Descending Stairs Detection Using Digital Image Processing to Guide Visually Impaired

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Abstract

Blindness refers to a condition in which an individual experiences limitations in their visual ability. Individuals with visual impairments require specific assistance to facilitate their movement from one location to another. The need for this assistance arises due to various obstacles scattered throughout their environment. One of the most significant challenges is navigating descending stairs. To address this issue, a descending stairs detection system based on digital image processing has been developed. Through this approach, the mobility of individuals with visual impairments can be enhanced. The descending stairs detection system is designed using the Gray Level Co-occurrence Matrix (GLCM) method to extract distinctive features of descending stairs and the surrounding floor surfaces. Seven GLCM features are incorporated into the development of this system, allowing it to differentiate between descending stairs and floors using the Extra Tree Classifier classification method. Through a series of tests, the system's accuracy is measured at 84%, demonstrating its adequate ability to identify descending stairs. Additionally, the average computation time for detecting descending stairs and floors is recorded at 0.121 (s), indicating the efficient performance of this system in supporting the mobility of individuals in need.

Keywords: Blindness, Gray Level Co-occurrence Matrix, Extra Tree Classifier.

I. INTRODUCTION

Visual impairment is a condition that affects individuals with impaired visual acuity. Within the population of visually impaired individuals, there are two main classifications: those with low vision and those with total blindness. Classification as blind depends on the level of visual acuity, where visual acuity is considered low if it measures less than 3/60 and the visual field is less than 10 degrees, encompassing a range from low vision to total blindness. Individuals with low vision are characterized by their inability to read standard-sized 12-point text under normal lighting conditions, even when aided by corrective glasses [1]. In 2020, it is estimated that around 2.2 billion people experienced moderate to severe visual impairment, with 39 million of them being blind. Nearly 9 million of these cases occurred in Indonesia, where 7.7 million people experienced moderate to severe visual impairment and almost 1.2 million people were blind. These numbers indicate a relatively high prevalence rate, particularly considering that Indonesia ranks fourth after China, India, and Pakistan in terms of the number of cases of visual impairment [2].

The number of individuals experiencing visual impairment in Indonesia does not match the quality and quantity standards of facilities provided by the government [3]. This imbalance poses the risk of accidents involving people with visual impairments. One significant challenge for individuals with visual impairments is navigating descending stairs. This condition presents potential dangers as a person who is blind may fall or slip when unable to see obstacles on the descending stairs ahead of them. Such incidents can result in serious injuries or even death for those who are blind due to slipping on the stairs. Therefore, to enhance their safety and independence, the development of tools capable of detecting and providing information about obstacles, particularly in the form of descending stairs, is necessary for individuals with visual impairments.

Several new advancements have been developed to provide assistance to individuals with visual impairments in recognizing obstacles around them. For instance, there is an obstacle detection cane equipped with an embedded ultrasonic sensor [4]. This cane can detect obstacles up to a distance of 1 meter from the sensor. Various obstacles that can be recognized include objects such as cloth, walls, humans, trees, iron, cardboard, and steel. Additionally, it has been reported that Dolly Indra and colleagues have also successfully created a similar cane [5]. This cane is designed to detect various floor obstacles within a maximum distance of 50 cm, and it provides auditory notifications when obstacles are detected. Although ultrasonic sensors can detect numerous obstacles, they often encounter difficulties in detecting objects below ground level, such as descending stairs. This is due to the operating principle of ultrasonic sensors, which emit waves according to the direction and precision of the sensor. Furthermore, a study titled "Substitute eyes for Blind using Android" proposes the use of two ultrasonic sensors and three vibrating motors as a notification system to avoid obstacles [6]. However, a limitation of this method is that ultrasonic sensors can only detect objects from three specific directions, thus limiting the accuracy of detection. Moreover, the physical form of this device resembling a finger knuckle restricts the hand's ability to engage in other activities, leading to inaccurate detection. Another study titled "A Cloud and Vision-based Navigation System Used for Blind People" attempts to utilize camera sensors as a means of obstacle detection [7]. However, it should be noted that this obstacle detection tool can only function when connected to the internet network.

Drawing upon insights from various prior research endeavors, the author endeavors to develop an advanced system tailored to the detection of descending stairs, leveraging cutting-edge camera sensor technology. This innovative system is designed to offer ubiquitous accessibility without reliance on an internet connection. The camera sensor operates by continuously capturing video imagery, with each frame meticulously analyzed to extract intricate texture features. Utilizing the sophisticated gray-level co-occurrence matrix (GLCM) method, the system meticulously identifies and delineates key texture attributes[8]. Through this process, a comprehensive array of seven distinct feature values is generated. Subsequently, these feature values undergo a rigorous classification procedure, facilitated by the implementation of an extra tree classifier algorithm. This algorithm adeptly segregates the data into two distinct classes: the 'floor' class and the 'descending stairs' class. If the classification identifies the presence of descending stairs, the system promptly triggers a notification mechanism, typically in the form of an audible alert, to apprise the user of potential hazards. This integrated approach amalgamates state-of-the-art sensor technology with advanced data processing algorithms, epitomizing a groundbreaking solution tailored to enhance safety and mobility for individuals with visual impairments.

II. METHODS

The primary objective of this research endeavor is to devise a sophisticated system capable of discerning obstacles, specifically in the form of descending stairs. To achieve this, the study employs a classification framework comprising two distinct categories: floors and descending stairs. Integral to the methodology is the utilization of digital images procured from camera sensors as input data. Illustrated in Figure 1, the research methodology unfolds across several stages. Initially, image acquisition is conducted, wherein data is captured by the camera. Subsequently, feature extraction is undertaken, focusing on the Gray Level Co-occurrence Matrix applied to the Region of Interest (ROI) within the image. This process yields seven distinct feature values derived from the texture feature extraction phase. Importantly, these values obtained from the Gray Level Co-occurrence Matrix serve as the foundational dataset for subsequent classification endeavors, employing the extra tree classifier algorithm. The outcomes of this classification process manifest in the form of notifications, alerting users to the presence of descending stairs should such categorization be discerned. By meticulously integrating advanced image processing techniques with robust classification algorithms, this study endeavors to pioneer a comprehensive solution for enhancing obstacle detection capabilities, particularly in scenarios involving descending stairs, thereby fostering heightened safety and autonomy for individuals with visual impairments.

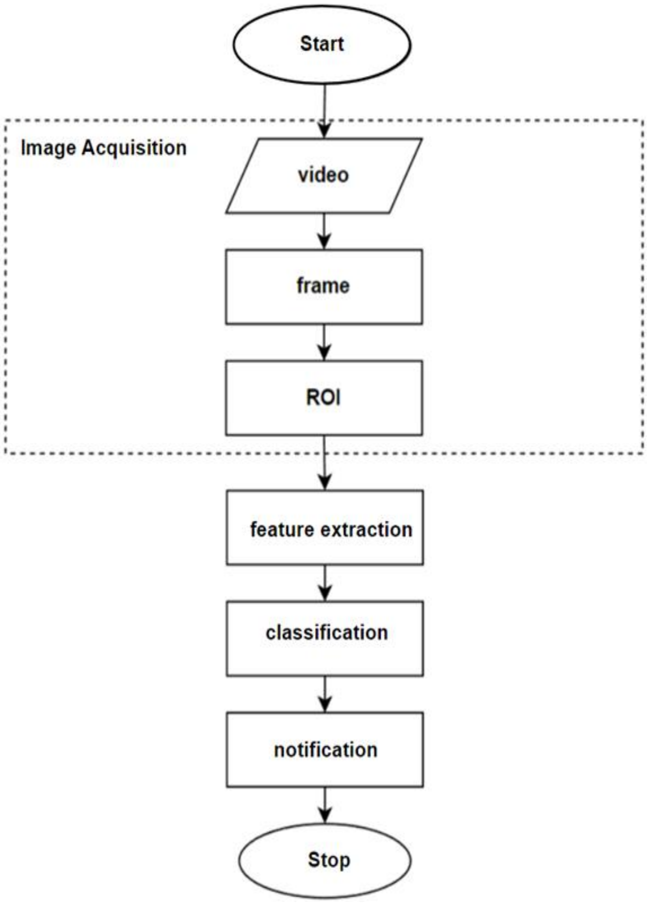

Figure 1. Research Methodology

A. Image Acquisition

The commencement of this study initiates with the crucial phase of image acquisition. At this juncture, digital images assume paramount importance as the primary input for the subsequent detection of descending stairs or floor surfaces. The research methodology involves the utilization of an extensive dataset comprising 500 training instances. Within this dataset, a balanced distribution is maintained, encompassing 250 images depicting floors and an equivalent number featuring descending stairs. Notably, these 500 training instances are sourced from diverse high-rise buildings, each exhibiting distinctive characteristics and variations in the coloration of ceramic floorings. Figure 2 elucidates a representative snapshot of the stairs and floor data employed in this investigation, offering a tangible glimpse into the dataset's composition. Prior to embarking on the texture feature extraction process, meticulous measures are undertaken to delineate the Region of Interest (ROI) within the images. This involves segmenting the images into regions measuring 400x150 pixels, thereby isolating specific areas indicative of either floor surfaces or descending stairs. This deliberate preprocessing step is pivotal in facilitating the subsequent extraction of salient features from the delineated regions, enabling nuanced analysis and classification.

Figure 2. Dataset Image of Descending Stairs and Floors

B. Gray Level Co-occurence Matrix

In this study, feature extraction constitutes a crucial step aimed at capturing the distinguishing characteristics inherent to the floor class and descending stairs. To accomplish this task, the gray level co-occurrence matrix (GLCM) texture feature extraction method is employed. This method is chosen due to its efficacy in delineating textural disparities between surfaces, wherein floors typically exhibit a uniform or smooth texture, while descending stairs tend to possess a more texture within the ROI.irregular and uneven texture. The GLCM technique facilitates texture analysis by scrutinizing pixel relationships within digital images, considering both distance and angle parameters [9][10]. Here, the distance parameter (denoted as 'd') typically spans values such as {1, 2, 3, 4}, while the angle parameter (denoted as '') encompasses commonly used angles such as {0°, 45°, 90°, 135°}[10]. From this GLCM feature extraction process, a comprehensive set of seven distinctive features is derived. These features encompass contrast, energy, entropy, angular second moment, correlation, dissimilarity, and homogeneity [11], each encapsulating specific aspects of texture characteristics pertinent to distinguishing between floors and descending stairs. The GLCM feature extraction process involves several sequential stages [12][13], outlined as follows:

- Initially, a GLCM matrix is generated, with its dimensions aligned to the Region of Interest (ROI) dimensions, set at 400x150 pixels. This matrix serves as the foundation for subsequent analysis, capturing pixel relationships within the specified region.
- Subsequently, the inter-pixel relationships are elucidated by leveraging distance and angle parameters. In this study, a distance parameter (denoted as 'd') of 1 and an angle parameter ('θ') of 0° are employed to delineate the pixel connections.
- The next step involves the creation of a symmetrical GLCM matrix by transposing the initially generated matrix. This symmetrical representation facilitates a comprehensive analysis of pixel relationships from both orientations.
- Following the generation of the symmetrical GLCM matrix, a normalization process is instituted. This normalization step entails adjusting the matrix values to a standardized scale, typically ranging between 0 and 1. By doing so, the matrix values are rendered uniform and conducive to subsequent analysis.
- With the normalized symmetrical GLCM matrix in hand, the ensuing step involves the computation of GLCM feature values. This research endeavors to extract seven distinct GLCM features, each encapsulating specific textural attributes intrinsic to the surfaces under scrutiny. These features encompass parameters such as contrast, energy, entropy, angular second moment, correlation, dissimilarity, and homogeneity, providing a comprehensive characterization of the texture within the ROI.

C. Extra Tree Classifier

The classification algorithm known as Extra Trees, also known as "extremely randomized trees," constitutes an innovative approach derived from random decision trees. It operates by partitioning the dataset into numerous sub-sections, wherein decision trees are constructed independently. Subsequently, the algorithm computes the average prediction across these diverse subsets, thereby enhancing the overall accuracy of predictions while mitigating the risk of overfitting [14][15][16]. This method diverges from traditional decision tree algorithms by introducing an additional layer of randomness in the selection of split points, further amplifying the diversity of the individual trees. By leveraging this ensemble learning technique, Extra Trees fosters robustness and resilience in classification tasks, making it a favored choice in diverse domains of machine learning and data analysis.

The Extra Trees Classifier employs a strategy of constructing random decision trees to initiate the classification process. This is done by building multiple decision trees randomly from the training data. In each tree, features and split values are randomly selected for each node. This process allows each tree to have different variations in its structure, aiding in overcoming the problem of overfitting. After the decision trees are formed, the algorithm calculates predictions for each tree based on the test data. These predictions are then used to make a majority decision in the final classification. By leveraging the majority vote from all trees, the algorithm can produce a more stable and reliable final prediction. One of the main advantages of the Extra Trees Classifier is its ability to control overfitting. This is achieved by introducing a higher level of randomness in the feature and split value selection process. By randomly choosing features and split values, the algorithm can construct trees that are more diverse and general, resulting in a model that is more generalizable. Thus, the Extra Trees Classifier offers an effective approach to addressing the problem of overfitting and building strong and reliable classification models.

III. RESULT AND DISCUSSION

The outcomes of this study encompass the findings derived from a meticulous examination focusing on the precision of stair and floor detection, alongside the computational time required for such detection tasks. A comprehensive approach outlined in Figure 3 delineates a series of steps meticulously executed to ascertain optimal accuracy and computational efficiency. Through systematic implementation of these steps, the research endeavors to attain the highest levels of precision in identifying stairs and floors, while concurrently minimizing computational time expenditures.

A. Pre-processing

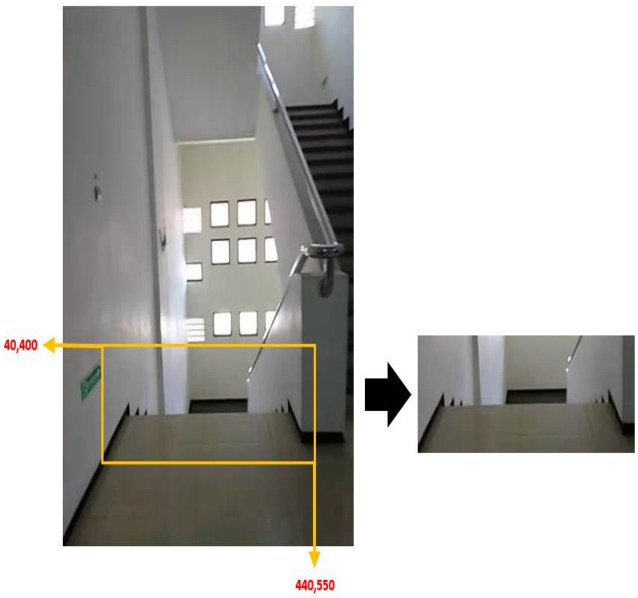

Figure 3. Steps to Get ROI

The initial phase of data processing, known as the pre-processing stage, marks the commencement of handling the input data, which predominantly comprises video data captured by a camera. Within this stage, the initial step involves extracting frames from the video feed, with each frame typically possessing a resolution of 480 by 640 pixels. Subsequently, a specific area within these frames, referred to as the Region of Interest (ROI), is delineated. This region is precisely defined by the coordinates (40,400) to (440,550) and spans a dimension of 150 by 400 pixels.

Illustrated in Figure 3 is an exemplification of the precise positioning for capturing the ROI. Following the delineation of the ROI, the final pre-processing task entails converting the RGB image within the ROI into a grayscale representation utilizing Equation 1. The fixation of the ROI's position is imperative as it aligns with the anticipated movement of the visually impaired individual, who will be advancing forward. Consequently, efficiency in detection is paramount, necessitating prioritized focus on the regions pertinent to the visually impaired individual's exploration.

$$Grayscale = \frac{Red+Green+Blue}{3} \tag{1}$$

B. Feature Extraction

The feature extraction phase unfolds subsequent to the conversion of the ROI image into grayscale format. Within this phase, the extraction of texture features is facilitated through the utilization of the Grey-Level Co-occurrence Matrix (GLCM) technique, employing specific distance parameters (d = 1) and angle (0°). This intricate feature extraction procedure is systematically applied across the entire training dataset, comprising a total of 500 images. The output of this texture feature extraction operation manifests in the form of seven distinct GLCM feature values, namely contrast, energy, entropy, angular second moment, correlation, dissimilarity, and homogeneity.

Enclosed within Figure 4 is the pseudocode delineating the step-by-step execution of the GLCM feature extraction process, elucidating the algorithmic intricacies involved in deriving the aforementioned texture features. This meticulous procedure serves as a crucial precursor to subsequent stages, laying the foundation for the comprehensive analysis and classification of the extracted features, thus contributing to the overarching objective of enhancing the system's performance and accuracy in discerning and interpreting visual data.

```
i = 1
for x in range(11) :
im = skimage.io.imread('D://', i+ '.jpg', as_gray=True)
im = skimage.img_as_ubyte(im)
g = skimage.feature.greycomatrix(im, [1], [0], 256,
symmetric=True, normed=True)
    a1 = skimage.feature.greycoprops(g, 'contrast')[0][0]
    a2 = skimage.feature.greycoprops(g, 'energy')[0][0]
    a3 = skimage.feature.greycoprops(g, 'homogeneity')[0][0]
    a4 = skimage.feature.greycoprops(g, 'correlation')[0][0]
    a5 = skimage.feature.greycoprops(g, 'dissimilarity')[0][0]
    a6 = skimage.feature.greycoprops(g, 'ASM')[0][0]
    a7 = skimage.measure.shannon_entropy(g)

    data = i, a1, a2, a3, a4, a5, a6, a7, 0
    print(data)
```

Figure 4. GLCM Pseudocode

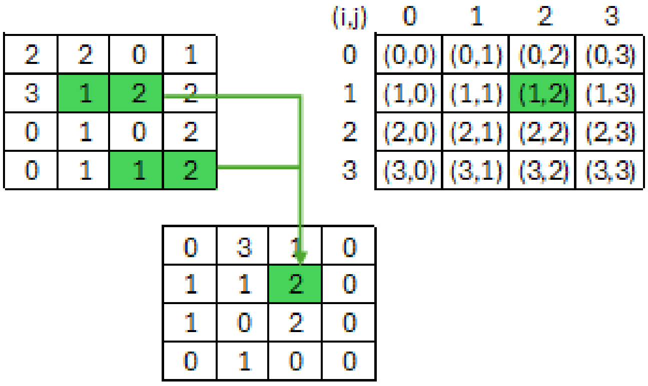

Figure 5. GLCM Matrix

In this study, the parameters used are distance (d) = 1 and angle orientation (θ) = 0. Figure 5 illustrates an example of the steps involved in obtaining the GLCM matrix. After the GLCM matrix is obtained, the next step is to combine it by making the matrix symmetrical through the process of transposition, as explained in Equation 2. Then, the resulting symmetrical matrix is normalized using Equation 3. This normalization process ensures that each element in the matrix reflects a proportional contribution to the entire matrix, thereby enabling fair and unbiased comparisons, even if there are differences in the size or scale of the original image.

$$\begin{bmatrix} 0 & 3 & 1 & 0 \\ 1 & 1 & 2 & 0 \\ 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 & 0 \\ 3 & 1 & 1 & 1 \\ 1 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 4 & 1 & 0 \\ 4 & 2 & 3 & 1 \\ 1 & 3 & 0 & 2 \\ 0 & 3 & 0 & 0 \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} 0 & 2/12 & 1/22 & 0 \\ 2/11 & 1/11 & 3/22 & 1/22 \\ 1/11 & 3/22 & 0 & 2/22 \\ 0 & 3/22 & 0 & 0 \end{bmatrix} \quad (3)$$

C. Classification Testing

The evaluation of the system's efficacy in obstacle detection is conducted through a comprehensive classification testing procedure, aimed at quantifying its accuracy. This evaluative process entails the utilization of a curated dataset comprising 200 test instances, comprising 100 images depicting descending stairs and an equal number depicting flat floors. Three pivotal test parameters are employed to gauge the system's performance: accuracy, precision, and recall.

Accuracy, the foremost metric, encapsulates the system's ability to correctly predict both positive and negative instances within the test dataset. It is quantified by computing the ratio of correct predictions to the total number of test instances, as delineated by Equation 4. Precision, on the other hand, delves deeper into the system's performance by focusing solely on the accuracy of positive predictions relative to all instances predicted as positive. This metric, as measured by Equation 5, offers insights into the system's ability to avoid false positive identifications [17][18].

Furthermore, recall, another crucial metric, pertains to the system's capability to correctly identify positive instances within the dataset, relative to all actual positive instances present. This measure, computed according to Equation 6, sheds light on the system's sensitivity towards detecting positive instances. The integration of these three metrics offers a holistic assessment of the system's performance, enabling a nuanced understanding of its strengths and areas for potential improvement. By systematically evaluating these parameters, the classification testing endeavors to furnish actionable insights to refine and optimize the system's obstacle detection capabilities, thereby enhancing its real-world applicability and reliability.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

The outcomes of the classification tests are meticulously documented in Table 1, providing a comprehensive overview of the system's performance across varied scenarios. Delving into the intricacies of the results, it is discerned that the precision metrics for floor identification and descending stairs classification stand at 0.90 and 0.81, respectively. These precision values reflect the system's adeptness in accurately identifying positive instances within their respective categories. Similarly, the recall metrics, indicative of the system's sensitivity in capturing positive instances, yield values of 0.78 for floor detection and 0.91 for descending stairs classification. These metrics underscore the system's robustness in correctly identifying instances from their designated categories. Moreover, the overarching accuracy of the classification system, calculated at 0.84, encapsulates its overall efficacy in correctly predicting instances across all categories within the test dataset. This consolidated metric serves as a holistic indicator of the system's performance, synthesizing its precision and recall capabilities into a singular measure.

It is noteworthy that these tests are conducted utilizing distinct test datasets separate from the training data, ensuring the evaluation's robustness and reliability. By employing diverse datasets for testing, the assessment captures the system's ability to generalize and perform effectively in real-world scenarios beyond the confines of its training environment. This rigorous evaluation framework enhances confidence in the system's utility and reliability, paving the way for its seamless integration into practical applications requiring accurate obstacle detection capabilities.

Tabel 1. Classification Result

Class	Precision	Recall	Accuracy
Floor	0.9	0.78	**0.84**
Descending Stair	0.81	0.91	

D. Time Computation

The analysis of Table 2 indicates the results of computational time testing for detecting floors and descending stairs across a set of examined images, along with the average time across all tests. Overall, the average time for detecting floors (0.122 seconds) is nearly equivalent to the average time for detecting descending stairs (0.121 seconds), suggesting a balanced performance of the system in detecting both types of objects. There is variability in detection times among the images, where floor detection times range from 0.112 seconds to 0.145 seconds, while descending stairs detection times range from 0.108 seconds to 0.152 seconds. This variability underscores the potential influence of external factors such as lighting or camera angles on detection performance. Although floor detection times tend to be faster than descending stairs detection, there are cases where descending stairs detection is quicker. Despite variation in detection times among the images, the average detection times for floors and descending stairs demonstrate a good level of consistency, indicating that the system maintains reliable consistency in performing both types of detection.

Tabel 2. Time Computation

Image	Floor (s)	Descending Stairs (s)
Image 1	0.126	0.132
Image 2	0.131	0.115
Image 3	0.112	0.115
Image 4	0.112	0.109
Image 5	0.119	0.109
Image 6	0.118	0.117
Image 7	0.123	0.126
Image 8	0.145	0.125
Image 9	0.118	0.152
Image 10	0.119	0.108
Average	**0.122**	**0.121**

V. CONCLUSION

The outcomes derived from the conducted research have led to the development of a sophisticated system tailored for the detection of descending stairs. This innovative obstacle detection framework harnesses the capabilities of camera sensors to capture digital image data, which serves as the primary input. Distinguishing between two distinct classes, namely the floor and descending stairs, forms the crux of this detection mechanism. To discern the nuanced disparities between these classes, the researcher employed the Gray Level Co-occurrence Matrix (GLCM) technique. Renowned for its efficacy in texture analysis, the GLCM method meticulously scrutinizes textural variations inherent in the floor and descending stairs. This analytical process yields a comprehensive set of seven distinctive features, encompassing contrast, energy, entropy, angular second moment, correlation, dissimilarity, and homogeneity. Furthermore, to effectively categorize the detected objects, the Extra Tree Classifier method is employed, facilitating precise classification of floors and descending stairs. The culmination of these methodologies is manifested in the system's commendable accuracy rate of 84%, as elucidated in Table 1, thereby underscoring its efficacy in discerning and accurately categorizing obstacles within its operational domain.

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