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Development and validation of a smart system for medullation and diameter assessment of alpaca, llama and mohair fibres

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ABSTRACT

Medullated fibres, due to their higher resistance to bending and pressure, constitute a problem for the textile industry. Thus, having practical instruments to identify them is essential. Therefore, the aim of this research was to develop and validate a novel, swift, automatic system (referred to as **S-Fiber Med**) for medullation and diameter assessment of animal fibres based on artificial intelligence. The medullation of 88 samples of alpaca, llama and mohair fibres (41, 43 and 4, respectively) was evaluated. Additionally, 269 samples of alpacas were considered for average fibre diameter (**AFD**) and the results were compared with the Portable Fiber Tester (**PFT**) and Optical Fibre Diameter Analyser (**OFDA**) methods (72 and 197 samples, respectively). The preparation of each sample to be analysed followed the procedure described in IWTO-8-2011. Version 5 of "You Only Look Once" and DenseNet models were used to recognise the type of medullation and diameter of the fibres, respectively. Within each image (n = 661 for alpaca), all fibres were labelled (as Non-Medullated, Fragmented Medulla, Uncontinuous Medulla, Continuous Medulla and Strongly Medullated) using the LabelImg tool. Data augmentation technique was applied to obtain 3 966 images. Such data set was divided into 3 576 and 390 images for training and test data, respectively. For mohair samples (n = 321), a similar process was carried out. The data to train the model used to infer the diameter contained 16 446 fibres labelled with his respective AFD. A complementary hardware composed of three subsystems (mechanical, electronic, and optical) was developed for evaluation purposes. *T*-test, Pearson and Concordance correlation, Bland-Altman plot and linear regression analyses were used to validate and compare the S-Fiber Med with other methods. Results indicate that there was no significant difference between medullation percentage obtained with the projection microscope and the S-Fiber Med. The Pearson and Concordance correlation analysis shows a strong, high and significant relationship (*P*-value < 0.001). The AFDs of alpaca and llama fibre samples obtained with the two methods are very similar, because no significant difference was found at the *t*-test (*P*-value > 0.172), and they have a strong, high and significant relationship between them, given the high Pearson correlation value ($r \geq 0.96$ with *P*-value < 0.001), high Concordance coefficient and bias correction factor. Similar results were found when PFT and OFDA100 were compared with S-Fiber Med. As a conclusion, this new system provides precise, accurate measurements of medullation and AFD in an expeditious fashion (40 seconds/sample).

Implications

Medullated fibres, due to their higher resistance to bending and pressure, constitute a problem for the textile industry. Thus, having practical instruments to identify them is essential. The system presented herein performs fibre evaluation in an accurate (no significant difference compared to existing methods) and swift fashion (40 seconds/sample). This has certain implications in a number of academic- and marketing-related topics, such as genetic improvement of fibres in animal production, textile purchase-sale practices, processing of fibres to verify their quality, or

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research on medullation to increase knowledge about alpaca, llama, mohair as well as another animal fibres.

Introduction

The strongly medullated fibres, also referred to as objectionable fibres (Hunter et al., 2013), as well as continuous medulla fibres from wool, mohair, cashmere, alpacas and llamas, constitute a problem for animal production and the textile industry. This is because the presence of such fibres increases the prickle sensation and the heterogeneity of fabrics, which leads to a decrease in fibre quality. Moreover, the consequences of the period of wool decline production in the 1990s, together with the high prices of meat, have led to an increased proportion of the merino ewe population, hence encouraged to mate with various other non-merino breeds. This has resulted in wool contamination by objectionable, pigmented and medullated fibres (Fleet et al., 2006).

Fleeces with these fibre types may be subject to penalties during their commercialisation (Fleet et al., 2006), because they would be responsible of causing the above-mentioned prickling issues. This is due to their higher resistance to bending and pressure (Frank et al., 2007), lower processing performance, and their pale or white appearance in dyed products (Wang et al., 2005). Therefore, having access to practical instruments and methods to quantify and identify medullated fibres in fibre samples is crucial to the field.

There has been previous and there is ongoing effort in the literature to approach this concern. The traditional gold standard method is based on the projection microscope (**PMic**). It allows measuring the incidence of medullated and non-medullated fibres. However, it lacks practical use, since it has been labelled as laborious, expensive, and time-consuming (Lupton and Pfeiffer, 1998). The Australian Government agency "Commonwealth Scientific and Industrial Research Organisation" developed a technique (referred to as "Dark and medullated Fibre Detector") in the early 1980s, but it suffers from the same disadvantages that the PMic (Fleet et al., 2002). Another, newer method has been proposed. It is based on the use of a solvent (usually, benzyl alcohol) with the same or very similar refractive index than the inside of the fibres. By this method, medullated fibres, due to their internal medulla, reflect incident light so that they appear white against a black background. Thus, it facilitates the examination of much larger sets of samples at one sitting compared with the previous technology (Ramsay and Humphries, 2005). However, it is unable to determine and identify fibres by type of medullation.

The ability of spectrophotometric methods, on the other hand, has been evaluated to measure relatively high concentrations of medullated fibre in wool and mohair, but the results were not efficient (Boguslavsky et al., 1992; Fleet et al., 2006). Other methods are based on the photoelectric technique (Wood, 2003; Balasingam, 2005). For example, the Wronz Medulometer, which refers to the medulla as a percentage of volume of the wool sample, is able to analyse about six to eight measurements per hour (Hunter, 1993). The sonic digitizer technique (Blakeman et al., 1988) is based on a number of equipments and procedures aimed at measuring the degree of medullation, but, due to practical reasons, it is not possible to find off-the-shelf commercial instruments. During the last years, certain modifications have been applied to the Optical Fibre Diameter Analyser (**OFDA**) to approach the problem. For example, by incorporating *ad-hoc* lighting and software based on opacity (Turpie and Steenkamp, 1995), the system is capable of measuring Average Fibre Diameter (**AFD**) and incidence of medullated and non-medullated wool and mohair fibres (IWTO, 2017a). However, it is not able to recognise fragmented, uncontinous, continous fibres, and thus, the evaluation of alpaca and mohair fibre medullation with the model OFDA 100 is still under debate (Lupton and Pfeiffer, 1998; Botha and Hunter, 2010; Cottle and Baxter, 2015; Pinares et al., 2019).

Currently, the emerging technology referred to as Artificial Intelligence (**AI**) has gained significant momentum. More specifically, deep learning techniques have proved to be efficient at fast object recognition (Goel et al., 2019). At the same time, they are able to reduce human error, automate and improve classification processes and provide greater precision, compared with the methods or techniques mentioned above, as long as the system is provided with a large amount of data (training set), or at least big enough to apply the data augmentation technique and thus avoid overfitting in training. Therefore, this technology could be useful for discriminating medullated and non-medullated fibres, being able to even perform the classification of different types of fibres by medullation. Nonetheless, to date, using AI for the analysis of fibres has not been approached in the literature, except for a related –albeit distinguishable– work from the authors (Quispe et al., 2022). In that paper, the authors developed and evaluated two programs based on digital image analysis and AI to determine whether an alpaca fibre sample belonged to the medullated or non-medullated class. However, the research presented herein constitutes a leap forward, since the authors propose and evaluate an automatic system (hardware and software) able to determine five medullation classes of alpaca, llama and mohair fibres, including the inference of their diameters. The authors recur herein to the previously acquired know-how and, by appropriately modifying the layers of the network, create new AI models that build the foundation of a novel, full-fledged equipment.

Thus, the aim of this paper is by no means to propose enhancements in the field of artificial intelligence *per se*, but to leverage the strong momentum of such discipline by applying its latest techniques to a long-term conundrum in the animal production and textile industries. More specifically, in this manuscript, the authors evaluate the ability of a whole new system (supported by AI along with electronics and mechatronics) to assess the overall quality of the animals' fleece by measuring the type of medullation and diameter of the fibres. The results are then compared with the golden standard methods and instruments available in the literature and the market. Due to the need of having a practical and efficient procedure for the identification and quantification of fibres according to their type of medullation in alpaca, llama and mohair fibre samples, the present work aims at developing and validating a novel, automatic system based on AI for medullation assessment, hereinafter referred to as **S-Fiber Med** (after "Smart Fiber Medullometer"). This instrument should be capable of swiftly quantifying and identifying fibres by type of medullation, classifying them in one of the five following types: Non-Medullated (**NM**), Fragmented Medulla (**FM**), Uncontinuous Medulla (**UM**), Continuous Medulla (**CM**), and Strongly Medullated (**SM**). The instrument shall be able to measure the AFD of the fibres of all these categories.

The scope of the paper encompasses the design, development and validation of the system from a technical point of view. Finally, although the backbone of the system are the AI models, the system requires other important subsystems (mechanical, electronic, and optical) and the design and validation described in this paper consider the system as a whole. The paper is organised as follows: first, the material and methods are described. This includes information about the research location and time span, the AI-based model designed and the parameters used, the hardware developed for using the AI-based software, how the samples were prepared, the trials to be carried out for the validation of the system, as well as the statistical analysis to be performed. Second, the results are described, which includes the presentation of the device designed and developed as well as the validation thereof. Third, the results

are discussed in the current context of the state of the art. Conclusions are drawn in the final section.

Material and methods

Research location and time span

The hardware and software design and implementation were developed at the Laboratory of Research and Technological Development of Maxcorp Technologies S.A.C (Lima, Peru). The validation of the system, using alpaca, llama and mohair fibre samples, was carried out at the Textile Fiber Laboratory of Natural Fiber's Tech S.A.C (Lima, Peru). The alpaca and llama fibre samples were obtained from individual animals raised in the Huancavelica and Puno regions (Peru), respectively, and mohair fibres were obtained from Bariloche, Argentina. The research was carried out from January 2020 to August 2021.

Model development using artificial intelligence

In 2016, "You Only Look Once" (**YOLO**) was first proposed (Redmon et al., 2016), a unified, real-time object detection. In this paper, version 5 of this model (Jocher et al., 2020) was used to recognise the type of medullation. To create the training data, 4 000 images, containing a total of about 40 000 individual fibres and corresponding to 40 different alpaca fibre samples, were used as image database. Approximately, 100 photographs were taken from each fibre sample, and each photograph contained an average of 10 individual fibres. The photographs were obtained with a projection microscope, using a 4X magnifying lens. Only 661 representative images (with different percentages of medullation) out of the 4 000 images were taken into consideration for the purpose of balancing the data. The rationale of selecting this technique to deal with unbalanced data is as follows. In our set of 4 000 images, we found, in abundant quantity, images with fibres only of the non-medullated type and, to a lesser extent, images with fibres with various types of medullation, but with a higher proportion of non-medullated fibres. Thus, 661 images of the latter group were selected manually to avoid a strong data imbalance. Additionally, to train the model, the parameter "--image-weight" was used. As explained by the main author of YOLOv5, this parameter "samples images from the training set weighted by their inverse mean average precision from the previous epoch's testing (rather than sampling the images uniformly as in normal training). This will result in images with a high content of low-mean average precision objects being selected with higher likelihood during training" (Jocher, 2021). Due to their similarity, the same model was reused for llama samples. For mohair samples, however, a similar process was carried out (n = 321). Subsequently, all representative individual fibres were labelled, classifying them into one of the preselected types (namely, NM, FM, UM, CM and, SM), according to their medullation (Frank et al., 2007). To label the individual fibres, a bounding box was manually drawn around each fibre using the LabelImg graphic annotation tool. After labelling, it was annotated whether it was a NM, FM, UM, CM or SM fibre and saved in the YOLO text configuration format.

In order to increase the initial data set and strengthen the resilience of the system, data augmentation was used (by means of the python-based Albumentations library). The images with labelled fibres were subject to a process of random changes in colour, lighting, blur and rotation. Even though the images derived from the augmentation procedure could seem alike to the human eye, the representation matrix of each of them is different, so the computer interprets them as different images. As a result of the process, a total of 3 966 images were available: the preliminary 661 images and an additional set of 3 305. Such data set was further divided into 3 576 images as training data and another 390 images as test data. For the training data, cross-validation with k-fold = 5 was used. Test data, on the other hand, was used as a validation set to provide a preliminary evaluation of a final model fit on the training dataset. Even though it would have been convenient to use a different set of images as training and test data, the distribution between the two sets (90–10%), selected randomly, along with the use of cross-validation allows to avoid overfitting and to find the number of optimal epochs to train. Secondarily, k-folding helps in guaranteeing the exactness of the predictions once the hyperparameters are configured. Validation error data versus train data error were saved in order to find the maximum number of epochs to train. Data indicate that each k-fold configuration keeps similar results as regards to the hyperparameters. The hyperparameters used for training the YOLO model were Architecture = YOLOv5 (Jocher et al., 2020), Image size = 640, Epochs = 200, Batch size = 16, Learning rate = 0.01, Optimizer = stochastic gradient descent, Image weights = true, and Patience = 50. More importantly, in addition to this first evaluation against the augmented dataset itself, the AI will be further evaluated with another dataset, in comparison with current methods (see below in subsection "Trials for validation of S-Fiber Med" and the "Discussion" section for further information).

A different model was used to infer the diameter of the fibres, given the labelled data set at our disposal and given that labelling is a highly time-consuming process, a different model was used to infer the diameter of the fibres. More specifically, a model based on DenseNet (Huang et al., 2017) was chosen. DenseNet is a convolutional network that connects each layer to every other layer in a feed-forward fashion, i.e. with shorter, denser connections between layers. This provides deeper, more efficient and accurate networks, even with a smaller dataset. This comes at a cost of computation load and memory usage during training, which nonetheless begins to be perceived as the number of layers increases (Zhou et al., 2022). Since the number of layers of our approach is reduced and given the fact that this is not a real-time detection job, the use of DenseNet provides a clear advantage (no extra, time-consuming labelling effort) with little nuisance (slightly slower in a non-real-time environment).

The data to train the model used to infer the diameter of the fibre contained 16,446 fibres labelled with their respective average diameter. To find the average diameter, the web-based Coco Annotator tool was used. Such software allows marking three equidistant diameters of each fibre, expressed in pixels. Then, the open-source NumPy library within the Python environment was used to calculate it. The hyperparameters used for training the DenseNet model were Architecture = DenseNet-121 (Huang et al., 2017), Image size = 224, Epochs = 500, Batch size = 8, Learning ate = 0.001, Optimizer = Adam, Criterion = Mean squared error loss, and Patience = 50. Before evaluating the trained model, which infers the fibre diameter, the equivalence of pixels to microns was found by linear regression. To do so, standard diameter fibres that varied from 15.71 to 35.37 microns were used.

Then, the trained models were evaluated by comparing the percentages of medullation obtained with the results of PMic method. As regards to the fibre diameter, the comparison was made against the Portable Fiber Tester (**PFT**). For this last purpose, 72 fibre samples of white alpaca were used. The most suitable models for alpaca, llama and mohair fibres were chosen by contrasting the automatically labelled fibres with a visual inspection of 200 images by fibre type, according to the animal species that produces them. Two models were fitted: one for alpaca and llama fibres and another one for mohair. The first one was created with alpaca fibres, since the diversity of medullation in alpaca and llama fibres is similar, whereas the mohair fibres show lower incidence of

medullation. Subsequently, each model was converted into specific AI-based software.

To train the models, a Google virtual machine with V100 or P100 graphics processing units and 25 GB of video random access memory was used. For the model evaluation process, a laptop with an NVIDA 1660 Ti graphics processing units hardware with 8 GB of video random access memory, a Central Processing Unit mounting a 9th generation Core i7 chip and 16 GB of random access memory was used. Microsoft Visual Studio 2017 was used to develop the graphical user interface in C#. This interface contains the controls to configure and make use of the system. It also serves as the orchestrator between the electronic subsystem, the optical subsystem and the AI models. Said orchestration is possible via Inter Process Communication (while the graphical user interface was developed in C#, the optical system relies on C++ libraries, and the AI models rely on Python modules). OpenCV was chosen as the image processing library for both C++ and Python, while the built-in image classes were chosen for the C# interface.

The orchestration during the analysis process is made as follows: images are taken with the optical system periodically (every 250 ms) and sent to a processing queue. The AI models are initialised at the beginning of the process. Then, the system waits for new images to arrive at the queue. All incoming images are processed, and the results are stored. When the last image is taken and queued up, a signal is sent to the AI models to finish the process after said image. When it ends, it calculates the results for the sample and sends them to the orchestrator. The orchestrator processes the information and shows it to the user on the graphical interface via statistics and charts.

Complementary hardware designed for using the artificial intelligence-based software

The whole system design is composed of three subsystems: mechanical, electronic, and optical. The Autodesk Inventor program was used for the design, thereby allowing the visualisation, simulation, and documentation of a digital prototype in three dimensions. Later, some pieces were printed in polylactic acid and resin with the help of 3D printers. The rest were mechanised using a computer numerical control milling machine, a laser cutter and a lathe, mainly.

For the electronic subsystem, an Arduino UNO, stepper motor drivers, a control shield, light emitting diode lights and a 110–220 V AC/12 V DC, 5A and 50/60 Hz power supply were used, which were properly connected to supply the necessary power to each electronic component. The respective algorithms (firmware) were developed in the Arduino integrated development environment and downloaded into the Atmel microcontroller. Thus, this subsystem could control the lighting, send and receive data from the computer, and control two stepper motors to slide the optical subsystem and sample holder in the "x" and "y" axes respectively, in an adequate and synchronised manner. The mechanic subsystem is comprised by several parts. In particular, the stage (with its respective sample holder), a support for the optical system, stepper motors, toothed belts and pulleys (so that the optical system can slide in both axis), a micrometric screw to focus on the samples, linear guides (where the optical system and the stage slide), supports for the stepper motors, limit switches, and casing, among others. The optical subsystem is composed of the following parts: first, an industrial universal serial bus digital camera, more specifically, the model VTEX120CPGS, with a complementary metal–oxide–semiconductor sensor, and a maximum resolution of 1280 × 960. This camera has a programmable exposure speed through the manufacture's software development kit (Contrastech Co, Ltd), an objective lens with 4x magnification, a diaphragm for better depth of field and clearer images, a 3 W LED to illuminate the fibre sample, and a 5 cm spacer. This subsystem was connected by toothed belts and pulleys to the stepper motor of the "x" axis, in such a way that it can slide and scan the fibre samples.

Finally, the entire S-Fiber Med system consists of the three subsystems described above and the set of algorithms and programming codes for the recognition of digital images based on AI (which was installed on a computer). These subsystems were integrated and interconnected, to allow the fibre samples to be adequately scanned, processed by AI and to show the results of the evaluation of the AFD and the incidence of medullation fibres on the graphical interface. In addition, statistical and supplementary information such as SD, CV, number of fibres evaluated, date and time of evaluation, diagram of the distribution of diameters (taking into account the medullated fibres (red bars) and non-medullated fibres (blue bars)), an image of focused samples, or a menu bar for custom settings, among others, are shown. A schematic diagram of the whole system is shown in Fig. 1.

Samples preparation

The incidence medullation of 88 white alpaca, llama and mohair fibre samples (obtained from a 2 cm × 2 cm section of the mid-side area of individual animals, over the 3rd last rib) corresponding to 41, 43 and 4 animals, respectively, was evaluated. Additionally, 269 fibre samples of individual white alpacas were considered for AFD assessment, in comparison with PFT and OFDA100 (72 and 197 samples, respectively). Each fibre sample corresponding to each animal (alpaca, llama and mohair) consisted of approximately between 8 000 and 18 000 individual fibres.

The IWTO-8-2011 guidelines (IWTO, 2017b) and those made by Quispe et al. (2022) were followed to prepare the samples: first, a solution made of 30% benzene and 70% 96-degree ethanol was used to clean the samples. Second, a rolling device together with a piece of drying fabric were used to dehydrate them. Third, from the dried samples, a number of fragments of fibre were extracted. Then, a micrometer, specialised in micro measurements, was used to measure and cut the lengths of such fragments, ranging from 0.4 mm to 0.8 mm. Subsequently, a rod was used to distribute equidistantly the fibres on an oil-impregnated plate. Finally, a cover glass was used to protect the fibres and prevent them from moving. The number of fragments placed on each image ranges from five to twenty, thereby avoiding undesirable fibre intersections and/or accumulation of fibres in one area.

Trials for validation of Smart Fiber Medullometer

For the validation, four trials were carried out: At trial number 1, three white samples fibre of alpaca and llama, and four white samples fibre of mohair were evaluated with S-Fiber Med. The percentage of NM, FM, UM, CM, SM and total medullation (sum of percentages of FM, UM, CM, SM) fibres and AFD were saved in an excel file automatically. In addition, the input and output images with automatically labelled fibres were stored in files. Then, the input images (including alpaca, llama and mohair fibre samples) underwent a direct counting process by means of a computer. The quantity of NM, FM, UM, CM, SM and total medullation fibres obtained by direct counting were saved and transformed in percentages. These data were then compared.

At trial number 2, the samples were prepared on slides and protected with a coverslip. The fibre samples included alpaca (n = 38) and llama (n = 40). The incidence of medullation and AFD was assessed with S-Fiber Med. Subsequently, the same fibre samples, mounted in the same slides, were analysed according to IWTO-8-2011 (IWTO, 2017b) using a PMic. Six hundred individual fibres per sample were evaluated. Data corresponding to the percentages of NM, FM, UM, CM, SM, and total medullation fibres of these two

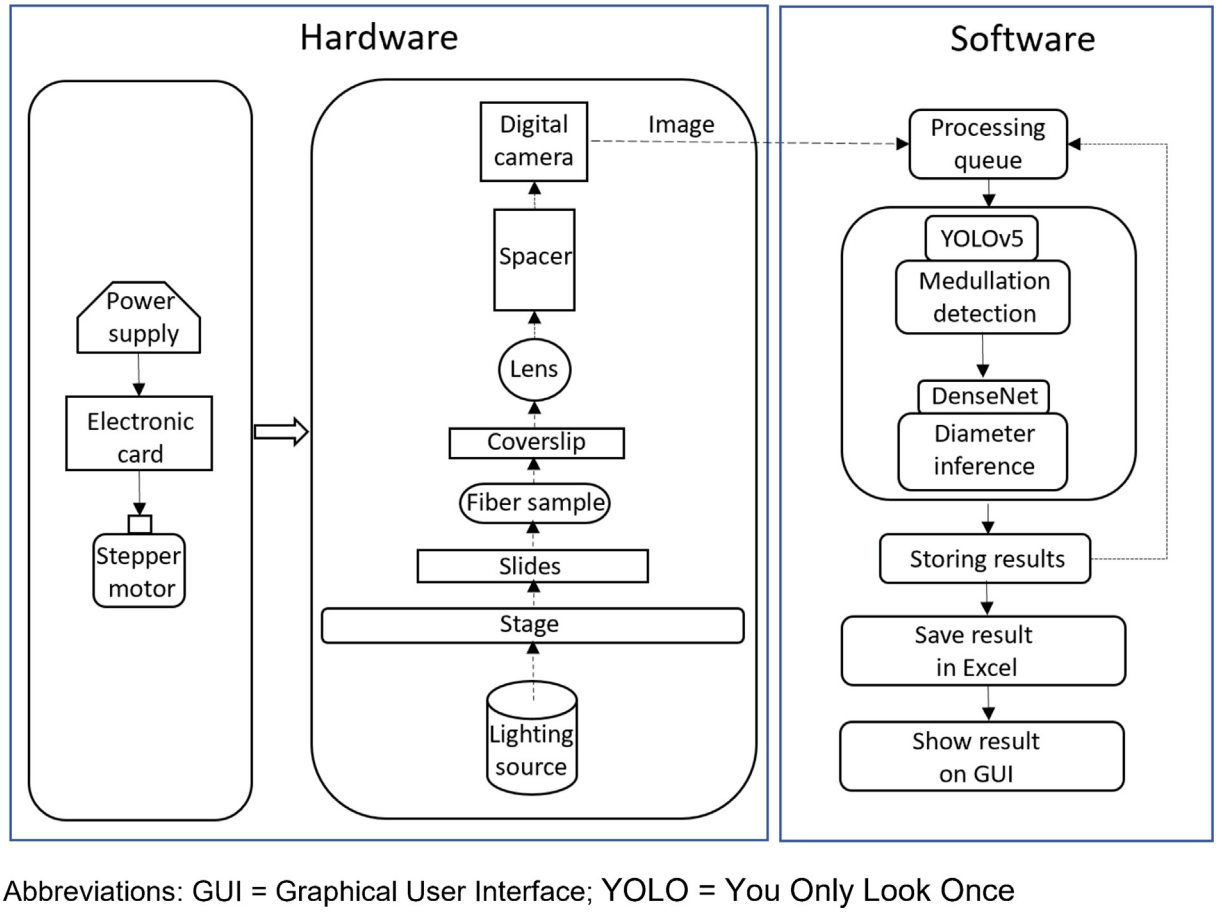


Fig. 1. Schematic diagram of the S-Fiber Med system for medullation and diameter assessment of alpaca, llama and mohair fibres.

methods (S-Fiber Med versus PMic) were then compared. However, 16 sample fibres from llamas had to be discarded, due to a high contamination with coloured fibres. Thus, only 24 fibre samples were considered for comparison of NM, FM, UM, CM, SM, and total medullation fibres. Percentages of UM + CM (sum of percentages of UM + CM fibres) were also compared. In addition, the AFD of all the fibre samples analysed with both methods were compared.

At trial number 3, S-Fiber Med was calibrated with seven international standard sheep tops of known AFD. Four sub-samples of each top were prepared, and the AFD was measured in pixels with the S-Fiber Med instrument. The results of the sub-samples of each top were averaged and matched with the known AFD. A regression analysis was performed and a prediction equation was obtained, which was considered for calibration. For validation, four sub-samples of each of the seven tops were measured with the already calibrated S-Fiber Med. The data obtained were used to determine both precision and accuracy. Precision was evaluated through standard error and the associated Confidence Interval (**CI**) of the AFD. Accuracy was evaluated based on the difference of the known AFD of each top and the average of the AFD measurements, obtained by S-Fiber Med. The closer the difference to zero, the better the accuracy (Walther and Moore, 2005).

At trial number 4, 72 fibre samples of white alpaca were assessed with S-Fiber Med and PFT, and 197 samples were assessed with S-Fiber Med and OFDA100. Each instrument was previously calibrated and validated using the international standard sheep tops. For evaluation, each sample was divided into two sub-samples. One sub-sample was used to assess the AFD with S-Fiber Med, while the other sub-sample was used to assess with PFT or OFDA100. The evaluation was performed according to the recommended methodology for evaluation with PFT (Quispe et al., 2017; 2020) and OFDA100 (IWTO, 2017a), respectively. The AFD data were then compared.

Statistical analysis

First, data medullation percentage and AFD measurements were subjected to tests of normality and homogeneity of variances using Shapiro and Levene tests, respectively. Percentages of FM, UM + CM and SM fibre showed no normal distribution and homogeneity of variances. Arcsine transformations were applied to these variables before their statistical treatment. The rationale of using the Arcsine transformation is that the variable (in this case, the percentage of medullation) has normal distribution and the variance is stabilised. Nevertheless, after the statistical analysis, they were changed back for result presentation.

Second, *t*-test, correlation, and linear regression analyses were used to validate and compare the S-Fiber Med with other methods for medullation and AFD assessment, according to the recommendation of IWTO-0, Appendix B (IWTO, 2017c). A *t*-test was used to compare the ability of direct counting and S-Fiber Med when assessing mean percentage distribution for different medullation types of alpaca, llama and mohair fibres. In addition, a two-proportion *z*-test was used to compare these two methods for percentage assessment of each medullation type. For the comparison of the percentages of different medullation types obtained with PMic versus S-Fiber Med, *t*-test, Pearson correlation and lineal regression analyses were carried out. For AFD, the same type of statistical analyses (IWTO, 2017c), Lin's Concordance correlation coefficient, Bias correction factor (C_b) for evaluation of precision and accuracy, (Lin, 1989) and Bland-Altman plot (Bland and Altman,

1986) were used to compare PMic versus S-Fiber Med, PFT versus S-Fiber Med, and OFDA100 versus S-Fiber Med. All statistical analyses were carried out with the free software RStudio (RStudio, 2020). Finally, the intercept and regression coefficient values were statistically evaluated by a *t*-test, under the null hypothesis that those values are equal to zero. Additionally, the regression coefficients (slopes) were also evaluated by a *t*-test, under the null hypothesis that they are equal to one.

Results

Smart Fiber Medullometer: The developed system

The developed system is comprised of three hardware subsystems and a fourth AI-based software subsystem. It has been named S-Fiber Med, after "Smart Fiber Medullometer". The four subsystems interact to capture dozens of fibre photographs by scanning samples prepared with fibre fragments. The fibre images are then processed through the AI-based software to identify different types of alpaca, llama and mohair fibres, and classify them according to their medullation: NM, FM, UM, CM and SM fibres (Fig. 2). The ability of the YOLOv5 model can be summarised with its confusion matrix, shown in Fig. 3. As it can be seen, the values on the diagonal are appreciably higher than the rest, which reveals the performance of the model. In addition, the number and percentages of NM, FM, UM, CM and SM fibres were obtained. This facilitates the calculation of the AFDs (both global and for each medullation type).

The optic subsystem captures the suitable fibre images for later analysis. The mechanical subsystem supports and covers all other parts of the system. The electronic subsystem allows automating and controlling the scanning process. Finally, the AI-based software performs the classification and saves the results. The software also allows entering sample identification data and viewing AFD histograms of fibres with and without medullation. The handling is straightforward, due to a friendly and easy-to-use interface (Fig. 4). The manual intervention has been reduced to a minimum, limiting thereby the potentially negative effects on the precision and accuracy of the results. In addition, the instrument can be considered as portable, since it weighs less than 4 kg, and has a small size (32 cm in height, 34 cm in length and 17.5 cm in width) and volume (19 dm^3).

The S-Fiber Med is able to identify and measure 144.60 ± 2.68 (mean ± SD) images/sample, that is, 1 736.95 ± 109.88 fibres/sample in just about 40 seconds/sample. The actual number of fibres measured will depend on the caution posed during the preparation of the samples. For this reason, the prepared samples must be clean, with uniform distribution, avoiding interwoven fibres, and with a density between 8 and 16 fibres per photograph. The results (the AFD, the number of fibres, global and per category, as well as the percentages of fibres) are saved automatically in an excel file. The instrument assesses the medullation of white, beige and light fawn fibres only, because its AI-based software needs to identify fibre images that display the different types of medullas. In images of dark coloured fibres (from medium brown to dark), a clear observation of fibre medullation is not possible with the proposed procedure.

Validation of the Smart Fiber Medullometer system

Tables 1 and 2 show the comparison of the percentages and proportions, respectively, assessed for different types of white fibres (by medullation type), obtained by direct counting and S-Fiber Med. After applying the two-sample *t*-test and the two-

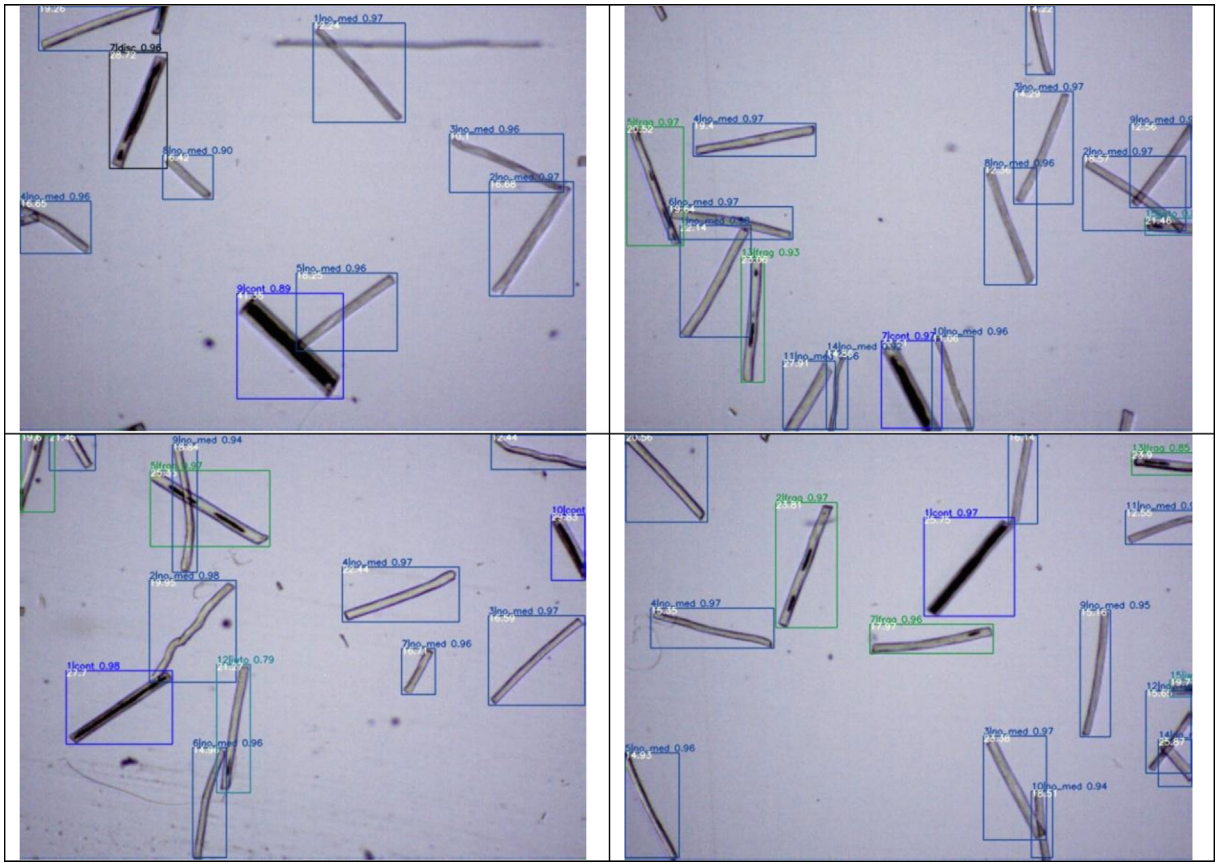
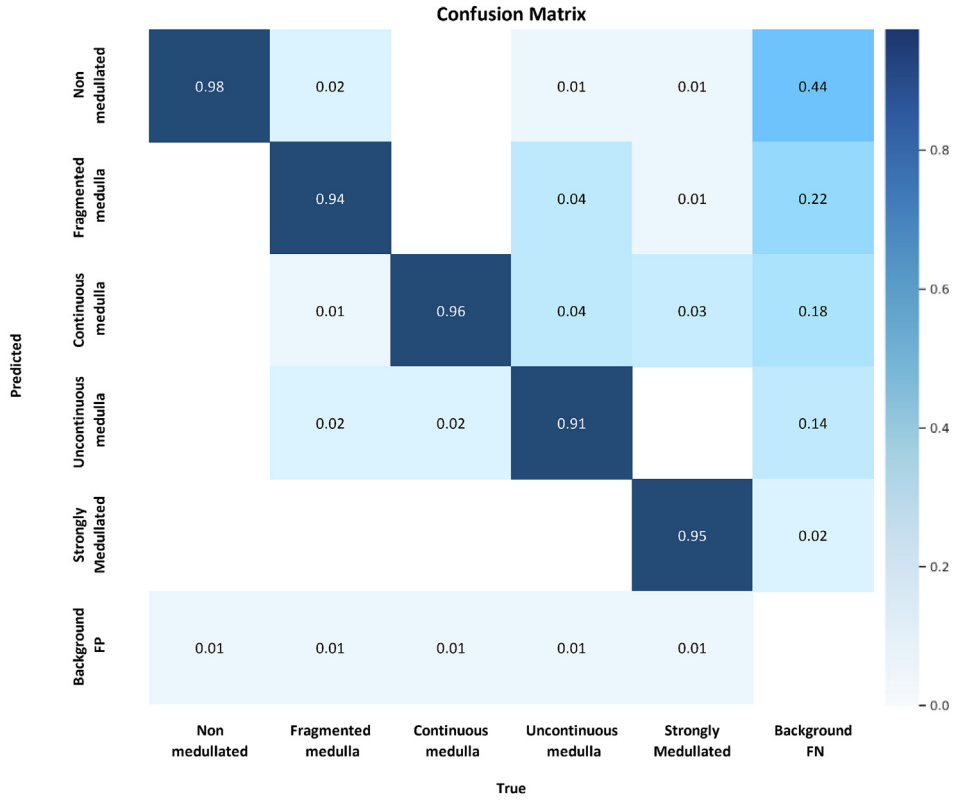


Fig. 2. An example of automatic recognition of llama fibres and the classification thereof according to their medullation.



Abbreviations: FP = False Positive; FN = False Negative.

Fig. 3. Confusion matrix showing the classification results between the different classes of alpaca fibre medullation.

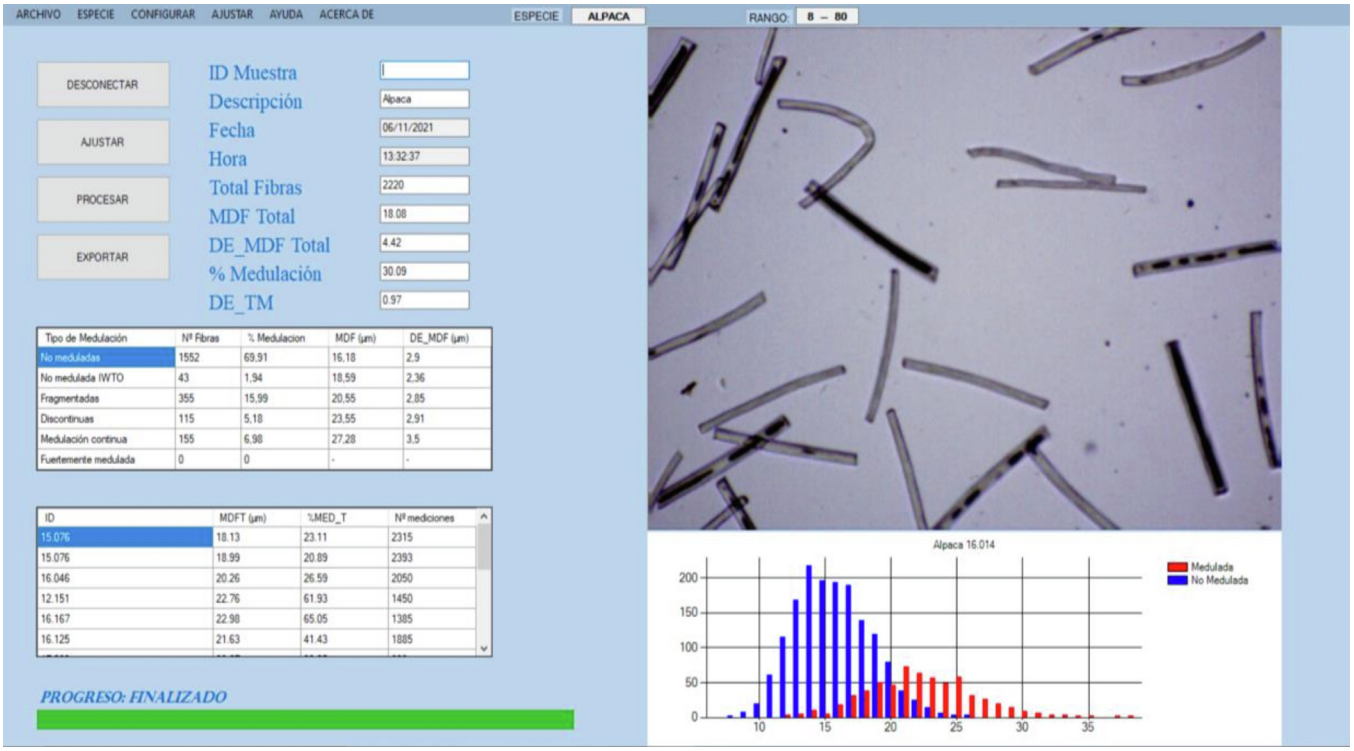


Fig. 4. Graphical user interface of the S-Fiber Med system. It shows the statistics results, a histogram of the average fibre diameter (AFD) of medullated and non-medullated fibres, as well as the alpaca fibre images.

Table 1
Two-sample *t*-test results for different medullation types of alpaca (n = 3), llama (n = 3) and mohair (n = 4) fibres, obtained with the direct counting and S-Fiber Med methods.

Variables/Type of fibre	Direct counting (%)	S-Fiber Med (%)	CI of difference	*P*-value
Alpaca fibre				
Non-medullated	44.70	43.50	[−4.39 1.96]	0.24
Total medullation	55.30	56.50	[−1.96 4.39]	0.24
Fragmented medulla	21.00	22.20	[−0.99 3.37]	0.15
Uncontinuous medulla	12.20	11.80	[−1.34 0.48]	0.18
Continuous medulla	21.10	21.90	[−0.71 2.33]	0.15
Strongly medullated	0.99	0.66	[−1.89 1.24]	0.46
Llama fibre				
Non-medullated	45.00	43.80	[−4.25 1.88]	0.23
Total medullation	55.00	56.20	[−1.88 4.25]	0.23
Fragmented medulla	23.30	24.00	[−0.55 1.83]	0.15
Uncontinuous medulla	7.92	8.15	[−0.81 1.27]	0.44
Continuous medulla	20.40	21.30	[−0.25 2.13]	0.08
Strongly medullated	3.42	2.80	[−2.38 1.14]	0.27
Mohair fibre				
Non-medullated	93.90	92.70	[−5.48 7.88]	0.68
Total medullation	6.10	7.30	[−7.88 5.48]	0.68
Fragmented medulla	0.30	0.89	[−1.62 0.44]	0.17
Uncontinuous medulla	0.17	0.91	[−1.88 0.41]	0.15
Continuous medulla	1.98	0.48	[−1.42 4.43]	0.21
Strongly medullated	3.65	5.02	[−6.62 3.87]	0.54

Abbreviations: CI = Confidence interval.

Table 2
Two-proportion *z*-test results for alpaca, llama and mohair fibre samples according to medullation type.

Sample	NM	FM	UM	CM	SM
01Llama	64.21	16.79	4.63	10.66	1.61
N_m = 1858	63.38	16.99	4.58	11.31	1.27
N_{FM} = 1813	0.60	0.87	0.94	0.52	0.38
02Llama	17.25	22.61	9.90	41.45	6.69
N_m = 1959	16.82	23.18	10.61	42.12	5.56
N_{FM} = 1980	0.72	0.67	0.47	0.67	0.06
03Llama	43.67	28.81	9.23	9.05	1.66
N_m = 1083	41.98	31.71	9.26	10.54	1.56
N_{FM} = 1091	0.42	0.14	0.24	0.99	0.85
01Alpaca	27.63	24.54	18.00	26.23	0.07
N_m = 1361	26.40	26.03	17.35	27.28	0.22
N_{FM} = 1360	0.47	0.37	0.54	0.66	0.32
02Alpaca	25.41	23.85	14.53	30.33	2.76
N_m = 1341	26.06	24.05	13.89	31.59	1.72
N_{FM} = 1339	0.69	0.90	0.48	0.63	0.07
03Alpaca	71.44	14.56	4.03	6.69	0.14
N_m = 2108	70.05	16.44	4.02	6.80	0.05
N_{FM} = 2117	0.32	0.09	0.98	0.88	0.32
01Mohair	98.79	0.52	0.00	0.00	0.69
N_m = 577	98.24	0.70	0.00	0.18	0.88
N_{FM} = 568	0.44	0.68	–	0.31	0.72
02Mohair	90.94	0.15	0.58	4.53	3.80
N_m = 682	89.56	0.45	1.06	1.97	6.96
N_{FM} = 661	0.39	0.30	0.33	0.01	0.01
03Mohair	94.24	0.82	0.10	1.85	2.98
N_m = 973	93.02	1.88	0.42	0.73	3.96
N_{FM} = 960	0.27	0.04	0.17	0.03	0.24
04Mohair	91.11	0.22	0.11	1.44	7.11
N_m = 901	89.99	0.54	0.43	0.75	8.29
N_{FM} = 929	0.41	0.27	0.19	0.15	0.34

Abbreviations: N_m = Number of fibres assessed by the direct counting method; N_{FM} = Number of fibres assessed with the S-Fiber Med method; NM = Non-medullated; FM = Fragmented medulla; UM = Uncontinuous medulla; CM = Continuous medulla; SM = Strongly Medullated.
Within each cell: the top value shows the percentage obtained by the direct counting method; the value in the middle shows the percentage obtained with S-Fiber Med method; and the bottom value shows the *P*-value of the two-proportion *z*-test.

proportion *z*-test, no significant difference was found between the various results for medullation obtained with direct counting and S-Fiber Med methods for alpaca, llama and mohair fibres. Only in two mohair samples, differences could be found (more specifically, when CM, SM or FM were compared).

Table 3 shows the *t*-test and correlation analysis results of medullation percentages obtained with PMic and the S-Fiber Med methods, per type of medullation of alpaca and llama fibres. Percentages of NM, FM, UM + CM, SM and total medullation for white alpaca and llama fibres, calculated by the two methods were

Table 3
T-test and correlation analysis of medullation percentages obtained with the projection microscope (PMic) and the S-Fiber Med methods, according to the medullation type of alpaca and llama fibres (n = 38 and 24). The asterisk indicates that the data have no normal distribution.

Variables	*T*-test				Correlation analysis	
	PMic %	S-Fiber Med %	Difference %	*P*-value	CI for Pearson's correlation	*P*-value
Alpaca						
Non-medullated	47.72	48.30	−0.58	0.922	[0.97 0.99]	<0.001
Total medullation	52.28	51.70	0.58	0.922	[0.97 0.99]	<0.001
Fragmented medulla	20.57	19.97	0.60	0.774	[0.90 0.97]	<0.001
Uncont + Cont Medulla*	30.92	30.00	0.92	0.859	[0.96 0.99]	<0.001
Uncont medulla	8.44	11.51	−3.07	0.038	[0.85 0.96]	<0.001
Cont medulla*	22.48	18.48	4.00	0.351	[0.92 0.98]	<0.001
Strongly Medullated*	0.78	1.74	−0.96	0.281	[0.97 0.99]	<0.001
Llama						
Non-medullated	57.83	54.67	3.16	0.571	[0.94 0.99]	<0.001
Total medullation	42.17	45.33	−3.16	0.571	[0.94 0.99]	<0.001
Fragmented medulla	18.17	14.46	3.71	0.112	[0.81 0.96]	<0.001
Uncont + Cont Medulla	22.70	29.26	−6.56	0.098	[0.84 0.96]	<0.001
Uncont medulla	6.01	14.41	−8.40	<0.001	[0.65 0.93]	<0.001
Cont medulla	16.64	14.85	1.79	0.470	[0.67 0.93]	<0.001
Strongly Medullated*	1.30	1.60	−0.30	0.608	[0.06 0.72]	<0.050

Abbreviations: CI = Confidence interval, Cont = Continuous, Uncont = Uncontinuous.

very similar, with differences of less than 1%. Only the differences of UM percentages of alpaca and llama fibres obtained with PMic and S-Fiber Med (3.07 and 8.40%, respectively) show significant difference (*P*-value = 0.038 and 0.001, respectively), but between both methods, there is a high, strong and significant relationship ($r_{Pearson} > 0.65$; *P*-value < 0.001). However, regarding the percentages of NM, FM, CM, SM, UM + CM and total medullation fibres, no significant difference was found between the two methods. The correlation analysis shows a strong, high and significant relationship (*P*-value < 0.001) between the percentage of medullation obtained with both methods, regarding NM, FM, CM, UM, SM, CM + UM and total medullation fibres, when alpacas and llama fibres are analysed. These results indicate that the S-Fiber Med provides similar percentages of medullation compared to the PMic method.

As shown in Tables 1–3, no statistically significant differences were found between our proposal and other methods. This fact validates the AI model previously tested against the augmented dataset. Even if the model could have seemed more accurate than in reality after the first evaluation, an actual divergence would had permeated to the rest of the evaluations and, in turn, to Tables 1–3. The relationship between the PMic and the S-Fiber Med methods when assessing the arcsine of percentages of NM, FM, UM + CM and SM fibre is shown in Fig. 5. In all the sub-figures, it can be observed that the intercepts have reduced values (ranging from −0.001 to 0.029%) and that the *t*-test shows no statistical significance (*P*-values varied between 0.101 and 0.697). In can also be seen in Fig. 5 that the regression coefficients are different to zero and that the *t*-test shows high significance (*P*-values < 0.001 in all cases), but they are close to one (varying between 0.88 and 2.20). They are not equal to one, since the *t*-test shows values different to one (*P*-values < 0.01), with the exception of NM (*P*-value = 0.47). In addition, the percentages variation of NM, FM, UM + CM and SM fibres obtained with PMic explain in high grade ($r^2 > 0.90$) the variation of these fibre types obtained with S-Fiber Med when simple linear regression is applied.

Table 4 shows the evaluation of accuracy and precision of S-Fiber Med when assessing the AFD with standard wool tops. The AFD range varies between 15.53 and 35.37 μm. The accuracy varies between −0.86 and 0.10 μm in comparison to standard top samples. All accuracies were close to zero and within the acceptable tolerance range (Baxter, 2002; Botha and Hunter, 2010; IWTO, 2017a). It should be noted that the accuracy decreases as the AFD of the samples increases, but accuracy values are very close to zero (between −0.15 and 0.10 μm) for samples with an AFD smaller than 20.66 μm. Regarding the precision, S-Fiber Med achieves similar results when measuring the AFD of a specific sample multiple times. This can be observed in the data, since SDs range from 0.04 to 0.48 μm and CI range from ±0.08 to ±0.94.

T-test and Pearson correlation analyses between PMic, PFT, and OFDA100 methods compared with S-Fiber Med for AFD assessment are shown in Table 5. AFDs of alpaca and llama fibre samples obtained with PMic and S-Fiber Med are very similar, because no significance difference was found at the *t*-test (*P*-value > 0.172), and they have a strong, high and significant relationship between them, given the high Pearson correlation value ($r \geq 0.96$ with *P*-value < 0.001). In addition, Lin's concordance correlation varied between 0.90 and 0.94 with mean differences ranging from −0.77 to −0.17 μm. and C_b was more higher (0.96). According to Bland-Altman plot (Bland and Altman, 1986), more than 95% of the differences are between the interval mean difference ± 2 SD, with the exception of AFD of llama fibre (Fig. 6). Similar results were found when PFT and OFDA100 were compared with S-Fiber Med, with mean differences of 0.77 and 0.20 μm, respectively. Lin's concordance correlation was 0.90 and 0.94, respectively, and C_b was 0.97 and 0.99. The Bland-Altman plot showed that, 95% of the differences lay between the interval mean difference ± 2 SD. No significant trend was found for AFD differences between PMic, PFT and OFDA100 compared with S-Fiber Med for llama, alpaca and alpaca fibre, respectively (*P*-value = 0.28, 0.48 and 0.88 μm, respectively). However, for PMic compared with S-Fiber Med in alpaca fibre, a very low trend was found (regression coefficient = -0.09), with statistical significance (*P*-value = 0.02).

Additionally, when analysing specific relationships between the AFD values of NM, FM, CM and global fibres obtained with both methods, the correlation and regression coefficients are close to one (from 0.76 to 0.98 and 0.73 to 1.6, respectively). Likewise, the intercepts of FM and global AFD are not different from zero (*P*-value = 0.319 and 0.778, respectively). However, the intercepts of the AFD of NM and CM fibres are different from zero (*P*-value < 0.001). In addition, the regression coefficients are not different than one for FM and global AFD (*P*-value = 0.06 and 0.43, respectively), but for the AFD of NM and CM, fibre are also different

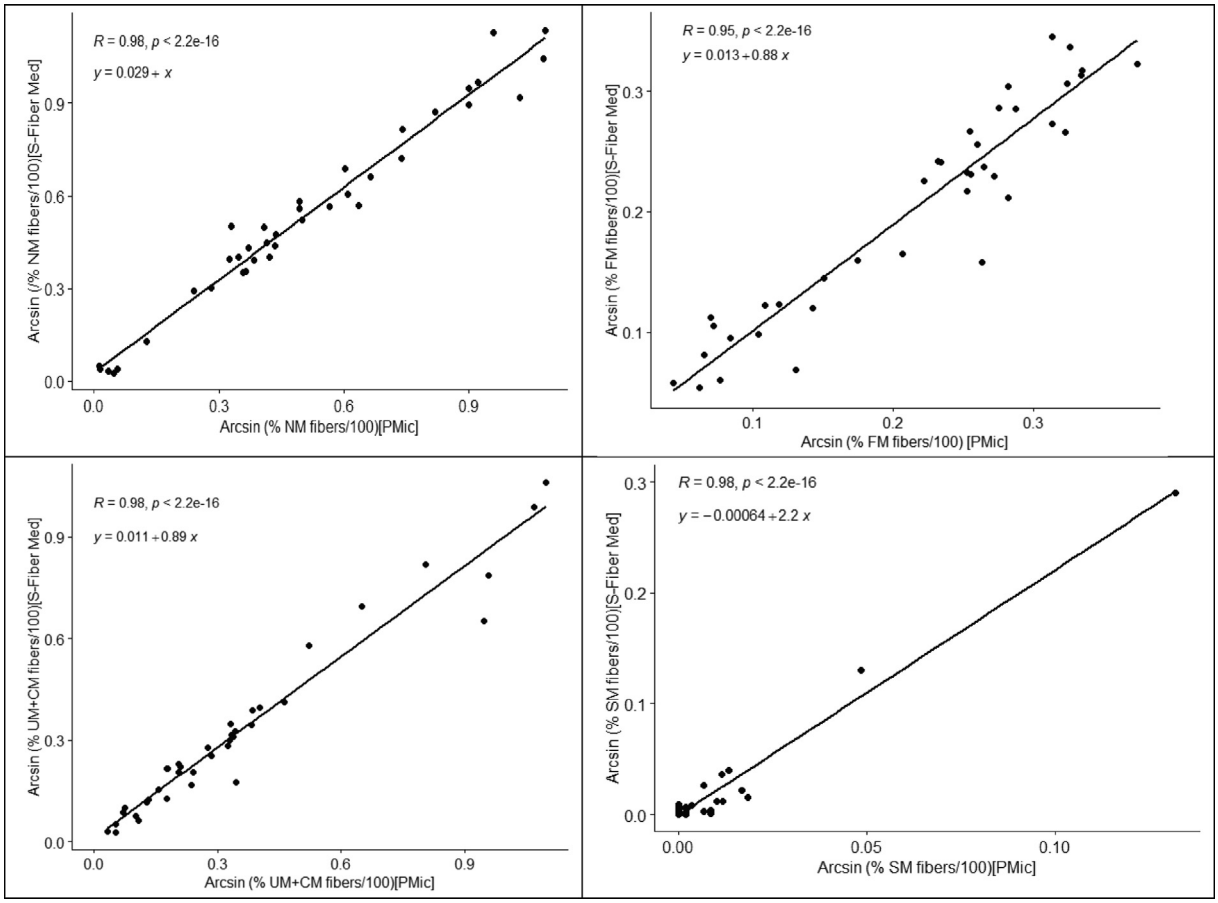


Fig. 5. Scatter plot of the percentages of non-medullated (NM), fragmented medulla (FM), uncontinuous + continuous medulla (UM + CM) and strongly medullated (SM) alpaca fibres obtained with the computerised projection microscope (PMic) and the S-Fiber Med methods. Pearson's correlation coefficients and their significance, regression equation and fit line are also shown.

Table 4
Average fibre diameter, accuracy and precision of S-Fiber Med, assessed with international standard sheep tops (n = 4).

AFD of standard tops	AFD measured with S-Fiber Med (μm)	Accuracy[1] (μm)	Precision (μm)	
		Difference	SE[2]	Confidence Interval[3]
15.53	15.63	0.10	0.04	±0.08
18.73	18.60	−0.13	0.07	±0.14
20.66	20.51	−0.15	0.22	±0.43
26.57	26.23	−0.34	0.48	±0.94
31.65	30.79	−0.86	0.22	±0.43
32.60	31.82	−0.78	0.07	±0.14
35.37	34.54	−0.81	0.07	±0.14

Abbreviations: AFD = Average fibre diameter.
[1] Difference between the AFD achieved with the S-Fibre Med and the standard tops.
[2] SE is a statistic value that evaluates the precision of S-Fibre Med.
[3] The confidence interval is a statistic value that evaluates the precision of S-Fibre Med.

from zero (*P*-value = <0.001 and 0.003, respectively, as can be seen in Fig. 7.

Discussion

The S-Fiber Med system is able to assess the medullation and the AFD of fibres with specifically designed hardware and AI-based software. Distinctive AI-based models were made for each fibre type (alpaca, llama and mohair). To date, there was no instrument or method in the literature or the market with the potential to determine in a practical way and in a short time (less than a minute) the different types of fibres according to their medullation (NM, FM, UM, CM, and SM), expressed in number of fibres and in percentages. The average time taken by two operators to measure 500 fibres per sample is approximately two hours and the method relies on a considerable amount of interpretation by operators. Therefore, the developed prototype provides a technological breakthrough in countries populated with South American camelids (i.e. Peru, Argentina, Bolivia and Chile) and angora goats (e.g. South Africa, United States of America, Lesotho, Turkey, Australia, or Argentina, among others). The size and weight of the S-Fiber Med instrument are smaller than other instruments available on the market (Laserscan, OFDA, Fiber EC, etc.). Moreover, the

Table 5
T-test, Pearson and Lin's Concordance correlation analysis of the Average Fibre Diameter (AFD) of alpaca and llama fibres (n = 38 and 40, respectively) when comparing the projection microscope (PMic) versus S-Fiber Med, the portable fiber tester (PFT) versus S-Fiber Med (n = 72), and the OFDA100 versus S-Fiber Med (n = 197).

Samples	*T*-test			Correlation analysis		Lin's Concordance correlation analysis	
	PMic (μm)	S-Fiber Med (μm)	*P*-value	R	*P*-value	ρ_c (CI)	C_b
Alpaca (n = 38)	21.77	23.16	0.172	0.97	<0.001	0.94 (0.90–0.97)	0.96
Llama (n = 40)	22.90	23.94	0.228	0.96	<0.001	0.93 (0.87–0.96)	0.96
	PFT	S-Fiber Med					
Alpaca (n = 72)	22.59	23.36	0.162	0.92	<0.001	0.90 (0.85–0.93)	0.97
	OFDA100	S-Fiber Med					
Alpaca (n = 197)	21.25	21.46	0.478	0.95	<0.001	0.94 (0.92–0.96)	0.99

Abbreviations: ρ_c = Lin's concordance correlation coefficient; CI = Confidence Interval of ρ_c; C_b = Bias correction factor.

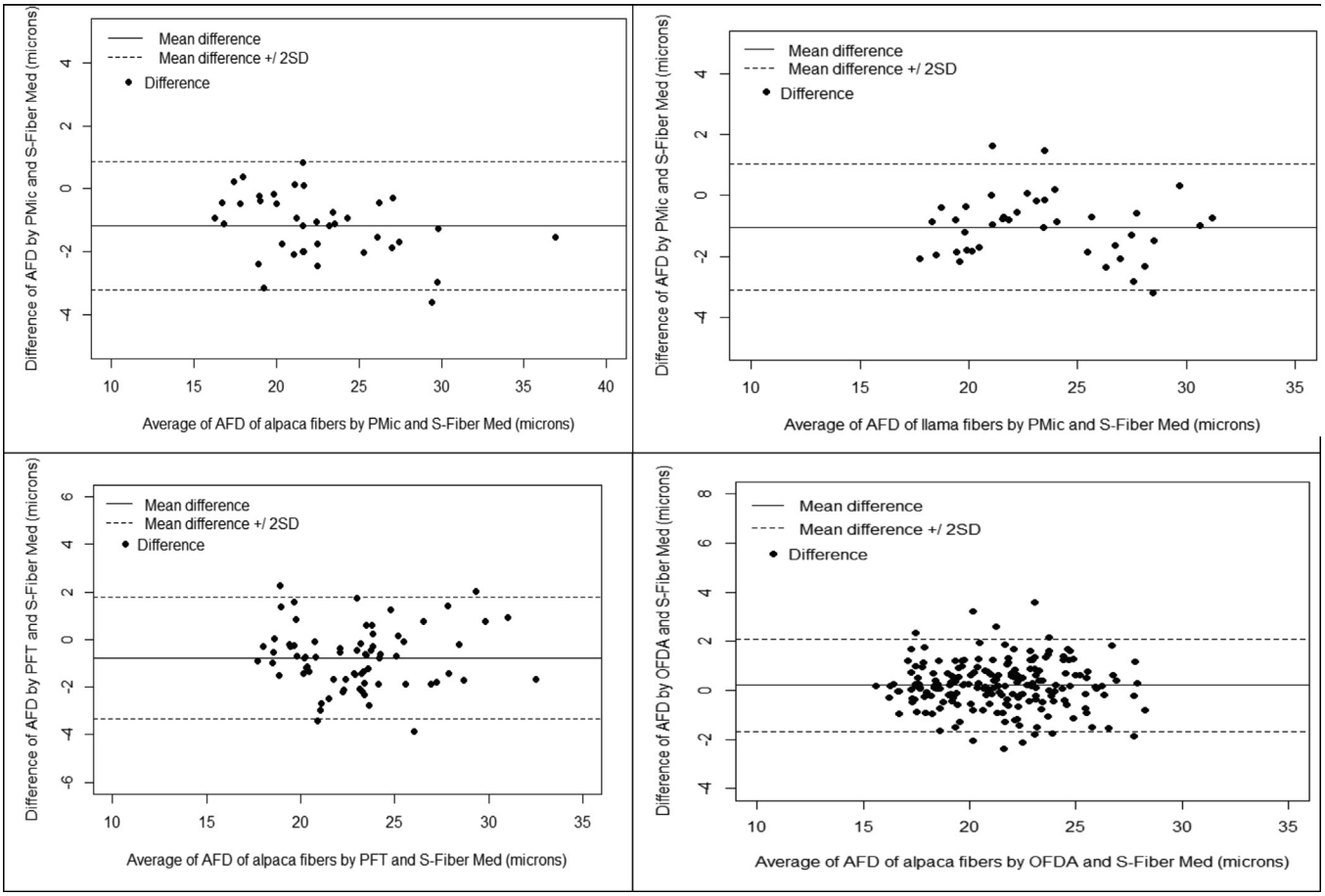


Fig. 6. Bland-Altman plots of average fibre diameter (AFD) of alpaca and llama fibres samples obtained with the projection microscope (PMic), the portable fiber tester (PFT) and the Optical Fibre Diameter Analyser (OFDA) compared with those obtained with the S-Fiber Med.

instruments available only evaluate fibre diameter, which further underpins the portability of the proposed instrument. This feature is very important because the production centres of South American Camelids are usually located in highland areas with difficult access.

In a similar way to the Fiber EC instrument developed in a previous effort by the authors (Quispe et al., 2017), S-Fiber Med shows a clear fibre image (Fig. 4) and allows the user to view the fibres under evaluation in real time, that is, while measurements are being carried out. In addition, the potential of identifying coloured or dark fibres in wool, which is a latent problem in merino sheep from Australia (Fleet et al., 2006), is also possible. The quality, accuracy, ergonomics, low cost, and portability of this piece of instrument facilitate a significant leap forward within the arena of fibre analysis instruments.

As regards to the test for dark and medullated fibres, due to the small amount of specimen that can be examined at one time (0.25–0.50 grams), several specimens must be examined to achieve the level of sensitivity required. Therefore, the Dark and Medullated Fiber Risk Scheme was introduced. Thus, a much larger quantity of wool can be examined without the risk of underlying dark or medullated fibres being missed (Ramsay and Humphries, 2005).

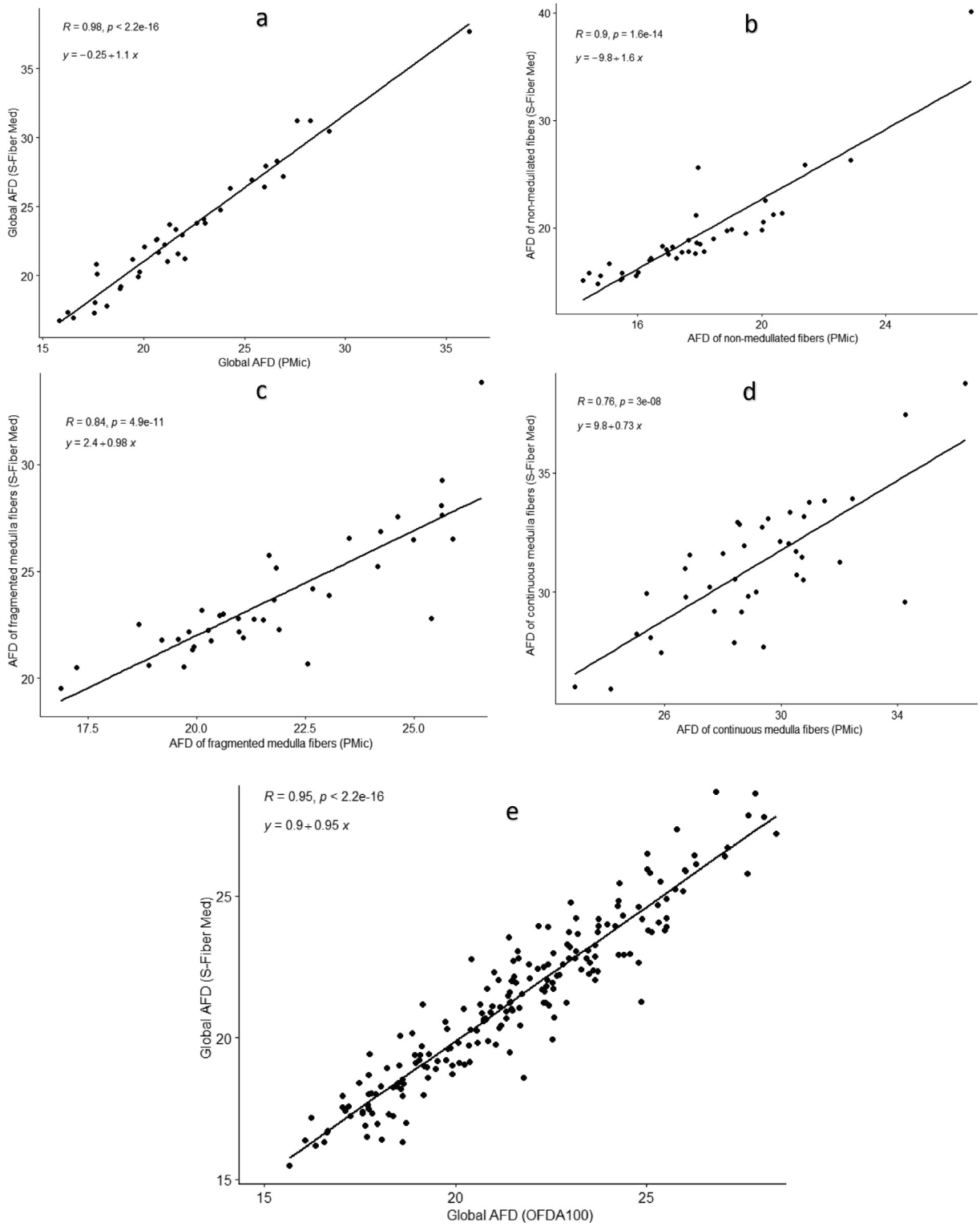


Fig. 7. Scatter plot of the average fibre diameter (AFD) of global, non-medullated, fragmented and continuous alpaca medulla fibres obtained with the projection microscope (PMic) and the S-Fiber Med methods (a–d). In (e), global AFD obtained with the S-Fiber Med and the OFDA100 methods is shown. In all figures, Pearson's correlation coefficients and their significance, regression equation and fit line are also shown.

For this reason, in order to have an average representative value of fibre samples for evaluation by S-Fiber Med, each sample should be sub-sampled at least to 3 or 4 parts.

The fragments and medulla of the alpaca, llama and mohair fibres have peculiar and distinctive characteristics (McGregor and Quispe, 2018). Therefore, the application of AI allows identifying them automatically based on thousands of equations (Goel et al., 2019). Thus, it was convenient to develop a model for each type of fibre. Therefore, the proposed system has the potential to evaluate the medullation of other types of fibre. To do so, it will only be necessary to develop a model for it. The condition for the analysis of the fibres is that they are white or very light in colour. Thus,

the different types of medullation can be identified by being immersed within a substance with refractive index similar to that of the fibre keratin (refractive index of wool and mohair: 1.553 and 1.557, respectively) but not the medulla. The refractive indices of various textile fibres are around 1.5 and 1.6. Exceptions are the acetate, which falls below, and Terylene polyester fibre, which is 1.725 (Fouda et al., 1989; Morton and Hearle, 2008).

The results of medullation percentages (Tables 1–3) and AFD (Tables 4 and 5) show high correlations (Figs. 5 and 6) of NM, FM, UM, CM, SM and total medullation measurements obtained by direct counting versus S-Fiber Med and PMic versus S-Fiber Med. Those were better than comparisons between PMic with OFDA100 carried out on wool and mohair fibres. Lee et al. (1996) reported that OFDA100 underestimate medullated fibres by a factor of 8.2%, and Lupton and Pfeiffer (1998), in an experiment with 124 fibre mohair samples, found significative differences in SM. However, in other experiments, they found that OFDA100 underestimated medullation percentages of FM + UM + CM in two percent or more, with significant difference for FM + UM + CM, SM and total medullation. Comparisons between OFDA and PMic in alpaca fibres showed greater differences (Pinares et al., 2018). Despite these differences, OFDA is an instrument that is within the international standard IWTO-57-2000 (IWTO, 2017a), and it is currently used in the evaluation of wool and mohair fibres (Turpie and Steenkamp, 1995; Botha and Hunter, 2010; McGregor et al., 2013), but also in alpaca fibres (Lupton et al., 2006). The system developed (S-Fiber Med) identifies and assesses medullation in alpaca, llama and mohair fibres providing results similar to PMic and with better performance than OFDA100, because it specifically provides five fibre types according to its medullation, with validation in alpaca fibre as well.

According to Table 4, the precision of S-Fiber Med system for AFD assessment in alpaca fibres is similar to the Sirolan Laserscan (Botha and Hunter, 2010), OFDA (IWTO, 2017a) and ADAS (Quispe et al., 2017). Cottle and Baxter (2015) shows CIs from 0.21 to 0.85, from 0.25 to 0.82 and 0.33 to 092 μm for Laserscan, OFDA and Airflow, respectively. Likewise, the increase in SD, SE and CI is similar to the findings of other researchers. Thus, Atkins (2005) found that the 95% CI increased by 0.11 ± 0.014 μm with each 1.0 μm increase in fibre diameter. Botha and Hunter (2010) point out that for an AFD of 20 and 35 μm, the maximum CI is 0.87 and 1.07, respectively.

In addition, the accuracy of S-Fiber Med system for AFD assessment ranges from 0.10 to 0.81 μm. These values are similar to the OFDA2000 and the ADAS, because the accuracy of the OFDA varies between 0.078 and 0.897 μm, and for ADAS, it varies between 0.034 and 1.317 μm (Quispe et al., 2017). For coarser fibres (31 μm and above), the accuracy declines to 0.86 μm. Nonetheless, this value is within the range accepted by IWTO-57-2011 (IWTO, 2017a). The focus of the fibres is very important to achieve good accuracy, but a proper calibration should not be neglected (Cottle and Baxter, 2015).

For measurements of AFD in alpaca and llama fibres, there is a high Pearson correlation (0.92–0.97) between PMic, PFT and OFDA compared with S-Fiber Med. Lin's Concordance coefficients are among moderate and substantial (Camacho-Sandoval, 2008) for PMic, PFT and OFDA compared with S-Fiber Med; but Bias correction factors are high, and Bland-Altman plots indicate that there is an agreement among PMic, PFT and OFDA100 methods compared with S-Fiber Med when AFD is assessed in alpaca and llama fibres. These results indicate that S-Fiber Med is a device precise and accuracy for AFD evaluation of alpaca and llama fibres. Van (2000) found a correlation of 0.99 for fibre diameter measurements when comparing Laserscan, OFDA and Airflow on raw wool samples. However, Baxter and Marler (2004) compared the performance of the two common on-farm fibre diameter measurement technologies (OFDA2000 using mid-side samples and Sirolan Fleecescan, using sampling of the whole skirted fleece) with traditional mid-side sampling followed by laboratory fleece measurement (OFDA100) and they found a correlation between 0.82 and 0.94. The evaluation was carried out even on one superfine and one fine-wool property in Victoria, and a medium-wool in South Australia.

In summary, results show that, when comparing the developed system with other methods, high correlation without significant differences is found. However, as explained in the manuscript, there are two caveats: first, the fibres should be from white, beige or light fawn colours. Second, the fibres must be immersed within a substance with a refractive index similar to that of the fibre keratin, but not the medulla. If these two prerequisites are met, the system will work regardless of the region, area, age, sex, variety, or any other characteristic of the animals or the fibres.

Finally, regarding the models developed, data augmentation was carried out before the dataset was divided into training and testing data. This could have caused model overfitting, thereby leading to a loss of inference capacity when processing new samples. However, as shown above, first, the IA model was tested independently and, after that, we further tested the S-Fiber Med system as a whole. These new tests used a completely different set of samples, not used before (more than 7 200 images coming from 41, 27 and 4z samples of alpaca, llama and mohair, respectively). Thus, this new data set was not used to train the model. Moreover, no augmentation process was performed upon this data set. Results show (Tables 1–3) that, statistically speaking (after *t*-test, correlation, and Two-proportion *z*-tests), the developed IA models are able to generalise properly and that model overfitting did not happen.

Conclusions

The S-Fiber Med is an instrument with four subsystems: optical, electronic, mechanical and the AI-based software. Those subsystems interact to capture thousands of images by means of scanning, which are then processed through AI-based software to provide measurements of medullation and AFD in an expeditious fashion (40 seconds). This instrument can be used for the evaluation of alpaca, llama and mohair fibres because it provides similar precision and accuracy that existing instruments.

The fibre assessments carried out comparing S-Fiber Med to other methods and instruments (such as PMic, PFT and OFDA) have shown a high correlation without significant differences. However, the enhanced portability, practicality, cost, easiness of use, and swiftness, among other distinctive features, are advantages of S-Fiber Med. In addition, while the measurements are being carried out, the S-Fiber Med shows sharp and defined images, allowing the user to view the images of the fibres in real time.

For all these considerations above, the use of this instrument, named Smart Fiber Medullometer, could be recommended to evaluate fibres for purposes such as genetic improvement of fibres in animal production, textile purchase-sale practices, and processing of fibres to verify the quality, as well as research on medullation to increase knowledge about alpaca, llama and mohair fibres. Moreover, after proper validation, it could be extended to evaluate fibres from all South American camelids, goats, sheep, or other fibres of animal origin.

Ethics approval

Not applicable.

Data and model availability statement

None of the data were deposited in an official repository, but they are available from the authors upon request.

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Declaration of interest

None.

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