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Human counting versus artificial intelligence for assessing medullation in mohair fibres

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Abstract

The fleeces of mammals with dense coats, such as the mohair fleeces of Angora goats, usually include medullated fibres. These fibres constitute a problem for the textile industry because of their structural characteristics. Three experiments were conducted in this study, with the aim of comparing human image analysis to digital image analysis and artificial intelligence (AI), in terms of their ability to determine the incidence of medullation in mohair samples. The experiments entailed determining the incidences of industry non-objectionable medullated (NOB) fibres and objectionable medullated (SME) fibres, as percentages of the non-medullated fibres. In each experiment, a set of samples was analysed by both laboratory personnel and by different AI models using a Smart Fiber Medullometer. Laboratory personnel showed better coincidence and higher correlations with the AI models when counting SME fibres (r = 0.64–0.97) than when counting NOB fibres (r = 0.57–0.87). This could be the result of the more clearly defined characteristics of SME fibres, in relation to NOB fibres. The results of this study indicate a great advance in the automatic detection of SME and NOB fibres in mohair samples. However, further adjustments of the AI models are required for counting NOB fibres.

Keywords: Angora goats, animal fibre testing, fleece selection for animal breeding, textile quality

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Introduction

The fleeces of mammals with dense coats, such as mohair, wool, cashmere, alpaca, and llama fleeces, usually include medullated fibres (Wildman, 1954; Hunter, 1993). These are fibres with a continuous or fragmented hollow or partially filled central canal running along their length, and are considered contaminants.

In mohair, medullated fibres constitute a problem for the textile industry because dyed medullated fibres appear much lighter than the surrounding dyed non-medullated fibres, and thus show up prominently in fabric. This occurs because the cells in the medulla affect the optical properties of the light passing through the fibre by diffraction (Hunter, 1993). Of all the types of medullated fibres, those collectively described as 'kemp' are the most visible and unwanted in the final product because they

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have a large medulla and are coarse in texture, and their presence consequently increases the prickle sensation and the heterogeneity of fabrics. Medullated fibres also have adverse effects on other quality characteristics of mohair yarn and fabrics, like handle, hairiness, and stiffness (Hunter, 1993). The presence of even a small amount of medullated fibres, in an otherwise high-quality fleece, may therefore have a pronounced adverse effect on its value and end-use potential (Hunter, 1993).

The standard, direct, and objective method to determine the incidence of medullation in most animal fibres is the use of a projection microscope. However, this procedure is laborious, expensive, and time-consuming (Lupton & Pfeiffer, 1998; Shakyawar *et al.*, 2013), and large-scale sample processing can thus be a problem. In addition, as for other subjective methods, the precision and accuracy of the results may be affected by the training level of the person determining the percentage of medullation. Therefore, having access to practical instruments and methods to quantify and identify medullated fibres is crucial for the production, commercialisation, and processing of mohair fleeces.

Along with the development of computer science and image analysis, research efforts have been made to develop algorithms that allow the processing of fibre images captured by cameras to measure fibre diameter and curvature, as well as some other fibre characteristics (Baxter, 1992; Qi *et al.*, 1995; Deng & Ke, 2010; Quispe *et al.*, 2017). As an example, Qi *et al.* (1995) and Shakyawar *et al.* (2013) used a projection microscope with image analysis software to determine the percentage of coarse and kemp-type fibres in sheep and goat fleeces, with high precision and accuracy.

In this context, artificial intelligence (AI) has been found to efficiently recognise arbitrarily shaped objects, when given large data training sets, or at least sufficient data to allow the application of data augmentation techniques, and thus avoid overfitting in training (Krizhenysky *et al*., 2012; Krizhenysky *et al.*, 2017). More specifically, deep-learning techniques have been proven to be efficient for fast object recognition (Goel *et al.*, 2019). Moreover, they can reduce human error, automate and improve classification processes, and provide greater precision in the metrics used in testing textile fibres. Therefore, AI could be useful for the recognition of medullated and non-medullated fibres, as well as for the recognition of different types of medullated fibres. In recent years, Quispe *et al.* (2017, 2022, 2023) have focused on the development of technology (instruments and AI models) for this purpose. These authors have developed and tested an automatic system, comprising both hardware (including mechanical, electronic, and optical components) and software, that is able to determine types of medullation in alpaca, llama, and mohair fibres, and this has provided the foundation for the further development of novel equipment and testing methods.

The use of AI has grown rapidly in recent years, with an increasing number of techniques and tools becoming available. At the same time, there is a growing need for a practical and efficient procedure to identify and quantify medullation in the mohair production and textile industries. Therefore, this study was carried out to compare human image analysis to digital image analysis and AI, in the context of determining the incidence of medullation in mohair samples.

Materials and methods

Sample source and preparation

Mohair mid-side samples (n = 72) were obtained, at shearing, from commercial herds of Argentine Angora goats. At the Textile Fibres Laboratory of the National Institute of Agricultural Technology (INTA) of Bariloche (Río Negro, Argentina), the samples were washed according to standard procedures (Australia/New Zealand standard for wool-fleece testing and measurement) to determine the individual animal washing yield. After washing, measurement slides were prepared according to ASTM D2968-95 guidelines (Anonymous, 2008). Samples were processed using a Hardy micrometre to obtain fibre fragments of 0.4–0.8 mm in length. The fragments were placed on a slide with immersion oil as the mounting medium and dispersed using a stirring rod. A coverslip was then placed on top of the fragments.

Sample measurement and fibre counting

Around 150 photographs (raw images), obtained using a Smart Fiber Medullometer (hereinafter referred to as an S-Fiber Med), were taken of slides containing fragments from each mohair sample, and were used for sample measurement and fibre counting. Each photograph contained an average of 15 fibres.

For manual medullation assessment (human counting), laboratory personnel trained in the determination of medullation by microprojection (ASTM D2968-95; Anonymous, 2008) from the Textile Fibres Laboratory of INTA Bariloche, Argentina (hereafter referred to as laboratory personnel A) and from the Natural Fibres Technology company of Peru (hereafter referred to as laboratory personnel C) performed the counts of the total and medullated fibres in the photographs. In each photograph, every fibre was labelled as being one of five types: non-medullated, fragmented medullation, discontinuous medullation, continuous medullation, and coarse fibres with strong medullation (medulla greater than 60% in diameter).

Subsequently, the same images were processed by different versions of AI models (v1, v3.3, and v3.4), based on YOLOv5m architecture (Ultralytics®), to detect, classify, and quantify the mohair fibres. For this purpose, a computer equipped with an NVIDIA GTX 1660Ti graphics card and an Intel Core i7-9750H CPU was used. For the training of the AI models, fibres in each photograph were labelled as the five original types (one non-medullated and four medullated). The labelling consisted of enclosing each fibre in a bounding box. A data augmentation technique was implemented to enhance the training sets, with 350 images for model v1 and 1201 images for models v3.3 and v3.4. The dataset exhibited significant class imbalance, with a predominance of non-medullated fibres, compared to medullated ones. To address this, specific class weights were adjusted in the loss function, to emphasise the detection of the less prevalent fibres. A Google Colab virtual machine powered by a V100 GPU was used for training purposes.

For the purposes of this analysis, medullated fibres were regrouped into two groups: non-objectionable medullated fibres (NOB; including fibres with fragmented medullation, discontinuous medullation, and continuous medullation) and objectionable medullated fibres (SME; including coarse fibres with strong medullation, in which more than 60% of the diameter was occupied by the medulla).

The trained models were then evaluated, comparing the percentages of NOB and SME medullation obtained by the AI models with those obtained by the human assessors.

Experimentation

Three separate experiments were conducted. In each case, mohair samples were processed using an S-Fiber Med, and 148–149 photographs – each containing 8–16 fibres – were obtained per sample (slide).

The photographs were processed at the laboratory by trained personnel (personnel A or C) and by different AI models (v1, v3.3, or v3.4), using S-Fiber Med equipment. A total of 27, 30, and 15 samples were analysed in experiments 1, 2, and 3, respectively (Table 1).

Table 1 Details of the three experiments performed, in which the incidence of medullated fibres in mohair samples was determined by either human personnel or artificial intelligence models

	Experiment 1	**Experiment 2**	**Experiment 3**
Samples analysed	27	30	15
Laboratory personnel	A	C	-
AI model	v1	v1 and v3.3	v1 and v3.4

Descriptive analysis

To visualise the results of the NOB and SME fibre counts for each sample, as detected by the laboratory personnel and the different versions of the AI models, we constructed dumbbell and scatter plots with linear trends and confidence intervals.

The relationships between the processing methods in each experiment were evaluated using their paired Pearson correlation coefficients.

Statistical analysis

Preliminary exploratory analysis of the SME and NOB variables indicated that they did not fit a normal distribution. We therefore used the generalised estimating equation (GEE) method (Liang &

Zeger, 1986), which is suitable for percentage-paired data with a non-normal distribution. In the GEE framework, the model can be written as:

$$Y_{ij} = \beta_0 + \beta_1 X_{ij} + s_i + \varepsilon_{ij}$$

Where:
Y_{ij}: Response variable for observation *i* and processing method *j*,
β_0: Overall intercept,
β_1: Processing method fixed effect,
s_i: Term for observation *i* to account for correlation between the paired outcomes,
ε_{ij}: Random error for observation *i* and processing method *j*, and
X_{ij}: Identity matrix relating observations to processing methods.

The correlation structure was defined as being exchangeable, which indicates that the observations within the same sample are more correlated than the observations between different samples.

We tested the null hypothesis that the different processing methods would have the same means as:

$$H_0: \beta_1 = 0 \text{ vs } H_1: \beta_1 \neq 0$$

The significance level used to reject H_0 was $P < 0.05$.

When the processing method effect was significant, the paired contrasts for the levels of the effect were estimated using the least squares means, adjusted using the Bonferroni method.

Results

Descriptive analysis – dumbbell plots

Figure 1 shows the dumbbell plots for the samples analysed in experiment 1.

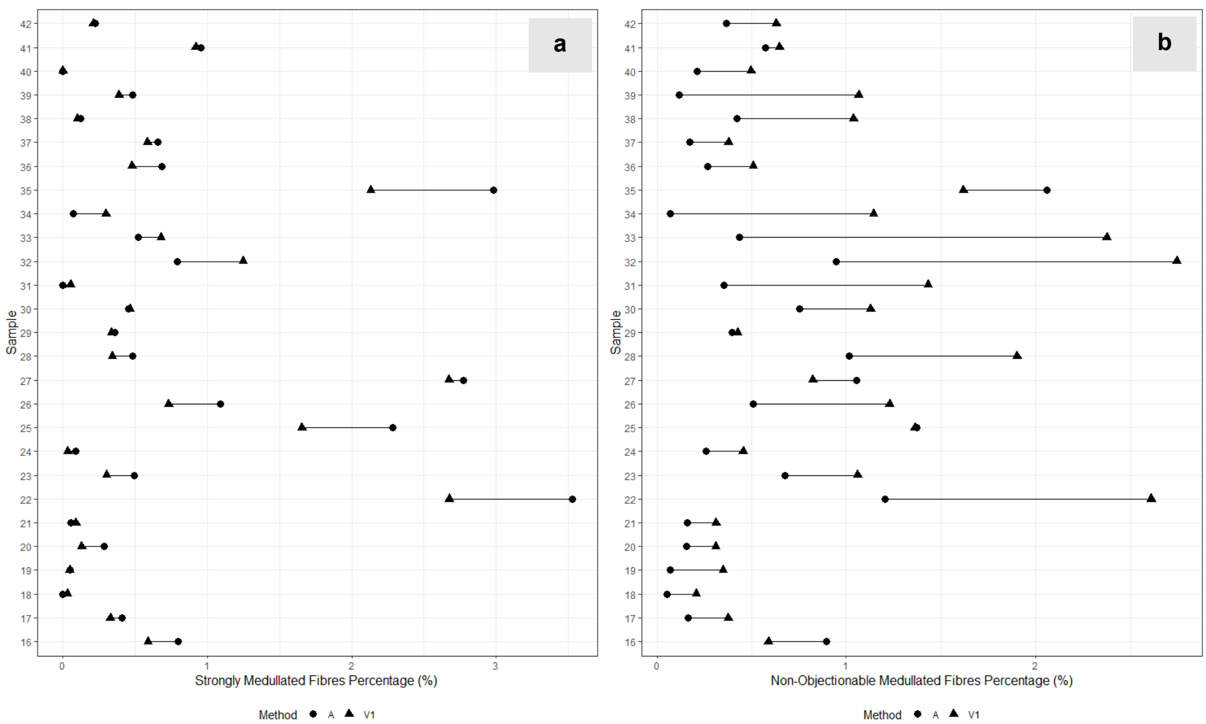

Figure 1 Dumbbell plots comparing the fibre counts performed by laboratory personnel A (●) and artificial intelligence model of image analysis v1 (▲) for (a) strongly medullated fibres and (b) non-objectionable medullated fibres in mohair samples.

As can be seen in Figure 1, for the samples analysed in experiment 1, laboratory personnel A and AI model v1 achieved more coincident results for SME fibres than for NOB fibres, based on the proximity of the fibre counts obtained by each method. Furthermore, for NOB fibres, model v1 counted more fibres than laboratory personnel A in 24 of the 27 samples analysed (89%).

In experiment 2, laboratory personnel C had better coincidence with AI model v3.3 than with AI model v1 for SME fibre counts. Model v1 frequently detected a higher number of SME fibres than both laboratory personnel C and AI model v3.3 (Figure 2). For NOB fibre counts, frequent coincidences were observed between the three processing methods.

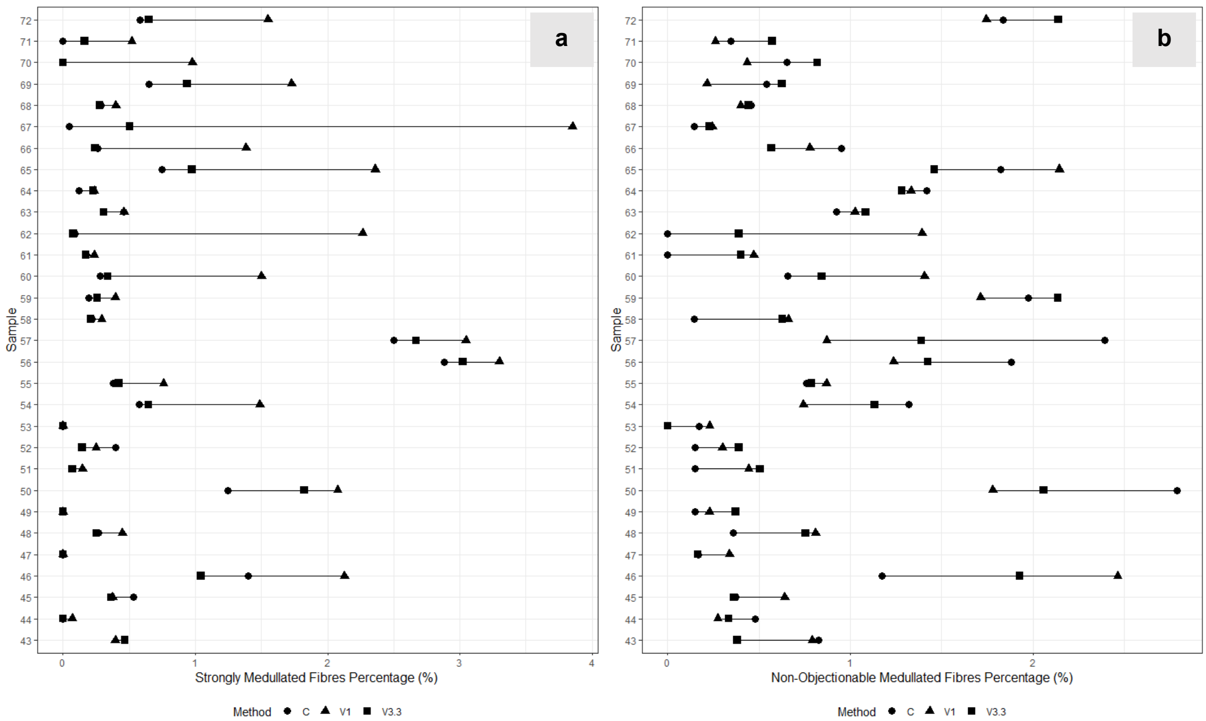

Figure 2 Dumbbell plots comparing the counts performed by laboratory personnel C (●), and AI models of image analysis v1 (▲) and v3.3 (■), for (a) strongly medullated fibres and (b) non-objectionable medullated fibres in mohair samples.

In experiment 3, AI models v3.3 and v3.4 showed good coincidence in detecting NOB and SME medullated fibres (Figure 3), with the exception of NOB fibres in sample number two.

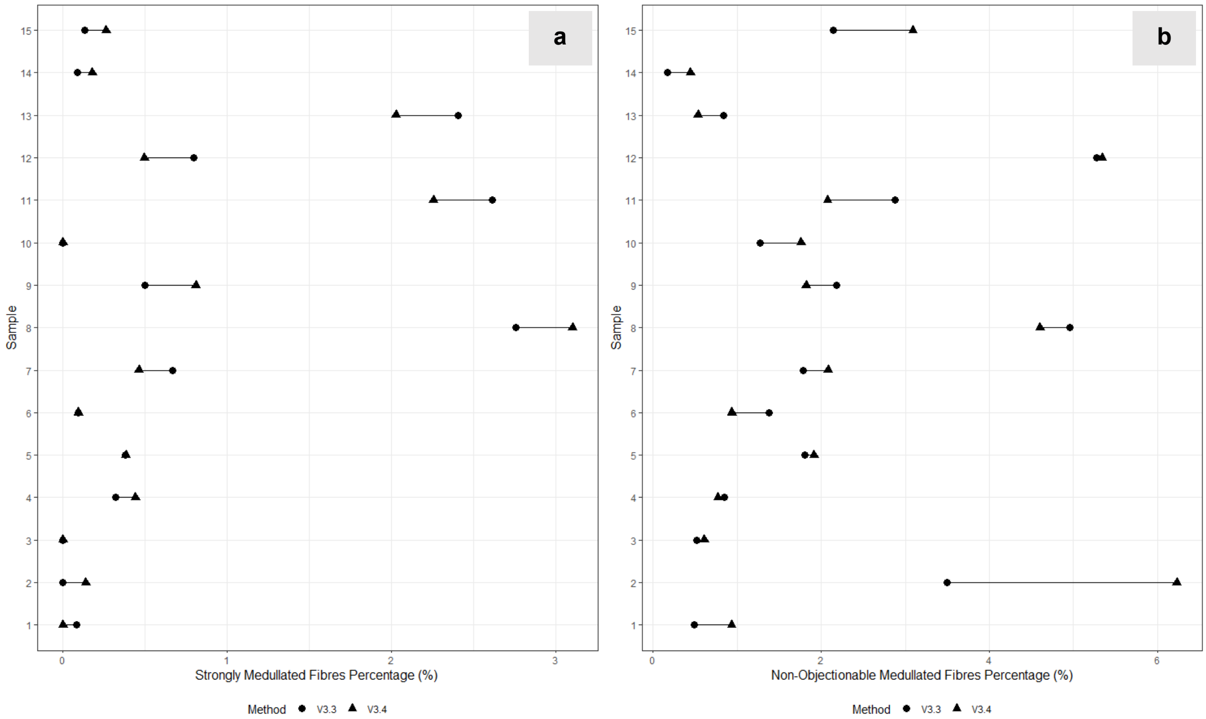

Figure 3 Dumbbell plots comparing the counts performed by two different AI models of image analysis (v3.3 ● and v3.4 ▲) for (a) strongly medullated fibres and (b) non-objectionable medullated fibres in mohair samples.

Descriptive analysis – scatter plots

In experiment 1, the scatter plots show high coincidence between the SME fibre counts performed by laboratory personnel A and those performed by AI model v1 (Figure 4a), with a correlation of 0.97 between the two methods. In contrast, Figure 4b shows high dispersion for NOB fibre detection, with more differences in higher than in lower values. The correlation for this group of fibres was 0.57.

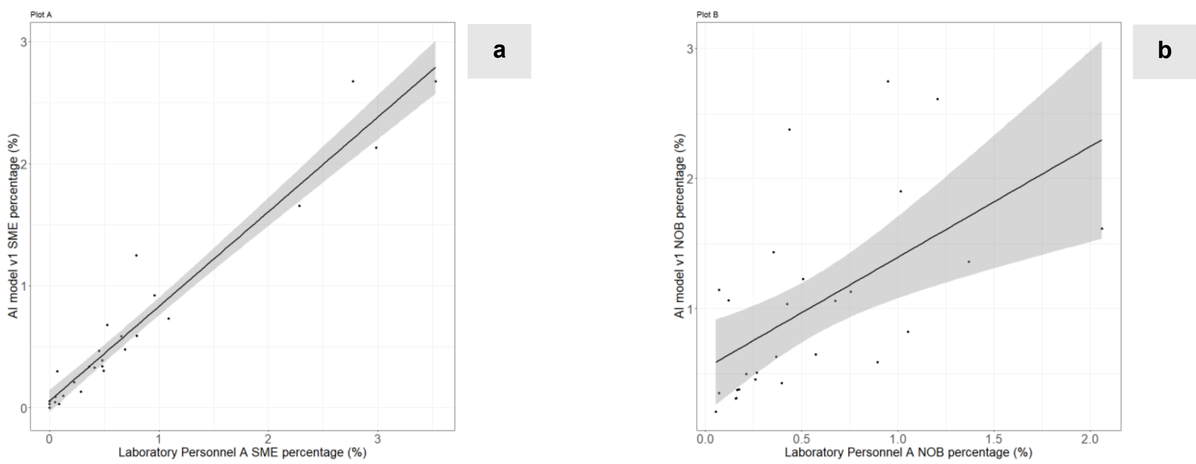

Figure 4 Scatter plots of counts performed by laboratory personnel A vs counts performed by AI model of image analysis v1 for (a) strongly medullated fibres and (b) non-objectionable medullated fibres in mohair samples.

In experiment 2, the highest coincidence in SME fibre detection was observed between the counts performed by laboratory personnel C and AI model v3.3 (Figure 5b). The correlation calculated in this experiment was 0.97. When the counts performed by AI model v1 were compared with those performed by laboratory personnel C and AI model v3.3, the correlations were lower (r = 0.64 and r = 0.72, respectively). The scatterplots also showed higher dispersion between the processing methods at higher medullated fibre incidences (Figures 5a and 5c).

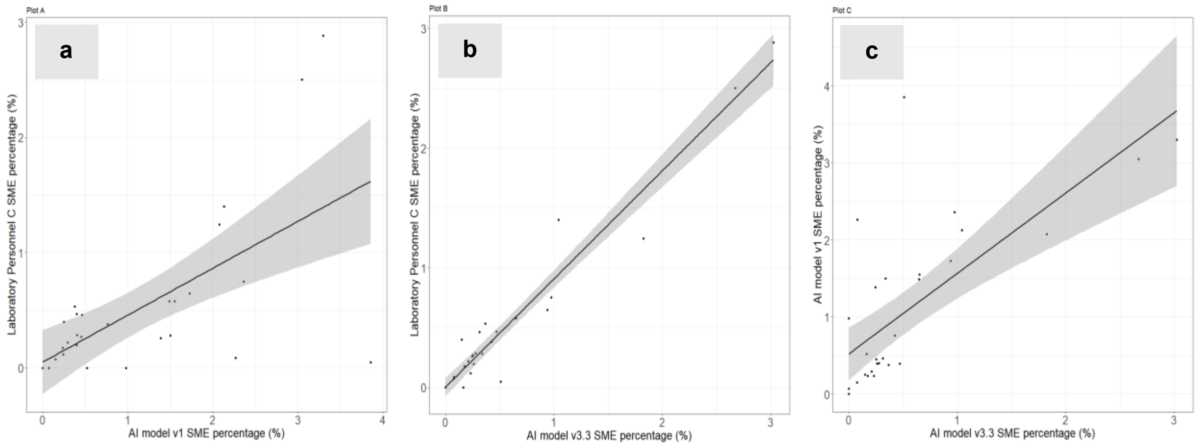

Figure 5 Scatter plots of counts performed by laboratory personnel C and AI models of image analysis v1 and v3.3 for strongly medullated (SME) fibres in mohair samples (a: C versus v1, b: C versus v3.3, c: v1 versus v3.3).

The results for NOB fibres showed high correlations and low dispersions between the counts performed by model v3.3 and the counts performed by personnel C (r = 0.87) and model v1 (r = 0.83) (Figures 6b and 6c). In contrast, high dispersion and low correlation (r = 0.68) was observed between model v1 and laboratory personnel C (Figure 6a).

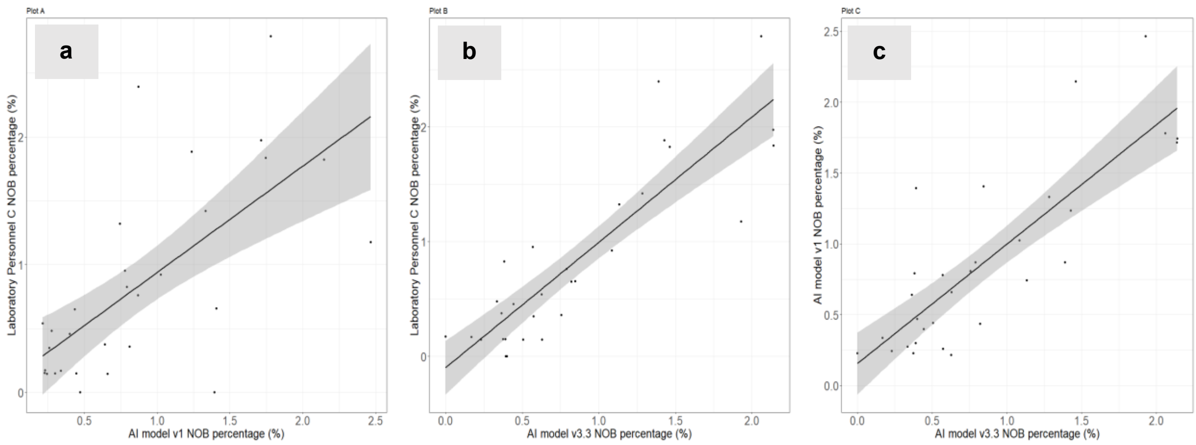

Figure 6 Scatter plots of counts performed by laboratory personnel C and AI models of image analysis v1 and v3.3 for non-objectionable medullated (NOB) fibres in mohair samples (a: C versus v1, b: C versus v3.3, c: v1 versus v3.3).

In experiment 3, the correlations for the counts of SME and NOB medullated fibres between AI models v3.3 and v3.4 were 0.97 and 0.89, respectively. The scatter plots show higher levels of coincidence in the counts of SME fibres than in the counts of NOB fibres (Figure 7).

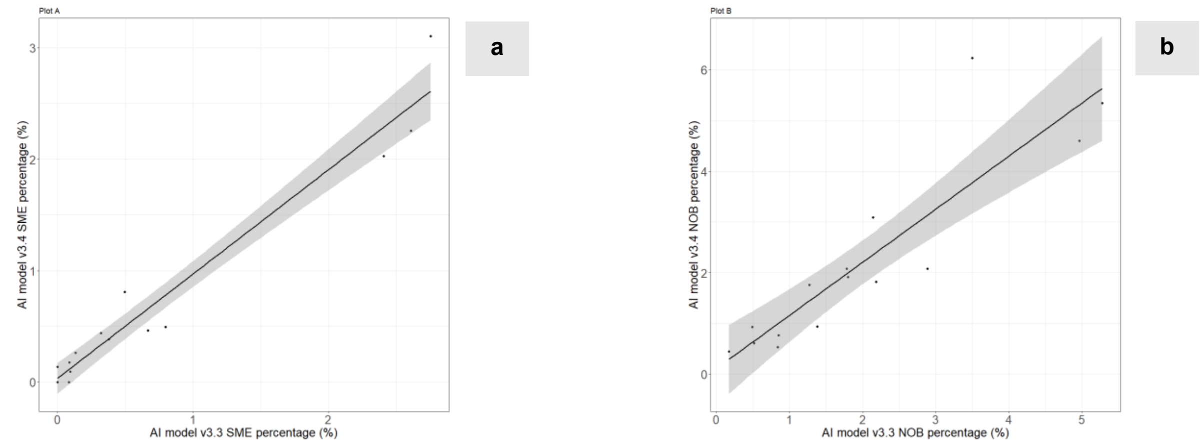

Figure 7 Scatter plots of counts performed by AI models of image analysis v3.3 and v3.4 for (a) strongly medullated (SME) fibres and (b) non-objectionable medullated (NOB) fibres in mohair samples.

Statistical analysis

Table 2 shows that the results of human (laboratory personnel A) and automated (AI model v1) counting methods were significantly different for both SME and NOB fibres in experiment 1. For SME fibres, laboratory personnel A counted more fibres than AI model v1. The opposite was observed for NOB fibre counts, with laboratory personnel A counting fewer NOB fibres than AI model v1.

Table 2 Analysis of the Wald statistics of the generalised estimating equation models, least squares means, and method contrasts (when significant) for strongly medullated (SME) and non-objectionable medullated (NOB) fibre determinations in mohair fleeces in experiment 1

	SME			NOB		
	Wald statistic	**Df**	***P*-value**	**Wald statistic**	**Df**	***P*-value**
Method	4.56	1	0.033*	16.9	1	4e-5***
Least squared means	**Estimate**	**SE**	***P*-value**	**Estimate**	**SE**	***P*-value**
Lab. pers. A	0.76	0.18		0.55	0.09	
Model v1	0.65	0.15		1.01	0.14	
Lab. pers. A – model v1	0.11	0.05	0.033*	-0.46	0.11	1e-4***

Df: degrees of freedom, SE: standard error, lab. pers. A: laboratory personnel A, model v1: artificial intelligence model version 1. ***: P <0.001, **: P <0.01, *: P <0.05.

Significant differences (P <0.001) between the counting methods were observed for SME fibre counts in experiment 2 (Table 3). The pairwise contrasts showed differences when AI model v1 was used. In both cases, model v1 counted about twice as many SME fibres as laboratory personnel C and AI model v3.3. For NOB counts, there were no differences between the processing methods (Table 3).

No differences between AI models v3.3 and v3.4 were observed in experiment 3 for the counting of SME and NOB fibres (Table 4).

Table 3 Analysis of the Wald statistics of the generalised estimating equation models and method contrasts for strongly medullated (SME) and non-objectionable medullated (NOB) fibre determinations in mohair fleeces in experiment 2

	SME			NOB		
	Wald statistic	**Df**	***P*-value**	**Wald statistic**	**Df**	***P*-value**
Method	16.2	2	3e-4***	0.155	2	0.93
Least squared means	**Estimate**	**SE**	***P*-value**	**Estimate**	**SE**	***P*-value**
Lab. pers. C	0.49	0.12		0.83	0.14	
Model v1	1.09	0.19		0.87	0.11	
Model v3.3	0.54	0.13		0.85	0.11	
Lab. pers. C – Model v1	−0.59	0.15	2e-4***	-	-	-
Lab. pers. C – Model v3.3	−0.05	0.03	0.434	-	-	-
Model 1 – Model 3.3	0.55	0.14	2e-4***	-	-	-

Df: degrees of freedom, SE: standard error, lab. pers. C: laboratory personnel C, model v1: artificial intelligence model version 1, model v3.3: artificial intelligence model version 3.3. ***: P <0.001, **: P <0.01, *: P <0.05.

Table 4 Analysis of the Wald statistics of the generalised estimating equation models, least squares means, and method contrasts for strongly medullated (SME) and non-objectionable medullated (NOB) fibre determinations in mohair fleeces in experiment 3

	SME			NOB		
	Wald statistic	**Df**	***P*-value**	**Wald statistic**	**Df**	***P*-value**
Method	0.044	1	0.83	1.01	1	0.31
Least squared means	**Estimate**	**SE**	***P*-value**	**Estimate**	**SE**	***P*-value**
Model v3.3	0.72	0.25		2.00	0.39	
Model v3.4	0.71	0.24		2.21	0.46	

Df: degrees of freedom, SE: standard error, model v3.3: artificial intelligence model version 3.3, model v3.4: artificial intelligence model version 3.4.

Discussion

The results of this study indicate a great advance in the automatic detection of medullated fibres in mohair samples, but some differences in the detection and counting of NOB and SME fibres were observed. Laboratory personnel A showed better coincidence and higher correlations with AI model v1 when counting SME fibres than when counting NOB fibres. Similar results were obtained when comparing laboratory personnel C with AI model v3.3 for fibre counts. Regardless of the models used and the personnel involved in carrying out the visual classification, the coincidences and correlations were higher for SME fibres than for NOB fibres. This could be a result of the clearly defined characteristics of SME fibres, relative to NOB fibres, and may indicate that AI learning tools may need to be improved.

When measuring fragmented, discontinuous, continuous, and strongly medullated fibres in alpaca (n = 3) and llama (n = 3) samples, Quispe *et al.* (2023) found no significant differences between the AI model v1 and direct counting. However, when measuring mohair (n = 4) samples, these authors found significant differences between the AI model and laboratory personnel for fragmented, continuous, and strongly medullated fibres. Furthermore, Lee *et al.* (1996) reported that an optical fibre diameter analyser (OFDA100) underestimated the number of medullated fibres by 8.2%. Lupton & Pfeiffer (1998), in an experiment using 124 mohair fibre samples, similarly found significant differences between projection microscope and OFDA assessments when measuring kemp-type fibres (equivalent to SME fibres), and quite low coefficients of determination for all types of medullated fibres, but particularly for kemp-type fibres (r^2 = 0.14). The most likely cause of the poor agreement between projection microscope and OFDA measurements of kemp-type fibres in mohair samples is the low accuracy and precision of the projection microscope measurements, when fewer than 1000 fibres are examined (Lupton *et al.*, 1994).

When evaluating alpaca fibres, Pinares *et al.* (2018) found that the correlation between measurements performed using the OFDA100 and a projection microscope was 0.56 for total medullated fibres and 0.79 for continuous medullated fibres. Although the OFDA100 does random punctual reads and does not differentiate the medullation type, it seems to produce values that are more related to the continuous medullated fibre content than to the total medullated fibre content (Quispe *et al.*, 2023).

A low incidence of medullated fibres represents a modelling challenge for mohair medullation testing. In the present study, the Wald statistics of the GEE models showed that AI model v3.3 improved counting performance, relative to AI model v1, for the determination of the percentage of medullated fibres in mohair fleeces, and no differences were observed between AI models v3.3 and v3.4. This reflects an improvement in the models implemented. However, the models require further adjustments for counting and classifying mohair fibres with non-objectionable medulla. A specific class weight adjustment is needed for NOB fibres, as is done for coarse and medullated fibres. Although AI model v3.3 identifies and counts SME fibres fairly accurately, the SME content is a key determinant of mohair quality and thus needs to be accurately quantified (Hunter, 1993; Atav & Hunter, 2023).

An issue not addressed in this study that should be highlighted is the measurement time for the different assessment methods examined. The average time taken to measure 1800 fibres (three slides containing 600 fibres each) by a laboratory operator using the microprojection method is 50–60 minutes, in addition to the time taken to prepare the slides, which is the same for all methods. The measurement time for human counting is related to the percentage of medullation in the samples. In llama or alpaca fibres, this percentage is greater, reaching up to 50%, whereas in mohair fibres it is less than 6%.

Conclusions

The AI-based models evaluated in this study are specifically designed to detect, count, and classify the different types of fibres according to their medullation. These models have the potential to assess the medullation content in mohair fibres in less than two minutes, and with high precision relative to human determination. The current AI model v3.3 identifies and counts SME fibres with acceptable accuracy; however, counting and classifying NOB mohair fibres will require an improved model.

The accuracy and speed of the measurements made by the S-Fiber Med instrument represents a significant leap forward within the field of fibre quality analysis. With the possibilities for improvement offered by the AI tools available today, we foresee a promising future for this technology in animal fibre textile chains, and, specifically, in the determination of the medullated fibre content of mohair fleeces.

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Authors' contributions

Nicolas Giovannini: methodology, statistical analysis, and writing (review and editing). Diego Sacchero: writing (original draft), conceptualisation, investigation, and resource organisation. Christian Carlos Quispe Bonilla: conceptualisation, software development, investigation, and writing (review and editing). Max Quispe Bonilla: conceptualisation, investigation, software development, field work and sampling, visualisation, and writing (review and editing). Edgar Carlos Quispe Peña: conceptualisation, software, field work and sampling, methodology, writing (review and editing), supervision, and resource organisation.

Conflict of interest declaration

The authors have no conflicts of interest to disclose.

References

Anonymous, 2008. ASTM D2968-95: Standard test methods for med ratio and kemp fibres in wool and other animal fibres by Micro-projection. [Online]. Available: http://www.astm.org/standards/D2968.htm.

Atav, R. & Hunter, L., 2023. Luxury Animal Fibres Part 1: Hair Fibres from Goats (1st edition). Nova Science Publishers, Inc., New York, USA. pp. 15–68.

Baxter, P., 1992. Description and performance of the Optical Fibre Diameter Analyzer (OFDA). *Journal of the Textile Institute*, 83(4): 507–526. DOI: 10.1080/00405009208631225

Deng, Z. & Ke, W., 2010. A new measuring method of wool fiber diameter based on image processing. In: 2nd International Conference on Signal Processing Systems (ICSPS). DOI: 10.1109/ICSPS.2010.5555676

Goel, R., Sharma, A., & Kapoor, R., 2019. Object recognition using deep learning. *Journal of Computational and Theoretical Nanoscience*, 16:4044–4052. DOI: 10.1166/jctn.2019.8291

Hunter, L., 1993. Chapter 11: Medullation and kemp. In: Mohair, A Review of its Properties, Processing and Applications. NMB Printers (Pty) Std., Port Elizabeth, South Africa. pp. 88–108.

Krizhenysky, A., Sutskever, I., & Hinton, G.E., 2012. ImageNet classification with deep convolutional neural networks. In: Annual Conference on Neural Information Processing Systems (NIPS).

Krizhenysky, A., Sutskever, I., & Hinton, G., 2017. ImageNet classification with deep convolutional neural networks. *Communication of the ACM*, 60(6):84–90. DOI: 10.1145/3065386

Lee, J., Maher, A., Frampton, C., & Ranford, S., 1996. Comparison of Medullation in the Same Fiber Sites Using an OFDA (report no. 14). IWTO Technical and Standards Committee, Cape Town, South Africa.

Liang, K.Y. & Zeger S.L., 1986. Longitudinal data analysis using generalized linear models. *Biometrika*, 73:13–22.

Lupton, C.J., Minikhiem, D.L., Qi, K., Pfeiffer, F.A., & Waldron, D.F., 1994. Measurement of medullation in mohair. Texas Agricultural Experiment Station Progress Reports, 5230, College Station.

Lupton, C.J. & Pfeiffer, F.A., 1998. Measurement of medullation in wool and mohair using an Optical Fibre Diameter Analyser. *Journal of Animal Science*, 76:1261–1266. DOI: 10.2527/1998.7651261x

Pinares, R., Gutiérrez, G., Cruz, A., Morante, R., Cervantes, I., Burgos, A., & Gutiérrez, J., 2018. Heritability of individual fiber medullation in Peruvian alpacas. *Small Ruminant Research*, 165:93–100. DOI: 10.1016/j.smallrumres.2018.04.007

Qi, K., Lupton, C.J., Pfieffer, F.A., Minikhiem, D.L., Kumar, N.S., & Whittaker, A.D., 1995. Automatic image analysis system for objective measurement of animal fibres. *Sheep and Goat Research Journal*, 11(2):71–77.

Quispe, M., Benavidez, G., Sauri, R., Bengoechea, J., & Quispe, E., 2017. Development and preliminary validation of an automatic digital analysis system for animal fibre analysis. *South African Journal of Animal Science*, 47(6):822–833. DOI: 10.4314/sajas.v47i6.10

Quispe, E., Quispe, M., Quispe, C., Poma, A., Paucar Chanca, R., Cruz, A., & McGregor, B., 2022. Relationships between the incidence and degree of medullation with the diameter of alpaca fibres evaluated using a novel device based on artificial intelligence. *The Journal of The Textile Institute*, 114(7):1016–1031. DOI: 10.1080/00405000.2022.2105110

Quispe, M.D., Quispe, C.C., Serrano-Arriezu, L., Trigo, J.D., Bengoechea, J.J., & Quispe, E.C., 2023. Development and validation of a smart system for medullation and diameter assessment of alpaca, llama and mohair fibres. *Animal*, 17(5):100800. DOI: 10.1016/j.animal.2023.100800

Shakyawar, D.B., Kadam, V., Surya, A.K., Ahmed, A., Pareek P.K., & Temani, P., 2013. Precise measurement of wool fibre diameter using computerized projection microscope. *The Indian Journal of Small Ruminants*, 19(2):190–192.

Wildman, A.B., 1954. The Microscopy of Animal Textile Fibres. Wool Industries Research Association, New York, USA.