International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

COMPUTER VISION BASED METHOD FOR SHADOW DETECTION

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ABSTRACT: Computer vision methods, like segmentation, tracking, object identification, and classification, can't work well when there are shadows in pictures and movies. So, we'd like to suggest a new way to use artificial intelligence to find shadows in photos and videos. It handles real-time frames with unnatural backgrounds and shadows nicely. This strategy aims to improve blind and low-vision aids. We used the suggested method in a number of different situations and places. A good result was getting a total accuracy of 92%.

Keywords *– Sensor applications , computer vision , image processing , segmentation , shadow detection*

INTRODUCTION

Seeing is the most important of the five senses. A lot of people have gone blind for a variety of reasons, such as being born blind or having an accident. According to the World Health Organization (WHO), about 2.2 billion people are blind or have trouble seeing in some way. It is possible to stop at least 1 billion of these blindness cases. WHO also reports that low- and middle-income regions had four times more distant vision deterioration than high-income ones. Shadows are common when lights are obscured. But shadows may reveal what's nearby, like interference, shape studies, etc. Because shadows don't always look the same, they can slow down the process of finding and recognizing objects, placing objects, and improving related information. For instance, people who use these help devices might think that the methods are bothersome and usually a way to make them less independent. Because of this, finding shadows is necessary for recognizing and placing objects. In picture processing [4, 5], shadow recognition can make things look and feel more real. Many shadow detection and detection methods have been developed over the years, but shadow detection is still an important issue in image processing that needs more work, even with the new methods that have been developed. [6]–[9]. Lighting, scene form, and materials all have an effect on the free shadow frame, which makes it hard to make a good one in real time. Shadow recognition is the main issue that needs to be fixed. Sometimes it's hard to find shadows because their properties don't match up with other instances of themselves. To be more exact, there is a good chance that two shadows will not look alike. The amount of brightness is the only thing that stays the same between the two, and it's usually low. A regular shade is caused by changes in the amount of light, the shape of the scene, and the materials of the items. So, it would be normal to find shadows that don't match up. Because of this, it would be hard to improve the lighting on the edges of the shade because it changes all the time in that area. These cases show that if an application is made to try to find these things, it would have to be able to deal with a lot of different situations and rules. This means the number of conditions and factors that must be met for shadow detecting results to be consistent.

When something blocks a light source, it casts a shadow. Computer vision algorithms like segmentation, tracking, and identification often get lost in shadows. Because the materials change, it's hard to tell the difference between shadow edges and edges. Computer vision can detect objects in photos and videos using object recognition. Object recognition techniques usually involve machine or deep learning for effective results. Computer vision includes image segmentation, object identification, face recognition, edge detection, pattern detection, image classification, and feature matching. A lot of computer vision is used in cars that drive themselves. It finds and sorts items (like traffic lights or road signs), makes 3D maps, and figures out how fast things are moving. It is a key part of making self-driving cars a reality. In the area of artificial intelligence called computer vision, computers are taught to understand what they see. Images and deep learning models can help computers correctly spot and group things and respond to them. If you give a computer vision system a two-dimensional picture, it has to figure out what items are in it and describe them as fully as possible by things like their shapes, textures, colors, sizes, and where they are in space, among other things.

LITERATURE REVIEW

G. D. Finlayson et.al., The goal of this work is to come up with a series of shadow-free picture representations. First, we show that making some assumptions about lights and cameras results in a grayscale, one-dimensional picture representation that stays the same no matter how much light hits it. Because of this, we show that pictures shown in this way don't have any shadows. Then, we turn this 1D representation into a 2D representation of the same kind that uses chromaticity. This paper shows that all the image cells can be relit in the same way in this 2D representation. This creates a 2D image representation that doesn't have any shadows. Finally, we show how to get back a 3D, full-color picture representation that doesn't have any shadows by first finding the edges of the shadows in the 2D representation. Then, we use edge in-painting to get rid of shadow lines in the original image's edge map. Finally, we come up with a way to merge this thresholded edge map, which gives us the desired 3D shadow-free picture.

A. E. Arbel et al., Discovering and getting rid of shadows in a single picture is very hard, and it's made harder by things like lighting, the shape of dark surfaces, and items that block the shadows. Post-acquisition changes, such as contrast improvement, make it harder to make high-quality pictures that don't have any artifacts or shadows. Studies that have already been done often make assumptions that make this complicated problem too easy to understand, which makes them less useful. Because of this, this study has two purposes. To begin, it gives a full look at all the problems that come up when you try to get rid of shadows from a single image, showing how complicated things can be. After that, it offers a new structure for shade reduction that aims to fix the basic problems that were already pointed out. Experimental results back up the suggested algorithm, showing that it can produce pictures without shadows and with fewer flaws. This helps us understand this complicated problem better and come up with better solutions.

I. A. Mohan et al., In this piece, we create tools for changing shadows in pictures where the edges of a dark area have soft edges that get sharper as they go along the sides. Shadow lines can be very sharp when they come from a

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

point light source and very soft when they come from a big area light source. This makes modeling them an interesting task. We suggest a picture-based shadow editing tool that can work with a single image. Modeling, changing, and creating shadow lines in a picture or a computer-generated image is made easier with this method. Users can separate the shadow from the rest of the image and change its position, sharpness, and strength as they please. These photos that can be changed by a computer can offer interactivity that could make images more expressive and help us study how boundary sharpness affects how we see object-to-object contact and how people use shadows to figure out how high an object is above a ground plane.

Boyadzhiev, I., et al. Lighting is one of the most important parts of photography and can make or break a picture. In standard studio sets, many light sources are carefully placed. However, a new way of doing things has come up, especially in building and business photos. Photographers take many pictures from a set position using a portable light source. They plan to improve the final picture afterward. This flexible, time-saving approach works well, but it can be hard to keep track of all the jumbled layers during blending. This paper solves this problem by suggesting ways to make it easier to put together input pictures into a set of ground lights, which is what most shooters want. Adding modifiers to common photography jobs makes the process even easier. The results of experiments show that this method greatly speeds up the blending step. This is especially helpful for new users who are intimidated by how hard it is to manage many layers, making advanced photography techniques more accessible.

Vasluianu, F. A., et al., Shadow recognition is a key part of computer vision that aims to find the shadow cast by a light source that isn't visible and restore the image's contents in a way that looks like the original. Decades of study have led to a wide range of hand-crafted repair methods. More recently, answers have been found by comparing training images with and without shadows. We present a single picture shadow detection method based on self-supervised learning and a conditioned mask in this work. We use self-supervision and learn deep models together to add and clear shadows from pictures. We come up with two different ways to learn from matched images and unpaired images. Our tests on the new ISTD and USR datasets show big gains in both quantity and quality compared to the current best practice for both paired and unmatched learning.

A. L. Zhang et al., We describe a new way to get rid of shadows in single nature images and color overhead images by using a light restoring optimization method. First, we adaptively break up the original picture into patches that overlap based on how the shadows are spread out. Then, we create a relationship between the shadow patch and the lit patch based on how similar their textures are. This lets us make an improved lighting restoring operator that gets rid of the shadows and brings back the texture information under the shadow patches. By using synchronous optimization processing between adjacent patches, we are finally able to get high-quality results that don't have any shadows and have even lighting. Our shadow reduction system is easy to use and works well. It can handle shadow images with a lot of different textures and shadows that aren't all the same. The lighting of results with no shadows is the same as the lighting in the surrounding area. We also show a number of shadow editing uses to show how flexible the suggested method is.

Algorithms.

We used things like YOLOV5 and FasterRCNN for this.

YOLOV5: One of the computer vision models in the You Only Look Once (YOLO) family is YOLOv5. A lot of people use YOLOv5 to find things. There are four main forms of YOLOv5: small (s), medium (m), large (l), and extra large (x). Each one has a higher success rate. It takes a different amount of time to train each type as well.

An Overview of the YOLOv5 Architecture

YOLOv5 is meant to be used for object recognition, which includes making features from pictures that are sent to it. After these features are put into a prediction system, boxes are drawn around items to guess what class they belong to.

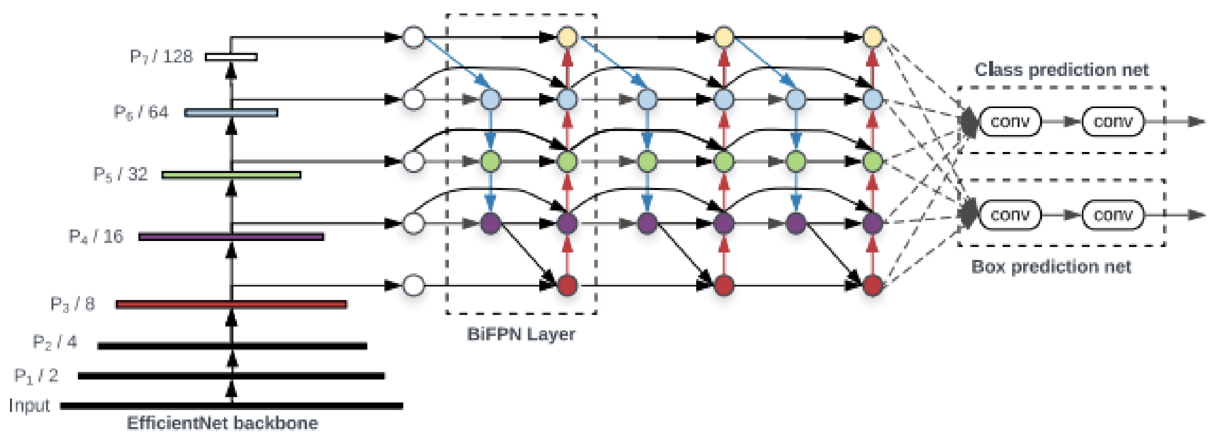

Fig 1 YOLOV5 architecture

It was the YOLO model that linked the process of predicting bounding boxes with class names in a way that was different from beginning to end.

There are three main parts to the YOLO network.

1. Backbone: A backbone is a convolutional neural network that takes in picture data and builds up features at different levels of detail.
2. Neck: A set of layers that mix and match picture traits so that they can be sent to forecast.
3. Head: Takes in information from the neck and does box and class forecast.

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International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
www.ijarst.in
ISSN: 2457-0362

FasterRCNN: For object detection, the "Faster Region-Convolutional Neural Network" (Faster R-CNN) is cutting-edge. Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun invented it 2015. The Faster R-CNN network aims to produce a unified design that can locate and properly put things in images. It combines the benefits of deep learning, CNNs, and RPNs into one network. The model becomes quicker and more precise.

There are two parts to the faster R-CNN design.

1. Region Proposal Network (RPN)
2. Fast R-CNN detector

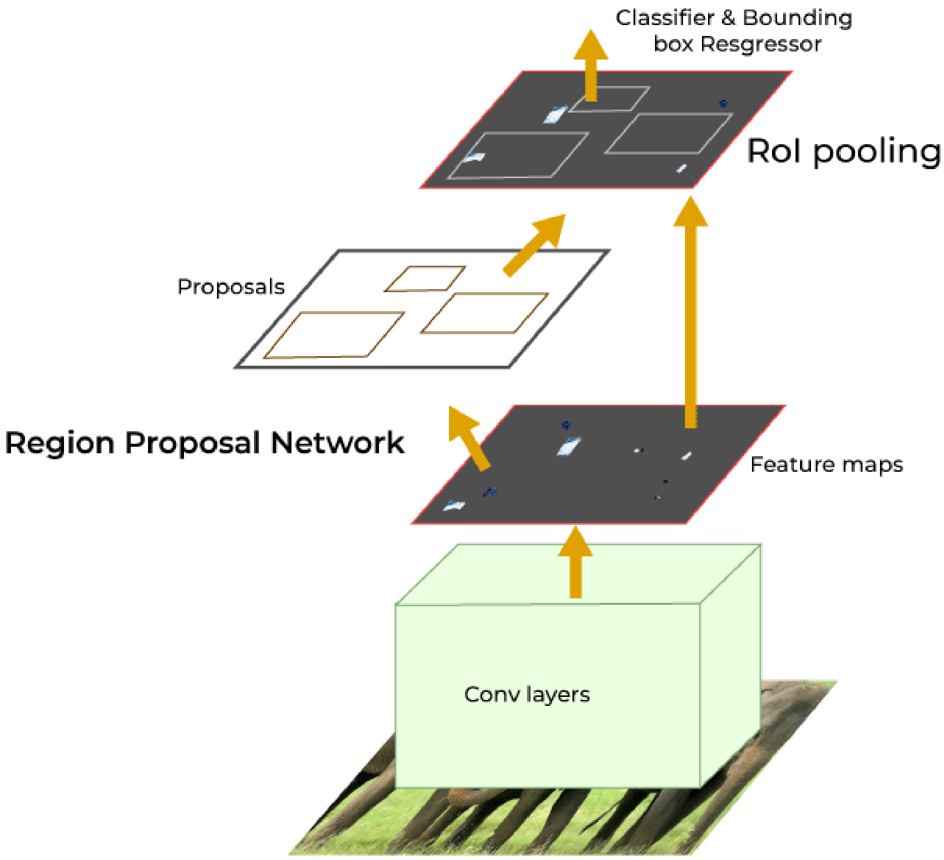

Fig 2 FasterRCNN architecture

Before discussing RPN and Fast R-CNN detectors, let's discuss the Faster R-CNN design's Shared Convolutional Layers. See figure? This CNN layer is utilized for RPN and Fast R-CNN detectors.

ARCHITECTURE

The suggested real-time shadow detecting system uses computer vision techniques to help people who are blind or visually impaired recognize objects better. First, the shadows are found by value extraction, then the regions are split

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

up, and finally, the Canny edges are found for each video frame. The Hough Line transform describes shadow edges using two lines. Finally, Hue saturation values within the given range are extracted. This one-of-a-kind method is meant to cut down on fake results, which will improve the general performance of the aid framework and make it easier for visually impaired users to live on their own.

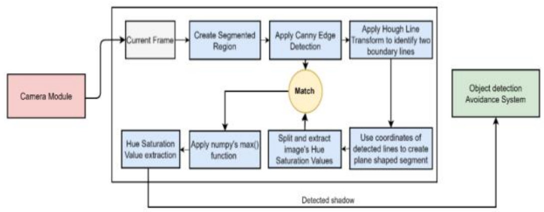

Fig System Architecture

COMPARISON TABLE

Table.1: Computer Vision Based Method For Shadow Detection

S. No	Title	Author/Reference	Method/Algorithm implemented	Advantage	Disadvantage
1	On the detection of shadows from images	G. D. Finlayson, S. D. Hordley, C. Lu, and M. S. Drew [2]	The proposed shadow detection algorithm begins by obtaining a 1D illuminant-invariant, gray-scale image representation. This is extended to a 2D chromaticity representation, allowing uniform relighting. The 3D	1. The algorithm achieves illuminant invariance at the pixel level, ensuring robust shadow detection across diverse lighting conditions. 2. The progression from 1D to 2D	1. The system heavily relies on specific assumptions about lights and cameras, making it susceptible to inaccuracies in real-world scenarios. 2. The multi-step process involving 1D to

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International Journal For Advanced Research In Science & Technology
A peer reviewed international journal
ISSN: 2457-0362
www.ijarst.in

			shadow-free image is reconstructed by identifying and inpainting shadow edges, resulting in a final shadow-free representation.	and finally 3D representations allows comprehensive shadow removal, preserving full-color image details effectively.	3D representations may incur computational complexity, potentially impacting real-time applications.
2	Shadow detection using intensity surfaces and texture anchor points	E. Arbel and H. Hel-Or [3]	Proposed method utilizes intensity surfaces and texture anchor points for robust shadow detection in single images. Overcoming challenges such as lighting variations and post-processing artifacts, our algorithm aims to produce high-quality, artifact-free shadow removal, demonstrated through comprehensive experimental results.	1. Utilizes intensity surfaces and texture anchor points for effective shadow identification, addressing challenges posed by diverse lighting conditions. 2. Mitigates post-processing artifacts, ensuring the production of high-quality shadow-free images indistinguishable from true shadow-free scenes.	1. The complexity of the shadow detection problem may restrict the proposed system's effectiveness to a specific class of shadow images. 2. Despite efforts to mitigate artifacts, postacquisition image processing transformations may still affect the shadow-free images in some scenarios.
3	Editing soft shadows in a digital photograph	A. Mohan, J. Tumblin, and P.	The proposed method employs	1. The tool allows precise	Developing and integrating the

		Choudhury [4]	image-based shadow editing for digital photographs, allowing users to separate and manipulate shadows with adjustable parameters such as position, sharpness, and intensity. This technique enhances image expressiveness and facilitates exploration of human perception in object interactions and shadow assessment.	control over shadow characteristics, enabling users to tailor position, sharpness, and intensity for realistic and customizable digital image enhancements. 2. Machine-adjustable photographs provide a dynamic and interactive editing experience, potentially improving image expressiveness and aiding research in human perception of object interactions and shadow assessments.	image-based shadow editing tool may require advanced technical expertise, limiting accessibility for non-expert users. 2. The algorithm's extensive adjustments may demand significant computational resources, potentially causing slower processing times for large or complex images.
4	User-assisted image compositing for photographic lighting	I. Boyadzhiev, S. Paris, and K. Bala [5]	Our method streamlines image compositing for photographic lighting. Through	1. Streamlining compositing reduces manual effort, enabling quick creation of	1. Initial adaptation to the proposed system may be needed, as users familiar

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ISSN: 2457-0362
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			optimizations, we automatically assemble input images into basis lights and introduce modifiers for common tasks. Tested with novice and professional users, our approach significantly reduces the time and complexity of the compositing process, especially benefiting casual users.	well-lit images, saving time for both novice and professional users. 2. The system's optimizations benefit casual users by simplifying the complex process of handling numerous layers, requiring less experience.	with traditional workflows may face adjustments. 2. Advanced optimizations may require understanding, limiting accessibility for users with minimal technical knowledge or experience.
5	Shadow detection with paired and unpaired learning.	F. A. Vasluianu, A. Romero, L. Van Gool, and R. Timofte [6]	They introduce a self-supervised approach for single-image shadow detection, utilizing conditioned masks. Our method employs deep models to simultaneously remove and add shadows through paired and unpaired learning. Validation on ISTD and USR	1. Self-supervised learning with conditioned masks enables both paired and unpaired shadow detection, enhancing adaptability to diverse datasets and scenarios. 2. Achieves significant quantitative and qualitative advancements,	1. Implementation may require advanced understanding of self-supervised learning and deep models, limiting accessibility for some researchers or practitioners. 2. Performance improvements are contingent on the

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ISSN: 2457-0362

			datasets showcases substantial quantitative and qualitative advancements over existing state-of-the-art techniques.	surpassing state-of-the-art results on ISTD and USR datasets in both paired and unpaired learning scenarios.	availability and quality of paired and unpaired datasets, potentially restricting applicability in certain real-world scenarios.

SUMMARY

This work suggests a real-time shadow recognition method that would improve the ability of help devices to find objects for people who are blind or have low vision. Using what has already been done, our method cuts down on false results, making the helpful structure better. Value extraction, area segmentation, and Canny edge recognition are used in a new computer vision method to find shadows. The Hough Line transform then draws the edges of the shadows, which lets you get accurate Hue saturation values within certain limits. The goal of this method is to cut down on guidance alerts so that visually blind people can be more independent.

CONCLUSION

Finding shadows might seem like a difficult task. The main reason shadows are hard to see in pictures and videos is that they move around a lot. It's rare for two shadows to look the same. Their shape, size, color, and even where they are placed can all be different. So, the goal of this study is to correctly find shadows so that the assistance device for the vision blind works better. Some of these devices can send fewer directions to the user when they see shadows. Most of the time, our system works very well and accurately; over 92% of the time, it tries to improve the avoidance systems of support devices for the visually challenged.

FUTURE SCOPE

Future study can look into how to apply and improve the shadow recognition system in real time, making sure it works well in settings that change over time. Improvements could include making the system work better in different lighting conditions and making the programs smarter so they can handle more complicated situations. Adding feedback systems based on shadows noticed could help improve user advice when integrating with assistive devices. Additionally, looking into adding machine learning methods could make the system even more flexible and better at helping people who are blind or have low vision.

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