

PARTICULATE MATERIAL CALCULATION AND CLASSIFICATION

Technical Field

5 The present invention relates, in general terms, to systems and methods for calculating and classifying particulate material. In particular, the present invention relates to, but is not limited to, calculating material packing porosity and using machine learning to classify particulate material.

10 Background

People deal with various granular materials existing in nature and industry, such as seeds, microorganism, nanoparticles, ores, catalyst powder, gaseous fuel, and others. These objects vary significantly in terms of the form (i.e., solid,
15 liquid, or gaseous), size, shape, colour, texture, viability, etc. In general, however, they share a similar granular morphology.

For such granular materials, an indispensable and fundamental requirement is to measure morphology related parameters, including number counting, particle
20 size measurement, particle shape measurement, and even individual particle evaluation based on colour, texture and potentially other requirements. One primitive way to do so is visual inspection by human experts in the industry. Although experts can count, measure, and evaluate, the effort needed is generally massive, thus making it expensive or even unpractical in some
25 industries. For example, to measure size distribution, mechanical sieving is adopted for solids particles like ores and sand, and laser diffraction is used for atomized fuel or small particulates. However, such methods have some main disadvantages: in addition to unknown particle shape information, it is of high cost to deploy laser diffraction instruments or low efficiency to operate
30 mechanical sieving.

Computer vision technology can afford counting and individual particle

assessment. Conventionally, granular materials are scattered and an image of the material is analysed to acquire particle parameters. However, this method requires particles to be well separated before scanning, otherwise overlapping and connecting particles are incorrectly recognized as a single individual
5 particle. Therefore, human interference is needed either to ensure particle isolation beforehand or to manually segment connecting particles in images afterwards.

Particle testing is one fundamental operation used in the abovementioned
10 industries. Take particle size distribution (PSD) for example, PSD is acquired by conducting professional methodology and sophisticated instruments. However, current methods are generally time-consuming, laborious, somewhat polluting, and expensive.

15 It would be desirable to provide a faster, more cost effective and less laborious solution, or at least to provide a useful alternative.

Summary

20 Proposed herein are methodologies for conducting particle analysis based on particle images using a machine learning algorithm. Through the workflows, the PSD can be obtained as well as other indices such as packing sample porosity, quantitative abnormality index, and particle classification.

25 To test the methodologies, sand particles were analysed. The methodologies herein conducted rapid, massive, and accurate particle mask labelling, with zero manual effort. The established particle training set can drive the current algorithm to segment contacting, overlapping, or even densely packed sand particles. Lastly, an analysis using particle size distribution (PSD) comparison
30 was conducted to quantitatively validate the segmentation process. This methodology can be transferred to other sand-like granular materials such as rice, diatoms in water, nanoparticles, coal, chemical catalyst, and atomised fuel,

to achieve fully autonomous granular matter characterizations.

Disclosed is a system for calculating particulate material packing porosity, comprising:

- 5 a receiver;
- a machine learning module;
- memory; and
- at least one processor, the memory storing instructions that, when executed by the at least one processor, cause the at least one processor to:
- 10 receive, at the receiver, data comprising particulate material dimensions, images of particulate material and packing density;
- apply at least one machine learning model, of the machine learning module, to the data to learn:
 - a distribution of particulate material dimensions against
 - 15 packing porosity; and
 - image features corresponding to each said predetermined quality measure, at least one said predetermined quality measure comprising a purity of the particulate material;
 - detect dimensions of a new particulate material from an image of
 - 20 the new particulate material; and
 - determine packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material,
- wherein the at least one processor detects dimensions of a new particulate
- 25 material by:
 - applying segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**);
 - measuring dimensions of the segmented image particles;
 - apply a said machine learning model to the image of the new particulate
 - 30 material to identify the predetermined quality measures of the new particulate material; and

classify the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

- 5 The data may be one or more images of particulate material, the at least one processor being configured to synthesise additional images to which the machine learning model is applied, by at least one of:
- changing a background of the one or more images;
 - inserting individual particles over other individual particles; and
 - 10 inserting individual particles in contact with other individual particles in the one or more images.

The at least one processor may detect dimensions of a new particulate material by determining particle dimension parameters comprising one or more of an
15 accumulated particle area, particle length and particle width of the segmented image particles. The at least one processor may detect dimensions of a new particulate material by detecting a particle size distribution from the particle dimension parameters.

- 20 Executing the instructions may further cause the at least one processor to determine a moisture content of the new particulate material, wherein the processor is caused to determine packing porosity of the new particulate material by applying the moisture content and the distribution to the dimensions of the new particulate material.

25 The data may comprise images of particulate material other than the new particulate material.

- The at least one processor may further be caused to:
- 30 apply segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**); and measure dimensions of the segmented image particles.

The at least one processor may apply segmentation by applying a masked region based convolutional neural network (MaskRCNN).

- 5 The at least one processor may measure dimensions of the segmented image particles with reference to dimensions of a background feature in the image of the new particulate material.

The system may further comprise:

- 10 calculating a difference between the new particulate material classification and a desired particulate material classification; and
mixing the new particulate material with one or more other particulate materials each having a predetermined classification, to reduce the difference.

- 15 Also disclosed is a system for classifying particulate material, comprising:
a receiver;
a machine learning module;
memory; and

- at least one processor, the memory storing instructions that, when
20 executed by the at least one processor, cause the at least one processor to:
receive, at the receiver, data comprising images of particulate material dimensions and packing density;

- apply one or more machine learning models, of the machine learning module, to the data to learn:

- 25 a distribution of particulate material dimensions against packing porosity; and

- image features corresponding to each predetermined quality measure of a plurality of predetermined quality measures, at least one said predetermined quality measure comprising a purity of the particulate
30 material;

detect dimensions of a new particulate material from an image of the new particulate material;

- determine packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material;
- apply at least one said machine learning model to an image of a new particulate material to identify the predetermined quality measures of the new
- 5 particulate material; and
- classify the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.
- 10 Also disclosed is a method for calculating particulate material packing porosity, comprising:
- receiving, at a receiver, data comprising particulate material dimensions and packing density;
- applying a machine learning model, of a machine learning module, to the
- 15 data to learn a distribution of particulate material dimensions against packing porosity;
- detecting dimensions of a new particulate material from an image of the new particulate material; and
- determining packing porosity of the new particulate material by applying
- 20 the distribution to the dimensions of the new particulate material.

- Detecting dimensions of a new particulate material may comprise:
- applying segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**); and
- 25 measuring dimensions of the segmented image particles.

- Detecting dimensions of a new particulate material may comprise determining particle dimension parameters comprising one or more of an accumulated particle area, particle length and particle width of the segmented image
- 30 particles. Detecting dimensions of a new particulate material may comprise detecting a particle size distribution from the particle dimension parameters.

The method may further comprise determining a moisture content of the new particulate material, and determining packing porosity of the new particulate material comprises applying the moisture content and the distribution to the dimensions of the new particulate material.

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Also disclosed is a method for classifying particulate material based on a plurality of predetermined quality measures, comprising:

receiving, at a receiver, data comprising images of particulate material;

applying a machine learning model, of a machine learning module, to the

10 data to learn image features corresponding to each said predetermined quality measure, at least one said predetermined quality measure comprising a purity of the particulate material;

applying the machine learning model to an image of a new particulate material to identify the predetermined quality measures of the new particulate

15 material; and

classifying the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

20 The data may comprise images of particulate material other than the new particulate material.

The method may further comprise applying segmentation to the image of the new particulate material, to identify individual particles in the image
25 (**segmented image particles**), and measuring dimensions of the segmented image particles.

Measuring dimensions of the segmented image particles may be performed with reference to dimensions of a background feature in the image of the new
30 particulate material.

The method may further comprise calculating a difference between the new particulate material classification and a desired particulate material classification and mixing the new particulate material with one or more other particulate materials each having a predetermined classification, to reduce the
5 difference.

Also disclosed is a method for classifying particulate material, comprising:

- receiving, at a receiver, data comprising images of particulate material dimensions and packing density;
- 10 applying one or more machine learning models, of a machine learning module, to the data to learn:
 - a distribution of particulate material dimensions against packing porosity; and
 - image features corresponding to each predetermined quality
 - 15 measure of a plurality of predetermined quality measures, at least one said predetermined quality measure comprising a purity of the particulate material;
 - detecting dimensions of a new particulate material from an image of the new particulate material;
 - 20 determining packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material;
 - applying at least one said machine learning model to an image of a new particulate material to identify the predetermined quality measures of the new particulate material; and
 - 25 classifying the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

Advantageously, the use of images taken by a phone or flatbed scanner enables
30 the machine learning model or algorithm to classify particulate material. This reduces cost and time when compared with traditional methods.

Advantageously, embodiments of the invention can predict bulk density based on particle analyses. This improves quality control in production lines and the like.

5 **Brief description of the drawings**

Embodiments of the present invention will now be described, by way of non-limiting example, with reference to the drawings in which:

10 Figure 1a is a schematic diagram showing components of an exemplary computer system for performing the methods described herein;

Figure 1b shows sand particles of varying coarseness;

15 Figure 2a illustrates a workflow for particle quality analysis;

Figure 2b is a 3-dimensional (3D) image of a sand particle;

Figure 2c is a 2-dimensional (2D) image of the sand particle of Figure 2b;

20

Figure 2d shows the Feret diameter calculation;

Figure 3 is a schematic of an algorithm (Mask region based convolutional neural network (R-CNN)) used for particle segmentation, being step 202 in Figure 2a;

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Figure 4 illustrates the particle Feret diameter, being step 204 in Figure 2a;

Figure 5 is a workflow of porosity prediction, being step 208 in Figure 2a;

30 Figure 6 shows input features chosen from a particle size (length/width) distribution curve;

Figure 7 illustrates a workflow of particle outline labelling;

Figure 8 illustrates labelled granule outlines on various forms of an image;

- 5 Figure 9 shows assessment criteria for the quality of rice, and rice spread over a sheet or background; and

Figure 10 is a photograph of grains in which boundaries of grains, including contacting grains, are identified using the present methods.

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Detailed description

This systems and methods described herein employ a workflow to conduct granular material testing using images of the material. Various embodiments of
15 the systems and methods perform particle segmentation, particle shape parameter extraction, density/porosity prediction, particle classification, and classification index calculation, such as the system 100 shown in Figure 1a that can be applied to analyse particles such as sand particles shown in Figure 1b.

- 20 Figure 1a is a block diagram showing an exemplary computer device 100, in which embodiments of the invention may be practiced. The computer device 100 may be a mobile computer device such as a smart phone, a wearable device, a palm-top computer, and multimedia Internet enabled cellular telephones, an on-board computing system or any other computing system, a
25 mobile device such as an iPhone™ manufactured by Apple™, Inc or one manufactured by LG™, HTC™ and Samsung™, for example, or other device.

As shown, the mobile computer device 100 includes the following components in electronic communication via a bus 106:

- 30 (a) a display 102;
(b) non-volatile (non-transitory) memory 104;
(c) random access memory ("RAM") 108;

- (d) N processing components 110;
- (e) a receiver or, presently, transceiver component 112 that includes N transceivers;
- (f) user controls 114; and
- 5 (g) a machine learning module.

Although the components depicted in Figure 1a represent physical components, Figure 1a is not intended to be a hardware diagram. Thus, many of the components depicted in Figure 1a may be realized by common constructs or
10 distributed among additional physical components. Moreover, it is certainly contemplated that other existing and yet-to-be developed physical components and architectures may be utilized to implement the functional components described with reference to Figure 1a.

- 15 The display 102 generally operates to provide a presentation of content to a user, and may be realized by any of a variety of displays (e.g., CRT, LCD, HDMI, micro-projector and OLED displays).

In general, the non-volatile data storage 104 (also referred to as non-volatile
20 memory) functions to store (e.g., persistently store) data and executable code. The system architecture may be implemented in memory 104, or by instructions stored in memory 104.

In some embodiments for example, the non-volatile memory 104 includes
25 bootloader code, modem software, operating system code, file system code, and code to facilitate the implementation components, well known to those of ordinary skill in the art, which are not depicted nor described for simplicity.

In many implementations, the non-volatile memory 104 is realized by flash
30 memory (e.g., NAND or ONENAND memory), but it is certainly contemplated that other memory types may be utilized as well. Although it may be possible to execute the code from the non-volatile memory 104, the executable code in

the non-volatile memory 104 is typically loaded into RAM 108 and executed by one or more of the N processing components 110.

5 The N processing components 110 in connection with RAM 108 generally operate to execute the instructions stored in non-volatile memory 104. As one of ordinary skill in the art will appreciate, the N processing components 110 may include a video processor, modem processor, DSP, graphics processing unit (GPU), and other processing components.

10 The transceiver component 112 includes N transceiver chains, which may be used for communicating with external devices via wireless networks. Each of the N transceiver chains may represent a transceiver associated with a particular communication scheme. For example, each transceiver may correspond to protocols that are specific to local area networks, cellular
15 networks (e.g., a CDMA network, a GPRS network, a UMTS networks), and other types of communication networks.

Image analysis largely relays on the acquisition of sample pictures with satisfying quality regardless the absolute particle features (i.e., size, colour,
20 texture, etc). The sand shown in Figure 2a comprises particles within a size range from 0.1 mm to 4.2 mm. Other sizes and materials may be used. The images may be captured by camera 116 or may be acquired from another source.

25 The system 100 of Figure 1a also includes a machine learning module for performing the methods described herein and an image capture device, presently camera 116. The camera 116 captures one or more images of granular (i.e. particulate) material that is then processed by the machine learning model of the machine learning module, under control of the one or more processing
30 components or processors 110.

It should be recognized that Figure 1a is merely exemplary and in one or more

- exemplary embodiments, the functions described herein may be implemented in hardware, software, firmware, or any combination thereof. If implemented in software, the functions may be stored on or transmitted over as one or more instructions or code encoded on a non-transitory computer-readable medium
- 5 104. Non-transitory computer-readable medium 104 includes both computer storage medium and communication medium including any medium that facilitates transfer of a computer program from one place to another. A storage medium may be any available medium that can be accessed by a computer.
- 10 Broadly, the system 100 receives, at the receiver 112, data comprising particulate material dimensions and packing density. That data may be extracted from remote storage, may be in the form of an image or images of the particulate material, and so on. The machine learning model is then applied to the data to learn a distribution of particulate material dimensions against
- 15 packing porosity. After training/learning, a new image is received of a new particulate material and the system can detect dimensions of that material and determine packing porosity of the new particulate material by applying the learned distribution to the dimensions of the new particulate material.
- 20 A more specific set of steps in performing methods according to the present teachings is shown in Figure 2a. At step 202, an image is received. At step 204, the image is processed to enable individual particles to be identified. Step 206 then detects dimensions of the particulate material – e.g. rice in this instance – based on the image processed according to step 204 – e.g. using segmentation.
- 25 Processing the image per step 204 may involve applying segmentation to the image of the new particulate material, performing edge detection and other methods. This processing step identifies individual particles in the image (segmented image particles). In segmentation tasks, a Mask R-CNN can be used
- 30 to do the particle segmentation.

Mask R-CNN is able to conduct pixel-level segmentation of the objects (particles). Mask R-CNN contains a series of submodules, including backbone network, Region Proposal Network (RPN), RoIAlign layer, a Fully convolutional networks (FCN) branch, and a network head for bounding-box recognition (classification and regression), as shown in Figure 3. The present Mask R-CNN architecture extracts feature maps – e.g. from a partial (windowed) or full image. In particles, Mask R-CNN uses ResNet-101-FPN as the backbone for feature map extraction from the whole image, and adopts a Region Proposal Network to propose an anchor box efficiently. Anchor boxes are a set of predefined bounding boxes of a certain height and width. These boxes are defined to capture the scale and aspect ratio of specific object classes you want to detect. The anchor box dimensions may be user defined or automatically determined by reference to the scale of particles in the material that can be individually identified. Mask-RCNN also preserved the spatial correspondence between the image and mask. It may, for example, use the RoIAlign to achieve this, thus enabling precise mask prediction at the pixel-level. Finally, the aligned feature maps of each Region of Interest (RoI) feeds two branches: one is a network for classification and bounding box regression, and the other (e.g. a Fully Convolutional Network (FCN)) is for predicting the segmentation mask. The loss function of the framework combines the loss of classification, bounding box regression, and segmentation mask, as expressed in Equations (1) and (2).

$$L = L_{cls} + L_{box} + L_{mask} \quad (1)$$

$$L_{mask} = \text{Sigmoid}(\text{mask}_k) \quad (2)$$

where L_{cls} is the loss of classification, L_{box} is the loss of bounding box regression, and L_{mask} is the loss of k^{th} mask. L_{mask} is defined as the average binary cross-entropy on the k^{th} mask and is computed by per-pixel sigmoid on mask_k .

The mask may be region based, such that particles (e.g. grains) are identified as regions of the image, such as regions of a colour or shading dissimilar to that of a background colour or shading. These particles can then be measured to determine dimensions. Measurement can be made with reference to the
 5 dimensions of a background feature in the image of the new particulate material, as reflected in Figure 9 in which a background 900 of known dimensions is used as a frame of reference for determining size.

The dimensions include one or more particle dimension parameters each being
 10 an accumulated particle area, particle length and particle width of the segmented image particles or other dimension. Particle parameters (such as width and length) are thus obtained based on the segmented particle outlines, as shown in Figure 4. $(\bar{x}, \bar{y})$ is the particle centre. The centre is detected by average all the particle boundary coordinates. For length and width, the
 15 projection of the particle in the direction of $\vec{n}$ is $(\text{Max}\{[(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n}\} - \text{min}\{[(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n}\})$. The particle length and width are the maximum and minimum length of the particle projections in all directions. In particular, when the particles images are prepared using a scanner, sand particles dive onto the scanner plate and bounce a few times before resting. Therefore, particles tend
 20 to rest on the plate at the most stable state. In contrast to mechanical sieving, which can only size particles if L_{inter} (see Figure 2b) is below the dimensions of the sieve, this means the 2-dimensional projection of a 3-dimensional particle captured by the scanner in the present case should contain the maximum length, L_{max} , and intermediate length, L_{inter} , as shown in Figure 2c, where the
 25 intermediate length, L_{inter} , corresponds to the sieve size for mechanical sieving. Therefore, when comparing with the mechanical sieving results, the intermediate length, L_{inter} (being which the minimum Fret diameter of the 2D projection) is used as the particle size. Based on the instance segmentation, the coordinates of the particle outline (in Figure 2d) can be obtained and the
 30 minimum and maximum Fret diameters can be calculated using Equations (3) and (4), respectively. In the calculation of the particle volume, an assumption

can be made that the particle shape can be approximated to be prolate spheroid, thus the volume of each particle can be acquired according to Equation (5).

$$L_{inter} = \min \left(\max \{ [(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n} \} - \min \{ [(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n} \} \right) \quad (3)$$

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$$L_{max} = \max \left(\max \{ [(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n} \} - \min \{ [(x^i, y^i) - (\bar{x}, \bar{y})] \cdot \vec{n} \} \right) \quad (4)$$

$$V = \pi L_{max} L_{inter}^2 / 6 \quad (5)$$

10 where V is the particle volume, L_{max} is the particle maximum length, L_{inter} is the particle intermediate length, (x^i, y^i) is any point coordinate on the particle outline, $(\bar{x}, \bar{y})$ is the particle center by averaging all the point coordinate on particle outline and $\vec{n}$ is a unit vector going through all direction in the plane.

15

Data labelling is an essential step in a supervised machine learning task, and the quality of the training data determines the performance of the trained model. Thus, the masking step can be highly useful in reducing the feature space of an image to only those features applicable to particles. Images can be
20 labelled using conventional techniques known to the skilled person

Per step 208, the processor 110 can then detect dimensions of a new particulate material by detecting a particle size distribution from the particle dimension parameters. The particle size distributions are based on particle length/width
25 obtained based on the statistical relationship between the accumulated particle area and particle length/width.

Per step 210, the porosity or bulk density of the granular materials sample can be obtained thereafter based on the particle size distribution and particle shape
30 given fixed package manner.

When applied to a new image of particulate material, steps 202 to 210 follow the general concept set out in Figure 5, of inputting or receiving an image (500), determining a particle size distribution (502), applying the now trained/learned machine learning model (504) to form a prediction (508). The average particle
 5 size distribution may be used to inform the machine learning model. The machine learning model may apply multivariate linear regression or another technique to form the prediction.

Along with the testing of the particle size distribution, the packing porosity can
 10 be determined with the algorithm of Figure 2a. To achieve this, particle size (length and width) refers to the size in a PSD plot corresponding to individual percentage interval, as shown in Figure 6. To obtain the PSD, the system may also count the number of grains in or below each percentage interval – see Figure 6. The size distribution is encoded into a column matrix per Equation (6):

15

$$x^{(i)} = \begin{bmatrix} 1 \\ x_1^{(i)} \\ x_2^{(i)} \\ \vdots \\ x_n^{(i)} \end{bmatrix} p^{(i)} = \text{bulk density (or porosity)} \quad (6)$$

The parameters of Equation (3) are inputting into a machine learning model of the machine learning module 122, an example of which is embodied by Equation
 20 (7):

$$P_p = \theta_0 + \theta_1 x_1 + \cdots + \theta_i x_i + \cdots + \theta_n x_n \quad (7)$$

Once θ_i is trained to a predetermined degree of accuracy, the machine learning
 25 model can be used to detect porosity of other particulate materials.

Based on the size of a known particulate material, the processor 110 may also be able to infer moisture content. For example, larger than usual grain size or average grain size may indicate greater moisture absorption by the grains. This

- is particularly the case if a sample of the same grains is measured at two different time points. A similar inference may be made if the grains are matted in appearance where they are typically shiny in appearance and vice versa, or using other appearance features of the grains. Moisture content can affect the amount to which grains stick to each other and to packing material. Therefore, packing porosity of a particulate material may be determined by applying the moisture content and the particle size distribution to the dimensions of the new particulate material.
- 10 The system 100 may also be used for classifying particulate material based on a plurality of predetermined quality measures. To do this, a machine learning model, of the machine learning module 122, is applied to data (images of particulate material) to learn image features corresponding to each predetermined quality measure. The trained machine learning model can then be applied to an image of a new particulate material to identify the predetermined quality measures of the new particulate material. Based on how the new particulate material performs against the quality measures, the new particulate material can be classified into a new particulate material classification. At least one of the predetermined quality measures will be a purity of the particulate material as discussed below.

Classification can be done in parallel to steps 206 to 210, since both rely on receiving and processing images per steps 202 and 204. After processing per step 204, image or surface features are extracted per step 212. The image or surface features may be colour, texture and others. The particles are then inputted into a convolutional neural network (CNN) per step 214, to recognize the particle classification based the particle surface. The CCN may also perform both steps 212 and 214, and may perform those steps either sequentially or concurrently. In this way, particle analysis based on its shape, texture, colour can be performed by processing the particle image.

An index indicating the quality of the particulate material can then be calculated respectively applied per step 216, to classify the particulate material.

With regard to machine learning in the specific area of testing granular materials, a method 700 for automatically labelling material outlines is depicted in Figure 7. Initially, a background sheet is prepared on which the particulate material is deposited for testing. The background sheet will typically have high colour contrast with the tested material that is then scattered across the sheet. For example, sand particles often have a relatively light colour and thus a dark background may be used. Using high contrast also helps to define the threshold for binarization. The material is then scanned (i.e. one or more images of the material are captured) to produce input image 700. The image may be captured in greyscale, or converted from a colour or other image format to greyscale. A threshold value is selected to define the boundary of materials and background, as reflected in image 702. When testing with sand particles, the threshold value was 0.18 with a black background. The value may be selected automatically or by user selection. The digital image is then binarized (704) and the connected area is detected (706). The threshold value should be carefully chosen so that the particle regions and their masks are precisely overlapped. The precise overlapping may need visual checking on the first occasion.

The connected areas are regions of the image that are considered to form a single grain or particle of material. Areas that are outside a material size range are assumed to be erroneous and are filtered out (708) and a material mask is then outputted (710). The mask is then used to label the original image. Such dataset established can be massively increased by changing different background sheet as shown in Figure 8. This increases the training data for Mask R-CNN. Thus, after receiving data at the receiver per step 202, and segmenting per step 204, the method can include developing a training data set by changing a background of each image received at step 202. In addition, developing a training data set can include cutting out individual particles from the original image(s) and synthesising additional images by overlapping individual particles

over other particles or contacting particles with other particles, to develop images comprising overlapping and contacting particles. Thus, the images received at step 202 may be captured of non-overlapping particles, to enable individual particle detection, with overlaps and contacts being synthesised
5 thereafter. This enables segmentation, which may employ a machine learning algorithm, to train to identify individual particles and be refined to identify contacting and overlapping particles. If producing labelled data, only the front particle of an overlapping pair may be labelled, since the partially obscured particle has incomplete dimension data. The segmentation process can then
10 learn to define a boundary for the front particle, and to learn overlapping and contacting particles features. This may also include ignoring the rear particles. By ignoring the rear particles, more accurate size information can be acquired for the particles. This enables far more accurate particle size distribution to be determined – Figure 10 shows a large number of particles (grains of rice) in
15 which the boundary for each non-overlapping grain, and each contacting grain, has been identified. Notably, non-overlapping may also include rear particles/grains where the length and width are still discernible or that the overlap is otherwise not so significant that a reasonable assessment of the size of the rear grain/particle cannot be made (e.g. 5% of the particle surface or any
20 other desired measure). Thus, the PSD will be calculated based on the size of each grain/particle for which the boundary is fully visible in the image, and the number of grains of that size. As set out above, in the PSD plot (see, e.g. Figure 6), the number or proportion of grains/particles below each size (underpass) can be determined from the count and dimensions extracted from the image.

25 In some instances, multiple batches of particulate material will be assessed. Some of these batches will be below a particular quality level or classification, whereas others will exceed that level or classification. In this instance, particulate materials of the same type but different qualities can be blended to
30 form a bespoke or new product of a specific quality level. To achieve this, the system 100 may calculate a difference between them classification of a particulate material and a desired particulate material classification, and mix

the particulate material with one or more other particulate materials each having a predetermined classification, to reduce that difference.

The system 100 may also combine the above methods of detecting packing porosity and quality. For example, a machine learning model of the machine learning module 122 may learn a distribution of particulate material dimensions against packing porosity and image features corresponding to each predetermined quality measure of a plurality of predetermined quality measures, at least one of the quality measures being the purity of the particulate material. Purity may be the number of particles/grains that have particular visual features that distinguish the type of particles/grains from other particles/grains – e.g. distinguishing long grain rice from short grain rice by grain length, or sand from gravel by colour. The system 100 then detects dimensions of a new particulate material from an image of the new particulate material, and determines packing porosity of the new particulate material by applying the distribution of particulate material dimensions to the dimensions of the new particulate material. The system 100 can then apply another machine learning model of the machine learning module 122 to an image of a new particulate material to identify the predetermined quality measures of the new particulate material, and then classify the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

The above methods can be applied to a wide variety of particulate materials, such as grains. Rice quality is a big concern for rice traders, and it is generally assessed based on a variety of parameters, such as moisture content, broken, abnormal colours, as shown in Figure 9. Parameters based on physical appearance are traditionally checked by manual inspection. This is time consuming. The present methods provide particle classification from a picture of the grain. By processing the image using algorithm such as Mask R-CNN, the boundary of each particle can be recognized. Afterwards, by using a CNN network, the classification for the rice particle can be acquired with a well-

trained model. This service can be provided through a phone APP, dramatically reducing cost over existing services.

This technology can be applied to do granular material testing in several areas.
5 For example, particle analysis may be performed based on a projected 2-dimensional shape such as particle size distribution, statistical distribution of particles based on width and length, etc. Such analyses relating to particle shape can be widely adopted for soil analysis in building and construction area and mineral analysis in mining industry. The present system and the methods it
10 performs can also be used to do particle analysis based on particle colour and texture of the particle surface, which relates particle quality in some industries, such as grain, seed, nuts, ingredient, and so on.

There are many industries dealing with granular materials, such as grains in
15 agriculture industry, ingredients in food industry, soil in building and construction industries, minerals in the mining industry, and so on. Nowadays, good quality images can be acquired using devices with built-in cameras or scanners. With the image acquisition devices and available computation recourse, granular material analysis can be conducted more efficiently using
20 images in contrast to the traditional methods.

It will be appreciated that many further modifications and permutations of various aspects of the described embodiments are possible. Accordingly, the described aspects are intended to embrace all such alterations, modifications,
25 and variations that fall within the spirit and scope of the appended claims.

Throughout this specification and the claims which follow, unless the context requires otherwise, the word "comprise", and variations such as "comprises" and "comprising", will be understood to imply the inclusion of a stated integer
30 or step or group of integers or steps but not the exclusion of any other integer or step or group of integers or steps.

The reference in this specification to any prior publication (or information derived from it), or to any matter which is known, is not, and should not be taken as an acknowledgment or admission or any form of suggestion that that prior publication (or information derived from it) or known matter forms part of
5 the common general knowledge in the field of endeavour to which this specification relates.

Claims

1. A system for calculating particulate material packing porosity, comprising:
- 5 a receiver;
- a machine learning module;
- memory; and
- at least one processor, the memory storing instructions that, when executed by the at least one processor, cause the at least one processor
- 10 to:
- receive, at the receiver, data comprising particulate material dimensions, images of particulate material and packing density;
- apply at least one machine learning model, of the machine learning module, to the data to learn:
- 15 a distribution of particulate material dimensions against packing porosity; and
- image features corresponding to each said predetermined quality measure, at least one said predetermined quality measure comprising a purity of the
- 20 particulate material;
- detect dimensions of a new particulate material from an image of the new particulate material; and
- determine packing porosity of the new particulate material by applying the distribution to the dimensions of the new
- 25 particulate material,
- wherein the at least one processor detects dimensions of a new particulate material by:
- applying segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image**
- 30 **particles**);
- measuring dimensions of the segmented image particles;

apply a said machine learning model to the image of the new particulate material to identify the predetermined quality measures of the new particulate material; and

5 classify the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

2. The system of claim 1, wherein the data is one or more images of particulate material, the at least one processor being configured to
10 synthesise additional images to which the machine learning model is applied, by at least one of:

 changing a background of the one or more images;
 inserting individual particles over other individual particles; and
 inserting individual particles in contact with other individual
15 particles in the one or more images.

3. The system of claim 1 or 2, wherein the at least one processor detects dimensions of a new particulate material by determining particle
20 dimension parameters comprising one or more of an accumulated particle area, particle length and particle width of the segmented image particles.

4. The system of claim 3, wherein the at least one processor detects dimensions of a new particulate material by detecting a particle size
25 distribution from the particle dimension parameters.

5. The system of any one of claims 1 to 4, wherein executing the instructions further causes the at least one processor to determine a moisture content
of the new particulate material, wherein the processor is caused to
determine packing porosity of the new particulate material by applying
30 the moisture content and the distribution to the dimensions of the new particulate material.

6. The system of any preceding claim, wherein the data comprise images of particulate material other than the new particulate material.
- 5 7. The system of any preceding claim, wherein the at least one processor is further caused to:
- apply segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**); and
- 10 measure dimensions of the segmented image particles.
8. The system of any preceding claim, wherein the at least one processor applies segmentation by applying a masked region based convolutional neural network (MaskRCNN).
- 15 9. The system of any preceding claim, wherein the at least one processor measures dimensions of the segmented image particles with reference to dimensions of a background feature in the image of the new particulate material.
- 20 10. The system of any preceding claim, further comprising:
- calculating a difference between the new particulate material classification and a desired particulate material classification; and
- mixing the new particulate material with one or more other
- 25 particulate materials each having a predetermined classification, to reduce the difference.
11. A system for classifying particulate material, comprising:
- a receiver;
- 30 a machine learning module;
- memory; and

at least one processor, the memory storing instructions that, when executed by the at least one processor, cause the at least one processor to:

- 5 receive, at the receiver, data comprising images of particulate material dimensions and packing density;
- apply one or more machine learning models, of the machine learning module, to the data to learn:
 - a distribution of particulate material dimensions against packing porosity; and
 - 10 image features corresponding to each predetermined quality measure of a plurality of predetermined quality measures, at least one said predetermined quality measure comprising a purity of the particulate material;
 - detect dimensions of a new particulate material from an
 - 15 image of the new particulate material;
 - determine packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material;
 - apply at least one said machine learning model to an image
 - 20 of a new particulate material to identify the predetermined quality measures of the new particulate material; and
 - classify the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.

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12.A method for calculating particulate material packing porosity, comprising:

- receiving, at a receiver, data comprising particulate material dimensions and packing density;
- 30 applying a machine learning model, of a machine learning module, to the data to learn a distribution of particulate material dimensions against packing porosity;

detecting dimensions of a new particulate material from an image of the new particulate material; and

determining packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material.

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13.The method of 12, wherein detecting dimensions of a new particulate material comprises:

applying segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**); and

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measuring dimensions of the segmented image particles.

14.The method of 13, wherein detecting dimensions of a new particulate material comprises determining particle dimension parameters comprising one or more of an accumulated particle area, particle length and particle width of the segmented image particles.

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15.The method of 14, wherein detecting dimensions of a new particulate material comprises detecting a particle size distribution from the particle dimension parameters.

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16.The method of any one of 12 to 15, further comprises determining a moisture content of the new particulate material, and determining packing porosity of the new particulate material comprises applying the moisture content and the distribution to the dimensions of the new particulate material.

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17.A method for classifying particulate material based on a plurality of predetermined quality measures, comprising:

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receiving, at a receiver, data comprising images of particulate material;

- applying a machine learning model, of a machine learning module, to the data to learn image features corresponding to each said predetermined quality measure, at least one said predetermined quality measure comprising a purity of the particulate material;
- 5 applying the machine learning model to an image of a new particulate material to identify the predetermined quality measures of the new particulate material; and
- classifying the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.
- 10
- 18.The method of 17, wherein the data comprise images of particulate material other than the new particulate material.
- 15 19.The method of 17 or 18, further comprising applying segmentation to the image of the new particulate material, to identify individual particles in the image (**segmented image particles**), and measuring dimensions of the segmented image particles.
- 20 20.The method of any one of 13 to 16 and 19, wherein measuring dimensions of the segmented image particles is performed with reference to dimensions of a background feature in the image of the new particulate material.
- 25 21.The method of any one of 17 to 20, further comprising:
- calculating a difference between the new particulate material classification and a desired particulate material classification; and
- mixing the new particulate material with one or more other particulate materials each having a predetermined classification, to
- 30 reduce the difference.
- 22.A method for classifying particulate material, comprising:

receiving, at a receiver, data comprising images of particulate material dimensions and packing density;

applying one or more machine learning models, of a machine learning module, to the data to learn:

5 a distribution of particulate material dimensions against packing porosity; and

 image features corresponding to each predetermined quality measure of a plurality of predetermined quality measures, at least one said predetermined quality measure comprising a purity of the particulate material;

10 detecting dimensions of a new particulate material from an image of the new particulate material;

 determining packing porosity of the new particulate material by applying the distribution to the dimensions of the new particulate material;

15 applying at least one said machine learning model to an image of a new particulate material to identify the predetermined quality measures of the new particulate material; and

 classifying the new particulate material into a new particulate material classification, based on the predetermined quality measures of the new particulate material.