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

COMPUTER VISION BASED METHOD FOR SHADOW DETECTION

Dr. T. Venugopal, Sandya Banoth

Vice Principal and Professor of department of Computer science and Engineering, dr.tvgopal@gmail.com
M Tech, Department of Computer science & Engineering (21JJ1D5802), banothsandhya2020@gmail.com

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. The goal of this suggested method is to make the assistance devices that are given to people who are blind or have low vision work better. 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*

1. 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

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

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.

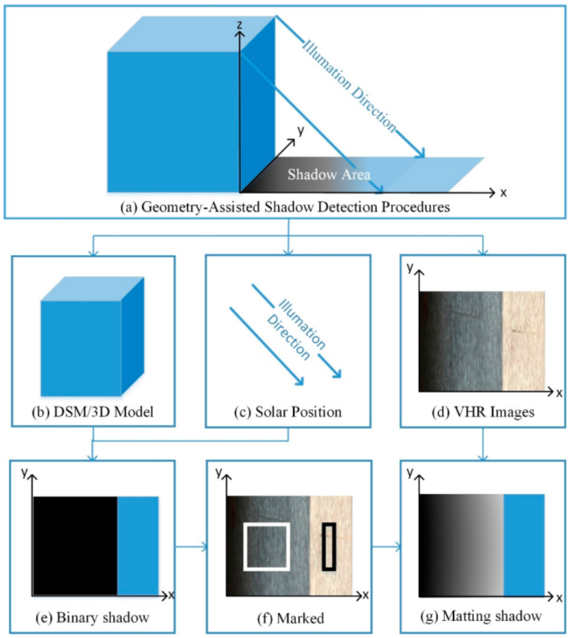

Fig.1: Example figure

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.

2. LITERATURE REVIEW

On the detection of shadows from images:

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.

Shadow detection using intensity surfaces and texture anchor points

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

Shadow recognition from a single picture is a hard problem to solve. Even more difficult is making a high-quality shadow-free picture that can't be told apart from a real scene with no shadows. Images' shadows are usually affected by many things in the scene, such as the lighting, the type and behavior of shaded surfaces, items that block the shadow, and so on. Also, shadow areas may go through changes in image processing after they are captured, such as contrast improvement, which can cause flaws to show up in pictures that don't have shadows. We suggest that the assumptions used in most studies are because finding shadows from a single image is hard, and these assumptions limit the types of shadow pictures that these methods can handle. This paper is meant to do two things: First, it gives a full rundown of all the issues and difficulties that can come up when trying to get rid of shadows in a single picture. We show our framework for shade removal in the second part of the paper. This is where we try to solve some of the main problems we talked about in the first part of the paper. The results of experiments that show what our program can do are shown.

Editing soft shadows in a digital photograph:

Getting shadows to show up in a single shot is hard to do. For even more trouble, try making a picture without any shadows that looks exactly like a real scene without any shadows. A lot of things in a picture can change an image's shadows, like the lighting, the type and behavior of dark surfaces, things that block the shadow, and so on. Also, after an image is taken, changes may be made to dark areas, such as making the contrast better. This can make flaws appear in pictures that don't have shadows. We think that most studies make the assumptions they do because it's hard to find shadows from a single image. These assumptions also limit the kinds of shadow pictures that these methods can work with. Two things are planned for this paper: The first thing it does is list all the problems that can happen when you try to get rid of shadows in a picture. In the second part of the study, we show how our method for getting rid of shade works. We will try to solve some of the main issues we talked about in the first part of the paper here. To show what our tool can do, the outcomes of tests are shown.

User-assisted image compositing for photographic lighting:

Good lighting can make or break a shot. Professional shooters usually work in a studio with a lot of carefully set up light sources. The goal is to get a picture that looks almost perfect at exposure time, with post-processing focused on things that aren't related to lighting. Recently, a new way of doing building and business photography has come about. Photographers take many shots from a defined angle as the light source moves. The idea is to gather important information that is subsequently processed in photo editing software to create a good-lit photograph. This new method is adaptable, requires less manual setup, and works well for short pictures. However, organizing tens of thousands of unorganized layers requires hours or days of manual effort and skilled photo editing abilities. This document simplifies writing. We discuss how to enhance input photographs to create basic lights that highlight edges and curved sections. We also discuss typical photographic gear like umbrellas and soft boxes for softening highlights and shadows. Our technique gets decent results fast for novice and expert users, whereas dealing with chaotic photos

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

takes longer. Casual users who are unfamiliar with layers may find our strategy beneficial.

Shadow detection with paired and unpaired learning:

Shadow identification is an important computer vision job that tries to find the shadow made by a light source that is hidden and restores the picture so that it looks like it did when it was first taken. Many hand-crafted repair methods have been developed over many years of study. More recently, answers have been found by comparing training images with and without shadows. We suggest a way to find shadows in a single picture using self-supervised learning and a conditioned mask in this work. We learn deep models together and rely on self-supervision to add and remove shadows from pictures. We find two different ways to learn from paired images and from images that are not paired. We tested our method on the new ISTD and USR datasets and found that it is much better than what was previously thought possible in both paired and unpaired learning situations.

Shadow Remover: Image Shadow Removal Based on Illumination Recovering Optimization

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. Based on texture similarity, we construct a link between the shadow and illuminated patches. This allows us create a better lighting restoration operator that removes shadows and restores texture information beneath shadow patches. After employing synchronous optimization processing across neighboring patches, we eventually acquire high-quality results with uniform illumination and no shadows. 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.

3. METHODOLOGY

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.

Drawbacks:

- Shadows can slow down object identification and recognition, object location, and related information improvement because they don't always look

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

the same.

- As a result, it would be hard to improve the lighting on the edges of the shade because it changes all the time in that area.

Our main goal is to come up with an accurate and real-time shadow spotting method that will help visually impaired people find objects and recognize assistance technology better. This way also builds on previous work to make our suggested system for helping the vision disabled work better. The main goal is to cut down on the false-positive results from earlier work, which will mean fewer guidance alerts. In this way, people who are blind or have low vision can become more independent. Computer vision techniques are used in this letter to show a new way to find shadows. First, we use value extraction, area segmentation, and Canny edge recognition to find the shadows in each frame of the movie. After finding the shadow, the Hough Line transform draws two lines around it. After identifying the region, Hue saturation values may be obtained and a mask constructed with obvious upper and lower boundaries.

Advantages:

- This suggested method showed that it could find free shadows in a number of situations. It's a simple method that works well.
- The process of matching the value extraction results with Canny edge recognition is what lets our method find and get rid of complicated and uneven shadows.
- And because of this, we think this way can make many systems that use picture processing better.

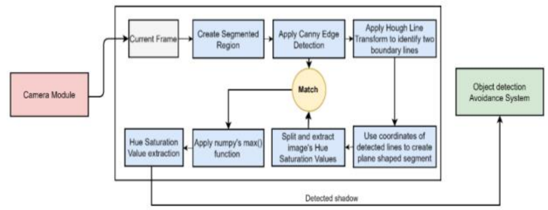

Fig.2: System architecture

MODULES:

To carry out the project mentioned earlier, we have created the following modules.

- Data exploration: Data will be imported using this module.
- Processing: This module reads and processes data.
- Splitting data into train & test: This module will separate data into train and test.
- Model generation: Build model – calculate accuracy values.
- User signup & login: You may register and log in using this module.
- User input: This module aids forecasting.
- Prediction: Last forecast

4. EXPERIMENTAL RESULTS

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

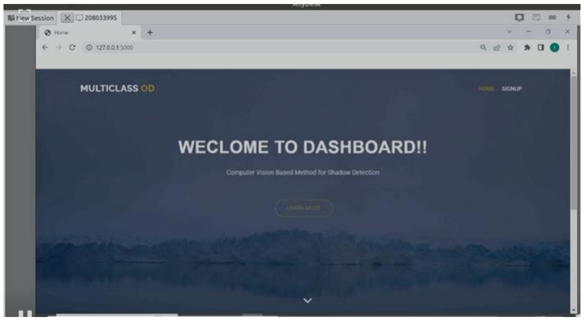

Fig.3: Home screen

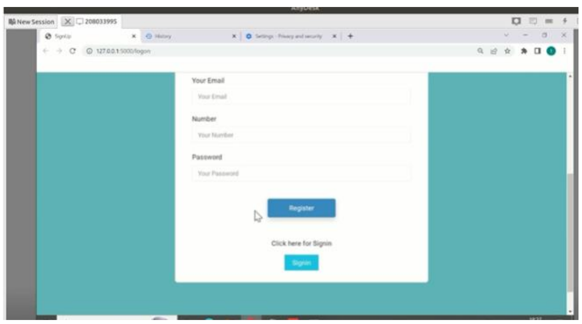

Fig.4: User signup

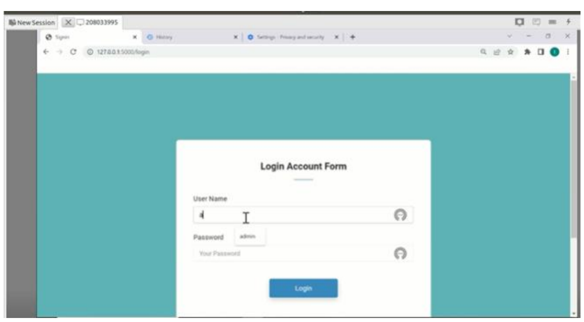

Fig.5: User login

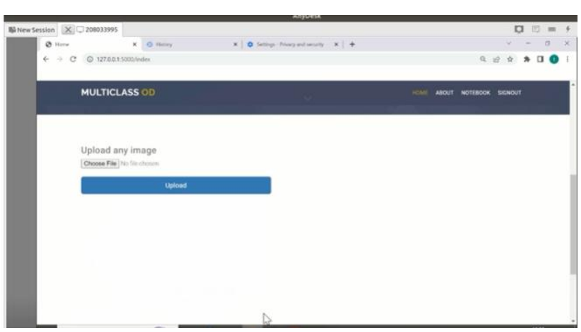

Fig.6: Main screen

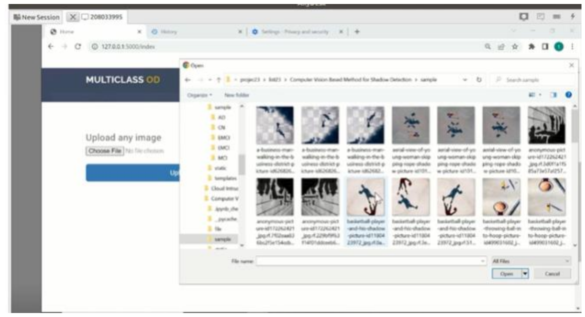

Fig.7: Input images

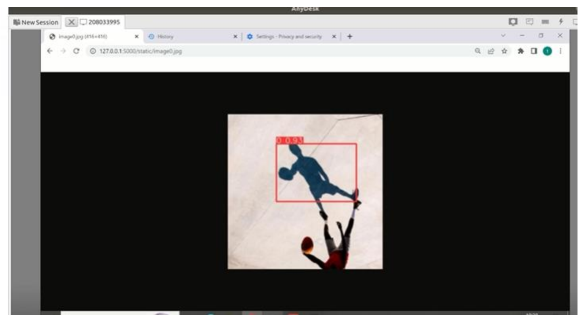

Fig.8: Classification of images

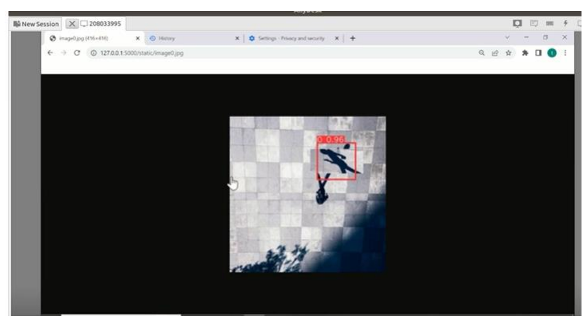

Fig.9: Prediction result

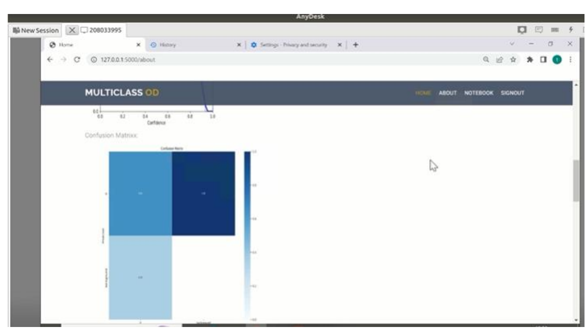

Fig.10: Confusion Matrix

5. 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.

REFERENCES

[1] “Vision impairment and blindness,” World Health Organization, Geneva, Switzerland. [Online]. Available: www.who.int/news-room/fact-sheets/detail/blindnessand-visual-impairment

[2] G. D. Finlayson, S. D. Hordley, C. Lu, and M. S. Drew, “On the detection of shadows from images,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 1, pp. 59–68, Jan. 2005.

[3] E. Arbel and H. Hel-Or, “Shadow detection using intensity surfaces and texture anchor points,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 33, no. 6, pp. 1202–1216, Jun. 2010.

[4] A. Mohan, J. Tumblin, and P. Choudhury, “Editing soft shadows in a digital photograph,” IEEE Comput. Graph. Appl., vol. 27, no. 2, pp. 23–31, Feb. 2007.

[5] I. Boyadzhiev, S. Paris, and K. Bala, “User-assisted image compositing for photographic lighting,” ACM Trans. Graph., vol. 32, no. 4, pp. 36–31, 2013.

[6] F. A. Vasluianu, A. Romero, L. Van Gool, and R. Timofte, “Shadow detection with paired and unpaired learning,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2021, pp. 826–835.

[7] T. Wang, X. Hu, Q. Wang, P. A. Heng, and C. W. Fu, “Instance shadow detection,” in Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit., 2020, pp. 1880–1889.

[8] C. Xiao, D. Xiao, L. Zhang, and L. Chen, “Efficient shadow detection using subregion matching illumination transfer,” Comput. Graph. Forum, vol. 32, no. 7, pp. 421–430, Oct. 2013.

[9] L. Zhang, Q. Zhang, and C. Xiao, “Shadow remover: Image shadow detection based on illumination recovering optimization,” IEEE Trans. Image Process., vol. 24, no. 11, pp. 4623–4636, Nov. 2015.

[10] W. M. Elmannai and K. M. Elleithy, “A highly accurate and reliable data fusion framework for guiding the visually impaired,” IEEE Access, vol. 6, pp. 33029–33054, 2018.

[11] V. N. Hoang, T. H. Nguyen, T. L. Le, T. T. H. Tran, T. P. Vuong and N. Vuillerme, "Obstacle detection and warning for visually impaired people based on electrode matrix and mobile kinect", Proc. 2nd Nat. Found. Sci. Technol. Develop. Conf. Inf. Comput. Sci., pp. 54-59, 2015.

[12] "Design boom - Blind inventor creates ‘smart cane’ that uses google maps to navigate visually impaired people", Sep. 2019.

[13] L. Kay, "An ultrasonic sensing probe as a mobility aid for the blind", Ultrasonics, vol. 2, no. 2, pp. 53-59, 1964.

[14] S. La Grow, "The use of the sonic pathfinder as a secondary mobility aid for travel in business environments: A single-subject design", J. Rehabil. Res. Develop., vol. 36, no. 4, pp. 333-340, 1999.

[15] E. Salvador, A. Cavallaro and T. Ebrahimi, "Cast shadow segmentation using invariant color features", Comput. Vis. Image Understanding, vol. 95, no. 2, pp. 238-259, 2004.

[16] A. Panagopoulos, C. Wang, D. Samaras and N. Paragios, "Illumination estimation and cast shadow detection through a higher-order graphical model", Proc. IEEE Conf. Comput. Vis. Pattern Recognit., pp. 673-680, 2011.

[17] J. Tian, X. Qi, L. Qu and Y. Tang, "New spectrum ratio properties and features for shadow detection", Pattern Recognit., vol. 51, pp. 85-96, 2016.

[18] Y. F. Su and H. H. Chen, "A three-stage approach to shadow field estimation from partial boundary information", IEEE Trans. Image Process., vol. 19, no. 10, pp. 2749-2760, Oct. 2010.

[19] S. K. Yarlagadda and F. Zhu, "A reflectance based method for shadow detection and removal", Proc. IEEE Southwest Symp. Image Anal. Interpretation, pp. 9-12, 2018.

[20] M. D. Levine and J. Bhattacharyya, "Removing shadows", Pattern Recognit. Lett., vol. 26, no. 3, pp. 251-265, 2005.