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Unveiling the Quality of MSand using Artificial Intelligence

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Abstract:- Easy access to portable cameras, as in the case of mobile phones, has made it possible to acquire images and process them for different applications. This motivates us to provide a system and method to detect the quality of M-Sand using Internet of Things and Artificial Intelligence integrated Mobile applications. This paper describes a system encompassing a remote application server configured to analyze the images to identify the quality of M-Sand and envisages to provide easy detection and classification of M-Sand as well as quality approximation at ease without visiting the site. The proposed model also makes it possible to find quality of M-Sand by comparing different images obtained in the site since it has different contaminants. This research is also imperative for differentiating the sand from other variabilities of M-Sand and using the process, M- Sand can be differentiated from other types of sand, M-Sand, clay or river sand. The quality of the M-Sand can be detected and ensured using this approach and promotes the construction industry to use quality M-Sand and produces better quality concrete.

Keywords: *Manufactured M-Sand, Artificial Intelligence, Clay, Process, Quality.*

1. Introduction

The demand of Manufactured Sand (M-Sand) or Artificial Sand (A-Sand) are increasing in India and in several countries recently because of the shortage in natural River Sand (R-Sand) supply. A well-known fact is that M-Sand, as opposed to the natural river sand, is produced by a mechanical crushing of virgin rock. It is also different in shape, grading, and the stone powder (micro fines) content of the material when compared to R-Sand. The properties (e.g. workability, water demand, mechanical properties) and durability of M-Sand concrete are also different from those of R-Sand concrete [4–7].

M-Sand is ideal for concrete due to its angular, cubical shape and gritty texture. There is no moisture in M-Sand. This sand is especially beneficial for Reinforced Cement Concrete (RCC), brick, and block applications. Compared to natural sand, M-Sand has less environmental impact. The image in Fig.1 shows the visual appeal of a M-Sand. To understand the properties of M-Sand concrete, and evaluate its behavior, it is essential to get the clarification on how concrete attributes are dependent on those properties. Visually, the particle shape of M-Sand is angular while the R-Sand has a rounded shape [7],[12], the natural sand has a smoother surface than M-Sand.

In the current scenario the M-Sand is mixed with many adulterated substances to compensate for the demand for construction which in turn affects the quality of construction. In India we see many serious effects on construction projects resulting in poor construction materials used which in turn affecting lives of people and economy. Some major problems with using poor quality M -Sand include:

- Structural weakness: M-Sand can contain extra silt, soil or organic impurities, which can weaken concrete and mortar. A poor relationship between cement and set reduces structural strength.
- Reduced durability: Polluting concrete structures such as asbestos, shells or salt materials can cause a long -term decline. The amount of high silt and dust can cause cracks and reduce the life of the building.

- Problems with usability: The impure M-Sand can adversely affect the water cement ratio and cause the ability and difficulty to function poorly in the concrete mixture. Increasing demand for water and cement increases construction costs.
- Environment and health hazards: The presence of harmful chemicals and minerals can lead to health problems for construction workers. Founded sand can free up fine dust particles and cause respiratory problems.
- Poor finish and beauty problems: Using low-quality M-Sand can lead to uneven polishing and poor surface treatment. It can lead to patches, cracks and weak plaster farming.
- Legal and compliance problems: Many design standards and rules prohibit the use of unclean or non-exclusive sand. Using counterfeit materials can lead to legal disputes, fines or demolition of unsafe structures.

To address these above-mentioned issues, it is important to have a solution to check the quality of M-Sand, Hence in this paper we have used an AI model integrated with IoT and mobile APP to check the quality of M-Sand with images as input and process these images and get the quality check at am ease remotely without going to the site. The model processes the images, classifies them based on particle, colour and texture features and sends quality report remotely using mobile application. The detailed explanation is given in the next sections.

The organization of the paper is as follows: Section 1 depicts the state of the art on the M-Sand. Section 2 gives insight of the related work carried out in developing M-Sand and it sustainability. In section 3 discusses the approach used to detect the M-Sand Quality. Finally, Section 4 depicts the key findings of the work carried out on Detecting Quality M-Sand.

Fig. 1: Aesthetic appeal of an M-Sand

2. Related Works

Most M-Sand concrete has higher strength than R-Sand concrete with equal composition of paste. M-Sand may behave better than R-Sand in concrete as the shape and surface texture of the particle of sand has less significant effects on the behavior of concrete than the stone powder, clay lump content and the gradation of M-Sand [1]. Observation reveals fresh concrete properties namely compaction factor and slump measurement are comparable and reveals no substantial variation. For hardened concrete, M-Sand concrete exhibits improved performance under compressive as well as flexural loading [2].

The natural sand depletion causes the shortage of river sand closer to the job site and raise the transportation charges many folds. Hence to substitute for natural river sand R-Sand for the construction industry needs an alternative material that uses the eco-friendly machine-made Granite rock sand from vertical shaft impact crushers called manufactured sand (M-Sand) as fine aggregates. Strength properties show that the compressive strength, modules of rupture and split strength increase nearly 20% more than the conventional concrete. Concrete with manufactured sand possess superior durability performance than conventional sand concrete [3].

The Manufactured Sand (M-Sand) is obtained by crushing the stones and hence the properties may vary based on the type of rock from which it is manufactured. The ANN approach is highly applicable and reliable for the prediction of the local compression capacity of stirrups-confined concrete and work is fundamentally important for the safety of concrete structures and the exploration of new effective prediction methods [4].

The paper presents a machine learning model based on neuro-fuzzy systems to predict the compressive capacity of stirrups-confined concrete columns. It utilizes experimental datasets to tune unknown parameters and evaluate accuracy, focusing on the ratio of ultimate axial capacity to bearing area, considering column properties such as concrete compressive strength, stirrups section area, and dimensions. This framework effectively determines the compressive capacity, demonstrating the applicability of neuro-fuzzy systems in structural engineering predictions [10].

The proposed method quantifies stone powder in machine-made sand (M-Sand) using support vector regression (SVR) based on image segmentation, achieving a high correlation (0.9239) with the methylene blue value, thus enhancing quality detection for construction applications [11].

The Relative Answer Quality (RAQ) method is proposed, and the accuracies of detecting broken rice using Watershed and Threshold algorithms are about 94% and 91% respectively Thus, this approach, being automated and promising in terms of quality assessment, can alleviate the problem of time-efficient segregation which improves the food security in the rice sector [20].

This paper involves rice grains quality detection based on image processing algorithms using suitable thresholding method (OTSU thresholding method). It also employs a method to overcome the limitations of a manual assessment that determines grain borders and physical characteristics (length, breadth) by accurately measuring them [21].

3. Methodology

The main intention of designing AI and IoT integrated Mobile Application is to check the quality of M-Sand remotely. The images are taken from a mobile phone, preprocessed and Classified using Image processing approach keeping texture, color and size features of different samples. After classification the quality is predicted based on a score and the results are sent to the mobile phone. The detailed description of it is described in the sections below. Fig. 2 depicts the general Approach to Detecting Quality M-Sand.

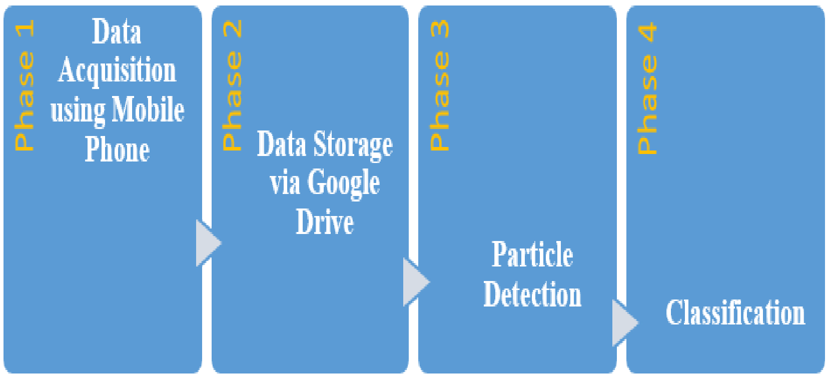

Fig 2: General Approach to Detecting Quality M-Sand

Data Acquisition using Mobile Phone

One of the key elements in collecting high-quality M-Sand images and constructing an M-Sand dataset involves utilizing the proper setup of equipment. The following are the necessary procedure needed to capture M-sand image.

A. Equipment Required:

- Smartphone (high-resolution is preferable).
- Proper lighting (natural light or ring light).

B. Prepare Different M-Sand Samples:

Different grades/types available are Superior, Moderate and Inferior M-Sand. Next is to make sure it is dry sand and doesn't clump in your hand.

Use a Consistent Hand Position: Take a handful of M-Sand in your palm. Fingers remain spread so the texture can be seen. Capture photos from different angles (bird-eye view, profile view, detail close-up)

Capture Multiple Variations: Another hand position (open palm, fingers pinching sand).Natural lighting conditions (day),Variety in sand colours and textures, Wet vs Dry M-Sand.

Data Storage: Use JPEG or PNG when saving images. Store in Google Drive.

Particle Detection:

Once the dataset is prepared images are pre-processed, and different features are extracted using a contour model. The main step of this model is explained below:

- **Colour Quantization:** To create a binary image, run KMeans cluster algorithms with 8 different clusters, apply grayscale, and then apply Otsu's threshold.
- **Remove noise and Filling:** Next, it's required to locate contours, gather each particle's (x, y) coordinate and area, and use contour area filtering to eliminate microscopic noise particles. This effectively obliterate the little particles on the binary mask by filling in these contours.
- **Masking:** Cover the original image with a mask. To emphasise the particle clusters in the original image, later bitwise filtered mask is applied.

Classification

Particles detection can be done in many different approaches such as blobs, contours, connected components. The approach explored in this paper is Contours. Using KMeans Colour Quantization, the image is divided into two groups with cluster since the particles are in white and the background is black. This will make it simple for us to tell particles apart from the background. As the particles could be quite small, it could be recommended to stay away from any morphological procedures that could change the outlines of the particles, such as dilation or blurring. The procedure followed in the paper is shown in Fig 3.

Implementation

Colour Quantization: Colour quantization is the technique of reducing the number of distinct colours in an image. This is helpful in use-cases like image compression, segmentation etc. It is necessary for presenting multicolored graphics on devices, such as IoT devices, where memory is limited and can only display a limited number of colours. Additionally, it enables effective compression of various image formats. The inside working of the colour quantization is explained below-

- Reshape of the 3D image (height × width × 3 colour channels) to a 2D array such that each row contains the RGB values of a pixel.
- Apply KMeans clustering – Divide the pixels into k=8 groups (each representing a dominant colour in the image)

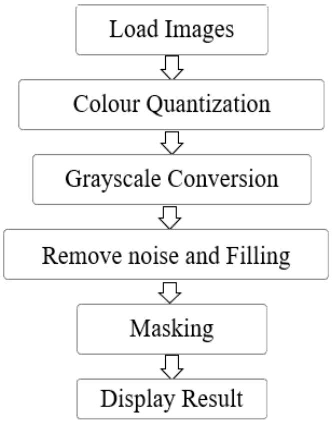

Fig 3: Overall Approach for the particle detection of the Good/Bad M-Sand.

- Assign all pixel values — Each pixel gets the colour of the closest cluster centre.
- Reshape the image back – Reshape the quantized pixel data to the original image format.
- To apply colour quantization using K-means clustering in an image and relate code is described below (Fig 4)

Step 1: Import NumPy and OpenCV, the necessary libraries.

Step 2: Use the cv2.imread() function to read two input pictures. Give the image's whole path. Resize the picture to a Mx3 array, where M is the total number of pixels in the picture. Change the datatype of the image to np.float32.

Step 3: Establish the number of clusters (K), the iteration termination criteria (criteria), and the K-means clustering method (cv2.kmeans()). To determine how initial centres are taken, pass either cv.KMEANS_PP_CENTERS or cv2.KMEANS_RANDOM_CENTERS.

Step 4: Proceed to convert back into uint8, then add centroid values to each pixel to create the final image with a certain amount of colours (K).

Step 5: Display the resulting image.

```
def KmeansColourQuantization(image, clusters=8, rounds=1):
    h, w = image.shape[:2]
    samples = np.zeros([h*w,3], dtype=np.float32)
    count = 0
    for x in range(h):
        for y in range(w):
            samples[count] = image[x][y]
            count += 1
    compactness, labels, centers = cv2.kmeans(samples, clusters,
            None, (cv2.TERM_CRITERIA_EPS
              + cv2.TERM_CRITERIA_MAX_ITER, 10000, 0.0001),
            rounds,cv2. KMEANS_RANDOM_CENTERS)
    centers = np. uint8 (centers)
    res = centers [labels. flatten ()]
return res. Reshape ((image. shape))
```

Fig 4: Code snippet for the Colour quantization

The technique analyses the histogram of the image and shown in Fig 5 Perform KMeans color segmentation, grayscale, Otsu's threshold.

```
kmeans = KmeansColourQuantization(image, clusters=2)
gray = cv2.cvtColor(kmeans, cv2.COLOR_BGR2GRAY)
thresh = cv2.threshold(gray, 0, 255,
cv2.THRESH_BINARY + cv2.THRESH_OTSU)
```

Fig 5: Code snippet for the KMeans colour segmentation

Gray Scale Conversion: The pixels in grayscale images have type equal to one intensity from 0 (black) to 255 (white). Then converting it to grayscale and threshold it with Otsu's thresholding to bring it to binary (black and white) image. Finally, results with a binary output after these steps.

Remove noise and Filling: The next step after having the binary image is:

- Find contours – Get all the connected components i.e., shapes/particle in the binary image.
- By area filter out contours – Get rid of small noise particles depending on their area.
- Fill valid contours – Fills in what you selected particles to create a more precise mask

Locate Contours

Contours are used to find the boundaries of objects in an image using OpenCV's (cv2). Now use the findContours () function to extract them and filter out the small contours as shown in the code (Fig 6). The cv2. contourArea (cnt) contour Area function to find the area of a contour. If the area is less than min_contour_area its discarded based on the assumption that it is noise. This function drawContours () draws the contours on a blank mask. Then it utilises the minEnclosingCircle () to obtain the minimum circle that bounds the detected contour exactly.

```
cnts, _ = cv2.findContours(thresh, cv2.RETR_EXTERNAL,
cv2.CHAIN_APPROX_SIMPLE) [-2:]
AREA_THRESHOLD = 2
for c in cnts:
  area = cv2.contourArea(c)
  if area < AREA_THRESHOLD:
    cv2.drawContours(thresh, [c], -1, 0, -1)
  else:
    (x, y), radius = cv2.minEnclosingCircle(c)
    points list. append((int(x), int(y)))
    size list. append(area)
```

Fig 6: Code snippet for Removing Noise

Masking: Bitwise mask is applied onto original image to extract the required region from the original image using the code below in Fig 7.

```
result = cv2.bitwise_and (original, original, mask=thresh)
```

Fig 7: Code snippet for Masking

4. Results and Discussions

The Table 1 provides a summary of essential details of the image in the aspects of the experiment carried out to analyse and visualize the image for the identification of the good quality M-Sand from the image by reducing the number of particles overall in the images and identifying the average particle size present in the image.

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It is observed that K-Means Colour Quantization reduces an image complexity preserving its visual integrity not only that, it also removes subtle textures or fine edges to simplify the colors as shown in the Second column of the Table 1. Next column the overlaying aids in recovering some finer features that may have been lost at the cost of preserving the advantages of quantization shown in the result table. Thus, the image shows the result when combining the two images, which is a hybrid of realism and abstraction.

Few of the resulting quantized images sometime showed too severe, or too blocky indication. The best option was to make use of the overlay modes that can create smoother transition and better definition of the edges.

It is also observed that once the threshold has been applied to the overlayed image the image separation becomes clearer between the foreground and background image and removing noise present in an image.

The final resultant image applying all the methods shows an image that assists in correctly detecting, segmenting, and analysing the particles, which then calculates the average particle size.

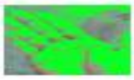
Using the powerful technology to automized the particle detection in M-Sand. Both particle size and average particle size tabulate results, help in reading the minimum and maximum range for each of the categories used in the paper.

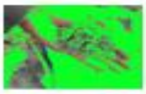
The Table 2 debits the possible range of particles present in the considered set of images by Categorizing them as Superior, Moderate and Inferior. Superior M-Sand referencing to premier quality M-Sand with better shape, particle quality and durability. In case of Moderate M-Sand referred as mid-range quality, as it is mixed with sand dust and moisture content is more along with particle distribution, Shape quality is acceptable and it's good enough for most construction work. Low grade, high is drawn through heavy and exasperating, with No moisture content which results in lower hardy and workability problems are classified as Inferior M-Sand.

Table 2: Categorizing the M-Sand based on the number of particles in the image

Sl. No.	Total Number of Particles	Classes	Features	Remarks
1	>131, <=200	Superior	Thin traces of particles and moisture	Reliable M-Sand
2	>200	Moderate	More Traces Particles mixed with dust and moisture	Reliable M-Sand
3	0 to130	Inferior	No traces of Particles or dust and moisture	Non-Reliable M-Sand

Table 1: Key Result Findings of the Experiment Conducted for detect the M-Sand Quality

Sl. No	Original Images	After Applying K Mean	Overlaying On The Original	After Applying Threshold	Resultant Image	Number Of Particle / Average particle size	Result Analysis
1						427 / 1067.33	Non-Reliable M-Sand
2						194 / 2718.32	Reliable M-Sand
3						30 / 61476.88	Plastic M-Sand

Sl. No	Original Images	After Applying K Mean	Overlaying On The Original	After Applying Threshold	Resultant Image	Number Of Particle	Average particle size	Result Analysis
4						88	20078.70	Plastic M-Sand
5						1004	1122.66	Non-Reliable M-Sand
6						502	2394.63	Non-Reliable M-Sand
7						656	1953.98	Non-Reliable M-Sand
8						147	11088.70	Reliable M-Sand

The present research aims to provide easy detection and differentiation of M-Sand as well as quality evaluation. The invention makes it possible to decide on M-Sand quality and can be identified from other types of sand, m-sand, mud, clay or sand. This innovation is crucial for differentiating the sand from other varieties of M-sand. As the most privileged and essential component of concrete due to its strong cohesive and compressive strength, it promotes the construction industry. It produces better-quality concrete because it has less contaminants. Aspects of present disclosure relate to a system and method to detect quality of M-Sand using IoT and AI integrated Mobile application. The system comprising of a remote application server connected to the mobile application, configured to analyse images to detect quality of M-Sand.

Conflicts of Interest (Mandatory)

No Conflict of interest.

Author Contributions (Mandatory)

"Conceptualization, Dr. Sridhar R and Dr.Vimuktha E Salis; methodology, Pathanjali Cho wdaiah and Sharmila Chidaravalli; software, Pathanjali Chowdaiah; validation, Sharmila Chidaravalli; formal analysis, Dr.Vimuktha E Salis; investigation, Dr. Sridhar R; resources, Dr. Sridhar R; data curation, Pathanjali Chowdaiah; writing—original draft preparation, Pathanjali Chowdaiah; writing—review and editing, Sharmila Chidaravalli; visualization, Pathanjali Chowdaiah; supervision, Dr.Vimuktha E Salis; project administration, Dr. Sridhar R; funding acquisition, self-funding"

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