Optimize the Estimation of Maize Height Using Sentinel-1: A Case Study in Umbria, Italy

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Abstract. Height is an important parameter to evaluate the crops growing state, being strongly correlated to plant other biophysical features. An accurate of this variable can allow farmers to carry out interventions aimed at optimizing crop development, which can be translated into an economic profit at the end of the cycle. The aim of the research is to explore key factors affecting the accuracy of remote sensing models in determining summer maize (*Zea mays* L.) height using Sentinel-1 SAR data. The study was conducted in 2023 on four fields in Umbria, Italy. The chosen approach is based on the construction of eight random forest (RF) models using different combinations of predictor variables, number of satellite images and speckle filters. In-situ maize height data and corresponding satellite images were acquired between 14th July and 4th September 2023. The results show that models constructed using four pre-full canopy coverage satellite image data (~150 cm) exhibited results with error ranging from 33.9 to 39.2 cm, while those built using all images yielded an error of 75.4 to 89.6 cm, thus demonstrating that maize height could be monitored effectively until to the point of complete canopy cover using SAR data. Future investigations are necessary could focus on refining model parameters further and exploring additional factors to enhance the robustness of the models.

Keywords: remote sensing · sentinel-1 · maize height · random forest

1 Introduction

The information obtained from biophysical parameters is fundamental for appropriate agronomic, ecological and economic management [1]. Periodic monitoring of plant height, biomass and Leaf Area Index (LAI) has a significant impact on company practices, considering the easy susceptibility of these variables to environmental conditions. Plants height, in particular, can represent a key factor in the growth state of crops, especially if associated with the phenological phase and biomass [2].

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Space-born images represent an opportunity to monitor spatial and temporal changes in crop growth. Tools such as UAV, Lidar and multispectral imaging have been widely employed to study and model plant height (see, e.g., [3–5]).

Active sensors such as SAR (Synthetic Aperture Radar), operating at microwave wavelengths and therefore not being influenced by the presence of cloud cover, allow images to be acquired both day and night and regardless of weather conditions [6, 7]. The capability of the SAR backscatter signal to penetrate not only the atmospheric components, but also the vegetation canopy, makes these types of sensors more suitable, compared to optical ones, for investigating biophysical properties of crops, such as the plant height [8].

Since the relation between plant height and SAR data is not linear [9] and is affected by a number of variables, prediction of plant height can benefit from machine learning (ML) techniques, a branch of Artificial Intelligence (AI) where algorithms are trained to emerge patterns and correlations from large data sets and make the best decisions and predictions based on those analyses. Among the numerous algorithms used, Random Forest (RF) is one of those that showed the best results for the estimation of plant biophysical parameters (see, e.g., [10, 11]).

The work aimed to assess whether satellite images obtained by Sentinel-1 were able to monitor the growth cycle of maize through the analysis of the height-backscatter signal relationship. Afterwards, the study focused onwhich RF predictor exerted the most significant impact of model accuracy, while keeping the model parameters constant. Much importance was given to the type of speckle filter used, because it represents a factor impacting the quality of speckle noise reduction in SAR images [12, 13]. In particular, the Lee Speckle Filter (LF, [14]) is effective at reducing speckle noise, it can also blur image details, especially in areas with high levels of speckle while Refined Lee Filter (RLF), thanks to additional steps tends to produce better results in terms of conservation and sharpness of image detail, simultaneously reducing speckled noise [15, 16].

In the bibliography, various approaches use data from multiple sensors as variables [see, e.g. [10, 11]. However, to maintain focus, we prioritize only the most common variables obtained from Sentinel-1, and the inclusion of additional SAR parameters, such as polarization intensity ratio and difference, as well as Radar Vegetation Index (RVI), would further improve accuracy, as noted in previous studies [see, e.g., [17–19]. Furthermore, we hypothesized that employing RLF-processed images and focusing solely on data from earlier maize growth stages could enhance model accuracy, leveraging the strong SAR-height correlations reported in prior research [9].

The detailed comparison of predictor selection and its impact on model accuracy represents a novel aspect of this study, not extensively explored in prior literature.

2 Materials and Methods

2.1 Study Area and Field Data

The experimentation was conducted in summer 2023 on four adjacent fields belonging to the “Foundation for Agricultural Education in Perugia” (FIA). All plots are located in the Tiber Valley, near Deruta, Umbria, Italy, and their total area amounts to approximately 60

hectares. The proximity with the Tiber River influences the soil component of the study area, thus characterized by a textural gradient from east to west. The experimental crop was biomass summer corn (Zea mays L.), sown at the end of the June. Previously, the pea (Pisum sativum Asch and Gr.) had been sown on the same fields. All the fields were managed with the same cultivation technique, respecting the principles of conservative agriculture.

Maize is a crop characterized by high water requirements, and in this area, the expected irrigation practice consists of complete irrigation from sowing to harvesting, using sprinkler irrigation in one-week shifts.

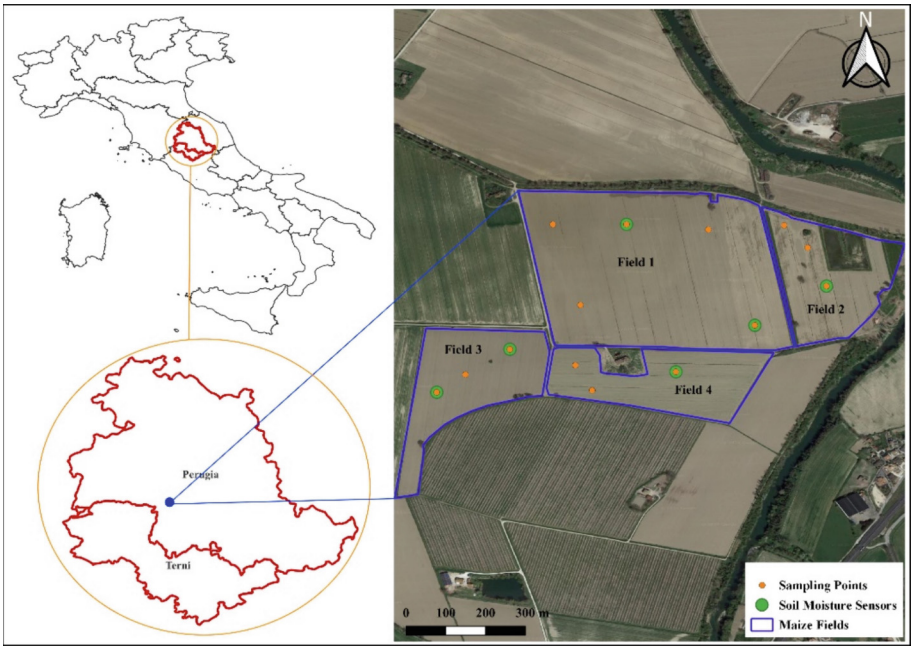

Fig. 1. The geographical location of the experimental plots.

Field data collection included measuring maize height in weekly intervals at 14 georeferenced locations (Fig. 1), photographing the growth process (Fig. 2), and recording field characteristics such as soil condition and crop health status. The field data was collected from 14th July to 4th September 2023. "Biologische Bundesanstalt, Bundessortenamt, and CHemische" (BBCH) [20] classification was applied to define the single development's stages of maize, while in-situ height measurements were obtained by the mean of three plant's heights for each sampling point.

Six soil moisture sensors were installed on the fields at a depth ~20 cm to acquire soil moisture data during the entire maize crop cycle. Data measurements occurred at 15 min intervals.



Fig. 2. Different growth stages of maize in the study area: **a)** Leaf development; **b)** Stem elongation; **c)** Flowering; **d)** Development of fruit.

2.2 Sentinel-1 Data

Seven Sentinel-1 Level 1 GRD images interferometric wide swath (IW) in descending pass direction were obtained from Copernicus Data Space Ecosystem [21]. The Sentinel-1 SAR data includes dual-polarization images in VV (Vertical-Vertical) and VH (Vertical-Horizontal) polarizations. We selected images based on their proximity to field measurement dates for optimal temporal alignment between satellite observations and ground truth data (Fig. 3). Probable irrigation dates, inferred from average soil humidity trends, also influenced our selection. In summer, with scarce precipitation, sudden humidity increases can likely be attributed to irrigation in irrigated crop areas (Fig. 4). Acquiring SAR images between irrigation periods helps mitigate the influence of water droplets and humidity on the typically stronger backscatter signal [22]. The acquired satellite data were subjected to preprocessing steps to prepare them for subsequent analysis and feature extraction. All preprocessing and feature extraction actions were done in Sentinel Application Platform (SNAP) software (version 9.0.8) [23]. The first step was to subset the images to a smaller area of interest (AOI). This was done to make the subsequent pre-processing steps more computationally feasible (larger images typically require more processing time). To convert the pixel values from integer digital numbers (DN) to backscatter coefficient or sigma-nought (σ°), radiometric calibration was performed. Next steps included terrain correction to project the pixels from the satellite reference system onto a geographic reference system and creation of a multitemporal stack to collocate the spatially overlapping products. The collocated images were then filtered using two speckle filters to reduce the effects of speckle noise: Lee filter with a window size of 7×7 (LF), and Refined Lee filter (RFL). Because SAR intensity can vary many orders of magnitude, the final preprocessing step was linear to dB conversion that compensates for very high dynamic range and expresses backscatter values in dB.

After preprocessing, five parameters were extracted from the SAR images to be used in modelling process: σ°VH, σ°VV, polarization intensity ratio and difference (σ°VH / σ°VV, σ°VH - σ°VV), and radar vegetation index (RVI), modified for dual-pol SAR data [24], as shown in Eq. (1). The workflow used in the study is shown in Fig. 5.

$$RVI = \frac{4\sigma^0 VH}{\left(\sigma^0 VH + \sigma^0 VV\right)} \tag{1}$$

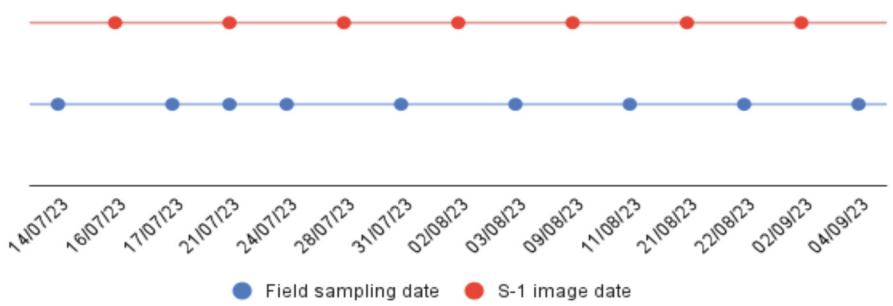

Fig. 3. Timeline of the field data collection and corresponding Sentinel-1 image acquisitions.

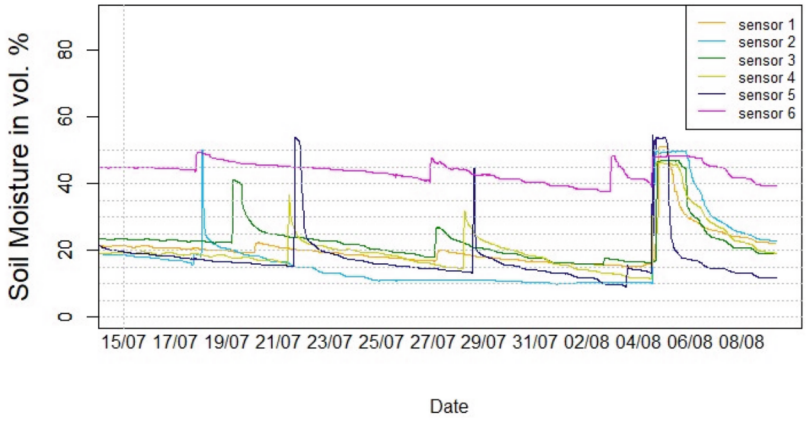

Fig. 4. Daily average soil moisture trend of six sensors.

2.3 Random Forest Modeling and Statistical Analysis

To assess the impact of key factors affecting model accuracy, eight Random Forest (RF) models were trained. Two sets of predictor variables were used: (1) σ°VH, σ°VV; (2) σ°VH, σ°VV, σ°VH / σ°VV, σ°VH - σ°VV, RVI. Moreover, two combinations of satellite image counts were used: (1) Data from all 7 images; (2) Data from the first four images,

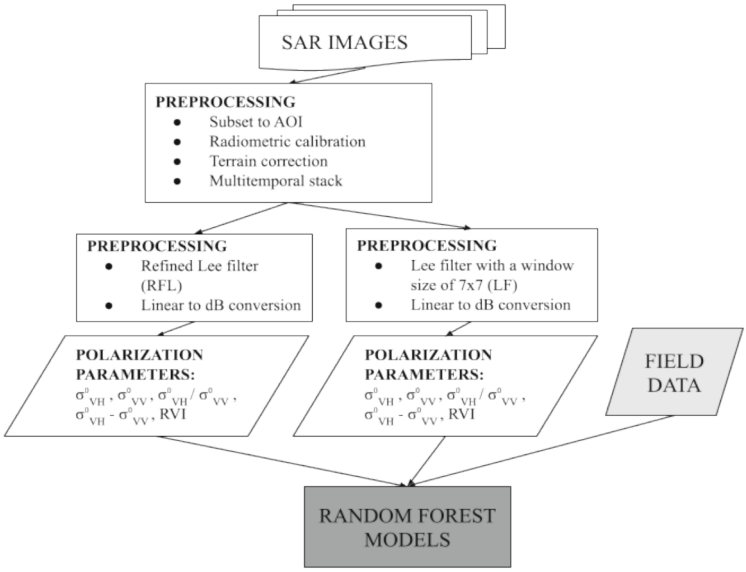

Fig. 5. Workflow for maize height estimation from Sentinel-1 images.

Table 1. Random forest models used in the study. Different sets of predictor variables were used while model parameters were constant.

Models	Predictors	Images (N)	Speckle Filter
RF1	σ°_{VH}, σ°_{VV}	7	RLF
RF2	σ°_{VH}, σ°_{VV}, $\sigma^{\circ}_{VH}/\sigma^{\circ}_{VV}$, σ°_{VH}-σ°_{VV}, RVI	7	RLF
RF3	σ°_{VH}, σ°_{VV}	4	RLF
RF4	σ°_{VH}, σ°_{VV}, $\sigma^{\circ}_{VH}/\sigma^{\circ}_{VV}$, σ°_{VH}-σ°_{VV}, RVI	4	RLF
RF5	σ°_{VH}, σ°_{VV}	7	LF
RF6	σ°_{VH}, σ°_{VV}, $\sigma^{\circ}_{VH}/\sigma^{\circ}_{VV}$, σ°_{VH}-σ°_{VV}, RVI	7	LF
RF7	σ°_{VH}, σ°_{VV}	4	LF
RF8	σ°_{VH}, σ°_{VV}, $\sigma^{\circ}_{VH}/\sigma^{\circ}_{VV}$, σ°_{VH}-σ°_{VV}, RVI	4	LF

and also two speckle filters: (1) RLF; (2) LF, while keeping model parameters constant, as shown in Table 1. The dependent variable was maize height measured in cm.

Random Forest is a type of ensemble learning method that can handle small datasets and help reduce overfitting by combining multiple decision trees into one model [25]. The advantage of using Random Forest lies in its ability to handle missing data and noisy predictors [26]. Modeling for each dataset was conducted in R 4.3.1 software [27] using Random Forest ('rf') method available within the caret (v6.0–94) [28] package. The number of variables used to construct each tree (mtry) was set to a range 1:4. Additionally, before building the RF model, data centering and scaling were used as pre-processing

steps. The effectiveness of the models was assessed through a 10-fold cross-validation process that compared the predicted and observed values of SOC in 70%–30% dataset splits. The following validation metrics were calculated to evaluate the performance of the models: root mean square error (RMSE) and coefficient of determination (R^2). Additionally, prior to modeling, Pearson correlation coefficients (r) and scatterplots were produced to display and measure the strength, direction and form of the relationship between backscatter coefficients and maize height. This was also conducted in the R environment using ggplot2 (v3.4.2) [29], and corrplot (v0.92) [30] packages.

3 Results and Discussion

3.1 SAR Parameters and Their Relationship with Maize Height

Higher sensitivity of both σ°VH and σ°VV was observed at the beginning of maize growth, which started to decrease once the crop reached ~150 cm in height (Fig. 6a and Fig. 6b). As the maize plants matured beyond the critical height of ~150 cm, the density of the canopy increased covering the soil and causing the dominance of volume scattering in SAR signal returns [31]. These results are consistent with what has been observed in the literature on maize [24, 32–34]. Moreover, σ°VH ($r = 0.53$) was found to be more strongly correlated to maize height than σ°VV ($r = 0.18$). These results could be explained by the fact that the development of large and randomly oriented maize leaves leads to a greater increase of the cross-polarized SAR backscattering [35]. Additionally, it has been found that σ°VV is sensitive to soil moisture levels even at high NDVI values (>0.7) [36], therefore it can be assumed that when maize canopy is well developed this sensitivity could affect the radar signal.

Contrary to the observed positive correlations with σ°VH and σ°VV, the σ°VH/σ°VV, as well as RVI (Fig. 6c and 6e) showed a negative correlation ($r = -0.3$) with maize height [37]. The backscatter difference (σ°VH - σ°VV) (Fig. 6d) was also positively correlated with maize height throughout the study period, and was not affected by the maize phenological stages, a phenomenon also observed in wheat fields [38]. This observation indicates the potential of σ°VH - σ°VV as a suitable predictor variable in modeling crop growth, but further research is needed to explore the underlying mechanisms driving these relationships and to refine the use of radar data for maize monitoring applications.

3.2 Random Forest Models

As can be seen in Table 2, the quality of speckle filtering has an impact on model accuracy. Contrary to our primary hypothesis, models using LF (RF 5-RF 8) showed improvement of RMSE from 10 to 15% when compared to models using a RLF dataset (RF 1-RF 4). For example, RF 6 showed a RMSE of 75.84 cm and a R^2 of 0.38, while RF 2 with the same model parameters, number of SAR images, and response variables showed a RMSE of 89.59 cm and a R^2 of 0.22. This result is probably caused by the nature of RLF that preserves image sharpness and detail near strong edges [14], which was not useful in a more homogenous, agricultural area studied here. LF with a 7×7 window size resulted in a smoother output image, and consequently created a dataset

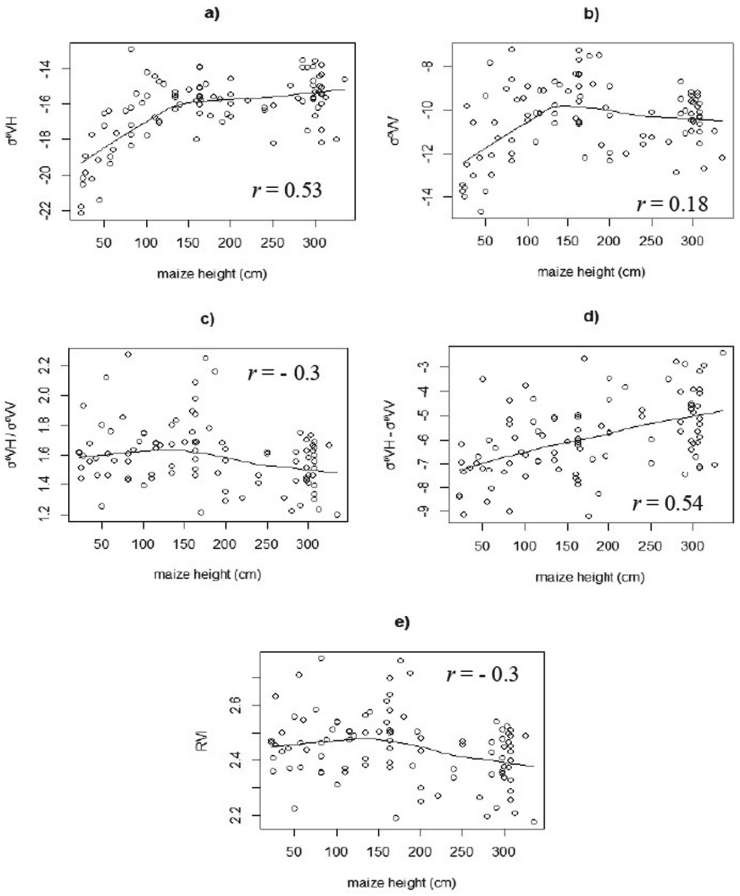

Fig. 6. Scatterplots and Pearson correlation coefficients (r) displaying the relationship between SAR parameters and maize height: **a)** σ°VH, **b)** σ°VV, **c)** σ°VH / σ°VV (ratio), **d)** σ°VH - σ°VV (difference), and **e)** Radar Vegetation Index (RVI). The images were produced using all satellite images (N = 7) and LF speckle filter with a window size 7×7.

of improved quality used in maize height modeling. More information on the effects of speckle filters on SAR image quality can be found in literature (see, e.g., [39]).

Furthermore, models constructed using four pre-full canopy coverage SAR data (RF 3, RF 4, RF 7 and RF 8) exhibited promising results, with RMSE ranging from 33.9 to 39.2 cm, while the models built using all SAR images (RF 1, RF 2, RF 5, RF 6) yielded an RMSE of 75.4 to 89.6 cm (Table 2). This is an improvement of 55 to 56% in model accuracy that strongly indicates that maize height could be monitored effectively until the point of complete canopy cover using SAR data, as previously observed [9, 10, 24, 32].

Finally, the performance of the RF models revealed a preference for fewer predictor variables as model inputs. Namely, RF 1, RF 3, RF 5, and RF 7 (RMSE = 86.53, 37.8, 75.43, and 33.88, respectively) performed better than RF 2, RF 4, RF 6 and RF

8 (RMSE = 89.59, 39.2, 75.84, and 34.26). Overall, the study observed an increase of model accuracy when using exclusively σ°VH and σ°VV as predictor variables by 0.5 to 4%. Compared to other factors that impact model accuracy considered in this study, this could be characterized as a minor improvement, indicating the primary focus should remain on refining preprocessing techniques and selecting appropriate SAR data, which have demonstrated more substantial impacts on model outcomes.

Table 2. Results of Random Forest (RF) and improvement (%) of the models with varying input used: different speckle filters, number of images and response variables. $\uparrow_{\text{filt. (\%)}}$ means RMSE improvement (%) of the model when using LF, $\uparrow_{\text{im. (\%)}}$ means RMSE improvement (%) of the model when using first 4 SAR images, $\uparrow_{\text{var. (\%)}}$ means RMSE improvement (%) of the model when using exclusively σ^0VH and σ^0VV as input variables.

Models	RMSE	R^2	$\uparrow_{\text{filt. (\%)}}$	$\uparrow_{\text{im. (\%)}}$	$\uparrow_{\text{var. (\%)}}$
RF1	86.53	0.23	–	–	+3.5
RF2	89.59	0.22	–	–	–
RF3	37.80	0.47	–	+56.3	+3.7
RF4	39.20	0.47	–	+56.2	–
RF5	75.43	0.42	+12.8	–	+0.5
RF6	75.84	0.38	+15.3	–	–
RF7	33.88	0.69	+10.4	+55.1	+1.1
RF8	34.26	0.60	+12.6	+54.8	–

4 Conclusions

The results of this study indicate that in the process of vegetation height modeling, several features should be considered to improve the accuracy of the models. Pre-full canopy coverage SAR data was a key contributor that enhanced model accuracy. This demonstrated that the temporal dimension is crucial for monitoring vegetation growth dynamics effectively. Moreover, the unexpected but significant improvements in model accuracy associated with LF filtering, particularly in the context of homogeneous agricultural landscapes, emphasize the importance of tailoring SAR preprocessing techniques to specific study areas.

Furthermore, the preference for fewer predictor variables as model inputs, namely σ°VH and σ°VV, emphasizes the importance of thoughtful feature selection in model construction, yielding enhancements in accuracy.

These findings not only advance our understanding of SAR-based vegetation height modeling but also offer practical insights for optimizing model performance in agricultural monitoring applications. The findings corroborate with previous studies on maize vegetation dynamics, underscoring the importance of considering crop growth stages in interpreting radar backscatter data.

Understanding the temporal dynamics of radar signatures in relation to crop height offers valuable insights into agricultural monitoring and management practices. These observations contribute to the refinement of remote sensing methodologies for assessing crop development estimation, thereby supporting informed decision-making in agricultural resource management.

This study assessed the RF machine learning technique for estimating maize height using Sentinel-1 data. However, the method has limitations, including the need for high-quality and sufficient ground truth data. Fluctuations in soil moisture due to irrigation practices could affect maize height estimation outcomes. Therefore, gathering data from additional seasons is recommended to enhance the robustness and generalizability of the findings.

It is also recommended to apply other types of ML algorithms for comparison with the employed model, in order to allow for a broader analysis.

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