Machine learning in high-frequency ultrasound skin imaging for cosmetics assessment

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Massufero Vergilio, Mariane[1]; Flamini Kiihl, Samara[2]; Batista Florindo, João[2]; Soares de Freitas, Luan[2]; Ribeiro Duzzi, Matheus[2]; Martins, Dieine[2]; Moretti Aiello, Laura[3]; Ricci Leonardi, Gislaine[1,3]

[1]School of Medical Sciences, University of Campinas, Brazil; [2]Institute of Mathematics, Statistics and Scientific Computing, University of Campinas, Brazil; [3]School of Pharmaceutical Sciences, University of Campinas, Brazil.

Introduction:

- An effective way to assess the *in-vivo* performance of anti-aging cosmetics is by using the high-frequency ultrasound (HFUS) skin image technique, a non-invasive approach that allows evaluating the content and organization of collagen fibers (1,2).

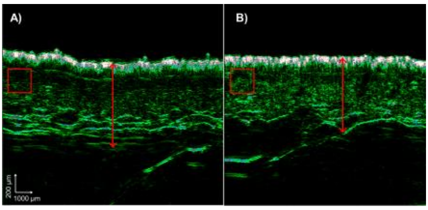

Figure 1. Skin images obtained from a 50 MHz HFUS equipment showing the changes in echogenicity and thickness caused by the application of a topical cosmetic.

- Manual measurements are operator-dependent and time-consuming (1). The advancements in machine learning based on image analysis have facilitated the automated detection of quantitative parameters.
- Models based on artificial intelligence was trained and tested/validated to automate the acquisition of HFUS image parameters from the skin.

Materials & Methods:

Data preparation

- 184 HFUS images from women forearms.

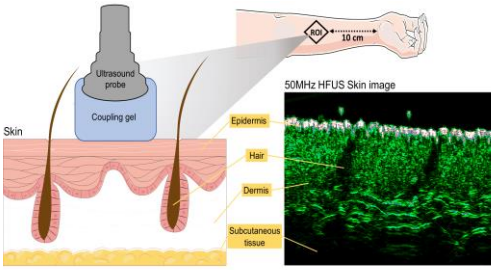

Figure 2. Scheme to obtain skin image using high-frequency ultrasound (HFUS) (1).

- Data set → HFUS images, age, echogenicity, skin thickness and layers per participant are first extracted using native non-machine learning methods.

Data modeling and evaluation

- Output: Prediction of the each target variable (echogenicity of dermis and epidermis, thickness of dermis and epidermis).
- Training (n=144) and testing (n=40) datasets.
- Several algorithms methods were tested → GLMNET, Random Forest, GBM (Gradient Boosting Machine algorithm), XGboost, SVM, KNN, PCR (Principal Component Regression), PLS (3,4).
- To extract the information from the HFUS images Local Binary Patterns (LBP) histograms were used (5).
- Quality control for the models → median absolute error (MAE) and root mean squared error (RMSE).

Results & Discussion:

Table 1. Performance of the best models for training and testing. datasets.

Target Variable	Best Model	Datasets	MAE	RMSE
Dermis echogenicity	GBM	Training (n=144)	**0.81**	**1.11**
Dermis echogenicity	GBM	Testing (n=40)	1.94	2.57
Epidermis echogenicity	GBM	Training (n=144)	6.25	8.54
Epidermis echogenicity	GBM	Testing (n=40)	10.41	12.98
Dermis thickness	PCR	Training (n=144)	102.68	127.53
Dermis thickness	PCR	Testing (n=40)	104.41	143.21
Edipermis thickness	PCR	Training (n=144)	8.86	12.37
Edipermis thickness	PCR	Testing (n=40)	8.13	10.77

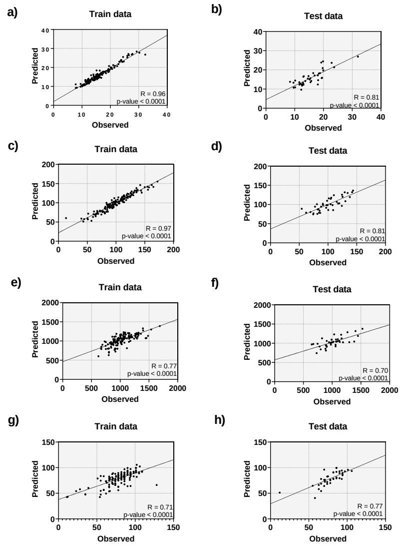

Figure 3. Prediction results of (A) training and (B) testing data from GBM algorithm for dermis echogenicity; (C) and (D) epidermis echogenicity; (E) training and (F) testing data from PCR algorithm for epidermis thickness; (G) and (H) dermis thickness by HFUS image. The x and y axis represent observed and predicted values respectively.

Conclusions:

The study developed here showed the possibility of automatic prediction of fundamental dermatological variables for the development and evaluation of cosmetics. In particular, the use of GBM machine learning algorithms showed promise especially in the prediction of dermis echogenicity. Through mathematical algorithms, the possibility arises of reducing these evaluations to minutes and further accelerating the development of new strategies for evaluating cosmetic claims.

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