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Malnutrition Risk Assessment in Frail Older Adults using m-Health and Machine Learning

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***Abstract*—Malnutrition represents a major public health concern worldwide, and it particularly harms older adults since it is frequently associated with several chronic health disorders. It significantly increases in institutionalised subjects, especially in presence of cognitive impairments. For this reason, it is essential to early detect nutritional deficiencies and unhealthy dietary habits and to timely trigger proper feedback and interventions. Malnutrition assessment in clinical settings is generally based on standard screening tools including questionnaires, rating scales, and biometrics. Technological solutions based on IoT and mobile devices, along with AI techniques for data analysis, could provide important advantages in the risk assessment and prevention. In this paper we present a Decision Support System for the early detection of malnutrition risk based on data collected by a m-health application for nutritional and body composition monitoring. The application has been in use in a nursing home in Italy from March 2018 and, considering drop-outs and the impact of Covid-19 pandemic, we have been able to collect consistent data over three different trial periods. In collaboration with a medical specialist, we performed feature engineering to estimate daily intake for the major food components, meal completeness, variability, considering also physiological data. Then, we ran several Machine Learning models using the results of Mini Nutritional Assessment rating scale as ground truth, and applying SMOTE and cost-sensitive learning to deal with the dataset imbalance. Obtained results indicate that the best performing ML models for malnutrition risk prediction reach median accuracy and recall values of 94% and 92%, respectively.**

***Index Terms*—m-health, Machine Learning, older adults, malnutrition**

I. Introduction

Nutrition plays a vital role in the aging process. An inadequate diet in terms of habits, nutritional and energy intake may lead to malnutrition, representing one of the leading causes for frailty, a geriatric syndrome characterised by cognitive deficits and a global loss of physical efficiency, with an increased risk of poor outcomes in multiple health domains [1]. In addition, malnutrition risk is also directly associated with diagnosed frailty, mainly due to cognitive and physical impairments and depression, which may influence nutritional habits in older adults. This two-sided relationship highlights an existing overlap among frailty and malnutrition concepts, thus posing the need of integrated screening, assessment, and treatment strategies to take into account both conditions [2]. Furthermore, malnutrition risk is significantly higher for institutionalised and hospitalised older adults. It has been estimated that approximately 20% of older adults living in Long Term Care (LTC) facilities suffer from a form of malnutrition [3].
To tackle malnutrition spread in clinical settings, many screening and assessment tools have been developed over the years to identify malnourished patients as well as subjects at risk of malnutrition, and to trigger targeted interventions. They mainly consists of periodic questionnaires to be conducted by healthcare professionals. Mini Nutritional Assessment (MNA) questionnaire and its short-form (MNA-SF) [4] are considered the most valid screening tools for older people since they include also an evaluation of cognitive impairments, dementia, and depression problems in the overall assessment. However, MNA is generally applied periodically, with a minimum period of 30 days in order to appreciate the impact of the nutritional intake on the general health condition of the subject. Currently, there is no clinical tool that allows a continuous nutritional monitoring.
To this aim, the recent diffusion of e-health and m-health systems offers novel opportunities to monitor nutritional status by collecting information about food intake, behavioural and physiological data on a daily basis from IoT devices and mobile technologies. In addition, Artificial Intelligence (AI), in the form of Machine Learning (ML) and Deep Learning (DL) techniques, may provide a scalable and effective solution to analyse such data and automatically build predictive models and/or discover novel risk factors for malnutrition [5]. In this paper we present a Decision Support System (DSS) for the early detection of malnutrition risk based on data collected by a m-health application for nutritional and body composition monitoring. This solution has been designed for institutionalised frail older adults, but the same framework could be used for other categories at risk (e.g., to monitor obesity risk in children).

II. Related Works

Smart ICT solutions employed in the domain of human nutrition are generally classified into three categories: food recognition, food intake monitoring, and malnutrition assessment [6]. State-of-the art solutions for automatic food recognition are based on DL models, mainly consisting of very deep convolutional neural networks, to detect items from food

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images generally taken by the smartphone camera [7]. At the same time, food intake monitoring can rely on manual food weighting as a widely accepted reference method, or on innovative solutions based on visual assessment and food image processing to estimate the consumed food volume [8]. However, both these systems present several drawbacks. They require huge food image datasets to train the classification algorithms, whose performances are highly dependent on the used datasets. In addition, they have to face with possible distortions in the pictures made by users (e.g., zoom, brightness, contrast, saturation), which require food segmentation techniques that impact on both food classification and volume estimation. As a result, methods based on 2-D images are still far from being satisfactory for nutrient and calories estimation [9].

Moreover, few technological solutions have been proposed for nutritional monitoring in older adults, especially in institutionalised subjects [10], but they often stop at the food recognition and food intake evaluation processes, without investigating the correlation between the nutritional behaviour and the malnutrition risk. In this paper, we exploit a simple yet efficient m-health application, called DoEatWell (DEW), designed to collect information about the nutritional preferences and intake of frail older adults living in a LTC facility. DEW is also integrated with a bioimpedance scale as additional sensing device to collect weight and body composition data. It is designed both to be used by the monitored subjects (also in independent living scenarios) and care givers, and it has been deployed in a LTC facility in Italy from March 2018.

Collected data have been analysed to define daily intake estimates for the major food components, behavioural and anthropometric markers to be used as input for several benchmark ML algorithms in order to provide a periodical malnutrition risk assessment. It is worth to notice that the proposed solution implements a quick and straightforward food intake monitoring method based on visual assessment, which does not rely neither on food weighting scheme nor on image-based food volume estimation. It represents a quantitative evaluation of food consumption for each subject, which is comparable with the clinical information requested by the reference clinical surveys and allows a reliable risk assessment.

III. Material and Methods

A. DoEatWell m-health application

DEW has been developed within the INTESA research project[1], funded by Tuscany region, in collaboration with the LTC facility "G.Tabarracci" in Viareggio (Italy), being part of ICARE srl[2]. DEW represents a module of a framework of personalised and innovative mobile and e-health services for multimodal health monitoring aimed at improving the quality of life and well-being of frail older adults, both living in their own homes and institutionalised. DEW design and implementation have already been presented in [11], while a preliminary system evaluation in terms of service reliability, user acceptance, and quality of experience can be found in [12]. Just to better understand the reference scenario and the collected data, we present DEW main functionalities in Figure 1. Specifically, DEW mainly focus on tracking the users' preferences and consumption in the 2 main daily meals (i.e., lunch and dinner), and it implements the daily menu proposed by the LTC facility internal canteen. Each menu is composed by 4 courses (i.e., first course, second course, side dish, fruit or dessert), and for each course users can choose between the dish of the day and some always-on-menu fixed choices. DEW tracks food intake through a simple and quick survey to be filled in at the end of each meal, consisting of a qualitative assessment (i.e., nothing, few, normal, twice) of the consumed food portions for each course, which is encoded as 0x, 0.5x, 1x, and 2x of the received food portion, respectively. In this way, selected food items with relative consumption can be correlated with the reference food percentage composition, in terms cereals, proteins, vegetables, and fruit, to estimate their intake. This information is obtained from a customised food database developed in collaboration with a medical specialist and maintained on DEW back-end module.

Finally, the mobile application is integrated with a commercial, low-cost bioimpedance scale to collect body weight, Body Mass Index (BMI), basal metabolic rate, bone mass, body fat, water, and muscle percentage, through Bluetooth Low Energy communication.

B. Data collection

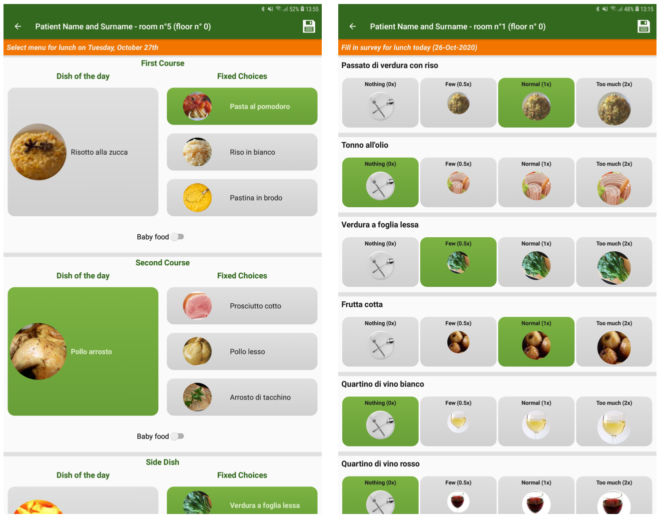
The major goal of DEW is to enable long-term data collection and analysis for a "hard-to-reach" subject category consisting of older adults, especially those suffering from multiple morbidities and frailty, leveraging a controlled and standardised context provided by the LTC facility to ideally achieve a more continuous monitoring with respect to in-home settings.

DEW has been deployed in the LTC facility since March, 2018, and it is still in use. Until today, it has been used alternatively by 13 caregivers to monitor up to +60 guests simultaneously. However, the concurrent deployment and usage of DEW with other monitoring services within the INTESA framework (i.e., stress, sleep, social interaction monitoring and many others) has imposed a significant overhead to the already busy daily schedule of nursing care personnel, negatively impacting on their effort to ensure a constant and long-term monitoring of a large number of subjects. Moreover, LTC facilities are often characterised by subjects' drop-out due to sudden and unpredictable events (e.g., health aggravations), and consequently to a frequent turnover that limits a prolonged monitoring of the same subjects. Finally, to validate our approach as a supervised learning task, we relied on the availability of a periodical clinical malnutrition assessment made by a clinical professional as basic requirement for our analysis. Specifically, we considered 3 trial periods as the most continuous and reliable nutritional monitoring sessions:

- T1: March-September 2018 (15 subjects, 22 weeks);

[1]http://www.progetto-intesa.it/

[2]http://www.icareviareggio.it/



(a) Food menu selection (b) Meal survey compiling

Fig. 1: DEW application main functionalities

- T2: December 2019-March 2020 (9 subjects, 17 weeks);
- T3: June-August 2020 (23 subjects, 13 weeks).

For each trial period we also selected a subset of the subjects able to undergo the body composition measurement under the medical supervision. In fact, the use of the bioimpedance scale requires the ability of the subjects to autonomously stand on the balance for a limited time (i.e., less than 1 minute) to collect a valid and reliable measure, but in some cases, physical impairments limit this ability. Specifically, we recruited 8 subjects in T1, 9 in T2, and 12 in T3. The nursing care personnel assisted these subjects 3 times per week on alternate days in order to provide a regular assessment.
Finally, the clinical nutritional assessment has been performed by a medical specialist on a monthly basis by using MNA-SF. MNA-SF leads to an overall score ranging from 0 to 30, which determines one of the following nutritional classes: "*Normal*","*Malnutrition Risk*", and "*Malnourished*".

C. Data preparation

1) Feature engineering and extraction: Considering that the clinical assessment is made on a monthly basis through MNA-SF, we analysed the complete dataset (i.e., T1+T2+T3) by taking into account weekly collected data and associating the nutritional class provided by MNA-SF to all the weeks in the same month. This is also supported by the fact that in each month all the subjects didn't experience additional health complications to generate severe changes in the nutritional status.
Feature extraction has been preceded by a feature engineering phase in collaboration with a medical specialist in order to identify the parameters that better reflect users' nutritional intake as well as dietary habits and behaviour. Moreover, these parameters have been selected according to MNA-SF items, albeit providing a more objective and precise evaluation. Considering that the offered menu follows the principles of the Mediterranean diet, we defined a custom algorithm to estimate the daily intake for the main components of the "*Healthy Eating Plate*" [13], namely cereals (C), animal proteins (P), vegetables (V), and fruit (F), which in turn contain all the major macro- and micro-nutrients necessary for a balanced diet. Specifically, cereals provide carbohydrates as main macronutrient along with fibers, whereas animal proteins also contain lipids. Finally, vegetables and fruit provide vegetal proteins, mineral salts, lipids, and vitamins. The daily intake estimate for each food component (i.e., C, P, V, F) is computed as a linear combination of lunch and dinner intakes, both equally contributing in our preliminary algorithm version. Then, the percentage intake estimate for each meal (M) is computed according to the following formula:

$$M(\%) = \sum_{i=1}^{4} C_i \cdot Q_i \cdot W_i \tag{1}$$

where:

- i = course number (1 = first course, 2 = second course, 3 = side dish, 4 = fruit/dessert);
- C_i = percentage fraction of the food component in the i_{th} course;
- Q_i = consumed portion for the i_{th} course (i.e., 0x, 0.5x, 1x, 2x);
- W_i = weight of the i_{th} course. These weights have been defined a priori by the same medical specialist and they are equal for both lunch and dinner.

Weekly intake is computed as the mean of all the available daily estimates. Moreover, for each food component we computed the average weekly intake variation as the mean of successive differences among daily intake values.
Afterwards, we focused on specific parameters that may reflect users' unhealthy dietary habits and behaviour that may lead to nutritional deficiencies. For instance, subjects may experience difficulties in consuming all meal courses due to hyporexia (i.e., decreased appetite) and anorexia, thus resulting in a reduced nutrient and energy intake. In addition, older adults tend to repeat the same choices in different meals due to apathy, depression, as well as smell and taste loss, which may often lead to food component over-intake and unbalanced diet. For these reasons, we defined lunch/dinner completeness and variability indexes. The former is the ratio between the number of complete meals (in which each course has Q$>$ 0) and the number of surveyed meals, while the latter is the ratio between the number of meals that do not contain any fixed choice and the number of surveyed meals. We also considered the variability index for first course, second course, and side dish separately, each defined as 1 minus the ratio between the number of selected fixed choices for that course and the overall number of surveyed meals (i.e., lunch + dinner). Fruit and dessert are always proposed as fixed choices.
As far as weight and body composition data is concerned, we computed the Fat Mass Index (FMI), an anthropometric marker widely used in the clinical practice since its reduction may usually result in an increased malnutrition risk [14]. FMI

TABLE I: Overview of data collected over the different trial periods.

Trial period	Body Composition (Y/N)	# Subjects	# Weeks	# Observations	Missing Nutritional Data (%)	Missing FMI (%)	# Normal	# Malnutrition Risk	Class Ratio
T1	N	15	22	306	3.6%	N.A.	252	54	4.7
T1	Y	8	22	160	0.6%	29.4%	133	27	4.9
T2	N	9	17	144	41.7%	N.A.	93	51	1.8
T2	Y	9	17	144	41.7%	22.9%	93	51	1.8
T3	N	23	13	286	2.1%	N.A	174	112	1.5
T3	Y	12	13	156	1.3%	16.7%	117	39	3.0
T1+T2+T3	N	31	52	736	10.5%	N.A.	519	217	2.4
T1+T2+T3	Y	17	52	460	13.7%	23.0%	343	117	2.9

is computed by dividing fat mass weight in kilograms (i.e., fat mass % $\times$ body weight) by BMI. We considered the average FMI resulting from all the available weekly measurements.

2) Missing value imputation: The prepared feature set still contains some missing values, due to both subject drop-out and deficiencies in monitoring service adherence. Specifically, 3 subjects dropped out during T1 and 2 subjects during T3. In these cases the missing observations are excluded from the analysis since the clinical assessment is not available. As far as the nutritional features is concerned, we considered valid a week in which at least half of the days present both lunch and dinner surveys. In case data of one of the two meals is missing, that day is not considered valid since it does not allow the macro-nutrient daily intake estimate. More details about the amount of missing data are reported in Table I. To overcome this limitation, we applied missing value imputation for each trial period separately, by replacing the missing entries with the average value of the previous and subsequent ones.

3) Data imbalance management: All the monitored subjects have been clinically evaluated in a normal nutritional status or at risk of malnutrition, thus making our case study a binary classification task. As it can be noticed from Table I, data collected in each trial period are unbalanced, with observations classified as "*Malnutrition Risk*" representing the minority class. As a result, the overall dataset obtained by integrating data from T1, T2, and T3 is still unbalanced, with a class ratio ranging from 2.4 to 2.9. In other words, the percentage of observations classified as normal and at risk of malnutrition is approximately 74.5% and 25.5% considering the complete dataset (including body composition data), and 70.5% and 29.5% in case of only nutritional data. To deal with data imbalance, we tested both data-based and algorithm-based methods in order to improve model performances. We first applied Synthetic Minority Oversampling Technique (SMOTE) to balance training data by adding new observations derived from minority-class instances [15]. However, SMOTE alters the original dataset with semi-synthetic data and it might introduce a bias. As a second evaluation, we applied cost-sensitive learning to address data imbalance during the learning process without modifying the original data. In case of binary classification, cost-sensitive learning introduces misclassification costs to penalise false positive (FP) and false negative (FN) errors with a different degree [16]. In our case, where the risk of malnutrition is the top-priority and the underrepresented condition to detect, we introduced a higher penalty when a subject at risk of malnutrition is classified as normal (FN). Specifically, being c_r the class ratio, e_{FN} the misclassification cost for FN and e_{FP} the one for FP, each ML model is provided with a misclassification cost matrix where e_{FP}= 1 and e_{FN} = *ceil(cr)*, where the *ceil* function rounds up to the nearest integer. Therefore, FN are penalised 3 times more than FP during training, in the attempt to lower FN rate. This should lead to better recall values, but it might slightly decrease precision due to a higher number of FP.

D. Model selection and evaluation

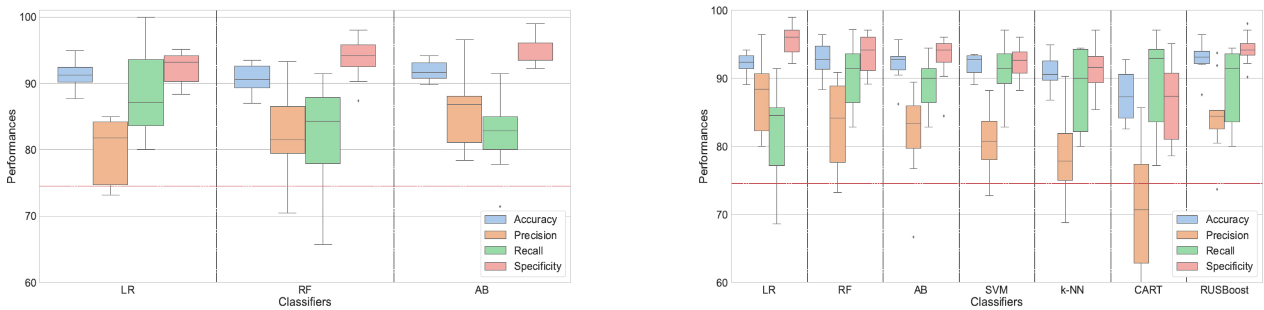
We investigated the performances of 6 benchmark ML algorithms, namely Logistic Regression (LR) with Least Absolute Shrinkage and Selection Operator (LASSO) regularisation, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Classification And Regression Tree (CART), Random Forest (RF), and AdaBoost (AB). In addition, we included Random Undersampling Boosting (RUSBoost) algorithm, which represents an ad-hoc solution to directly classify from highly-unbalanced data. RUSBoost takes N, the number of minority class observations within training data, as basic unit for undersampling the other classes. As a result, each weak learner in the ensemble is trained with a balanced subset of the original training data, using the same boosting procedure of AB for re-weighting and constructing the ensemble at every iteration. To evaluate single model performances, we split the overall dataset into two random hold-out partitions (70% training, 30% test), applying stratification to maintain the same class ratio. Then, model selection and training has been performed using 10-fold stratified cross-validation, applying Bayesian optimisation algorithm to find the hyperparameter setting that yields to the lowest misclassification rate.

It is important to underline that LASSO regularisation for LR acts as both model and feature selection method, thus making Bayesian optimisation unnecessary in this case. In fact, LASSO regularisation works by performing coefficient shrinkage in order to drive the importance of the less contributing features towards zero, by iteratively testing multiple penalty coefficient (λ) values in the range 0-1.

As far as the model evaluation is concerned, we selected a set of metrics to provide a comprehensive, fair, and reliable performance analysis, including model accuracy together with precision, recall (i.e., sensitivity), and specificity to take into account data imbalance. The overall procedure has been repeated 10 times in order to provide more robust outcomes.

IV. Results and Discussions

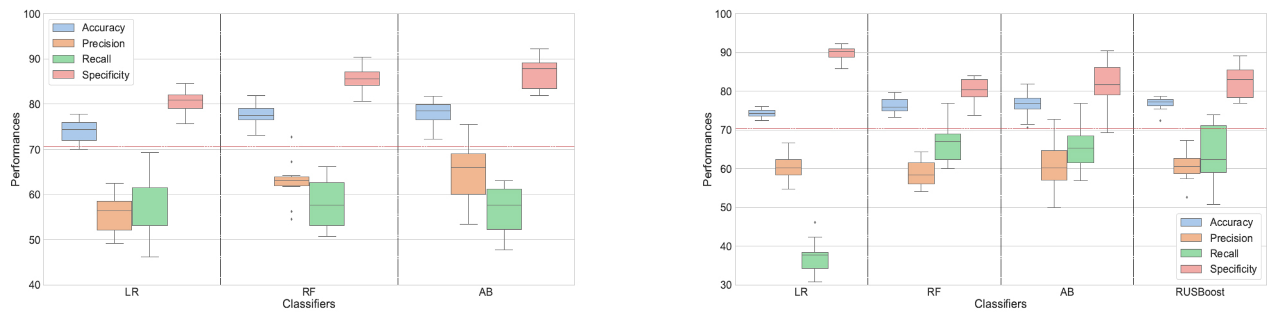
We analyse separately classification performances obtained using nutritional and body composition data (Figure 2), and



(a) SMOTE

(b) cost-sensitive learning and RUSBoost

Fig. 2: Classification performances with nutritional and body composition data.



(a) SMOTE

(b) cost-sensitive learning and RUSBoost

Fig. 3: Classification performances with only nutritional data.

those obtained only by nutritional data (Figure 3). To take into account data imbalance, we consider as default reference a biased classifier, which always assigns new observations to the majority class. The biased accuracy is indicated in each figure by a red dotted line, and it is equal to the percentage of test observations labeled as "*Normal*" in each case (as reported in section III-C3). In addition, it's worth pointing out that such biased classifier provides 0% recall, 100% specificity, and *NaN* precision. In the first case, we compare SMOTE (Figure 2a) and cost-sensitive learning (Figure 2b) approaches for data imbalance management, reporting only the best performing ML models. LR with LASSO regularisation, RF, AB, and RUSBoost represent the best performing models to detect users' nutritional status using both SMOTE and cost-sensitive learning. These classifiers exhibit very similar accuracy (median values ranging from 90% to 94%) and specificity (median values ranging from 92% to 96%) in both cases. However, there are some differences in recall and precision that need to be highlighted. As it might be expected, cost-sensitive learning improves model capabilities to correctly detect all the observations at malnutrition risk with respect to SMOTE, thus leading to an increased recall, with median values between 90% and 92% as shown in Figure 2b. On the other hand, it slightly increases FP rate and consequently decreases precision, even if performances remains comparable with SMOTE. This trend is valid for both RF and AB, whereas LR provides an exception, probably due to the intrinsic model selection process implemented by LASSO regularisation that prioritises penalties against model complexity, overriding the imposed misclassification costs. In this case, training a LR model with balanced data seems to be more beneficial for recall, even if it marginally reduces precision.

RUSBoost performances are shown in Figure 2b just for visualisation purposes, since this algorithm is naturally designed as a standalone solution to classify from unbalanced data. RUSBoost outcomes are in line with the other models, with 93.1% median accuracy, 84.5% median precision, 91.4% median recall and 94.2% median specificity, demonstrating its effectiveness in directly handling unbalanced data. We also evaluated SVM, k-NN, and CART classifiers, which provide median accuracy similar to the best performing ML models, but they obtain lower precision and recall performances, especially using SMOTE (SVM: accuracy = 89.8%, precision = 86.6%, recall = 71.4%, specificity = 96.1%; k-NN: accuracy = 90.6%, precision = 84.4%, recall = 77.1%, specificity = 95.1%; CART: accuracy = 87.7%, precision = 73.5%, recall = 87.1%, specificity = 89.3%). As it can be noticed from Figure 2b, cost-sensitive learning demonstrates its benefits in improving recall also for these classifiers with respect to SMOTE, while maintaining similar median accuracy varying from 87.2% (CART) to 90.6% (k-NN), up to 92.7% (SVM). Specifically, median recall values are equal to 91.4%, 90.0%, and 93.0% for SVM, k-NN, and CART, respectively. On the other hand, cost-sensitive learning again generates a precision loss, especially for k-NN (77.8%) and SVM (80.7%), while the decrease is limited for CART (70.6%).

However, system applicability using body composition data has to rely on subjects' abilities to autonomously maintain the standing position and the balance for a certain time, which may limit its usage by frail older adults affected by severe physical impairments. In order to extend our analysis to a larger population, we evaluated the best performing ML models by considering the data collected from subjects who only participated in the nutritional monitoring. Results are shown in Figure 3a (SMOTE) and Figure 3b (cost-sensitive learning and RUSBoost), respectively. Median accuracy values using SMOTE range from 74.4% and 78.5%, with a low median precision (from 56.3% to 66.1%) and recall (from 57.2% to 61.5%). Cost-sensitive learning improves recall for both RF (65.3%) and AB (62.3%) with respect to SMOTE, whereas median recall drops down to 37.7% using LR. Instead, there are no noticeable variations in precision (from 58.3% to 60.2%) and accuracy (from 74.2% to 77.0%). Finally, RUSBoost performances do not significantly differ from those of LR, RF, and AB (accuracy = 77.2%, precision = 60.6%, recall = 62.4%, specificity = 82.0%).

For a general point of view, these outcomes are unsatisfactory if compared with those obtained using also body composition data.

V. Conclusions

Malnutrition assessment and risk prediction is fundamental to ensure health and wellbeing of institutionalised older adult. In this paper we exploited data collected by a m-health solution for nutritional monitoring in a LTC facility, integrated with a bioimpendance scale for body composition data. The system is empowered with ML-based data analysis and inference in order to provide automatic malnutrition risk prediction, with the ultimate goal of enhancing and/or replacing standard MNA/MNA-SF tools with a semi-continuous assessment. Obtained results demonstrate that LR with LASSO regularisation, RF, AB, and RUSBoost provide high accuracy and recall in detecting individual nutritional status by combining nutritional intake, dietary habits, and body composition data. Results also indicates that cost-sensitive learning is the most effective approach to deal with data imbalance with respect to SMOTE, pushing also SVM, k-NN, and CART performances close to the best performing ML models. We also extended the evaluation to a larger dataset including only nutritional data, since some subjects were not able to autonomously maintain the standing position on the bioimpedance scale. However, obtained results show lower accuracy and recall performances with respect to the complete feature set, highlighting the importance of the body composition data in the malnutrition risk assessment. To further enhance the overall system, we are collecting data also from subjects with different malnutrition risk levels, in order to update ML models and improve classification capabilities. In addition, we are considering the correlation between the malnutrition risk and other behavioural patterns (e.g., sleep disorders and physical activity), which can be monitored through unobtrusive sensing devices.

References

[1] M. Yannakoulia, E. Ntanasi, C. A. Anastasiou, and N. Scarmeas, "Frailty and nutrition: From epidemiological and clinical evidence to potential mechanisms," *Metabolism*, vol. 68, pp. 64–76, 2017.

[2] C. V. Laur, T. McNicholl, R. Valaitis, and H. H. Keller, "Malnutrition or frailty? overlap and evidence gaps in the diagnosis and treatment of frailty and malnutrition," *Applied Physiology, Nutrition, and Metabolism*, vol. 42, no. 5, pp. 449–458, 2017.

[3] C. L. Bell, A. S. Lee, and B. K. Tamura, "Malnutrition in the nursing home," *Current Opinion in Clinical Nutrition & Metabolic Care*, vol. 18, no. 1, pp. 17–23, 2015.

[4] A. Valentini, M. Federici, M. A. Cianfarani, U. Tarantino, and A. Bertoli, "Frailty and nutritional status in older people: the mini nutritional assessment as a screening tool for the identification of frail subjects," *Clinical interventions in aging*, vol. 13, p. 1237, 2018.

[5] V. Sharma, V. Sharma, A. Khan, D. J. Wassmer, M. D. Schoenholtz, R. Hontecillas, J. Bassaganya-Riera, R. Zand, and V. Abedi, "Malnutrition, health and the role of machine learning in clinical setting," *Frontiers in Nutrition*, vol. 7, p. 44, 2020.

[6] D. Trtovac and J. Lee, "The use of technology in identifying hospital malnutrition: scoping review," *JMIR medical informatics*, vol. 6, no. 1, p. e4, 2018.

[7] C. Liu, Y. Cao, Y. Luo, G. Chen, V. Vokkarane, M. Yunsheng, S. Chen, and P. Hou, "A new deep learning-based food recognition system for dietary assessment on an edge computing service infrastructure," *IEEE Transactions on Services Computing*, vol. 11, no. 2, pp. 249–261, 2017.

[8] M. Sun, L. E. Burke, Z.-H. Mao, Y. Chen, H.-C. Chen, Y. Bai, Y. Li, C. Li, and W. Jia, "ebutton: a wearable computer for health monitoring and personal assistance," in *Proceedings of the 51st annual design automation conference*, 2014, pp. 1–6.

[9] V. Bruno, S. Resende, and C. Juan, "A survey on automated food monitoring and dietary management systems," *Journal of health & medical informatics*, vol. 8, no. 3, p. 272, 2017. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/30101038

[10] Y. Lu, T. Stathopoulou, M. F. Vasiloglou, S. Christodoulidis, Z. Stanga, and S. Mougiakakou, "An artificial intelligence-based system to assess nutrient intake for hospitalised patients," *IEEE Transactions on Multimedia*, pp. 1–1, 2020.

[11] F. Delmastro, C. Dolciotti, F. Palumbo, M. Magrini, F. Di Martino, D. La Rosa, and U. Barcaro, "Long-term care: how to improve the quality of life with mobile and e-health services," in *2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, 2018, pp. 12–19.

[12] F. Delmastro, C. Dolciotti, D. La Rosa, F. Di Martino, M. Magrini, S. Coscetti, and F. Palumbo, "Experimenting mobile and e-health services with frail mci older people," *Information*, vol. 10, no. 8, p. 253, 2019.

[13] W. Willett and P. J. Skerrett, *Eat, drink, and be healthy: the Harvard Medical School guide to healthy eating*. Simon and Schuster, 2017.

[14] D. J. Tomlinson, R. M. Erskine, C. I. Morse, and G. L. Onambélé, "Body fat percentage, body mass index, fat mass index and the ageing bone: their singular and combined roles linked to physical activity and diet," *Nutrients*, vol. 11, no. 1, p. 195, 2019.

[15] N. V. Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, "Smote: synthetic minority over-sampling technique," *Journal of artificial intelligence research*, vol. 16, pp. 321–357, 2002.

[16] A. Fernández, S. García, M. Galar, R. C. Prati, B. Krawczyk, and F. Herrera, "Cost-sensitive learning," in *Learning from Imbalanced Data Sets*. Springer, 2018, pp. 63–78.