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## Background:

The most effective strategy for addressing the management of cancer pain remotely should be better defined. It is mandatory to design a hybrid pathway by combining remote consultations with face-to-face re-evaluations.

## Methods:

The analyses of AI were performed on a dataset (n=267) obtained from video consultations for cancer pain management (March 2021 to February 2022). Different methods of Artificial Intelligence (AI) were tested to design the more accurate predictive model. The models included the classification and regression tree (CART), random forest (RF), gradient boosting machine (GBM), single hidden layer artificial neural network (ANN), and the LASSO-RIDGE algorithm (elastic model). Thirteen demographic, clinical, and therapeutic variables were adopted to define the process that can affect the number of hospital admissions (Figure 1).

Data were analyzed using the R software version 4.1.3. The toolkit included the MICE Suite for imputation of missing data, CARET for implementation of classifiers, pROC and pRROC for the construction and visualization of ROC curves. Graphics packages included ggplot, ggpubr, and cowplot.

## Results:

After the exclusion of 109 records due to not available or incomplete data, the AI-based predictive analyses were carried out on 158 remote consultations. In the training set, the accuracy was about 90% for both ANN and RF. Nevertheless, the best accuracy on the test set was obtained with RF (77%) (Figure 2).

## Discussion:

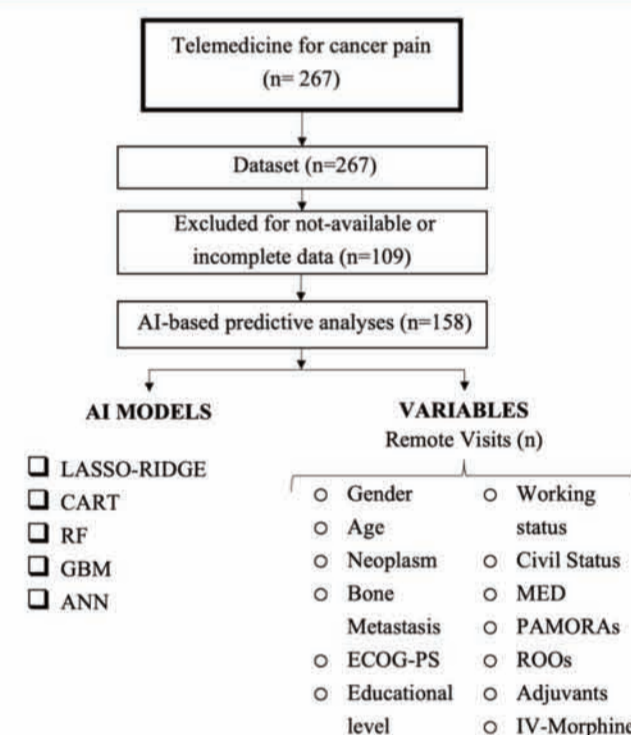
**The aim is to design a model of care that is generalizable while being able to guarantee a patient-centered treatment.** In this complex scenario, we adopted different ML models for predicting the need for more remote consultations.

In ML analyses, preprocessing and EDA are key elements of the process and take a large part of the time used for the whole analysis. During these phases, it emerged that the variable “age” offered useful information for the model construction and understanding. The variable was categorized into three age groups (younger, mean age, and older patients). Consequently, it was found that younger patients underwent more visits (p=0.03). This data was used in the predictive analysis (simulations). For example, the application of the chosen model (RF) showed that younger patients (≤55 years old) with bone metastases and ROOs administration for BTcP treatment have an increased risk for more consultations, especially if affected by lung cancer. This data must be interpreted very carefully.

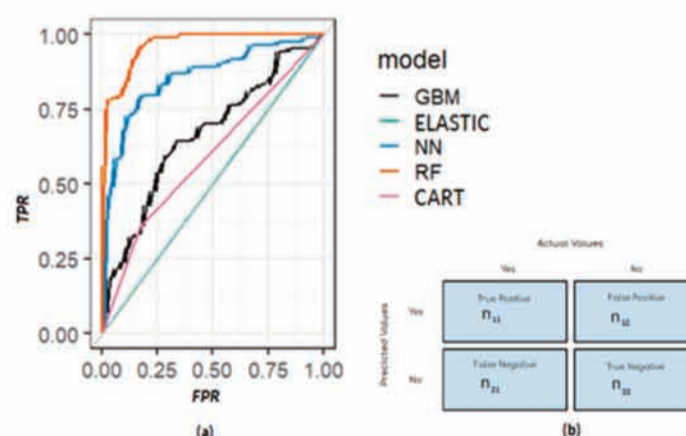
## Conclusion:

Despite the growing use of telehealth methods, scientific evidence is still scarce to establish the correct pathways to be followed. AI-based analyses can allow clinicians to identify the best model for predicting the need for hospital access and in-person pain evaluation or treatment.

Medical Ethics Committee: protocol code 41/20 Oss; date of approval, 26 November 2020.



**Figure1: Study flowchart.** Abbreviations: AI, Artificial Intelligence; CART, classification and regression tree; RF, random forest; GBM, Gradient boosting machine; ANN, artificial neural network; ECOG-PS, Eastern Cooperative Oncology Group Performance Status; MED, morphine equivalent dose; PAMORAs, peripherally acting  $\mu$ -opioid receptor antagonists; ROO, rapid onset opioids; IV-Morphine, intravenous morphine.



**Figure2: The area under the Receiver Operating Characteristic (ROC) curve (AUC) of the considered models. The AUC allows you to identify the most specific and sensitive classifier among those examined (Figure 2a). Reducing the false positive rate (FPR) and at the same time increasing the true negative rate (TNR). It means acting on the first row in the 2x2 confusion matrix (Figure 2b), thus maximizing the element to the first term of the first row (n11) and decreasing it to the second term of the same row (n12). Abbreviations: LASSO, LASSO-RIDGE regression; GBM, Gradient boosting machine; NN, neural network; RF, random forest; CART, classification and regression tree.**

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