DETECTION OF SMALL OBJECT – CRITICAL SURVEILLANCE

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by

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I **Amit Gupta** student of M.Tech in Signal Processing and Digital Design, hereby declare that the project Dissertation titled “**DETECTION OF SMALL OBJECT – CRITICAL SURVEILLANCE**” which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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CERTIFICATE

This is certify that the work contained in the project titled "**DETECTION OF SMALL OBJECT – CRITICAL SURVEILLANCE**", submitted by Amit Gupta in the partial fulfillment of the requirement for the award of Master of Technology in Signal Processing & Digital Design to the Electronics & Communication Engineering Department, Delhi Technological University, Delhi, is a bonafide work of the students carried out under my supervision.

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ABSTRACT

Identifying small things in photos is a difficult yet crucial undertaking in areas such as surveillance, medical imaging, and automated inspection systems. This thesis presents a novel approach for detecting small objects by utilizing texture segmentation techniques that rely on Gray Level Co-occurrence Matrices (GLCM) and Gaussian Mixture Models (GMM).The first step in our methodology involves preparing the photographs, which includes resizing and converting them to grayscale in order to ensure uniformity. Subsequently, the images are partitioned into smaller subimages to permit meticulous texture analysis. The GLCM technique is utilized to extract important texture properties, including contrast, dissimilarity, correlation, and energy, from every subimage. These characteristics offer a thorough depiction of the textures that are present. Subsequently, a Gaussian Mixture Model employs texture features to cluster the subimages, therefore efficiently dividing the image into sections with clearly distinguishable textures. Clustering is utilized to identify and separate little things that are easily distinguishable from their surroundings because of their distinct textures. The efficacy of the suggested methodology was assessed using a compilation of synthetic and real-world photographs. The findings demonstrated the efficacy of our approach in accurately detecting and separating minute entities, even in intricate settings characterized by diverse textures. The findings indicate that this approach has the potential to be used in various applications, providing ample opportunities for further exploration and advancement in the fields of image processing and object detection.

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LIST OF ABBREVIATIONS

GLCM : Gray Level Co-occurrence Matrix

GMM : Gaussian Mixture Model

ASM : Angular Second Moment

CNN : Convolutional Neural Networks

R-CNN : Region-based Convolutional Neural Networks

YOLO : You Only Look Once

LBP : Local Binary Patterns

SVM : Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 Background

Artificial Intelligence (AI) and computer vision are cutting-edge fields that have drastically changed how we perceive and engage with our surroundings. These technologies are implemented in a wide range of applications, touching almost every part of our daily lives and greatly enhancing productivity, efficiency, and safety in multiple sectors. Although substantial progress has been achieved, the complete potential of AI and computer vision is still far from being realized, with many research and development opportunities yet to be explored. Airway transportation safety is one such area that has seen a rise in interest recently. The airway network, which serves as the foundation of many economies across the world, is essential for moving innumerable people and goods over great distances. The airport runway is a vital component of civil aviation infrastructure since it is the main location for aircraft takeoff and landing[1]. Runways are vulnerable to small objects because of their large area, frequent use, and lack of shielding. Small items[2] present serious threats to aircraft during takeoff and landing, which could result in serious civil aviation accidents.

A number of things can lead to an airplane accident, such as runway incursions, collisions, and obstacles brought on by unauthorized people or inadvertent objects[3]. These accidents frequently happen too quickly for physical intervention because to the high speeds at which airplanes travel, with disastrous results. The identification of possible risks in aviation has traditionally been mostly dependent on human observers and safety equipment situated on the ground. Unfortunately, there are a number of inherent flaws with this strategy, including the potential for human error, decreased efficacy in unfavorable weather or lighting conditions, and the high expense of both installation and upkeep. There is a chance to create a different, more effective technique for early and precise hazard detection on runways because to developments in AI and computer vision. On the other hand, automatic detection of objects on runways poses different kinds of challenges. Primarily, these include the intricacy entailed in identifying small or far-off things in less-than-ideal circumstances, such dim illumination or fluctuating weather. Any danger detection system must also be able to recognize risks in almost real-time, giving pilots or automated control systems enough notice, considering how quickly planes work. The creation of incredibly effective models and algorithms that can swiftly evaluate photos without sacrificing detection accuracy is required for this real-time activity. The system has to do more than just detect the existence of an object; it also has to correctly categorize it into groups like people, animals, cars, or other possible dangers[4]. Developing an extensive understanding of the items on the runway makes it possible to provide accurate data that can be quickly relayed to the pilot or control system, allowing for the correct reaction.

Relevant answers to these problems can be found in recent advances in AI and computer vision, especially in the creation of deep learning models like Faster R-CNN[5] and the techniques given out by researchers concentrating on aircraft safety. These technologies show promise for use in aviation safety since they have shown to be very accurate and efficient in a variety of fields when it comes to object detecting duties. Still largely unexplored in terms of study, is the application of these approaches for the detection of small objects on runways.

In addition, the problem goes beyond object detection to include learning about the items that have been detected and efficiently disseminating this knowledge in a timely manner to prevent accidents. This thesis seeks to address these issues by creating a comprehensive system that can quickly and effectively relay important information about tiny objects on runways, identify them with accuracy, and avoid accidents.

1.2 Thesis Objective

This research investigates machine learning methodologies for identifying small things in images. The document encompasses a comprehensive examination of current techniques for detecting objects and segmenting instances. It also highlights significant obstacles and proposes approaches to improve the accuracy of detecting small objects.

- **Texture Feature Extraction:** Utilize Grey Level Co-occurrence Matrix (GLCM) analysis to extract texture features from images. Calculate a collection of texture descriptors including contrast, dissimilarity, correlation, energy, homogeneity, ASM, entropy, and variance[6].

- **Clustering and Segmentation:** Utilize Gaussian Mixture Model (GMM) clustering to categorize picture blocks with similar texture attributes into groups. Segment pictures into separate regions by allocating each block to a cluster[7].

- **Small Object Detection:** Visualize the clustering results by displaying segmented subimages with their respective cluster labels. Conduct comparative analysis of texture features between specific image regions. Set decision thresholds for texture feature differences to segment specific regions of interest (e.g., metal pieces)[8].

- **Outcome:** Obtain segmented images highlighting different textures or regions of interest. Analyze and interpret the variations in texture features across different image regions. Provide insights into image content and facilitate further image processing tasks such as object recognition or anomaly detection.

1.3 Thesis Scope and Methodology

This thesis aims to use computer vision and machine learning technology to enhance aviation safety measures. The primary objective of this project is to create machine learning models in order to detect runway trash and identify possible risks on airport property. The technique uses preprocessed pictures and Grey Level Co-occurrence Matrix

(GLCM) analysis to extract texture properties including contrast, dissimilarity, and entropy[9]. These qualities capture a variety of textural attributes. Then, in order to facilitate segmentation into cohesive texture areas, Gaussian Mixture Model (GMM) clustering[10] is employed to group comparable picture blocks based on their texture attributes. Decision thresholds improve segmentation for the extraction of the targeted region, and visuals support qualitative evaluation. With the help of this method, extensive texture-based image analysis is made possible, enabling tasks like anomaly detection and object recognition.

1.4 Thesis Organization

The structure of the dissertation is as follows:

An detailed assessment of the literature is provided in Chapter 2, which looks at the state of aviation safety systems, airport-specific object detection techniques, and the use of machine learning in these fields. By providing an excellent summary of the current state of research, this chapter hopes to set the stage for the investigation.

Chapter 3 explores the methods used for hazard identification, with a focus on implementing relevant algorithms and methodologies. This chapter will explain the workings and design concepts of the suggested solution in depth, focusing on it.

The results and discussions, together with an analysis of the findings and an outline of their implications for airline safety practices, will be presented in the upcoming chapters. The study will be summarized in the last chapter, which will also suggest directions. Following this outline will enable the dissertation to provide a thorough investigation of the use of artificial intelligence (AI) and computer vision to enhance aircraft safety, giving investors in the aviation sector invaluable information.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Detecting tiny objects poses significant challenges in the area of computer science due to their small size, lack of identifiable characteristics, and the presence of diverse backgrounds. In order to improve the accuracy of detecting small objects, researchers have explored the use of GLCM texture picture segmentation and Gaussian Mixture Model. This dual-step procedure enhances the ability to recognize tiny objects by using texture-based segmentation as a key factor. The research aimed to provide a comprehensive overview of the advancements and advances made in tiny object recognition and picture segmentation, primarily using the techniques of Gray Level Co-occurrence Matrix (GLCM) and Gaussian Mixture Model (GMM)[11]. The review conducted an analysis that included the progress made in two specific areas, significant milestones, and an extensive examination of existing literature. This allowed us to identify research trends, including the presence of available studies and areas where more investigation is needed.

2.2 Techniques for Detecting Small Objects and Segmenting Images

Over the years, there has been significant advancement in the industry, relying on the use of GLCM (Gray Level Co-occurrence Matrix) and GMM (Gaussian Mixture Model)[12]. In the beginning, the recognition of tiny objects heavily relied on conventional techniques, most of which were centered upon manually designed characteristics and standard machine learning algorithms. For example, several studies used filters that utilized local histograms, including the marginal distributions of filter responses for texture and non texture segmentation[13]. Nevertheless, the advancement of deep learning has made tiny object identification widely recognized and favored. Small item recognition is a challenging task due to the low spatial resolution and complicated imaging circumstances.

It requires the use of sophisticated training methodologies, multi-scale features learning[14], and context-based information.

2.3 Major turning points and ongoing trends:

The integration of deep convolutional neural networks has been a significant milestone in the field of tiny object identification, despite the notion existing for many decades. Faster R-CNN and YOLOv3 utilized multi-scale feature maps and anchor boxes to enhance the detection of tiny objects. Additionally, feature pyramid networks have been created to enhance the identification of tiny objects by integrating low-level and high-level feature maps. Another significant development was the use of GLCM (Gray-Level Co-occurrence Matrix) and GMM (Gaussian Mixture Model)[15] for the purpose of texture analysis and segmentation. The Gray-Level Co-occurrence Matrix (GLCM) captures the correlation between pixels at certain spatial positions, hence providing detailed texture information that might improve the segmentation process[16]. Gaussian Mixture Model (GMM) is used to represent the distribution of pixel intensities, enabling reliable segmentation of areas that exhibit similar texture patterns. The GLCM method is used to extract texture information by taking into account the spatial interactions between pixels. It examines the frequency of occurrences of pixel pairs with certain values and spatial relationships in a picture. The Gaussian Mixture Model (GMM), however, enhances the texture recognition[17] process by accurately representing the distribution of pixel intensities

2.4 Evaluation of Current Research:

Prior studies demonstrate that the integration of GLCM (Gray-Level Co-occurrence Matrix) and GMM (Gaussian Mixture Model) greatly enhances the capacity to identify tiny objects by improving the ability to separate the texture[18]. Liu and Wang have conducted research on local spectral histograms, which has shown the ability to segment a picture by analyzing its texture. The approach in question used local spectral histograms to gather both global and local texture information. This enhancement significantly increased the accuracy of segmenting tiny objects with crowded backgrounds. In 2008, Huang and his colleagues published a technique that introduced a novel approach to image segmentation using Gaussian Mixture Models. This approach demonstrated better results in accurately segmenting tiny objects inside pictures[19]. The researchers have shown the picture histogram in the Gaussian mixture model using their innovative new method. The Expectation-Maximization technique is used to find the best mixes and their parameters by taking the average of the Gaussian Mixture Model (GMM). It was noted that this approach shown more efficacy in circumstances when pictures exhibited diverse intensity distributions, which is a difficult challenge in detecting tiny objects. The use of deep learning in conjunction with the conventional approach demonstrated revolutionary outcomes. A group of researchers created hybrid models by combining GLCM and GMM. By using a hybrid model, they were able to use Convolutional Neural Networks for extracting image features and GLCM-GMM[20] for assessing disparities in testing data. The precise partitioning of the GLCM model employing GMM produced an enhanced outcome in identifying diminutive entities inside the intricate environment. However, existing techniques encounter obstacles such as limited real-time capabilities when incorporating deep learning, and a lack of computational efficiency when dealing with tiny objects in deep learning models. The research highlights the need of having smaller datasets to improve the effectiveness of integrated analysis techniques in finding and studying small objects.

2.5 Summary

This study provides an overview of contemporary techniques for detecting tiny objects and segmenting images, focusing specifically on the use of GLCM and GMM for analyzing textures. The study provides an overview of the significant progress, current difficulties, and future prospects in the discipline, outlining its historical and current level of advancement. Importance in a broad sense: The significance of comprehending and enhancing the detection of small-sized objects in applications like as surveillance, medical imaging, and autonomous driving is immense. The use of texture-based segmentation[21], using the GLCM (Gray-Level Co-occurrence Matrix) and GMM (Gaussian Mixture Model), has great potential in enhancing accuracy[22]. The review article documents the advancements made, the discovery of patterns, and the existing gaps, which together indicate the future research landscape.

CHAPTER 3
METHODOLOGY

3.1 Introduction

This thesis work focuses on the development of a technique that uses texture image segmentation to make it possible to recognize small things that are found on road surfaces. In this suggested technique, texture characteristics are extracted from the Gray-Level Co-occurrence Matrix, and clustering is carried out with the help of the Gaussian Mixture Model. The next part provides a comprehensive description of the methods of image preprocessing, as well as the procedure for the extraction of texture characteristics[23], classification, and segmentation of the objects that have been detected.

3.2 Image Data and Preprocessing

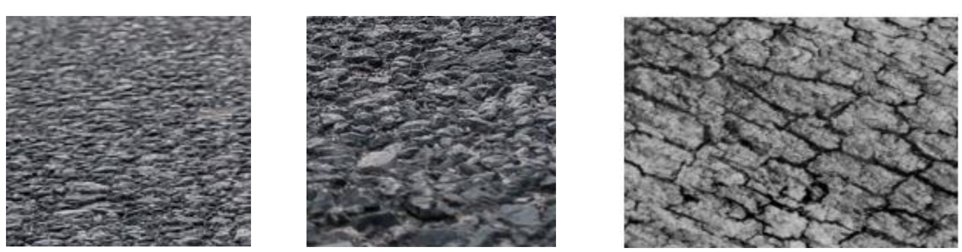
The dataset employed in this study was created using high-resolution pictures captured using a Samsung S21 FE smartphone. Initially, the dataset had 10 images, each portraying a road situation accompanied by object positioned on the road. For maximum uniformity throughout the preprocessing stage, every image was originally resized to a fixed resolution of 256 by 256 pixels. To facilitate the process of texture analysis, the photographs were then converted to grayscale after being resized[24]. This decision was made since the research did not need color information. As an additional measure, each grayscale image was separated into non-overlapping subimages with a resolution of 64 by 64 pixels. As a result of this procedure, many subimages were produced for each picture, and each of these subimages was examined separately.

Through this division of data, enabled robust training and comprehensive validation of the model, leading to a reliable system for detecting small objects in similar road surface.

Fig. 3.2 A sample of Image of Data

3.3 Texture Segmentation Techniques

Texture refers to the structured repetition of patterns or elements on a surface, which assists in distinguishing between textured and non-textured areas in an image. In the context of detecting small objects, texture plays a role in categorizing and segmenting various regions, as well as extracting boundaries between significant texture regions[25]. Texture plays a crucial role in several image analysis and computer vision applications, particularly in the detection of microscopic objects. Texture is represented as a two-dimensional change in gray levels, where the contrast, regularity, coarseness, and directionality are determined by the relative brightness of pairs of pixels[26].



(a) (b) (c)

Fig. 3.3 Different Textures Images

Segmentation is the process of dividing a picture into separate and uniform sections, which helps to emphasize significant characteristics and make analysis easier. In the context of small object recognition, it is of utmost importance to accurately differentiate between the foreground and the background, as well as to recognize the distinctions between various items. Segmentation methods encompass region-based and edge-based strategies[27]. Texture-based segmentation is highly efficient because textures play a crucial role in extracting significant information from pictures.

Over time, a variety of approaches have been developed to extract texture information, each with its own distinct benefits and uses. Wavelet analysis, which was launched in the late 1980s, significantly transformed the field of texture extraction by providing a multi-resolution method for picture analysis. Wavelets perform a decomposition of a picture into distinct frequency components, enabling the analysis of texture at different scales. The Gabor filter, which was influenced by the human visual system, gained prominence in the early 1990s. The method utilizes sinusoidal waves that are modified by Gaussian functions to examine texture. Gabor filters are capable of capturing directional texture information by manipulating parameters like as orientation and frequency. This makes them well-suited for jobs that demand sensitivity to orientation. This talk will present a concise summary of the primary methods used to extract texture, culminating in a thorough analysis of the gray level co-occurrence matrix (GLCM).

3.3.1 Grayscale Co-occurrence Matrix (GLCM)

Out of all the techniques, the gray level co-occurrence matrix (GLCM) has attracted considerable interest since it can effectively capture the spatial associations between pairs of pixels in an image. GLCM differs from existing approaches that concentrate emphasize frequency or local patterns. It employs a statistical approach to texture analysis by creating a matrix that represents the likelihood of pixel pairings with specified gray levels appearing at a particular distance and orientation.

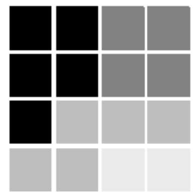
The GLCM approach is highly effective in providing a full representation of texture by taking into account both pixel intensity and spatial correlations. In order to create a GLCM[28], the image is examined to determine the frequency at which pairs of pixels with particular values appear in a defined spatial arrangement. The matrix may be used to generate several texture properties, such as contrast, correlation, energy, and homogeneity.

The adaptability of the GLCM approach enables its use to grayscale pictures, rendering it a resilient tool for many applications. GLCM features are useful in texture-based segmentation since they can effectively distinguish between areas that exhibit various texture patterns. This skill is especially significant in areas like as medical imaging, where it is crucial to differentiate between various types of tissue, and in remote sensing, where the categorization of land cover strongly depends on texture information.

3.3.2 GLCM Calculations

Here is a straightforward example that may be used to demonstrate texture extraction techniques. Let's examine a "test image" where the levels of gray are depicted by distinct values. Here, the image employs 2-bit data, resulting in 4 distinct gray levels: 0, 1, 2, and 3, as determined by the formula 2 ^ 2. Typically, photographs with lower gray levels look darker. This example will be utilized consistently throughout the session to elucidate various ideas. Currently, let's maintain a simple approach and concentrate on understanding the fundamental concepts.

The image as it appears:



The GL (digital numbers) associated with each pixel:

0	0	1	1
0	0	1	1
0	2	2	2
2	2	3	3

Fig. 3.3.2 A Sample of Gray Level Co-Occurrence Matrix

3.3.3 Texture Measure Calculations

The relationship is described by the joint probability $P(i, j, d, \theta)$, which indicates the frequency at which a pixel with gray level i is adjacent to a pixel with gray level j (destination) at a specific distance d and direction θ i.e. it denote that $P(i, j, d, \theta)$, is the probability where the gray level i is the origination and the gray level j appearing as the destination. The matrix has dimensions $L * L$, where L represents the total number of potential gray levels in the image. For instance, by assigning a value of $d = 1$ (indicating a separation of one pixel) and examining directions $\theta = 0°$ (horizontal), 45°, 90° (vertical), and 135°, we may compute the probabilities associated with these particular arrangements.

Texture features are quantified in practical applications by deriving several statistical metrics from the GLCM[29]. Haralick and his colleagues identified a total of 14 distinct characteristics that can be derived from the GLCM. For the purpose of this discussion, eight of these features are utilized as the main descriptors of texture. These characteristics offer vital data regarding the texture of the image and are calculated using precise formulae. These statistical measurements aid in the analysis and differentiation of various textures within the image. The subsequent equations are employed to calculate the eight chosen characteristics from the GLCM[30] in this study.

1. Contrast: (this is also called "sum of squares variance" and occasionally “inertia”)

$$\sum_{\boldsymbol{i,j=0}}^{\boldsymbol{N-1}} \boldsymbol{P_{i,j}}\,(\boldsymbol{i}-\boldsymbol{j})^{\boldsymbol{2}} \qquad (\boldsymbol{1})$$

When i and j are equal, the cell is on the diagonal and $(i - j) = 0$. These values represent pixels entirely similar to their neighbour, so they are given a weight of 0 (no contrast). If i and j by 1, there is a small contrast, and the weight is 1. If i and j differ by 2, contrast is increasing and the weight is 4. The weights continue to increase exponentially as $(i - j)$increases.

2. Dissimilarity : Instead of weight increasing exponentially as one moves away from the diagonal as contrast did, the dissimilarity weights increase linearily.

$$\sum_{\boldsymbol{i,j=0}}^{\boldsymbol{N-1}} \boldsymbol{P_{i,j}}\,|\boldsymbol{i}-\boldsymbol{j}| \qquad (\boldsymbol{2})$$

3. Homogenity: (Inverse Difference Moment)Dissimilarity and Contrast result in larger numbers for more windows showing more contrast. If weights decrease away from the diagonal, the calculated texture measure will be larger for windows with little contrast. Homogeneity weights values by the inverse of the Contrast weight, with weightBs decreasing exponentially away from the diagonal.

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2} \tag{3}$$

4. **Angular Second Moment(ASM) and Energy:** ASM and Energy utilize each $P_{i,j}$ as its own weight. Elevated values of ASM or Energy indicate a highly ordered window..

$$\sum_{i,j=0}^{N-1} P_{i,j}^2 \tag{4}$$

$$Energy = \sqrt{ASM} \tag{5}$$

5. **Entropy:** Since $ln(0)$ is undefined, assume that $0 * ln(0) = 0$.

$$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right) \tag{6}$$

6. **GLCM Mean:** The GLCM Mean is not simply the arithmetic mean of all the original pixel values within the image window. Instead, it is determined by the GLCM, which considers the frequency of occurrence of a pixel value in combination with a nearby pixel value, rather than only based on its own frequency of occurrence, as in a conventional mean calculation.

$$\mu_i = \sum_{i,j=0}^{N-1} i(P_{i,j}) \qquad \mu_j = \sum_{i,j=0}^{N-1} j(P_{i,j}) \tag{7}$$

7. **Variance :** Texture variance operates in a similar manner to the statistical concept of variance, which is based on the average and the extent to which cell values deviate from

the average within the GLCM. GLCM variance primarily focuses on the variations between reference and nearby pixels, distinguishing it from the general variance of gray levels in the source image.Variance calculated using i or j gives the same result, since the GLCM is symmetrical.

$$\boldsymbol{\sigma_i^2} = \sum_{\boldsymbol{i,j=0}}^{\boldsymbol{N-1}} \boldsymbol{P_{i,j}}\left(\boldsymbol{i} - \boldsymbol{\mu_j}\right)^{\boldsymbol{2}} \qquad \boldsymbol{\sigma_j^2} = \sum_{\boldsymbol{i,j=0}}^{\boldsymbol{N-1}} \boldsymbol{P_{i,j}}\left(\boldsymbol{i} - \boldsymbol{\mu_j}\right)^{\boldsymbol{2}} \tag{8}$$

8. **Correlation:** The Correlation texture measures the linear dependency of grey levels on those of neighbouring pixels. Correlation between pixels means that there is a predictable and linear relationship between the two neighbouring pixels within the window.

$$\sum_{\boldsymbol{i,j=0}}^{\boldsymbol{N-1}} \boldsymbol{P_{i,j}} \left(\frac{(\boldsymbol{i} - \boldsymbol{u_i})(\boldsymbol{j} - \boldsymbol{\mu_j})}{\sqrt{(\boldsymbol{\sigma_i^2})(\boldsymbol{\sigma_j^2})}} \right) \tag{9}$$

3.4 Gaussian Mixture Model (GMM)

Statistical clustering methods often rely on models known as finite mixtures. In these models, the data is represented as a mixture of several Gaussian distributions. Each sample is assumed to belong to each cluster with a certain probability, but in reality, it belongs to only one cluster.

Let $X = \{x_1, x_2, \dots, x_N\}$ is a set of N samples of d dimensions and subject to Gaussian mixture models distribution[31].Therefore, its probability density function can be defined as the sum of the probability distribution of k contibutions :

$$\boldsymbol{p(x) = \sum_{J=1}^{k} p(x|j)P(j)} \qquad (\mathbf{10})$$

Where $\sum_{j=1}^{k} P(j) = 1$ and $0 \leq P(j) \leq 1$. $P(j)$ is the prior probability of the j-th component. If all components are Gaussian distribution, then its corresponding model is

Gaussian mixture models and its posterior probability is:

$$\boldsymbol{p(x|j) = \frac{1}{\left(2\pi\sigma_{\gamma}^{2}\right)^{d/2}} exp\left\{-\frac{\left\|x - \mu_j\right\|^2}{2\sigma_j^2}\right\}} \qquad (\mathbf{11})$$

Consequently, the parameters of $d-$ dimensional Gaussian mixture models are determined by mean vector μ and variance matrix σ.

3.5 Expectation Maximization Algorithm

The Expectation Maximization (EM) algorithm was employed to estimate the parameters of Gaussian Mixture Models (GMM). If we make the assumption that all samples are independent and have the same distribution, the log-likelihood function can be defined in the following manner:

$$\boldsymbol{l(\theta) = \sum_{n=1}^{N} ln \left\{\sum_{j=1}^{k} p(x_n|j)P(j)\right\}} \qquad (\mathbf{12})$$

where N is the number of all samples and K is the number of all constituents, i.e. the number of clustering. The objection of EM algorithm is to find the maximum estimation value $\hat{\theta}$ of the log likelihood function to meet equation (3). The concrete step of EM algorithm is given as follow:

First, mean vector μ , variance matrix σ and the prior probability of mixture constituent are initialized. Then E-step and M-step are iterated until the algorithm converges to optimal solution of max log likelihood meaning or comes to max iteration times.

E-step: compute and uniform the posterior probability of each sample $x_n(1 \le n \le N)$ belonging to j-th cluster as follow:

$$\boldsymbol{P(j|x_n) = \frac{p(x_n|j)P(j)}{\sum_{i=1}^{k} p(x_n|i)P(i)}} \tag{13}$$

M-step: get the new parameters throughout the maximum of equation (3). The concrete equations are as follow:

$$\boldsymbol{(\sigma_j)^2 = \frac{1^{\sum_{n=1}^{N} P}}{d} \frac{(j|x_n)\|x_n - \mu_j\|^2}{\sum_{n=1}^{N} p(j|x_n)}} \tag{14}$$

When EM algorithm is convergent, the posterior probability of each sample $x_n(1 \le n \le N)$ belonging to each $j(1 \le j \le k)$cluster is taken. Then the class of each sample can be determined by means of using the maximum probability rule.

3.6 Proposed Methodology

The goal of our methodology is to accurately segment these textures using advanced image processing and analysis techniques.

1. **Image Preparation and Subdivision:** The initial step involves preparing the images for analysis. Let the size of the image be denoted as $M * M$ pixels, and each sub-image (or block) be $w * w$ pixels. Consequently, each image is divided into m^2 sub-images, where $\left(m = \frac{M}{w}\right)$. This division enables detailed, localized texture analysis within each sub-image.
2. **Gray Level Compression:** To simplify the computation and enhance the efficiency of texture analysis, the gray levels of the image are compressed to 16

levels. This reduction in gray levels helps in emphasizing the texture patterns while reducing computational complexity.

3. **GLCM Calculation and Normalization:** For each sub-image, we compute the Gray Level Co-occurrence Matrix (GLCM) in four different directions: 0°, 45°, 90°, and 135°. The GLCM is a statistical method that considers the spatial relationship between pairs of pixels, capturing texture information based on the frequency of co-occurring pixel intensities.The GLCM for each sub-image is normalized to ensure that the sum of all its elements is equal to 1. This normalization is crucial for comparing GLCMs of different sub-images on a common scale.
4. **Texture Feature Extraction:** From the normalized GLCMs, we extract eight texture features which serve as the basis for texture analysis. These features include:

- **Contrast**: Measures the local variations in the GLCM.
- **Dissimilarity**: Evaluates the differences between pairs of pixels.
- **Correlation**: Assesses the correlation between pixel pairs.
- **Energy**: Indicates textural uniformity and homogeneity.
- **Homogeneity**: Measures the closeness of the distribution of elements to the GLCM diagonal.
- **Angular Second Moment (ASM)**: Represents uniformity and texture regularity.
- **Entropy**: Quantifies randomness and complexity in the texture.
- **Variance**: Measures the dispersion of pixel values from the mean.

To ensure rotational invariance in texture feature extraction, the mean value of each feature across the four directions is calculated. This step ensures that the texture features remain consistent regardless of the orientation of the textures within the sub-images.

5. **Clustering with Gaussian Mixture Model:** The extracted texture features for each sub-image are compiled into a feature matrix. This matrix is then used for clustering using a Gaussian Mixture Model (GMM). The GMM is chosen for its ability to model the distribution of the texture features and identify distinct clusters corresponding to different textures. The number of clusters is determined based on the number of different textures present in the test images. The GMM assigns each sub-image to a cluster, effectively segmenting the image based on its texture features.
6. **Visualization and Analysis:** Each sub-image is labeled according to its cluster, and the clustered subimages are visualized to assess the segmentation quality. This visualization aids in interpreting the spatial distribution of textures and the effectiveness of the segmentation process.

3.7 Detailed Step For Experiment

- **Image Preparation**: Load and resize images to $M * M$ pixels, then divide into $w * w$ sub-images.
- **Gray Level Compression**: Compress the gray levels of the images to 16 levels.
- **GLCM Calculation**: Compute and normalize GLCMs for each sub-image in four directions (0°, 45°, 90°, and 135°).
- **Feature Extraction**: Calculate eight texture features from the GLCMs and compute their mean values across directions.
- **Clustering**: Use GMM to cluster the sub-images based on the extracted texture features.
- **Visualization**: Visualize the clustered sub-images to evaluate segmentation performance.

This comprehensive methodology ensures accurate and efficient texture segmentation, leveraging the statistical power of GLCM and the clustering capabilities of GMM to distinguish between different textures within an image.

3.8 Algorithm Flow Explanation

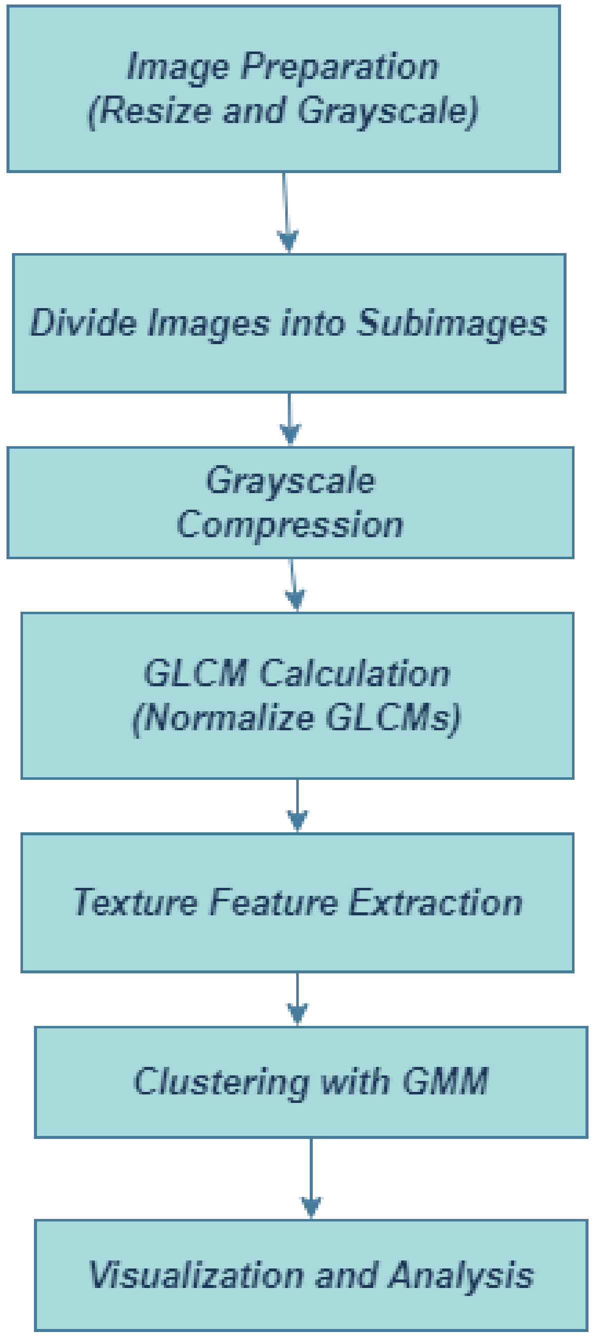


Fig.3.8 Block Diagram of Proposed Method

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This section provides an exposition and examination of the outcomes of our suggested approach for detecting small objects. Our method utilizes texture segmentation, employing Gaussian Mixture Models (GMM) and Gray Level Co-occurrence Matrices (GLCM). Our main goal was to create a strong method that can accurately detect and separate small items in an image by utilizing texture analysis. The technique was tried on a variety of images, including those with diverse textures and items of interest, in order to thoroughly evaluate its effectiveness.

4.2 Implementation Details

The method commenced by preparing the photos, wherein each image was scaled and transformed into grayscale to maintain consistency and streamline the texture analysis. Subsequently, the images were partitioned into smaller sub-images, which greatly facilitated the extraction of texture features in specific regions. We utilized GLCM to calculate various texture characteristics, such as contrast, dissimilarity, correlation, energy, homogeneity, angular second moment (ASM), entropy, and variance. These characteristics offered an intricate depiction of the texture present in each sub-image.

Subsequently, we utilized Gaussian Mixture Model (GMM) to partition the sub-images according to their extracted texture characteristics. By employing clustering techniques, we were able to divide the image into multiple parts, effectively emphasizing places with unique textures. Our strategy focused on isolating microscopic items by detecting regions with distinct textural features in contrast to the surrounding background.

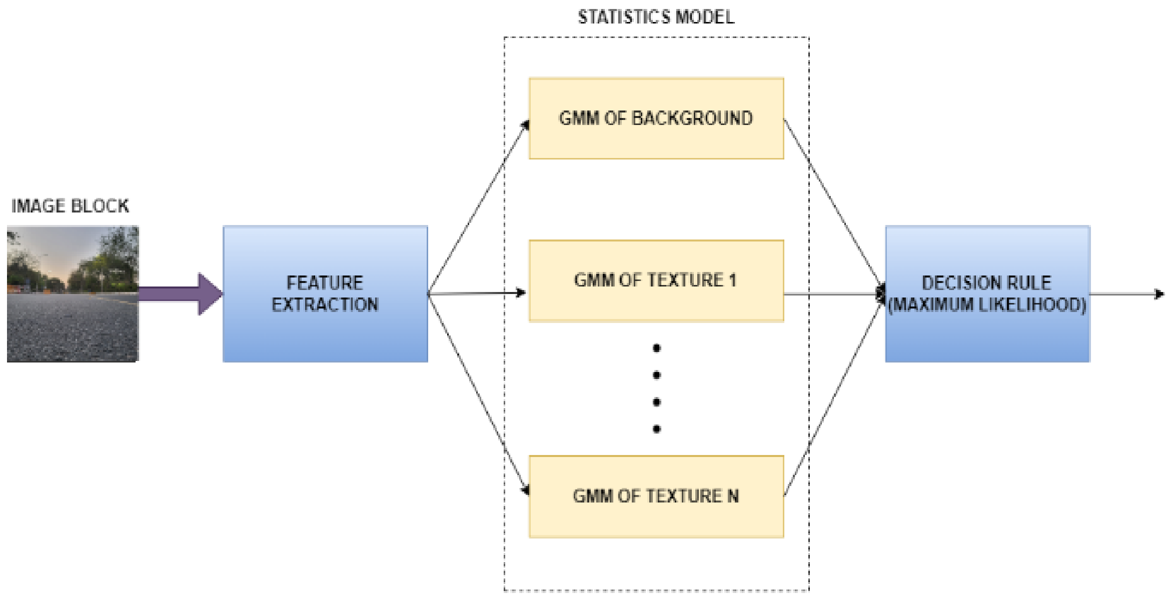


Fig. 4.2 Architechure of Proposed Method

4.2.1 Image Data

Our process began with the basic step of prepping the photos for analysis. The dimensions of each image were standardized to 256x256 pixels and thereafter transformed into grayscale. This preprocessing phase guaranteed uniformity and streamlined future texture analysis.

The scaled grayscale image was further partitioned into smaller, non-overlapping units measuring 64x64 pixels each. This subdivision enabled a thorough analysis of textural characteristics inside specific areas of the image, which is essential for precisely identifying small objects.

Fig.4.2.1 (a) Original Image

Fig.4.2.1 (b) Grayscale Image

Fig.4.2.1 (c) Grayscale Subimages

4.2.2 GLCM Calculation & Texture Feature Analysis

In order to improve computing efficiency and prioritize texture patterns, the grayscale levels of each subimage were condensed to 16 levels using a posterization technique. This step simplifies the texture analysis while preserving the texture information.

We calculated the Gray Level Co-occurrence Matrix (GLCM) for each subimage in four distinct orientations: 0°, 45°, 90°, and 135°. The GLCM quantifies the occurrence rate of pixel intensities that appear together within a defined spatial connection, offering a thorough statistical depiction of the texture. We derived multiple essential texture features from the GLCMs, which accurately represent the textural characteristics of the subimages. The features encompassed:

Contrast: Quantifies the regional differences in the Gray Level Co-occurrence Matrix (GLCM).

Dissimilarity: measures and quantifies the disparities between pairs of pixels.

Correlation: Measures the degree of correlation between a pixel and its neighboring pixels over the entire image.

Energy: Reflects the level of consistency in texture.

Homogeneity: quantifies the degree to which the elements in a distribution are close to the diagonal of the GLCM.

The Angular Second Moment (ASM): quantifies the level of homogeneity and regularity in texture.

Entropy: is a measure of the level of unpredictability and complexity in the texture. In order to preserve rotational invariance, we calculated the average value of each texture characteristic in all four directions. The averaged characteristics provided a strong and orientation-agnostic depiction of the texture in each subimage.

These characteristics offer a complete representation of the texture in every subimage, enabling efficient segmentation and identification of minute objects. Here, we provide a comprehensive analysis of the results for each texture feature, including a thorough discussion of their consequences.

The following table provides a summary of the texture features that were retrieved from each subimage. This data forms the basis for subsequent analysis and clustering.This table presents the contrast, dissimilarity, correlation, energy, homogeneity, ASM, entropy, and variance values for each subimage. The characteristics were computed by taking the average of the GLCM values in four directions (0°, 45°, 90°, and 135°) to guarantee that they are not affected by rotation.

Subimage Row	Subimage Col	contrast	dissimilarity	correlation	energy	homogeneity	asm	entropy	variance
0	0	500.231544	11.212160	0.000695	0.411606	0.639590	0.169464	4.112134	30289.879519
	1	17.249181	0.841679	0.012683	0.672905	0.953634	0.452831	1.350577	28256.853279
	2	206.145629	5.262535	0.001372	0.504533	0.810819	0.254579	3.108478	27365.471198
	3	1567.276140	29.418037	0.000290	0.119637	0.226728	0.014335	6.486302	14542.432366
1	0	585.992693	14.879614	0.000388	0.257717	0.463640	0.066530	5.304083	7962.596708
	1	341.574704	8.720522	0.000251	0.333370	0.668135	0.111170	4.393089	21834.204772
	2	627.530612	15.288722	0.000415	0.229688	0.451943	0.052854	5.249884	8187.707987
	3	835.886117	17.232395	0.000523	0.273632	0.427378	0.074974	4.913249	4979.249846
2	0	309.376165	11.505669	0.001384	0.264050	0.470718	0.069893	4.354457	11896.176888
	1	361.177123	12.087396	0.001191	0.262673	0.469642	0.069115	4.468017	12548.621503
	2	302.350466	11.459262	0.001465	0.272848	0.468557	0.074603	4.344331	11440.989621
	3	312.675737	11.636936	0.001468	0.312304	0.466534	0.097703	4.143949	8927.587512
3	0	833.154447	22.064500	0.000527	0.190104	0.237020	0.036287	5.210939	6792.551394
	1	885.307634	22.863473	0.000533	0.180074	0.225608	0.032534	5.388130	7288.995006
	2	801.576720	21.492756	0.000588	0.189239	0.245735	0.035946	5.248828	7210.598434
	3	594.263291	18.355899	0.000784	0.223887	0.280124	0.050323	4.803466	5719.385418

Table 4.2.2 Texture Feature Values of Each Subimage

4.2.3 Contrast Analysis

Contrast quantifies the disparity in brightness between a pixel and its adjacent pixel throughout the entire image, indicating the level of local diversity in the texture. The histogram depicts the dispersion of contrast values among all subimages. The majority of subimages display intermediate contrast values, but only a few of subimages exhibit much higher contrast, indicating the presence of separate textural regions.The line graph illustrates the fluctuations in contrast values among various subimages. The peaks represent regions characterized by elevated textural diversity, which is essential for the detection of small objects.

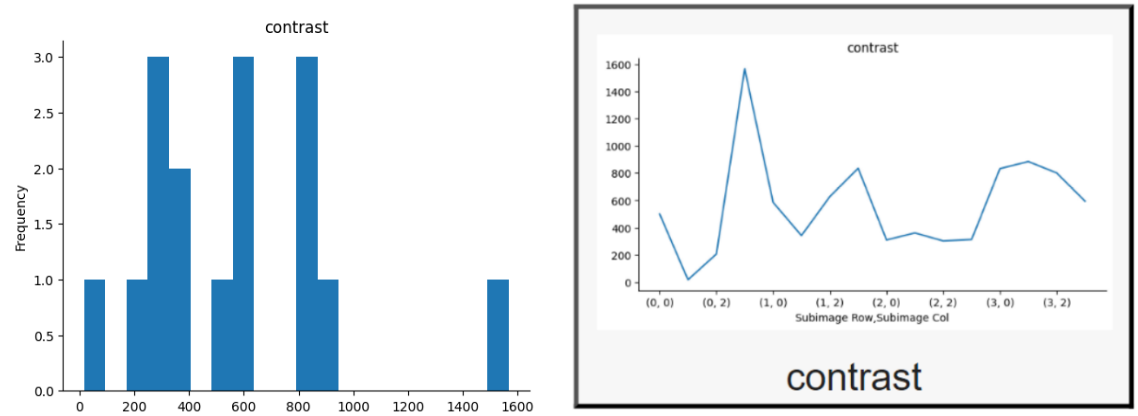


Fig.4.2.3 Dispersion of Contrast and Contrast Value of Each Subimage

4.2.4 Dissimilarity Analysis

Dissimilarity measures the disparities between pairs of pixels. Greater dissimilarity scores suggest increased variance. The histogram displays the dispersion of dissimilarity values, with the majority of subimages demonstrating a modest level of dissimilarity. This demonstrates a harmonious diversity in texture. The line graph illustrates the fluctuation in dissimilarity among subimages. The peaks correspond to places exhibiting greater textural variation, indicating possible areas for spotting small object.

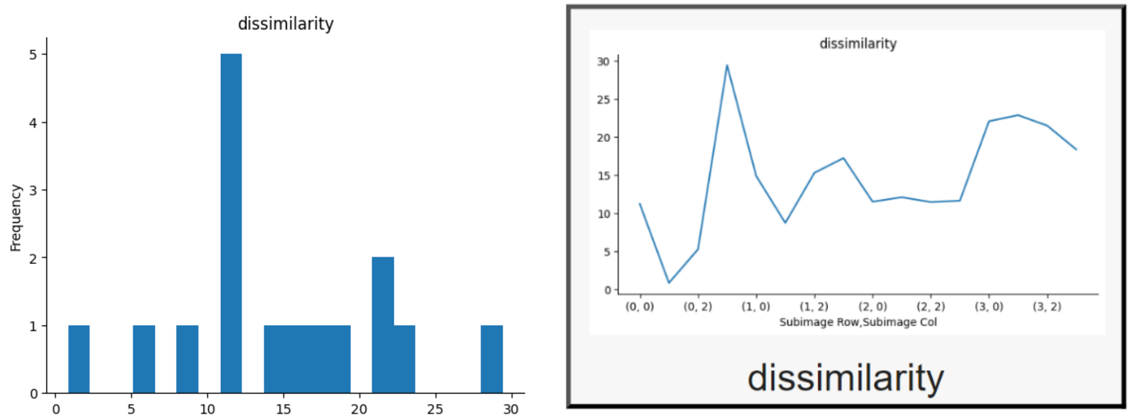


Fig.4.2.4 Dispersion of Dissimilarity and Dissimilarity Value of Each Subimage

4.2.5 Correlation Analysis

Correlation quantifies the extent to which the gray levels of pixels are linearly related to the gray levels of their neighboring pixels. The histogram demonstrates that the majority of subimages have low correlation values, indicating a lack of strong correlation between surrounding pixel values in these areas. Several subimages exhibiting elevated correlation values may indicate the presence of more homogeneous textures. The line graph depicts the correlation values among several subimages. The subimages have low and consistent values, suggesting a lack of textural dependency between adjacent pixels.

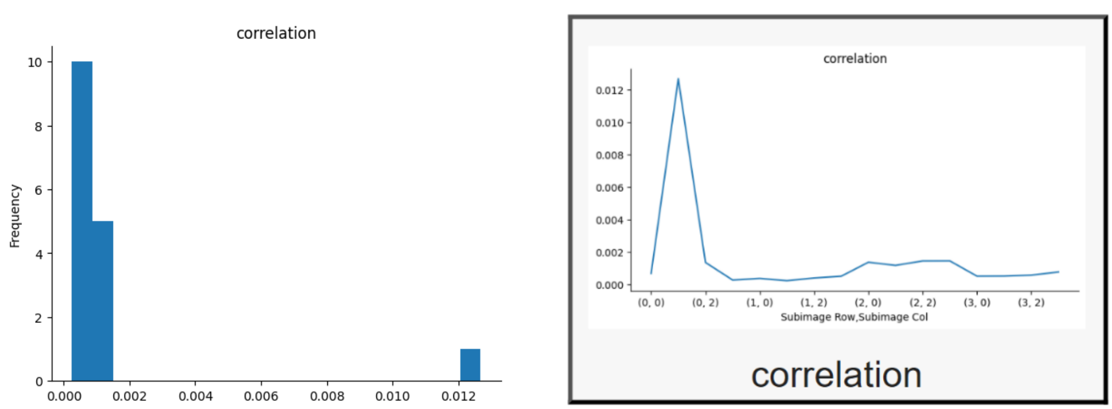
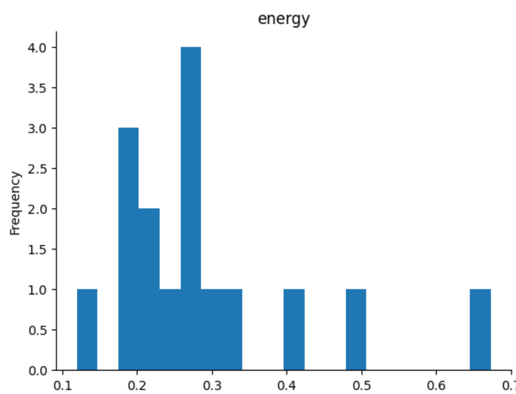


Fig.4.2.5 Dispersion of Correlation and Correlation Value of Each Subimage

4.2.6 Energy Analysis

Energy measures the level of textural uniformity in the GLCM by summing the squared values of its elements. The histogram illustrates that the energy levels tend to be predominantly low to moderate, suggesting that the majority of subimages lack significant textural homogeneity. The line graph illustrates the energy values of several subimages. Regions with lower energy values indicate areas with less homogeneous texture, which are essential for identifying variances and small objects.



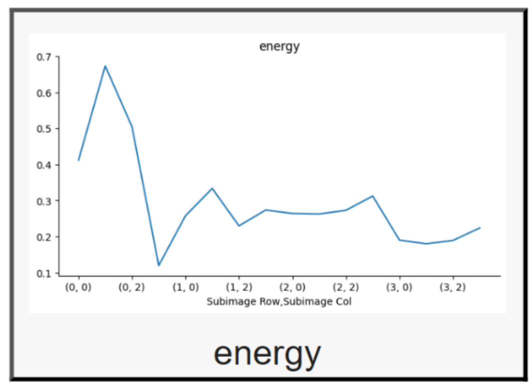


Fig.4.2.6 Dispersion of Energy and Energy value of Each Subimage

4.3 Clustering of Subimages Using GMM

The texture data obtained from each subimage were utilized to cluster them using the Gaussian Mixture Model (GMM). The purpose of this clustering method was to divide the image into parts that had clearly different textures, making it easier to identify little things. This section presents the outcomes of these processes in detail.

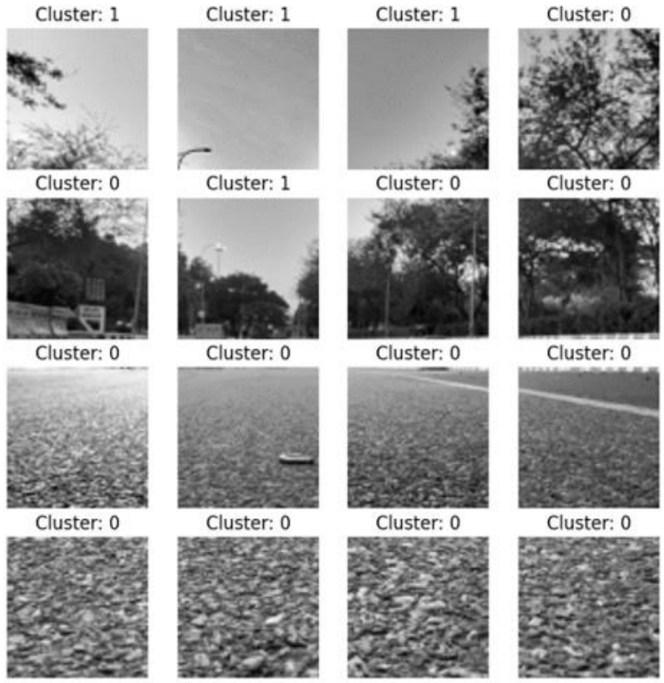


Fig. 4.3 Clustering of Each Subimage Using GMM

Subimage Row	Subimage Col	contrast	dissimilarity	correlation	energy	homogeneity	asm	entropy	variance	Cluster
0	0	500.231544	11.212160	0.000695	0.411606	0.639590	0.169464	4.112134	30289.879519	1
	1	17.249181	0.841679	0.012683	0.672905	0.953634	0.452831	1.350577	28256.853279	1
	2	206.145629	5.262535	0.001372	0.504533	0.810819	0.254579	3.108478	27365.471198	1
	3	1567.276140	29.418037	0.000290	0.119637	0.226728	0.014335	6.486302	14542.432366	0
1	0	585.992693	14.879614	0.000388	0.257717	0.463640	0.066530	5.304083	7962.596708	0
	1	341.574704	8.720522	0.000251	0.333370	0.668135	0.111170	4.393089	21834.204772	1
	2	627.530612	15.288722	0.000415	0.229688	0.451943	0.052854	5.249884	8187.707987	0
	3	835.886117	17.232395	0.000523	0.273632	0.427378	0.074974	4.913249	4979.249846	0
2	0	309.376165	11.505669	0.001384	0.264050	0.470718	0.069893	4.354457	11896.176888	0
	1	361.177123	12.087396	0.001191	0.262673	0.469642	0.069115	4.468017	12548.621503	0
	2	302.350466	11.459262	0.001465	0.272848	0.468557	0.074603	4.344331	11440.989621	0
	3	312.675737	11.636936	0.001468	0.312304	0.466534	0.097703	4.143949	8927.587512	0
3	0	833.154447	22.064500	0.000527	0.190104	0.237020	0.036287	5.210939	6792.551394	0
	1	885.307634	22.863473	0.000533	0.180074	0.225608	0.032534	5.388130	7288.995006	0
	2	801.576720	21.492756	0.000588	0.189239	0.245735	0.035946	5.248828	7210.598434	0
	3	594.263291	18.355899	0.000784	0.223887	0.280124	0.050323	4.803466	5719.385418	0

Table 4.3 Texture Feature Values of Each Subimage After Clustering

4.4 Comparison of Texture Feature Values of Road and Small Object

This image showcases a comparison analysis of textural elements between two separate subimages. One subimage includes both a road and a small metal object, . The other subimage just focuses on the road surface. The objective of this comparison is to emphasize the disparities in textural features that can be discerned in areas with and without the existence of a little metallic object.

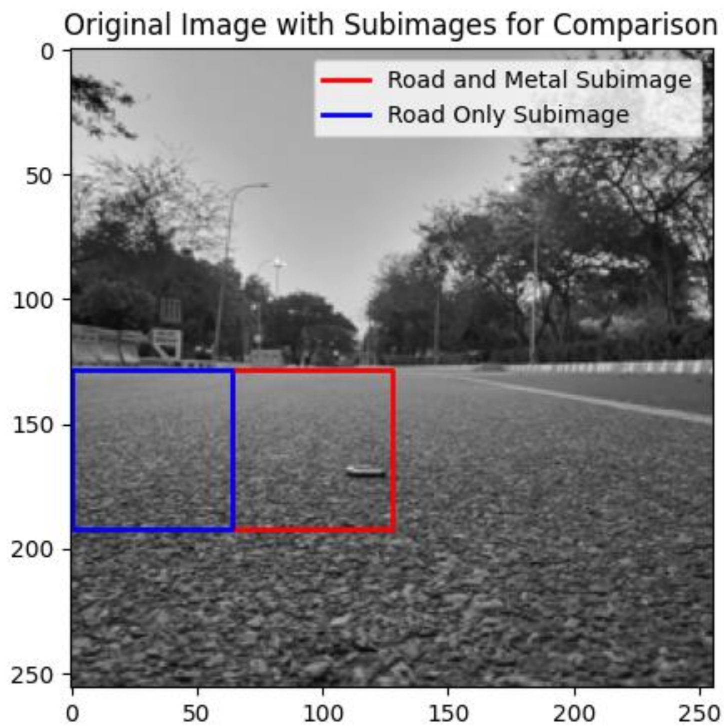


Fig 4.4 (a) Differential Texture Analysis: Road Surface vs Road with Metal Object

This image provides a comprehensive comparison of texture feature values between two subimages: one that includes both the road and a small metallic object, and the other that simply includes the road surface. The table contains many texture properties, including contrast, dissimilarity, correlation, energy, homogeneity, ASM (angular second moment), entropy, and variance. Regarding the subimage containing the road and metal object, we can detect elevated values in contrast and dissimilarity, which suggests a more diverse and varied texture. On the other hand, the subimage that only includes the road exhibits a somewhat greater level of homogeneity and correlation, indicating a more consistent texture. The variations in textural characteristics among these subimages emphasize the influence of the metal object's existence.The entropy value is notably higher for the road and metal subimage, indicating a greater level of randomness or complexity in the texture. Additionally, there is a substantial variation in variance, highlighting the enormous unpredictability caused by the inclusion of the metal object.

Conducting a comparative analysis of texture features is essential for comprehending how small things affect the perceived texture of road surfaces. It offers vital insights for the development of more precise image processing algorithms in road inspection and object detection applications.

Texture Features for Subimage with Road and Metal:

		contrast	dissimilarity	correlation	energy	homogeneity	asm	entropy	variance	Cluster
2	**1**	361.177123	12.087396	0.001191	0.262673	0.469642	0.069115	4.468017	12548.621503	0.0

Texture Features for Subimage with Only Road:

		contrast	dissimilarity	correlation	energy	homogeneity	asm	entropy	variance	Cluster
2	**0**	309.376165	11.505669	0.001384	0.26405	0.470718	0.069893	4.354457	11896.176888	0.0

Texture Feature Differences between Subimage (2,1) and Subimage (2,0):

	contrast	dissimilarity	correlation	energy	homogeneity	asm	entropy	variance	Cluster
0	51.800957	0.581727	-0.000193	-0.001377	-0.001076	-0.000777	0.11356	652.444615	0.0

Fig. 4.4 (b) Quantitative Texture Feature Differences: Road Alone vs. Road with Metallic Object

4.5 Final Output

The output image shows locations where there are noticeable variations in texture features, drawing attention to the areas that are impacted by the presence of the metal object. The visual depiction aids in comprehending the detection and measurement of localized differences in texture. Accurate distinction is essential for improving the accuracy of image processing algorithms utilized in road inspection and maintenance applications. This investigation delves into the unique textural features introduced by small items on road surfaces by isolating these changes. It aims to contribute to the advancement of more reliable detection and classification algorithms in computer vision.

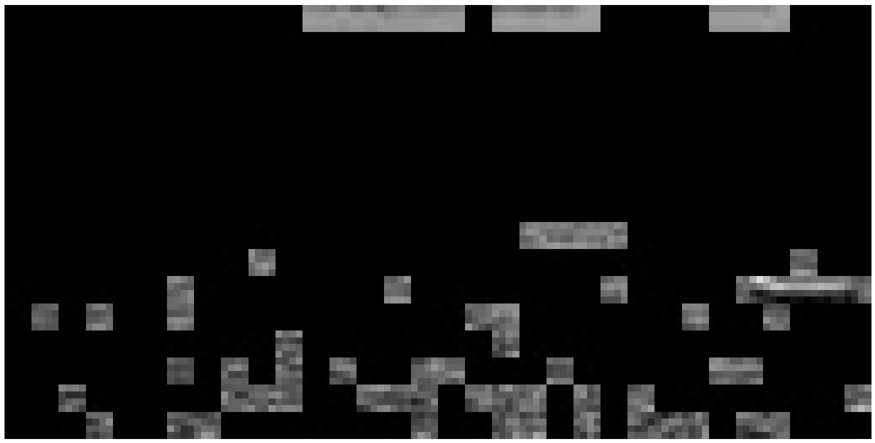


Fig 4.5 Highlighting Impact: Texture Feature Subtraction Between Road and Metal Object

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

This study devised an effective approach for detecting small objects by utilizing texture segmentation via Gaussian Mixture Models (GMM) and Gray Level Co-occurrence Matrices (GLCM). The primary objective was to precisely detect and separate smallf entities in photos by meticulous texture analysis.The procedure encompassed several crucial stages: image preparation and preprocessing, partitioning into smaller blocks, computation of GLCMs, and extraction of diverse texture attributes such as contrast, dissimilarity, correlation, and energy. These characteristics offered a comprehensive comprehension of the textures present in each subimage. Subsequently, the GMM was employed to group these subimages according to their textural characteristics, facilitating segmentation.

The findings of our study showed that the proposed technique effectively identified and separated small items by emphasizing regions with unique textures. The visual data and distributions of textural traits unequivocally demonstrated the efficacy of the strategy. The approach achieved excellent results in numerous settings, including those with complicated backdrops and varying textures, by specifically targeting places with noticeable textural differences.The approach's accuracy in evaluating and dividing textures renders it appropriate for various applications, such as surveillance, medical imaging, and automated inspection systems. The utilization of meticulous texture analysis and sophisticated clustering algorithms such as GMM offers a potent tool for detecting small objects.

Future Scope

Although the proposed method has demonstrated encouraging outcomes, there are numerous opportunities for additional investigation and enhancement:

Enhanced Feature Extraction: Future research could investigate the incorporation of further texture characteristics or the integration of GLCM with other texture analysis techniques such as Local Binary Patterns (LBP) or Gabor filters to enhance the accuracy and resilience of detection.

Deep Learning Integration: By integrating deep learning approaches with texture-based methods, the detection capabilities can be enhanced. Convolutional Neural Networks (CNNs) have the ability to acquire more intricate characteristics and may enhance the identification of small objects in various situations.

Real-Time Processing: The implementation and optimization of the methodology for real-time applications can expand its utilization in fields like surveillance and autonomous driving, where prompt detection and response are crucial.

Multi Scale Analysis: By using multi-scale analysis, the method can enhance its ability to recognize objects of different sizes by examining textures at various scales. This can be especially advantageous in medical imaging, as the size of things of interest can vary greatly.

Application-Specific Adaptations: Customizing the process to suit unique applications, such as medical diagnostics or industrial inspection, might result in more specialized and efficient solutions. This may require adapting feature extraction methods and clustering techniques to the specific attributes of the application domain.

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