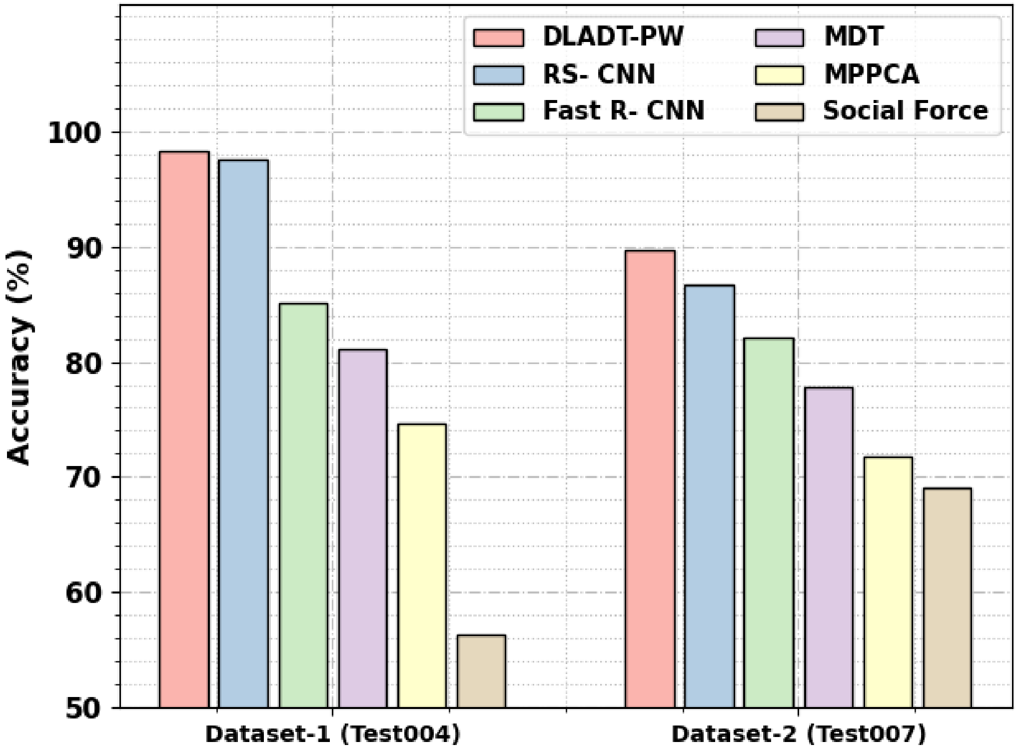

Fig. 1. Accu_y analysis of various anomaly detection approach on two databases

Table 2 and Fig. 2 grant the accuracy analysis of the different methods on datasets 1 and 2. The outcomes specify that the DLADT-PW approach and RS-CNN method reach improved outcomes. On dataset 1, the RMPD-DCNNEL algorithm and DL method offer increased AUC_score of 99.30% and 97.69% correspondingly. On the contrary, the Social Force, AMDN, MDT, ST-CaAE, and optical flow-GAN methodologies reach reduced AUC_score of 67.13%, 92.20%, 81.88%, 90.96%, and 97.09% correspondingly. In addition, on dataset 2, the RMPD-DCNNEL method and DL approach offer increased AUC_score of 97.92% and 94.63% correspondingly. On the contrary, the Social Force, AMDN, MDT, ST-CaAE, and optical flow-GAN models reach reduced AUC_score of 63%, 90.97%, 82.13%, 92.09%, and 93.08% correspondingly.

Table 2 AUC_score analysis of various anomaly detection approach on two databases

AUC Score (%)		
Methods	**Dataset-1 (Test004)**	**Dataset-2 (Test007)**
RMPD-DCNNEL	99.30	97.92
Social Force	67.13	63.00
AMDN	92.20	90.97
MDT	81.88	82.13
ST-CaAE	90.96	92.09

Optical flow-GAN	97.09	93.08
Deep Learning	97.69	94.63

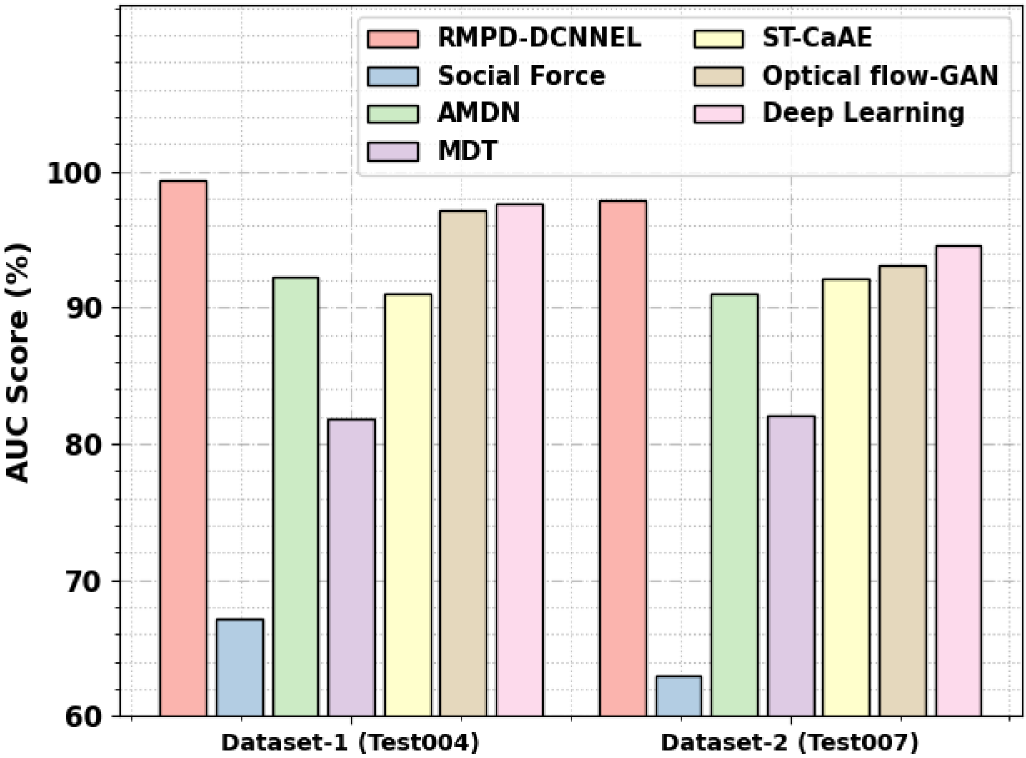

Fig. 2. AUC_score analysis of various anomaly detection approach on two databases

6. Conclusion

In this study, a detailed analysis of anomaly detection method developed especially for pedestrian walkways. It highlights the necessity for efficient and robust methods potential top handle occlusions, crowded scenes, and complex environment conditions. Moreover, it emphasizes the potential of fusing anomaly and object detection method for a more detailed pedestrian safety method. The study begun by emphasizing the importance of pedestrian safety and the challenges related to detecting anomalies in walkway settings. Then, it proposes a comprehensive investigation of different anomaly detection technique involving machine learning-based approaches, deep learning techniques, and statistical modeling method. The applications, strengths, and limitations of all the methods are investigated, with a specific focus on the efficiency to detect anomalous behavior in pedestrian walkways. It deliberates the specific challenges and considerations related to identifying all the types of anomaly and proposes related algorithms and approaches that were developed. Also, the review paper addresses the evaluation and benchmarking of anomaly detection method in pedestrian walkways, which emphasizes the significance of performance analysis, proper datasets, and evaluation metrics. Lastly, the study discusses future directions and emerging trends in anomaly detection methods for pedestrian walkways. It emphasis the necessity for adaptive and real-time anomaly detection systems, the incorporation of various sensor modalities, and the integration of contextual data to improve the robustness and accuracy of anomaly recognition. This survey acts as a valuable resource for policymakers, researchers, and practitioners included to develop the pedestrian safety solution. The insights provided will aid to understand the modern approaches, fostering advancements, and identifying challenges in anomaly detection and object detection approaches to ensure pedestrian safety in walkways.

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