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Proactive approach in primary health care: a reference model for chronic disease risk prediction

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1 INTRODUCTION

Primary Health Care (PHC) is the first level of health care provided by the Public and Private Systems (PHS) of many countries. It is characterized by a set of individual and *collective health* actions. This level of health care has been the best strategy to date to ensure the sustainability of health systems in much of the world. However, the movements to tackle these SPP with a reactive approach to the prevention and control of Chronic Non-Communicable Diseases (NCDs) are limited in their actions. The reactive approach of preventing and controlling these movements was called into question during the COVID-19 crisis, proving to be insufficient to ensure the sustainability of health systems .

COVID-19 has collapsed public and private health systems around the world. In Brazil, the Unified Health System (SUS), although organized in a decentralized manner, through different levels of health care based on parameters determined by the World Health Organization (WHO), has not achieved the expected result since several states of the federation have not been able to support the demand for care. The SUS service structure is basically divided into three groups/levels of health care according to the complexity of the measures required to accommodate the population. The first level refers to Primary Health Care (PHC), consisting mainly of Basic Health Units (UBS), whose focus is on prevention, disease risk reduction and health protection. In the work of (Mendes, 2018), the author notes that PHC is structured through multiprofessional action organized, primarily, in teams of the Family Health Strategy (ESF).

In recent years, there has been an improvement in PHC services, leading to reinterpretations and redefinitions of the concept of PHC. According to (Draeger et al., 2022), PHC has advanced in the paradigm of coordination of the Health Care Network (RAS) and in the resolution of collective health problems, due to its potential to identify risks to the health of the population, carry out community education and guidance with longitudinal, comprehensive, family-centered care. The second level, called Secondary Care (SC), is composed of specialized services such as pediatrics, cardiology, orthopedics, etc. found in hospitals or Emergency Care Units (UPA). In general, when necessary, the

HA receives patients referred by the PHC. Finally, the tertiary level provides high-complexity care such as oncology, transplants and high-risk deliveries. These are large hospitals with a high demand for technological, human and scientific resources and financial investments.

In recent decades, the capacity to provide health services in primary care has been compromised due to the gradual increase in NCDs, with emphasis on patients in the Cardiovascular, Cancer, Respiratory and Diabetes (CCRD) groups. According to (Suplici et al., 2021), the premature mortality rate for the four main groups of NCDs CCRD is a health indicator used worldwide to monitor one of the proposed health targets in the Sustainable Development Goals (SDGs). These groups of diseases overburden health services due to complications, and disability, affecting the demands for care . Data from the Ministry of Health show that in Brazil more than 730 thousand deaths from NCDs were registered in 2019. Of these, 308,511 (41.8%) occurred prematurely. This total is much higher than what was registered in 2021 of deaths in Brazil by covid-19. For (Bernal et al., 2019), NCDs are a problem of global magnitude, being responsible for a decrease in quality of life, negative economic impacts for families, communities and society, and also for a high number of deaths. (Malta et al., 2017), highlight that NCDs represent the greatest burden of morbidity and mortality in Brazil, which drives rapid and frequent changes regarding the sociodemographic and clinical aspect of users seeking care in PHC. Data from (WHO, 2022) show that NCDs lead to the death of about 41 million individuals each year, accounting for 74% of deaths worldwide. In Brazil, according to (Bernal et al., 2019) they correspond to 75% of the causes of death.

Although there is a great effort by many SPPs to use models for tackling NCDs, starting from a reactive approach to NCD prevention and control, they are limited in their actions. It focuses efforts on early stages of the disease, i.e. for already established health conditions, and lacks the resources of clinicians and to monitor the extent to which patients follow their recommendations and maintain treatment regimens. This reactive approach to prevention and control was called into question during the COVID-19 crisis, demonstrating that it is ~~insufficient~~ to ensure the sustainability of health systems.

The main models of chronic disease prevention and management in the world are: the expanded CCM by (Barr et al., 2003), the Ontario Chronic Disease Prevention and Management Model (OMCDPM) (OMH, 2007) and the Chronic Conditions Care Model (CCCM) by Mendes (2011). They have been put to the test, but have not been sufficient to contain the impacts caused by NCDs and COVID-19 together. These last two models have in common their extensions based on the Chronic Care Model (CCM) and were developed in response to health situations with high prevalence of chronic conditions. They have become the basis for the reorganization of health systems, prioritizing primary care with regard to the planning and articulation of actions to combat chronic diseases. In general, these models direct prevention and control efforts towards chronic diseases in their early stages, i.e. towards health conditions that have already been established.

2 OBJECTIVE

To develop a reference model for predicting the risk of chronic non-communicable diseases in order to assist health professionals in the early detection of an individual developing one or multiple NCDs.

3 METHODOLOGY

The model object of this work has as background models applied in machine learning. To achieve the objective of this work two steps were carried out.

Literature review

Initially, we conducted a comprehensive literature review of papers related to the use of *Machine Learning* (ML) models for NCD prediction. The result directed us to obtain baselines to identify existing gaps and assisted in proposing a solution. Table 1 shows the relevant works for the domain under discussion for each of the four Chronic Disease Groups (CDG), including 1: Cardiovascular; 2: Cancer; 3: Respiratory and 4: Diabetes.

Table 1 - Machine learning algorithms for each of the disease groups and their datasets

						Accuracy %	
GCD	**Author**	**Year**	**dataset**	**Resources**	**Classifiers**	Hom	Woman
1	Chun et al.	2021	interviewer-adm electronic	10	Gradient boosted trees (XGBoots)	83.3	83.6
	Yang et al.	2020	electronic health record - Zhejiang	30	Random Forest	78.7	
	Singh et al.	2018	California Irvine Repository (UCI)	11	Logistic regression	87.1	
	Sharma et al.	2017	Cleveland	14	Decision tree	93.2	
2	Hussan et al.	2022	electronic health record (EHR)	25	Gradient Boosting	86.0	
	Naji et al.	2021	Breast Cancer Wisconsin	11	SVM	97.2	
	Oyewo et al.	2020	Github	9	Ensemble	99.06	
	Nasser	2019	site data world	15	ANN	96.67	
3	Spathis and Vlamos	2019	Clinical patients Thes, Greece,	20	Random Forest (Asthma-Copd)	80.3	
				20		97.7	
4	Li et al.	2021	EHR Optum	10	XGBoost	80.0	
	Rani	2020	Kaggle	8	Decision Tree	99.0	

Consult medical specialists

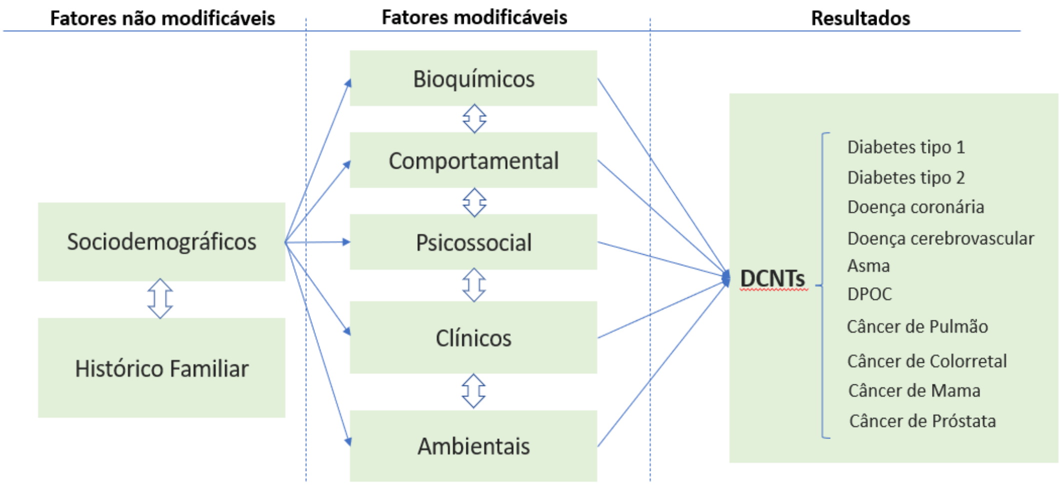
In this section, approximately 2000 specialist physicians from across Brazil and Portugal were consulted on a type of NCD within their specialty via an emailed survey. The various specialty physician groups consulted included cardiologists, endocrinologists, pulmonologists, oncologists and mastologists. Specialists in their respective fields responded to the survey. Together, they amount to 365 years of experience in the field of medicine.

The focus of the expert survey was to identify significant predictive risk factors and variables for the top ten NCDs (Type 1 and 2 Diabetes, Cardiovascular Diseases (CAD and Stroke), Respiratory Diseases (Asthma and COPD), and Colorectal, Breast, Prostate and Lung Cancer) in adult males and females. The structure of the research is formed by modifiable and non-modifiable risk factors.

4 DEVELOPMENT OF THE DCNT RISK PREDICTIVE MODEL

The reference model of this paper is supported by a background of the literature with its respective extensions of the various features of the machine learning models presented here and expert consultations. The reference model under development has in its structure three sets of overarching elements that are theorized as ordered (see Figure 1). The first set of elements focuses on Non-Modifiable Predictor Factors (NMPFs). The second set of elements focuses on Modifiable Predictor Factors (MPF). Finally, the third set of elements presents the results of NCD probabilities. Together, NMF and MPF total 38 attributes, including numerical and categorical. It is theorized that as the modifiable predictors are positively balanced, it suggests that the person is in a healthy health condition. Conversely, if negative changes are identified, i.e. an imbalance in any of the non-modifiable factors together with any of the modifiable factors, an instability will occur, which may result in the likelihood, or not, of a person developing one or multiple chronic diseases.

Figure 1: Reference model for a NCD prediction system



Source: Prepared by the authors

Non-Modifiable Predictors (NPMF)

The non-modifiable predictors of the model have in their structure a set formed by sociodemographic factors and family history . They were taken from the studies of (Deberneh and Kim, 2021; Matheson et al. 2018; Queiroz et al.,2021; Akella and Akella, 2020; Rodrigues et al., 2020; Syed et al.,2019; Wells et al., 2014; Lee et al., 2019; Chaurasia et al., 2018; Albright et al., 2015; Barber et al.,2018; Pasquelli et al., 2020). Non-modifiable predictors are characterized by not being controlled. Some examples are: age, gender, family history, and race or ethnicity. In general, these factors are significant for predicting most NCDs .

Modifiable predictors (MPF)

The modifiable predictors of the model present in its structure a composition formed by biochemical, behavioral, psychosocial, clinical and environmental factors .

Biochemical factors

Biochemical factors such as blood pressure, blood glucose, hemoglobin, cholesterol, triglycerides, PSA etc., when isolated or combined and imbalanced play key roles in influencing the occurrence of diabetes, cardiovascular diseases, colorectal and prostate cancer (Liu et al.,2019; Yang et al., 2020; Rho et al. 2020; Theerthagiri, 2021; Deberneh and Kim, 2021; Geetha et al., 2021). In this sense (Benjamin et al., 2019; Murthy and Meenakshi, 2014) corroborate by highlighting that many factors can cause heart disease, such as dynamic changes in lifestyle, smoking, eating habits, lack of physical activity, obesity, diabetes and biochemical factors such as blood pressure or glycemia.

Behavioral factors

Behavioral factors such as low fruit/vegetable consumption, smoking, alcohol consumption, physical inactivity, etc., when isolated or combined and unbalanced play key roles in influencing the occurrence of diabetes, respiratory, cardiovascular diseases, colorectal, breast, prostate and lung cancer (Chuarasia et al, 2018; KIM et al.,2018; Matheson et al. 2018; Ahmad and Mayya, 2020; Kopitar et al.,2020; Aleksandrova et al.,2021; Chun et al.,2021; Deberneh and Kim,2021). These factors strongly affect survival. According to (WHO, 2005) the sum of risk behaviors is associated with decreased life expectancy.

Psychosocial factor

Psychosocial factor such as stress, when isolated or combined, play key roles in influencing the occurrence of type 2 diabetes, respiratory and cardiovascular diseases (Toskala and Kennedy, 2015; Akella and Akella, 2020; Tigga and Garg, 2020). In this regard (Santos et al.,2021) report that psychological factors, including stress at work or in family life collectively, may play a role in the development of cardiovascular diseases.

Clinical factors

Clinical factors such as affected cough, affected breathing, chest pain, fatigue, late age of first pregnancy, change in breast density etc., when isolated or combined play key roles in influencing the occurrence of respiratory, cardiovascular diseases, lung and breast cancer (Mccoy et al., 2006; Giardiello et al., 2019; Almustafa, 2020; Vikas and Kaur,2021). In this sense (Al-Hajj et al.,2003) corroborate highlighting that late age of first pregnancy, menopause and early age of menarche (first menstruation occurs before the age of eight) are linked to a considerable increase in the development of breast cancer.

Environmental factors

Environmental factors such as pollution in your place of residence, pollution in your workplace and occupational hazards, when isolated or combined, play key roles in influencing the occurrence of respiratory diseases and lung cancer (Matheson et al. 2018; Vikas and Kaur,2021). Global estimates suggest that *outdoor* environmental pollution causes 1.15 million deaths worldwide (corresponding to about 2% of total deaths) and is responsible for 8.75 million fewer years lived or disability (WHO, 2009). Indoor pollution causes approximately 2 million premature deaths and 41 million fewer years lived or years with disability (Oberg et al., 2011).

5 FINAL CONSIDERATIONS

The main groups of NCDs have in common modifiable and non-modifiable factors, which paves the way for the development of this work. The aim of this study was to develop a reference model for a NCD risk prediction system to assist health professionals in the early detection of an individual developing one or multiple NCDs.

The model synthesizes studies and consultations with medical experts, and extends the various features of the empirical models presented here. The structure of the proposed model presents three sets of overarching elements that are theorized as ordered. The fact that the model integrates and vectors modifiable and non-modifiable factors of the four main groups of NCDs represents an important step in the expansion and improvement of PHC health services strategies, in the improvement of Previne Brasil indicators, as well as a new approach towards tackling NCDs before the diseases manifest themselves. Acting at this level implies improving epidemiological surveillance; reducing the incidence and mortality from NCDs; enhancing the identification of health risks to the population in Primary Health Care to reduce the overload of health services due to complications and disability; mitigating the condition of patients and their families during treatment outside the home; reducing the flow of patients and hospitalizations; and availability of relevant information for the assertive targeting of public health campaigns in municipalities.

The paper makes four important contributions . First, it contributes to the revitalization of research on NCD prediction, which can certainly inspire new studies to address this complex problem. Second, the study contributes in gathering, combining, integrating and vectorizing the significant predictors to predict the likelihood of the four main groups of NCDs. The third contribution is directed towards the body of knowledge, adapting and extending models to predict the likelihood of NCDs. Finally, it contributes to extending and improving PHC health services using a proactive approach towards digital transformation, reinforcing PHC responsibilities towards people's health and well-being needs. The next steps are to validate and operationalize the model, using the potential of Artificial Intelligence in an intelligent chronic disease risk prediction system, in order to increase the efficiency of PHC service delivery, the experiences of health professionals and the extension of benefits to patients worldwide.

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