13th International Conference Series on
Laser-light and Interactions with Particles
Optical Particle Characterization follow-up !
August 21-26th, 2022, Warsaw, Poland

CLASSIFICATION OF MILK FAT CONTENT CATEGORIES BASED ON SPECKLE PATTERN USING MACHINE LEARNING

Kwasi NYANDEY[1-2], and Daniel Jakubczyk[1,*]

[1]Institute of Physics, Polish Academy of Sciences, Al. Lotników 32/46, 02-668 Warsaw, Poland
[2]Laser and Fibre Optics Centre, Department of Physics, School of Physical Sciences, College of Agriculture and Natural Sciences, University of Cape Coast, Cape Coast, Ghana

**Corresponding author: jakub@ifpan.edu.pl*

Abstract

Fat globules in milk are known to be secreted as droplets of variable sizes and in different amounts. Hence for industrial, commercial and consumption purposes, there is always the need to accurately and speedily determine fat globule size distribution and classify content into appropriate amounts in each milk batch produced.

We propose a direct approach to classifying speckle images produced by laser light scattering of cow milk with different fat contents using convolutional neural network (CNN). Because the random intensity distribution (speckle) that is observed when coherent light is scattered by a rough surface or transmitted through a scattering medium carries information which can be termed as a fingerprint of the scatterers in question.

We have trained our CNN on four classes of cow milk fat content categories (0.5% 1.5%, 2.0% and 3.2%) with approximately 51,000 images in each class. Our neural network was able to recognize the milk fat content categories from independent as well as mixed dairy plants

1 Introduction

Milk, an important and nutrient-rich liquid food is also a naturally occurring suspension with diverse constituents. Fat globules in milk are known to be secreted as droplets of variable sizes [1] and in different amounts. Hence for industrial, commercial and consumption purposes, there is always the need to accurately and speedily determine fat globule size distribution and classify content into appropriate amounts in each milk batch produced.

In literature, there have been several advancements in tackling these problems [1, 2]. Among these are optical techniques exploiting light scattering phenomena, of which dynamic light scattering is prominent but rarely applied in the industrial setting. Because there is still an inverse problem of particle size determination, concentration and possible contamination during sample preparation.

Recent report of the possibility to directly recognize suspensions with different nanoparticle materials, sizes and concentrations in thin cuvette using speckle technique and machine learning (ML) [3], is promising. Because the technique eliminates the above-mentioned problems. Also speckles are known to carry information which can be termed as a fingerprint of the scatterers [4] in question. In the case of suspension, whose particles are in constant random motion, the movement of speckles is expected to be random but specific. Hence, each recorded speckle image will represent an instance of the fingerprint of these particles, their sizes and/or concentrations. However, the analysis of dynamic speckle with ML still remains a problem mainly due to very high computer resource requirements. With recent GPU capabilities, it is possible to apply ML because it is known to learn rich feature representations of a wide range of images [5].

2 Experiment

A flat thin cuvette was prepared by sticking a 0.05 mm thick adhesive tape on a microscope slide and cutting out a 10 mm circular cross-section from the centre of the tape. The milk sample (10 μL) was loaded into the cuvette and gently covered with a 0.19 mm thick coverslip. As represented in Figure. 1, the sample stage was levelled so that the motion of fat globules will be purely Brownian. The sample was illuminated perpendicularly with a green frequency-doubled Nd:YAG laser at 532 nm, 5 mW and 1.7 mm collimated beam. The illumination was such that the speckle exited through the thin coverslip to minimise lateral shift of speckles. A 14-bit colour camera (Pike F-032C, AVT) was used to record the speckle at 26.9° angle, taking into account the velocity of the speckle movement and camera's available frame rate. Also an IR filter was mounted on the camera to account for the leak of the fundamental and pump frequencies from the laser source in infrared.

The milk was purchased from supermarkets where fresh milk was refrigerated but ultra-high-temperature (UHT) milk was left on the open shelf. The samples were mainly from 3 dairy plants (see Table. 1) and according to the fat content categories produced by such plants. Mlekovita with 1.5% fat content was added to bring diversity since we intended to create a separate training

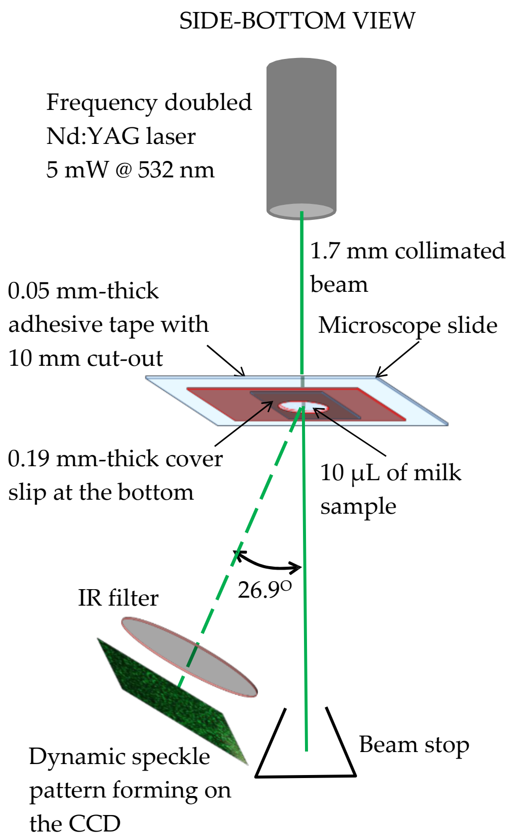


***Figure 1** Experimental setup for recording dynamic speckle movies, adapted from [3]*

sample with mixed dairies. For each fat content category (0.5%, 1.5%, 2.0% and 3.2%), there were 5 replicas of 1 L of milk with different batch/lot numbers. For each lot, 10 movies were recorded at 10 different locations on the sample in the cuvette. Initially, 6.5 s (75 fps) movies were recorded at a single illumination point. Later, 13 s (75 fps) movies were recorded to increase the number of images since the 10-locations on the same sample was exhaustive.

The recorded movies were extracted into frames with the 640 x 480 pixel frames serving as speckle images. During extraction the background (taken to be static speckles resulting from possible glass imperfections or immobile sample particles and averaged over 200 consecutive images) is subtracted from each image. Furthermore, each image was normalised by its highest intensity to within the 0-1 grayscale level. This operation, as reported by [3], is very beneficial since it suppresses intensity variations between raw images and ensures numerical stability of the learning algorithm.

The network used for training is the same as described in [3] and GitHub [6] nicknamed "*t7g24*" since it has produced remarkable classification of speckle images generated by colloidal suspensions. Besides that, this research represents an aspect of a continuous study of suspensions using light scattering and machine learning. The network was trained on all images (640 x 480 pixels) extracted from the movies with a randomised selection of 8:1:1 proportion for training, validation and test sets respectively. All images recorded from the 5 lots of the

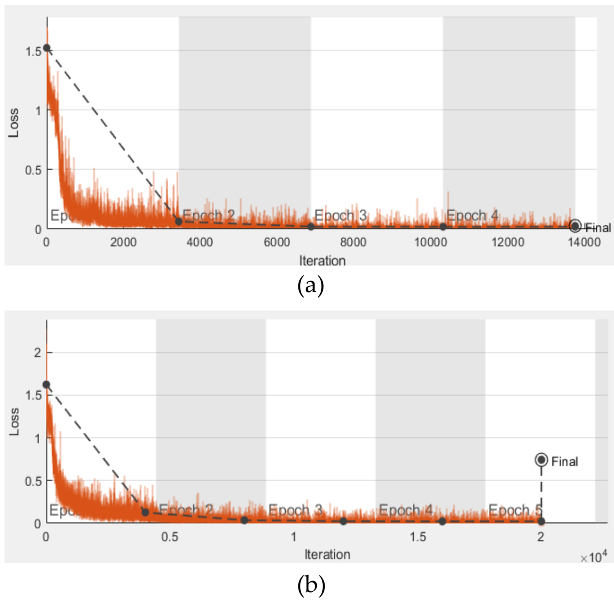


***Figure 2** The loss function optimisation progress over each epoch for training and validation subsets of (a) Carrefour and (b) mixed dairies*

same fat content category belonged to the same class. The network was first trained to recognise the milk fat content category from the same Dairy plant and then mixed dairies.

Market label	Fat content %	Milk type
Carrefour	0.5	UHT
	2.0	UHT
	3.2	UHT
Łaciate	0.5	UHT
	2.0	UHT

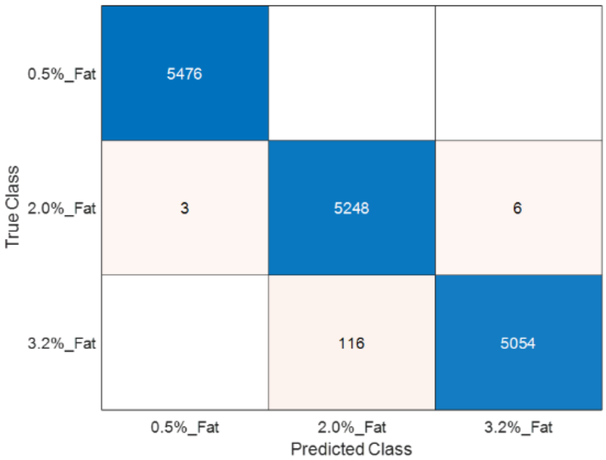
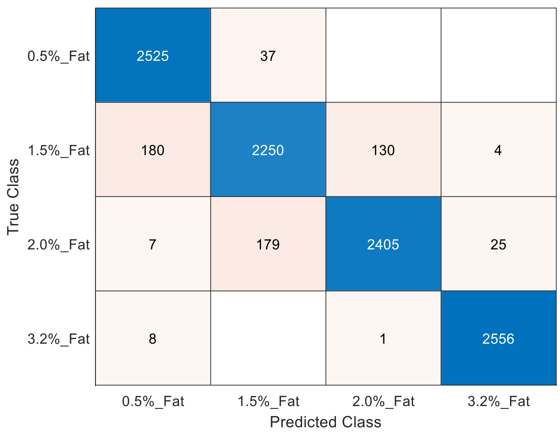


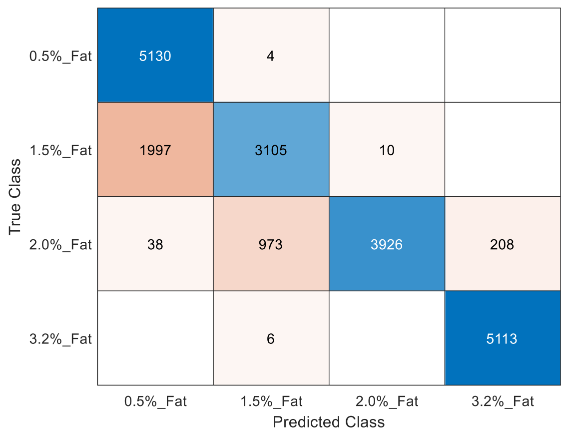
Figure 3 *Classification confusion matrix of speckle images (test set) generated by cow milk with 3 different fat content categories produced by Carrefour*

	3.2	UHT
Mleczna Dolina	0.5	UHT
	1.5	UHT
	2.0	Fresh
	3.2	UHT
Mlekovita	1.5	UHT

Table 1 *Distribution of cow milk types and fat content categories according to market labels*



(a)



(b)

Figure 5 *Classification confusion matrix of speckle images (test set) generated by cow milk with 4 different fat content categories produced by (a) Mleczna Dolina and (b) mixed dairies. The 1.5% fat content in (b) was created by mixing images from Mleczna Dolina and Mlekovita*

3 Results and Discussion

In Figure. 2 (a) and (b) we present the loss function evolution during training of the network on Carrefour and mixed dairies. The loss functions for Mleczna Dolina and Łaciate (not shown) were similar to Carrefour and mixed dairies respectively. The cross entropy loss optimisation during training of network for all data sets progressed steadily until the end, where there is a sudden fall of validation accuracies for both Łaciate (not shown) and mixed dairies (Figure. 2 (b)). This sudden jump (sometimes termed as the "variance shift") is a known occurrence in CNNs with batch normalisation layer as explained in [7]. We obtained accuracies of 99.18%, 95.11%, 87.61% and 84.04% respectively for Carrefour, Mleczna Dolina, Łaciate and mixed dairies.

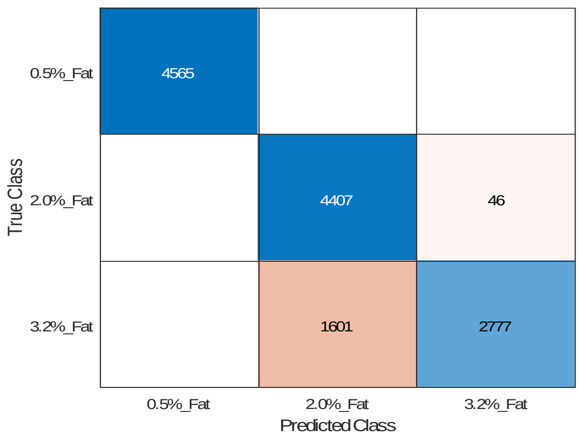


Figure 4 *Classification confusion matrix of speckle images (test set) generated by cow milk with 3 different fat content categories produced by Łaciate*

The classification confusion matrices for test sets of Carrefour and Łaciate are presented in Figure. 3 and 4 respectively, while the classification confusion matrices for test sets of Mleczna Dolina and mixed dairies are presented in Figure. 5 (a) and (b) respectively. For the mixed dairies, we mixed approximately equal proportions of images in the same fat content category from the 3 dairy plants.

These results beat our expectation because we anticipated differences in speckle due to differences in concentration of fat content as well as similarities in speckle due to milk, (which in our case represents the dispersion medium). Because, unlike pure liquids, milk (without fat globules) has its unique particle distribution which also scatters light. Hence, the few misclassifications could be attributed to these similarities due to the influence of other components of milk. While the large misclassifications observed were attributed to the abrupt fall in accuracies at the end of training.

4 Acknowledgement

This research was funded in whole or in part by National Science Centre, Poland, grant number 2021/41/B/ST3/00069. For the purpose of Open Access, the author has applied a CC-BY public copyright licence to any Author Accepted Manuscript (AAM) version arising from this submission.

5 Refferences

[1] El-Loly M. M. Composition, properties and nutritional aspects of milk fat globule membrane-a review. Polish Journal of Food and Nutrition Sciences, 61(1) (2011)

[2] Michalski M. C., Michel F., Geneste C., Appearance of submicronic particles in the milk fat globule size distribution upon mechanical treatments. Le Lait, 82(2): 193-208 (2002)

[3] Jakubczyk, T., Jakubczyk, D., Stachurski, A., Assessing the properties of a colloidal suspension with the aid of deep learning Journal of Quantitative Spectroscopy and Radiative Transfer, 261: 107496 (2021)

[4] Dainty J. C. (Ed.), *Laser speckle and related phenomena* (Vol. 9) (Springer science & business Media, 2013)

[5] https://www.mathworks.com/help/deeplearning/ug/ train-deep-learning-network-to-classify-new-images.html

[6] Supplementary material for T. Jakubczyk's Masters Thesis n. d. https://github.com/sigrond/MGR

[7] https://www.mathworks.com/matlabcentral/answers/445800-why-do-i-see-a-drop-or-jump-in-my-final-validation-accuracy-when-training-a-deep-learning-network