Effective Machine-Learning Based Traffic Surveillance Moving Vehicle Detection

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Received: December 15, 2022; Accepted: January 18, 2023; Published: March 30, 2023

Abstract

The traffic surveillance is an integral part of the traffic monitoring. Automatic vehicle recognition is mostly used in efficient traffic management systems. Basic indicators of a successful traffic monitoring system are its resilience and dependability. In this study, we replace the pixel-by-pixel approach with a block-level technique, which drastically decreases the computing time and complexity by using a transform domain which naturally shortens the process's runtime. This is because discrete cosine transforms (DCT) makes it simple to extract the variations in intensities that are characteristic of many ecosystems. In most cases, the low-frequency component is where the most important information is stored inside the DCT blocks since it is less susceptible to noise. In this acquiring the edge shape feature of the detected item alongside the texture feature that provides the obvious moving top and bottom, the discriminative robust local ternary pattern (DRLTP) edge extraction is suggested which indistinct limits that improve detection efficiency. By summing the values of robust local ternary pattern LTP (RLTP) and differential LTP, we get the DRLTP, which is used for edge extraction (DLTP). RLTP is the greatest absolute value of LTP and its complement, whereas DLTP is the greatest absolute value of the difference between LTP and its complement.

Keywords: Machine Learning, Discrete Cosine Transform, Traffic Video Monitoring, Robust Local Ternary Pattern (DRLTP).

1 Introduction

Possessing the ability to monitor or follow cars is incredibly useful, both for private use and in public transit systems. When machine learning is combined with software. By acquiring this knowledge, we may effectively address difficult challenges. Our project's overarching goal is to develop a method for automatically monitoring moving targets using a continuously recorded video feed from a closed-circuit television camera in real time. Applying object detection allows for quicker object recognition for real-time tracking. We'd be looking out for things like the vehicle's colour and licence plate number as well as the vehicle's kind, whether it a car or a bike, for example. The programme would first extract individual frames from the live video feed, making it possible to recognise the characteristics with more precision. Second, crop the surrounding region to only the necessary component (for example, if we were utilising the automobile, the licence plate would be removed so that the result would be as precise as possible (Sui et al., 2022) Last but not least, the programme would save the necessary information in a database for later retrieval. Object recognition is the process of locating and recognising certain items

Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications (JoWUA), volume: 14, number: 1 (March), pp. 95-105. DOI: *10.58346/JOWUA.2023.I1.008*

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inside a digital picture or video clip. An easy-to-use computer programme can quickly and accurately identify a large number of things in an image; however, it is nevertheless a truth that the image of the objects may alter considerably in other views, in different sizes and scales, or even when they are translated or rotated. Although some obstruction may exist, the items can still be identified (Kumaran et al., 2022; Qin et al., 2022; Shi et al., 2022). When it comes to computer vision, it's a tough job. Over the course of several decades, numerous strategies have been put into place. Category recognition and detection are the two main components of object recognition.

The goal of category recognition is to assign a given item to one of several established classes. Detection is crucial because it allows us to pick out individual things from a cluttered scene. It's not easy to recognise objects in different situations. The goal is to identify items in a crowded, loud environment.

2 System Model

Edge-texture features, as well as the Discriminative Robust Local Binary Pattern (DRLBP), and the Discriminative Robust Local Ternary Pattern (DRLTP), are discussed in the suggested system. DRLBP solves the issues with LBP by calculating the absolute difference and weighted total of an LBP code and its complement. DRLTP is the difference between the original LTP code and its inverted representation. A comparison is made between the extracted characteristics of a picture and those of reference samples. As a result, a group of photographs that are visually comparable to the reference samples is discovered. The Euclidean distance is used as the standard of comparison (Karahan et al., 2022; Kalyan et al., 2020; Murugan et al., 2019).

DRLBP and DRLTP address the inability of LBP and LTP to distinguish between a light object and a dark backdrop, respectively. Further, it saves contrast data that's essential for accurately portraying object shapes. Two indicators are utilised to assess performance. These metrics are known as the accuracy and recall rates, respectively.

3 Previous Work

Sui et al. (2022) deployed the whole architecture on an AI demo board with the goal of automatically identifying and properly evaluating traffic incidents using surveillance recordings. To begin, we use motion interaction field (MIF), a method with the capacity to identify collisions in a video, to pinpoint the damaged cars based on interactions between several moving objects. Second, we use the YOLO v3 model to pinpoint exactly where the wrecked cars are lying. Using a hierarchical clustering technique, we are able to reconstruct the pre-collision paths of the vehicles involved. Finally, the perspective transformation is used to project the trajectory to a vertical view, making it easier for traffic cops to make decisions. The unbiased finite impulse response (UFIR) method, which estimates the vehicle's speed without prior knowledge of the noise's statistical characteristics, is used in this case. The vertical perspective adds valuable information to the investigation of a traffic incident, including the estimated velocity and contact angle. Lastly, an experiment is conducted on a Huawei AI demo board called HiKey970, on which all of the aforementioned algorithms have been coded in order to demonstrate the usefulness and implementation performance of the suggested technique. The demo board takes its input from a number of different accident surveillance footage. Successful accident detection and recovery of vehicle paths are achieved (Sui et al., 2022).

Santhosh et al. (2002) says that using publicly accessible surveillance video datasets, the authors show that the suggested technique is able to detect traffic abnormalities such as lane infractions, unexpected changes in speed, the sudden stopping of a vehicle in mid-movement, and cars going in the opposite direction (Kumaran et al., 2022). As compared to common neural networks-based classifiers on many datasets, the accuracy of trajectory classification using the suggested high-level features improves by a margin of 1-6%. Anomaly detection precision is increased by 30–35% thanks to the gradient representation.

Qin et al. (2022) conducted study purpose of which was to verify the efficacy of algorithms by contrasting them with those of other systems. Thanks to the enhanced visual background extractor (ViBe) algorithm, the success rate of vehicle extraction while in motion has increased to 97.4 percent. Vehicle licence plate identification has a 98.3 percent success rate, while typical character recognition has a 97.8 percent success rate and takes 34.2 milliseconds. Our experiment's outcomes proved that our system's algorithms work as intended.

Shi et al. (2022) suggested a unique GFM-guided background modelling approach, which involves adaptively upgrading the backdrop model based on the discrepancies between the foreground masks generated by the GFM technique and a background modelling approach, such Zivkovic's method. Hence, the suggested approach not only enhanced foreground recognition but also identifies the foreground objects that have ceased moving. Second, the suggested technique incorporates a boosting mechanism to reduce noise-induced false positives. The performance of the proposed technique is assessed using actual traffic footage. The proposed GFM guided background modelling approach is able to recognise halted foreground objects, such as stopped automobiles, in real time, as shown by experimental findings utilising the actual traffic recordings from the New Jersey Department of Transportation (NJDOT).

Recognizing licence plates and detecting and counting moving objects are also crucial tasks in traffic surveillance (Karahan et al., 2022). This research details the evolution of algorithms for tracking the location and number of moving objects, as well as for reading licence plates. Gaussian mixture models are utilised for video object detection, tracking, and counting. In the lower left corner of the final video frame, the algorithm displays the overall count of moving objects. Optical character recognition and the Prewitt operator are used to identify the owner of a vehicle. There is no character restriction on the licence plate locations or kinds that can be recognised by the algorithm. The technique used to recognise and tally moving items is evaluated on many video examples of such things in motion. Then, pictures of numerous automobiles are used to put a licence plate recognition algorithm to the test. The algorithms for detecting and counting moving items and recognising licence plates on passing vehicles have been shown to perform well in their respective evaluations.

As a result of its widespread use, vehicle detection and categorization have risen to prominence in recent years (Kalyan et al., 2020). Controlling and regulating traffic is one of the primary uses. The attempt to use image processing to reduce traffic accidents is greatly aided by vehicle recognition and tracking. Keeping an eye on surveillance footage and catching people in action both need the ability to follow moving targets. In light of the significance of this problem, a fast approach is given for employing image processing to identify cars in a picture. The picture was taken in front of the cars. In order to do this, the algorithm takes use of the frontal view to identify automobiles. The size of each vehicle is used to identify it. Edge recognition and morphological processing are the primary methods used by this approach. Among the many purposes for image processing, detecting edges and performing morphological operations are two that stand out. Objects in a picture may be improved with the use of edge detection. Object detection in a picture sometimes requires morphological operations to be performed first, since they are used to clean up the image and make it more clear what's there. A very potent scientific programme called MATLAB is used to do simulations of this technique.

It is essential for traffic surveillance software to be able to automatically identify and recognise moving vehicles (Murugan et al., 2019). Murugan et al. (2019) first, extracted the frames, estimated the backgrounds and then removed using a box filter. Background estimate based on box filters are used to dampen the abrupt changes brought on by the motion of vehicles. Then, the differences between the estimated backdrop and the input frames are analysed pixel-by-pixel to identify moving vehicles. Once a car has been located, the identification stage may begin so that different types of vehicles can be categorised. For vehicle identification using region suggestions, the computational intelligence architecture Region based Convolutional Neural (RCNN) is employed. There is less of a need for computational multiplicity in RCNN because to the inclusion of region proposal. The effectiveness of the suggested technique for vehicles is measured using accuracy, sensitivity, specificity, and precision metrics.

4 Related Work

Detecting objects in static photographs is a well-known open topic. Cars are often studied in processor ghost research because of their rigidity. structure, little external change, and ubiquitous appearance in daily settings (Qin et al., 2022; Shi et al., 2022; Karahan et al., 2022; Kalyan et al., 2020; Murugan et al., 2019; Satpathy and Jiang, 2014). Earlier methods relied on numerical techniques like support vector machines (SVM) [4, 5], principal component analysis (PCA) (Kalyan et al., 2020; Murugan et al., 2019), neural networks (NN) (Satpathy and Jiang, 2014; Ahonen et al., 2006), and Bayesian decision making (Bay et al., 2008; Agarwal et al., 2004); all of which aimed at high accuracy and remember rather than real-time act. The cascaded classifier (Ahonen et al., 2006) pioneered a strategy for preparing a sequential classification working on simpleton-evaluate like features and affirmed its true presentation on the face detection problem, ushering in a new era in the application of mathematical knowledge methods to real-time entity detection. There are literally hundreds of articles out there on the topic of civilising the near and applying it to a wide variety of tasks, including automobile detection (Bay et al., 2008). This research is particularly interested in approaches that routinely cascade classifiers in preparation, with an eye towards improving both accuracy of classification and the mean arrangement time (Sui et al., 2022; Agarwal et al., 2004). They provide for the direction of a time-precision optimised cascaded classifier, without the necessity for the tedious human intervention experienced in the unique case. In Papageorgiou and Poggio (2000), researchers use the success of component-based detectors in the Pascal VOC Challenge (Qin et al., 2022) to inspire a new approach. Despite the successful detection result, the method's complexity limits the scheme's framerate to 1-2 fps. As the issue is static and thought to be particularly challenging, driving assistance systems designed for urban areas need rather complex algorithms (Caputo et al., 2005). A variety of relatively basic heuristic-based car detectors have been envisaged in the reports for less demanding circumstances like highway driving. Authors Chen et al. (2010) and Viola et al. (2005) take use of the fact that the outside borders of a car may be approximated by a U-shaped curve to construct theories about the shadows cast on the road by the vehicles. The stability of the vehicle is the primary indicator for others (Levi and Weiss, 2004; Boiman et al., 2008). Concurrently, techniques that limit the space of possible vehicle placements to be evaluated by focusing on realistic on-road situations are typically effective (Balachandran and Anitha, 2013). While these algorithms operate in real time, this benefit comes at the cost of making too simplistic assumptions about the scenarios they see. As a matter of fact, such articles often lack careful quantitative evaluation on some publicly accessible dataset and comparison to other approaches. While the aforementioned techniques show promise in vehicle tracking and achieve promising trial results in confined situations by concentrating on vehicle shape fitting, they fail to account for colour information while conducting tracking. To add insult to injury, the restrictions for the multiple cores in the 3-D (vehicle) space will shift when the vehicle travels owing to the varied view aspects since the multiple kernels tracker is based on the 2-D (picture) space and the 3D vehicle model is described in the 3-D (vehicle) space. As a consequence, the vehicle's tracking features may become less reliable over time, which might lead to an increasingly inaccurate tracking result. For this reason, we proposed an automatic vehicle system that makes advantage of the 3D particular vehicle and is based on 3D restricted multiple kernels. The proposed solution uses 3-D tracking of the vehicle itself rather than 2-D tracking of kernels. Color data is retro-projected from the images, and the many vehicle kernels are mean-shifted and conditionally limited to fit into the required 3D space. As a result, a gradient-based method is developed to closely mimic the shape of the anticipated 3-D automobile model (Balasundaram and Saravanan, 2009; Bennewitz et al., 2005; Brakatsoulas et al., 2004; Brilingaitė and Jensen, 2007). Therefore, the suggested technique is able to successfully generate 3-D new vehicles in line with the geometry fitness evaluation, and it also tracks the vehicle well while keeping the understanding of 3-D geometry.

Block Diagram

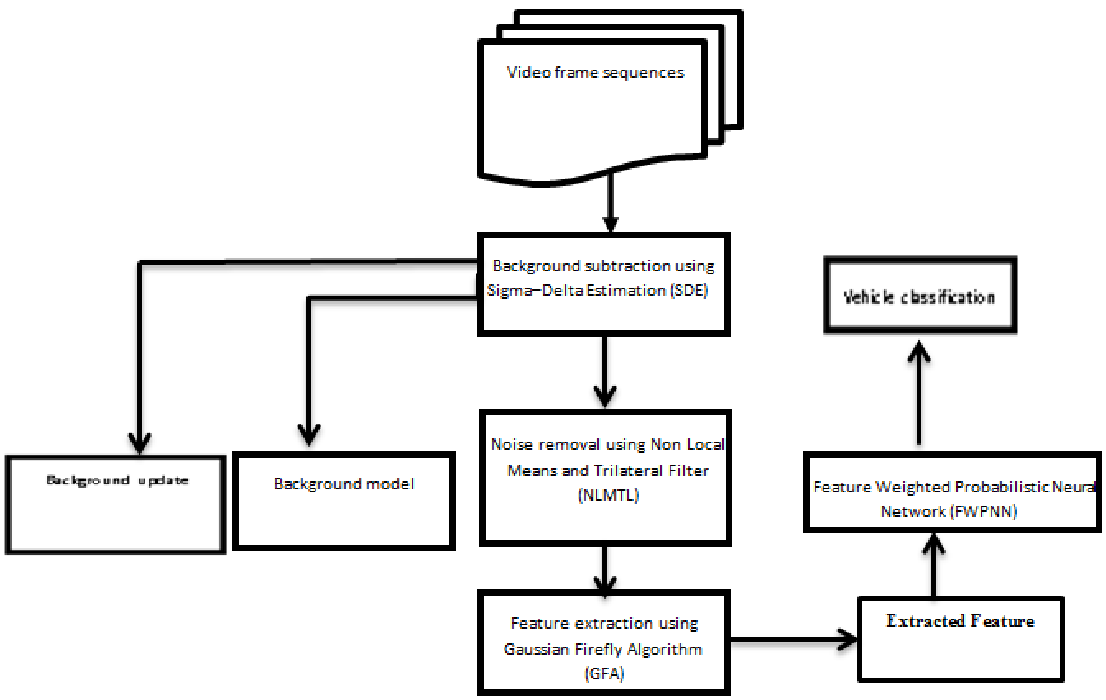

Figure 1: Overall Architecture Diagram

Background removal: The purpose of the background-updating method is to uniformly update a background picture during peak traffic times. In the first stage of processing, sounds in the picture and the time of day are used to determine the lighting scenario (day or night). It may also decide on the Regions of Interest (ROI) that can be searched for characteristics and perform camera stabilisation to eliminate vibrations for improved position estimate of the vehicle (Celik et al., 2007; Chon et al., 2001; Jensen et al., 2007). To identify the vehicle's features, the image features extraction process must be carried out. To save processing time, image characteristics may be extracted simultaneously the above Figure 1 explains the overall architecture.

Selecting features: This process may choose features mechanically such that they gain strong invariance to changes in the background and maintain a high detection rate for foreground items.

Candidates for vehicle feature detection:

1. Combines visual features to look for likely candidates, such windows and lights, in a vehicle's exterior. Parallel processing may be used to features that are independent of one another.
2. A confidence value has been assigned to each car feature.
3. The matching procedure between the old and new features is also performed by the vehicle feature layer, which receives the candidate vehicle features.

Vehicle characteristics (such as lights and windscreens) are tracked along the road plane by the tracker. This is useful for optimising performance through the rules of the traffic domain.

Vehicle Detection and Classification

Binary image segmentation and vehicle classification are the two main processes in vehicle detection using a stationary camera. To segment the foreground of a picture is to separate the important details from the background and remove any distractions.

Taking out as much of the scenery as possible. The extracted blobs are then labelled as vehicles or non-vehicles using vehicle categorization. Foreground segmentation using a stationary camera is a mature technique (Whitley, 2001). For example, the background difference technique primarily utilises the difference between the target and background images in terms of colour, edge, intensity, and gradient direction in order to determine what should be extracted as the foreground.

The shift in camera view between two frames is used by both the inter-frame difference technique and the optical flow method to focus on the foreground while blurring away the background (Montana, & Davis, 1989). Vehicle classification may be broken down into two major groups: template-based approaches and appearance-based methods. With template-based vehicle classification, a known vehicle's template is compared to comparable regions in an image. The active shape model (DPM) uses a root and several component templates to characterise the various parts of a vehicle. Template components are physically joined to the vehicle's root template using the geometry specifications. It is the job of the detectors employed by appearance-based algorithms, such as Scale-invariant feature transformation (SIFT), oriented gradient histograms (HOG), and local binary pattern, to first extract the visual data (LBP). We then feed the results of the feature extraction into a vehicle classification that has been pre-trained on data from both vehicles and non-vehicles, using a number of different machine learning methods like support-vector machine (SVM), augmentation by gradient descent (AdaBoost), neural network convolutional (CNN), and so on. The classifier will determine if the retrieved item is a car or not.

Illustration of Vehicle Model Fitting Evolutionary Procedure

From the aforementioned experiment, we pick just one picture frame that has a silver sedan automobile to demonstrate the evolutionary process of 3D vehicle model fitting. The examples in Figure 2 depict the iterative steps of the vehicle model fitting process. In the first generation, the graphic shows, a wide variety of unusual car models are developed as shown in **figure 2**

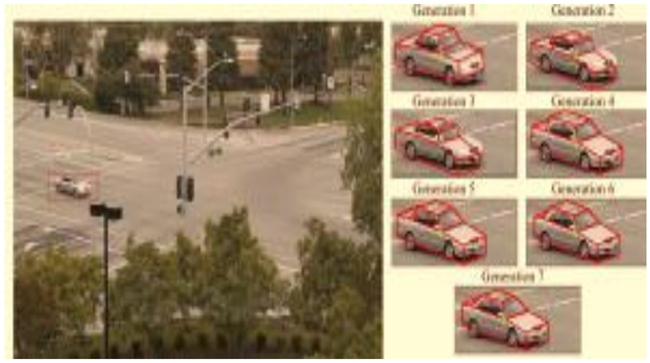

Figure 2: 3D Vehicle Model Fitting Evolutionary Procedure of the Sliver Sedan

Occlusion

Static camera video monitoring typically fails to capture important details about passing cars because of obstructions in the frame, such as trees and lights poles at intersections shown in **Figure 3**. The occlusion problem is well addressed by the proposed system since it uses 3D object modelling and 3DCMK surveillance systems. Strong occlusion management is a feature of the sampling approach used in 3D vehicle modelling. After the three-dimensional model is projected into in the display case and the buried lines are eliminated, the iterations are completed by normalising the viewable region and destroying sampled locations outside the specified bounding box shown in **Figure 4 and 5**. The occluded zones wouldn't provide enough noise to significantly alter the results of the evolutionary process. It is only when the three - dimensional (3d vehicle model is built, 3DCMK tracking is performed, and the occluded components in the model are given no weight that the measurements for the Extended kalman update may be considered reliable. The 3-D simulation and 3DCMK track are both rendered worthless if the automobile is completely hidden, but the Proposed method can predict its location in a short period of time. If the car ever reappears at the location, the information provided may be used to properly identify it.

Figure 3: Results of a Sedan Passing by a Lighting Post and a Tree Branch

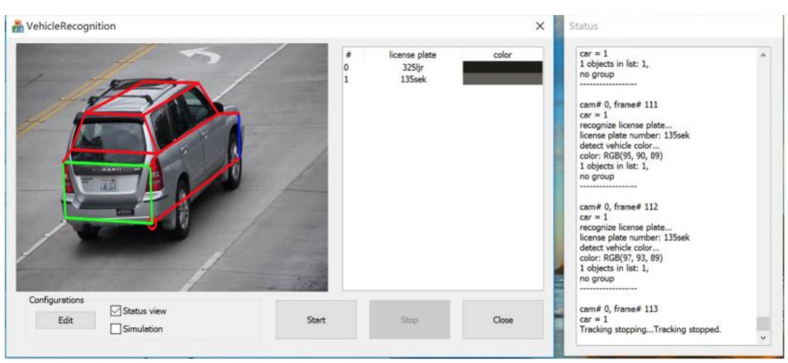

Figure 4: Vehicle Feature Extraction

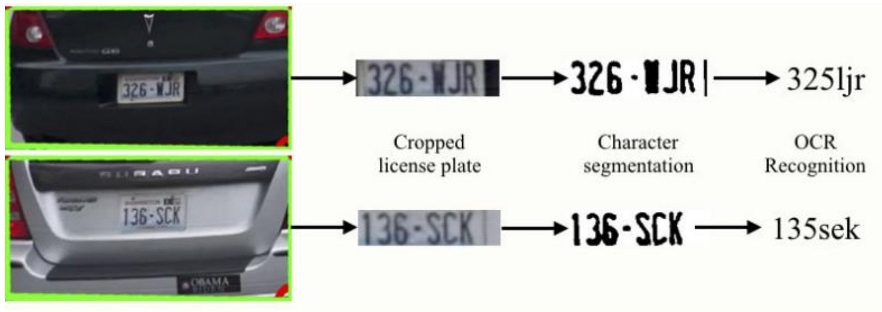

Figure 5: Example of Vehicle Recognition by Using 3D Vehicle Model

Table 1: The Similarity Score of the Comparison

01	**02**	**03**	**04**	**05**
01	0.456	0.534	0.551	0.689
02	0.786	0.459	0.677	0.676
03	0.658	0.754	0.989	0.777
04	0.647	0.669	0.878	0.679
05	0.487	0.798	0.746	0.468
06	0.598	0.452	0.974	0.977
07	0.741	0.782	0.447	0.787

5 Findings

Vehicle detection and classification models are crucial to traffic monitoring; hence these are where the proposed approach focuses. Collection and the appropriate uses for it. Models for vehicle identification and classification need a hierarchical approach to template matching-based object detection, using either probabilistic or non-probabilistic classification algorithms as shown in Table 1 above. Problems in implementing cutting-edge systems for vehicle categorization and modelling are common. We offer a new-generation model for vehicle identification and classification using a large-scale vehicle database in this work. Currently, the suggested model is being refined using cameras that only capture two or three frames per second. The suggested model would analyse the various vehicle types and accurately categorise them to assess the traffic density for each vehicle category. The suggested model would be used to analyse peak hours and the causes of congestion during rush hour in order to inform traffic management policy decisions. Optimal measures, such as preventing large weight carriers from accessing the crowded roadways, might be used during rush hours to increase the average speed at which traffic moves. It is anticipated that the suggested approach would lead to significant gains in precision, accuracy, and recall for vehicle categorization. The suggested model would eventually be used to accomplish the desired aim of vehicle categorization and detection in traffic surveillance camera footage.

1. The camera calibration technique was improved by identifying two vanishing points, which resulted in a 50% decrease in the camera calibration error.
2. The inaccuracy in automated speed measurement from a monocular camera is reduced by 86% when using the novel approach for scene scale inference, whereas it is decreased by 19% when using the manual calibration method.
3. The findings and Evaluation in Table 2 demonstrate that the fully automated technique (requiring no human intervention) can outperform the gold standard of manual calibration. This discovery has potential applications beyond traffic monitoring.

Evaluation of DRLBP and DRLTP

Table 2: Shows that When it Comes to Texture Analysis and Retrieval, DRLTP and DRLBP Perform Better. Improved Results in DRLTP are also being Shown

	No. of similar images obtained	Precision rate	Recall rate
DRLBP	9	.5625	0.4500
DRLTP	11	.6250	0.5

6 Conclusion

The presentation of two novel sets of edge-texture features that may be used in object identification is the objective of this work. Both the Ternary Pattern and the Discriminative Robust Local Binary Pattern (DRLBP) are examples of patterns that are suitable for this description.

We are incapable of produce an appropriate representation of something like the contour with only the texture data. In light of these flaws in LBP, LTP, and RLBP, Researchers would like to suggest two new characteristics called DRLBP and DRLTP. In order to address the issues with LBP, LTP, and RLBP, new features have been implemented that take into consideration the weighted sum and comparison differentiation of something like the divisions of the LBP and LTP codes. These new features are robust to image perturbations, which are commonly generated by the intensity inversion. Within the context of the histogram, they can also be employed to differentiate between various visual topologies.

7 Acknowledgements

The authors would like to thank the editors and reviewers for their review and recommendations and also to extend their thanks to King Saud University

Funding

This research did not receive any specific grant from funding agencies in the public.

Data Availability Statement

The database generated and /or analysed during the current study are not publicly available due to privacy, but are available from the corresponding author on reasonable request.

Declarations

Author declares that all works are original and this manuscript has not been published in any other journal.

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