Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7766296

OBJECT DETECTION AND RECOGNITION IN DARK USING YOLO

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ABSTRACT

The discipline of computer vision makes extensive use of object detection, which is essential for many different applications. The approach to object recognition at this time has essentially grown into two categories: deep learning and classic machine learning approaches using a variety of computer vision techniques. Object detection methods are reviewed in this article. Initially, a summary and introduction of the current machine learning approaches are provided. In everyday life, it is usual to use video cameras to monitor the campus. The majority of these surveillance methods employ people to keep an eye on what is happening in the target region. Yet, employing humans for monitoring has drawbacks of its own. To get around this restriction, researchers are developing automated visual surveillance systems. Environment modelling, motion segmentation, object categorization, tracking, behavior comprehension, person identification, and data fusion are the phases that make up the visual surveillance process. Finding moving objects in a video sequence is the first and most important step in visual surveillance. A person, a car, or another item may be the moving object of interest. The technology known as object detection is concerned with determining the semantic class of the moving item in the video sequence. Hence, Object Detection is crucial for following moving objects and analyzing their behavior in the provided video sequence. This study discusses the many object detection techniques that are available, taking into account the significance of object detection in visual surveillance

1. Introduction

A computer vision approach called object detection finds occurrences of things in pictures or movies. With contemporary algorithms, the process of identifying an item is rather straightforward. And machine learning's skills are sufficient to properly deal with it. Among the things found are people, vehicles, chairs, stones, structures, and animals. You Only Look Once is known by the acronym YOLO. This programme identifies and finds different things in an image. A computer vision implementation known as object detection enables a system (an algorithm) to make an educated guess as to where specific things are located within a digital scene, such as an image or video[17]. Typically, a bounding box is drawn around the recognised item, making it easier for people to find the object than in raw photos. An object in this context is the picture that represents a real-world object (URL)[18]. It is a distinguishable area of an image that may be interpreted as a single unit in image processing. This stands in stark contrast to the common belief that an image or an item may be substituted for one another. In most cases, an image contains one or more objects, the visibility of which is crucial. For instance, the number of items that may be included in a single picture can range from one to as many as numbers, almost infinite. Although "detection" may refer to finding a concealed thing, it may also refer to an intelligence's capacity to indicate the existence and identification of an object. It is not necessary to conceal the thing in question[20]. The form on which we founded this thesis is the latter. There are several methods for interpreting the object localisation for object detection, such as drawing a bounding box around the item or highlighting each pixel in the picture that it includes (called segmentation). An object detection model should thus be able to determine whether of a known set of items may be present and offer information about their locations within the picture given an image or video stream. Several computer vision tasks, including picture annotation, activity recognition, object detection, object recognition, and video object co-segmentation, make extensive use of object detection. It is also utilised for object tracking[22]. Examples of its numerous applications include monitoring a ball during a football game, tracking the movement of a cricket bat, or tracking a person in a movie. Essentially, there are two methods for detecting images: methods based on machine learning and methods based on deep learning. In more conventional ML-based methods, groupings of pixels that may comprise an object are identified by analysing different aspects of a picture, such as edges or the colour histogram. Artificial intelligence is a technique for teaching a computer, a robot operated by a computer, or software to think critically and creatively like a human mind. AI is achieved through examining the cognitive process and researching the patterns of the human brain. These research projects provide systems and software that are intelligent. Large-scale, intelligent, iterative processing algorithms are combined to create AI systems. AI can now learn from patterns and characteristics in the evaluated data thanks to this combination. An artificial intelligence system checks and evaluates its performance after each cycle of data processing, using the outcomes to gain more knowledge. Artificial intelligence is used by developers to communicate with clients, find trends, and solve issues more quickly than they could manually. Developers that want to work with AI should be familiar with algorithms and have a background in mathematics. It is advisable to start modest when employing artificial intelligence to develop an application. There are no boundaries to where artificial intelligence can lead you once you've successfully accomplished a few modest tasks. Depending on its level of development or the tasks being carried out, artificial intelligence can be arranged in a variety of ways. For instance, it is well knowledge that AI development occurs in four stages.

Reactive machines: Limited AI that only reacts to different kinds of stimuli based on preprogrammed rules. Does not use memory and thus cannot learn with new data. IBM’s Deep Blue that beat chess champion Garry Kasparov in 1997 was an example of a reactive machine.

Limited memory: Most modern AI is considered to be limited memory. It can use memory to improve over time by being trained with new data, typically through an artificial neural network or other training model. Deep learning, a subset of machine learning, is considered limited memory artificial intelligence.

Theory of mind: Theory of mind AI does not currently exist, but research is ongoing into its possibilities. Reactive machines: AI with limited capabilities that only respond to various inputs in accordance with predetermined rules does not employ memory, making it unable to learn from new information. A reactive machine is IBM's Deep Blue, which defeated world chess champion Garry Kasparov in 1997. Most contemporary AI is thought to have a limited memory. By being taught with fresh data over time, generally using an artificial neural network

or other training model, it may use memory to get better. Deep learning, a subtype of machine learning, is regarded as artificial intelligence with a restricted memory.
Mind-set theory: There is no theory of mind AI at the moment, but study on its potential is ongoing. It depicts AI with decision-making abilities comparable to those of a human, including the ability to recognize and recall emotions and respond in social settings the same way a person would.Being self-aware goes beyond theory of mind.
Self-aware AI: It refers to a fantastical robot with the same mental and emotional faculties as humans, which is conscious of its own existence. Self-aware AI is a hypothetical concept that does not yet exist.By what the computer is capable of, varieties of artificial intelligence may be more extensively categorized. All of the technology we now refer to as artificial intelligence is referred to as artificial "narrow" intelligence since it can only carry out a limited range of tasks thanks to its programming and training.An AI algorithm employed for object categorization, for example, won't be able to process natural language. Google Search, predictive analytics, and virtual assistants are examples of narrow AI. The capacity for a machine to "detect, think, and act" exactly like a person would be known as artificial general intelligence (AGI). AGI doesn't exist right now. The next stage would be artificial superintelligence (ASI), when a computer could perform tasks better than a person could.

2. Literature Survey

A computer tool called object detection pinpoints the precise location and dimensions of human objects in random (digital) images shown in [2]. Any other things in the digital image, such as trees, buildings, bodies, etc., are disregarded in favor of the face features. It may be said that this is a "specific" example of object-class detection, where the objective is to locate and determine the dimensions of all objects in a picture that fall under a particular class. Object localization may be thought of as a more "general" kind of object detection. Finding the locations and measurements of a known quantity of items is the goal of object localization (Usually one). There are essentially two different methods for identifying face features in a given picture. for example, a feature- and image-based method. The feature-based technique aims to extract picture features and compare them to known object characteristics. While the image-based method seeks to match training and testing pictures as closely as possible.

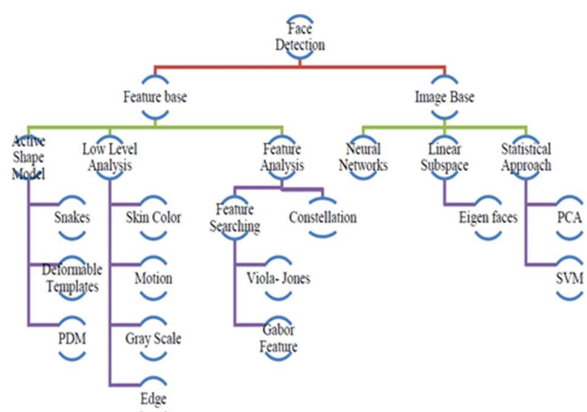

Fig:1 Detection Method

Jianwu Dang and Wenbo Lan, 2018 There will be some loss of pedestrian data after passing through the deep network, which will result in the removal of slopes and imprecise pedestrian recognition. This study suggests a novel network structure called YOLO-R and enhances the YOLO algorithm's network structure. First, the initial YOLO network was expanded with three Passthrough layers. The Route layer and the Reorg layer make up the Passthrough layer. Its function is to link the high and low resolution pedestrian features as well as the shallow layer pedestrian characteristics to the deep layer pedestrian features. The function of the Route layer is to transmit to the current layer the pedestrian characteristic data from the specified layer, and then to reorganize the feature map with the help of the Reorg layer so that the feature map of the next layer may fit the recently introduced Route layer feature. The three Passthrough layers included in this technique effectively transmit shallow pedestrian fine-grained feature information from the network to the deep network, allowing the deep network to learn shallow pedestrian feature information more effectively. In order to improve the network's capacity for information extraction from the shallow pedestrian characteristics, this article additionally reduces the layer number of the Passthrough layer connection in the original YOLO technique from Layer 16 to Layer 12. On the INRIA pedestrian dataset, the improvement was evaluated. The results of the experiments indicate that this technique may significantly increase the accuracy of pedestrian recognition while lowering false detection and missed detection rates, and detection speed can reach 25 frames per second.

3. Existing System

Unified Detection Model – YOLO

Joseph Redmon initially introduced the YOLO model in his work "You only look once, Unified, Real-time object detection." The algorithm's approach uses a single neural network to predict the bounding boxes and class labels for each bounding box straight from the input of an image. On speed-optimized versions of the model, this could achieve rates of up to 155 frames per person and up to 45 frames per second while having reduced prediction accuracy, which was mostly caused by more localization mistakes. The model works by first dividing the input picture into a grid of cells, with each cell being in charge of predicting a bounding box if a bounding box's centre falls inside it. Each grid cell has a bounding box that includes an evaluation criterion for quality called a confidence score, the x, y, width, and height. Additionally, a class prediction is based on every cell. An example will be given to provide greater emphasis. A 7 x 7 grid, for instance, might be used to split a picture into cells that each forecast two bounding boxes, yielding a total of 94 predictions. The final set of bounding boxes and class labels is created by combining the bounding boxes with confidences and the map of class probabilities. The YOLO was not without flaws; the algorithm had certain restrictions on the amount of grids it could operate on, in addition to some other problems that will be discussed later. First, the model employs a 7 7 grid, and because each grid can only identify one item, it caps the number of objects that can be detected at 49. Second, because each grid can only identify one object, the model exhibits what is known as a near detection model. It won't be able to find it if a grid cell has more than one object in it. Thirdly, since an object's position could extend outside a grid, there is a chance that the model would mistakenly identify the object more than once. The aforementioned difficulties faced when running YOLO made it quite clear that the system's translation error and other issues needed to be fixed. As a result, YOLOv2 was developed as an enhancement to address the problems and queries raised by its forerunner.

Bounding Box Prediction: A bounding box is a very small area that can contain a point, an object, or a collection of items. The cell that is in charge of detecting an item according to YOLO is the cell that contains the object's centre. Each cell will forecast B bounding boxes and provide a box-by-box confidence score. The confidence score will range from "0.0" to "1.0," with "0.0" denoting the lowest confidence level and "1.0" denoting the greatest. The confidence score should be "0.0" if there isn't anything in that cell, and "1.0" if the model is 100 percent confident in its forecast. These degrees of confidence reflect how confident the model is on the existence of an object in that cell and the precision of the bounding box. The x, y, width, height, and confidence are the five numbers that make up each of these bounding boxes. The anticipated bounding box's centre is indicated by the coordinates "(x, y)," and the width and height are fractions of the total picture size.

4. Proposed Work

Approaches of object recognition:

The object recognition problem can be approached using either a geometric (feature-based) or a photometric method. (View based). Three of the numerous algorithms that were created as the object recognition research community's interest in the field grew were extensively researched in the object recognition literature.

YOLO in the Dark: The other domain B model forecasts data Z based on data Y. It is expected that data Y a and Y b are of the same data type. As an illustration, model A generates an RGB image from a RAW image, whereas model B generates an item class and location from the RGB image. This approach extracts model fragments with the boundaries of the latent features A and B after training both models A and B. The new model is made out of pieces of models A and B that have been joined together with adhesive.

5. Implementation

Enhancing low light. Brightness issues are frequently encountered during image capturing. Enhancing lighting has been the subject of extensive research. In earlier techniques, lighting and design modification tactics were manually modelled. The intensities on the histogram are redistributed via histogram equalization and its modifications. Dehazing-based approaches first invert photos and then employ dehazing algorithms, treating low light as a dark haze. Images are divided into two signals by the retinex algorithm: a reflectance field and a shading field that indicate the illumination of the scene. Based on this, several techniques first separate illumination and reflectance before processing the two elements individually or concurrently. In recent years, neural networks have been frequently employed for low-light improvement due to the rapid growth of deep learning. Some models use retinex theory whereas others analyze pictures end-to-end[4]. RAW photos are further considered in a number of studies. a thorough investigation and benchmarking can be found in [1]. Existing techniques for low-light improvement can boost human vision, but they do not adequately account for downstream machine learning and machine vision tasks. In this article, we examine the fundamental relationship between pixel-level restoration and high-level perception and suggest appropriate fixes.

SqueezeNet: The name of a DNN for computer vision is SqueezeNet. Researchers from Stanford University, DeepScale, and the University of California, Berkeley collaborate to build SqueezNet. The authors' objective in designing SqueezeNet is to produce a smaller neural network with fewer parameters that can more readily fit in computer memory and be transferred across a computer network. SqueezeNet was first made available in 2016. The Caffe deep learning software framework served as the foundation for the initial implementation of SqueezeNet.SqueezeNet has been ported to a variety of additional deep learning frameworks by the open-source research community. Eddie Bell further published a piece of SqueezeNet for the Chainer deep learning framework in 2016.

A piece of SqueezeNet for the Apache MXNet framework was provided by Guo Haria in 2016. In 2016, Tammy Yang made SqueezeNet available for the Keras framework. SqueezedNet was shown in 2017 by businesses including Baidu, Xilnx, Imagination Technologies, and Synopsys working on low-power computing devices like smartphones, FPGAs, and custom CPUs. The source code for several deep learning frameworks, including PyTorch, Apache MXNet, and Apple CoreML, includes SqueezeNet.In addition, SqueezeNet implementations compatible with frameworks like TensorFlow have been produced by independent developers. A list of frameworks that support SqueezeNet is shown below.

InceptionV7: A popular picture recognition model, Inception v7, has demonstrated accuracy of more than 78.1% on the ImageNet dataset. The model is the result of several concepts that scholars have worked on for years. Its foundation is Szeged's "Rethinking the Inception Architecture Computer Vision." Convolutions, average pooling, max pooling, concats, dropouts, and fully linked layers are some of the symmetric and asymmetric building pieces that make up the model. The model makes more use of batchnorm and applies it to activation inputs. Softmax is used to calculate loss.

One of the newest neural networks for visual object detection is called DenseNet, which stands for densely connected convolutional networks. ResNet is comparable, however there are several key distinctions.

The ImageNet classification dataset's DenseNet and ResNet Top-1 error rates are compared as a function of learnt parameters and test-time failures. This article makes use of prior understanding of convolutions and neural networks. We start with a basic picture, say one with the form of (29, 34, 31). After applying a set of convolution or pooling filters on it, the width and height are reduced but the size of the feature is increased.

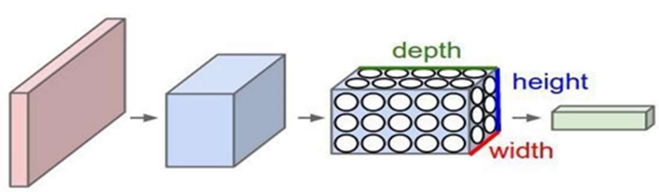

Fig:2 Li Layer

The ResNet architecture is suggested for residual connections[22] between layers one and two. The outputs from earlier layers are combined to obtain the input to the Li layer. Additionally, during transition layers, features will be condensed in addition to width and height. Thus, after a transition layer and having an image form after one block (28, 28, 48), we will obtain (14, 14, 24).

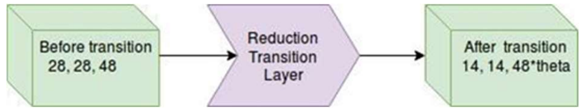

Fig:3 Transition Layer

Theta — certain levels of reduction, in the range (0, 1). DenseNet's bottleneck layers will divide the maximum depth by two when used. As a result, if you previously had 16 3x3 convolution layers with a depth of 20, some of those levels were transition layers, and you now have 8 1x1 convolution layers in addition to 8 3x3 convolution layers. Finally, a word about data preparation. Per channel normalization was applied in the article. Using this method, the mean and standard deviation of each picture channel should be decreased and divided, respectively. Another normalization was employed in many implementations; it simply included dividing each picture pixel by 255 to provide values for the pixels in the [0, 1] range. Observation on the per channel normalization numpy implementation. Images come with data type unit by default. It is recommended to convert the photos to any float format before performing any changes. Because if such happens, a program would crash without any errors or warnings.

6. RESULT AND DISCUSSION

Input image:

Fig:4

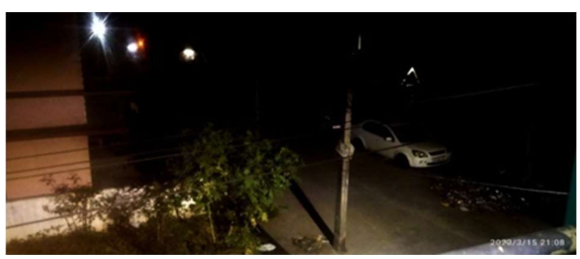

Fig:5

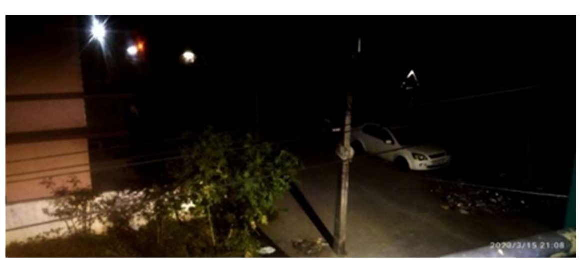

Fig:6

We compare 24 cutting-edge techniques. Five categories—object identification, picture enhancement, image darkening, feature adaptation, and fully supervised learning—are covered by the comparative approaches for a thorough analysis.

Enhancement: Here, we look at the strategy of brightening first, then detecting. Although Small Hard Faces[5] and DSFD[8] are equal on low-light photos, DSFD[8] often outperforms tiny hard objects. The DSFD[8] has superior resilience and generalization, according to this result. As a result, in the trials that follow, we use DSFD as the baseline for object detection. We compare eight approaches for adjusting the lighting. Even while the majority of them may significantly boost detection effectiveness, certain techniques are harmful. This is due to the excessive visual distortion that these techniques generate.

Improving Supervised Learning: Supervised learning can benefit from our unsupervised adaption strategy as well. The mAP is increased from 46.0% to 48.1% for fine-tuning DSFD with labels when our adaptation techniques are combined.

DETECTING OBJECT: Many other options offered by ImageAI are helpful for customization and deployments that may be used in production for object detection jobs. The following are a few supported features:

Changing the Minimum Probability: By default, any items that have a probability of less than 50% are not displayed or reported. For situations requiring a high level of assurance, you may increase this amount; for situations requiring the detection of every potential item, you can decrease it.

Detection of Custom Objects: You may instruct the detection class to report detections on one or a small number of unique objects by using the given CustomObject class.

Detection Speeds: By changing the detection speed to "fast," "faster," and "fastest," you may shorten the time it takes to detect an image.

Types of Input: As the input image, you can define and parse in a file path to an image, a Numpy array, or a file stream of an image.

Output Types: The find Objects From picture method allows you to specify whether it should output the picture as a file or a Numpy array.

Output Image:

Fig:7

Fig:8

Fig:9

This is an example image that we feed to the algorithm, and we want it to find and name the objects in the image in accordance with the class that was given to them. By doing so, we first use a high low adaption method to brighten the picture, then YOLO V7 to detect and identify the image that is provided as input.

7. Conclusion

The most advanced real-time object detection method is YOLO since it is substantially faster than previous algorithms while yet maintaining a high level of accuracy. Although the YOLO network is capable of understanding generalized object representation, the precision is limited for adjacent and smaller objects due to spatial restrictions. This issue is addressed in a more recent iteration of the algorithm called YOLOv4, which is also quicker and more accurate. Overall, YOLO is a popular approach for real-time object recognition because to its speed and accuracy. With the help of this thesis and based on the outcomes of the experiments, we are able to recognize each item separately and pinpoint its specific placement in the image in the x, y axis. This study evaluates the efficacy of each strategy for item detection and identification while also providing experimental findings for several approaches. The computational models used in this project were selected after careful consideration, and the positive testing outcomes show that the researcher's decisions were sound. Due to the sparse usage of eigen objects in the CNN transform, the system with manual object identification and automatic object recognition did not achieve recognition accuracy levels of above 90%. In this experimental investigation, the system was put through highly rigorous testing, and it is expected that real-world performance would be far more accurate. The completely automated frontal view object detection system demonstrated nearly flawless accuracy, and the researcher believes that more study in this area is not necessary. The completely automated method for object detection and recognition in the dark was insufficiently reliable to attain a high level of recognition accuracy. The object identification subsystem did not exhibit even a minimal level of invariance to scale, rotation, or shift defects of the segmented object picture, which is the only explanation for this. One of the system requirements listed there was this. However, performance will improve to levels equivalent to the manual object identification and recognition system if some additional processing, such an eye detection algorithm, is used to further normalize the segmented object picture. It wouldn't take much further research to build an eye detection mechanism because it would just be a small change to the current system. The deformable template and convolutional neural network methodologies performed admirably in all other systems that were built. The most practical real-world uses for object detection and identification systems are surveillance and mugshot matching. When it comes to user access and user verification applications, which demand a very high level of precision, there are superior methods available, such as iris or retinal identification and object recognition utilizing the thermal spectrum. Crowd surveillance applications would be excellent for the real-time automatic posture invariant object detection and recognition system suggested in chapter seven. The potential for finding and tracking suspects for law enforcement authorities is enormous if such a system were to be broadly used. While the established manual object detection and automated recognition system is appropriate for mugshot matching, the fully automated object detection and recognition system (with an eye detection system) might be employed for basic surveillance applications like ATM user security. The frontal view object identification technique should provide a recognition accuracy significantly greater than the findings achieved in this investigation, which was done under unfavorable settings, since controlled conditions are present when mugshots are gathered. In addition, a lot of the test individuals didn't give the system an expressionless frontal view. It would be of enormous practical use in law enforcement if an object recognition technology could cut from 10,000 to even 100 the number of photos that a human operator must sift through for a match. The performance and robustness of the automated vision systems used in this thesis were not even close to that of a human's intrinsic object recognition system. They do, however, provide a glimpse into what computer vision could look like in the future.

REFERENCE

1. J. Liang, J. Wang, Y. Quan, T. Chen, J. Liu, H. Ling, and Y. Xu, “Recurrent exposure generation for lowlight object detection,” IEEE TMM, 2021.

2. Dr.N. Palanivel, "Recommendation System Based Smart Shopping Cart", International Journal of Emerging Technologies and Innovative Research, ISSN:2349-5162, Vol.7, Issue 5, page no.908-914, May-2020.

3. A. D’Innocente, F. C. Borlino, S. Bucci, B. Caputo, and T. Tommasi, “One-shot unsupervised cross-domain detection,” in ECCV, 2020.

4. C. Guo, C. Li, J. Guo, C. C. Loy, J. Hou, S. Kwong, and R. Cong, “Zero-reference deep curve estimation for low-light image enhancement,” in CVPR, 2020.

5. Z. Zhang, W. Shen, S. Qiao, Y. Wang, B. Wang, and A. L. Yuille, “Robust face detection via learning small faces on hard images,” in WACV, 2020.Dr.N. Palanivel, “Image Forgery Detection using Support vector Machine”, International Research Journal of Engineering and Technology, Vol 6,Issue 3, e-ISSN: 2395-0056 on Mar 2019.

6. S. Luo, X. Li, R. Zhu, and X. Zhang, “SFA: small objects attention object detector,” IEEE Access, vol. 7, pp. 171 609– 171 620, 2019.

7. J. Deng, J. Guo, Y. Zhou, J. Yu, I. Kotsia, and S. Zafeiriou, “Retinaobject: Single-stage dense object localisation in the wild,” arXiv, 1905.00641, 2019.

8. J. Li, Y. Wang, C. Wang, Y. Tai, J. Qian, J. Yang, C. Wang, J. Li, and F. Huang, “DSFD: dual shot object detector,” in CVPR, 2019.

9. Ren, Y.; Ying, Z.; Li, H.; Zheng, G.L. LECARM: Low-light image enhancement using camera response model. IEEE Trans. Circuits Syst. Video Technol. 2019, 29, 968–981.

10. Chen, X.; Wang, S.; Shi, C.; Wu, H.; Zhao, J.; Fu, J. Robust Ship Tracking via Multi-view Learning and Sparse Representation. J. Navig. 2019, 72, 176–192.

11. Wei, W.; Zhou, B.; Połap, D.; Woźniak, M. A regional adaptive variational PDE model for computed tomography image reconstruction. Pattern Recognit. 2019, 92, 64–81.]

12. Rumin Zhang, Yifeng Yang, ”An Algorithm for Obstacle Detection based on YOLO and Light Filed Camera”, 2018 Twelfth International Conference on Sensing Technology (ICST)

13. Schiller, F.; Valsecchi, M.; Gegenfurtner, R.K. An evaluation of different measures of color saturation. Vis. Res. 2018, 151, 117–134.]

14. Cai, J.R.; Gu, S.H.; Zhang, L. Learning a Deep Single Image Contrast Enhancer from Multi-Exposure Images. IEEE Trans. Image Process. 2018, 27, 2049–2062.

15. X. Tang, D. K. Du, Z. He, and J. Liu, “Pyramidbox: A context-assisted single shot object detector,” in ECCV, 2018.

16. Chengji Liu ,Yufan Tao ,Jiawei Liang, Kai Li1, Yihang Chen, ”Object Detection Based on YOLO Network” 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC 2018) .

17. Dr.N. Palanivel, “PCA AND RF: AN AUTOMATIC PLANT LEAF DISEASE DETECTION USING TEXTURE, SHAPE AND COLOR FEATURES”, International Journal of Engineering Applied Sciences and Technology, 2017 Vol. 2, Issue 5, ISSN No. 2455-2143, Pages 120-125.

18. Dr.N. Palanivel, “Identification of Leaf disease using Fuzzy c-mean and kernal fuzzy c-mean and suggesting the pesticides”, International Journal of Advanced Research in Science, Engineering and Technology (IJARSET), Volume 2 Issue 2, May 2017.

19. N.Palanivel, M.Vasanthapriya and R.Heera, “Moving object detection and methods: A Review”, International Journal of Computing Technologies, (2278 – 3814) / # 27 / Volume 4 Issue 11, 2015.

20. K. Seetharaman, N. Palanivel and Sowmya.D “Video Segmentation in Dynamic Texture Using Weber’s Law for Monitoring Different Environments”, IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 1 Issue 2, April 2014.

21. K. Seetharaman, N. Palanivel and R. Indumathi “Post Invariant Face Recognition Using HMM and SVM with PCA for Dimensionality Reduction”, International Journal of Advanced and Innovative Research ISSN : 2278-7844, Volume 3, Issue 1, January 2014.

22. K. Seetharaman and N. Palanivel “Texture characterization, representation, description, and classification based on full range Gaussian Markov random field model with Bayesian approach”, International Journal of Image and Data Fusion, ISSN: 1947-9832 Volume 4, Issue 4, 2013, pages 342-362.