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Healthcare Crisis for Vulnerable People: Research on XAI Application to NCD

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Extended Abstract

Summary: In this study, we approach the solution of the disease crisis that is a problem for the vulnerable in terms of artificial intelligence. In other words, we describe diseases that are problematic in the vulnerable and NCDs that are problematic in our life journey, propose an artificial intelligence technique that can be explained to one of the NCD types, and design the framework. And to help readers understand, we present the conversation between the doctor and the patient as an example and show the results in the framework.

Therefore, first, what is the vulnerable group, and the classification and problems of the vulnerable groups in developed and underdeveloped countries are examined. In particular, it identifies the problems of the vulnerable group in terms of the medical environment and in underdeveloped countries. Since one of these problems is NCD, which is a non-transmissible disease, this paper describes the definition and characteristics of NCD in the introduction. And then to design the XAI Framework, we explain an Explainable Artificial Intelligence (XAI). At this time, we use DeepSHAP based explainable deep learning framework (Davagdorj 2021), also, to help the reader understand, we present the process of a patient going to a hospital and hearing the results of the examination to a doctor as an example. Finally, we conclude this paper by showing the interaction between a patient and a medical doctor and describing challenges, and the results were shown from the XAI Framework so that the patient can understand the examination results when the patient and the doctor talk.

Introduction: The definition of the socially vulnerable group varies largely depending on the country and social situation, and on the research field and subject. For example, the vulnerable group is expressed as a vulnerable group or a marginalized group, but it is not clear who it refers to (Roger Steel, 2004), etc. However, if the vulnerable group is defined by referring to (Roger Steel, 2004), it can be seen that in general, the vulnerable group has relatively limited opportunities for social participation compared to other groups due to economic, physical, environmental conditions, etc. In other words, elements such as personal attributes, social position, accident, and life course are included, and accordingly, a socially disappointed group or an economically disappointed group is formed. Therefore, these groups can be seen as meaning a class created to receive equal treatment or benefits as a member of society or humanity, and human life as a member of society. In this paper, we limit the vulnerable to long-term disease exposure due to little or no medical benefits. In particular, in the case of underdeveloped countries such as Africa, we focus on Healthcare Crisis in our study and target non-communicable diseases (NCDs) that do not spread to others among diseases that occur in human life. The term NCDs refs to a group of conditions that are not generally affected by an acute infection, result in long-term health concomitant and open state a need for long-term treatment and care (WHO 2018). These NCDs are usually caused by unhealthful behaviors.

NCD is a problematic disease not only in underdeveloped countries in Africa, but also in advanced countries such as Europe and North America, and it is also a problematic disease in Korea. In other words, Chronic noncommunicable diseases (NCDs) are the number one cause of death and disability in the world (Valeria Calcaterra and Gianvincenzo Zuccotti, 2022). In particular, it is difficult to manage this disease due to economic problems in the vulnerable group. This problem has emerged as a Healthcare Crisis, one of the important keywords of this study.

According to NCDs global status report by the World Health Organization (WHO), NCDs are the leading cause of death accounting for 41 million people dying each year. It equals 71% of the 57 million deaths globally (WHO, 2018). Particularly, 15 million people die prematurely in adults from 30 to 70 years old annually, and NCDs are mainly the leading cause of these deaths. Major NCD diseases include cardiovascular disease, diabetes, cancer, and chronic respiratory disease. for deaths due to NCDs annually Looking at the number of NCDs that occur each year, cardiovascular disease is the most common at 17.9 million, followed by cancer at 9 million, respiratory disease at 3.9 million, and non-communicable diseases such as diabetes at 1.6 million. (Forouzanfar et al., 2016). In this study, we design the XAI Framework for cardiovascular disease cardiovascular disease cardiovascular disease, which accounts for an important proportion of NCDs.

Explainable Artificial Intelligence (XAI): XAI is a set of processes and methods that enable users to under stand and trust the results and outputs generated by machine learning algorithms. XAI describes AI models and their expected impact and potential biases (IBM 2024). The XAI program aims to create a suite of machine learning techn iques that: 1) Produce more explainable models, while maintaining a high level of learning performance (prediction a ccuracy); and 2) Enable human users to understand, appropriately trust, and effectively manage the emerging generati on of artificially intelligent partners (DARPA 2024).

Explainable Artificial Intelligence framework: Artificial intelligence (AI) is widely used in industry as well as in everyday life to support decision-making and make recommendations. We use computers and mobile phones almost daily and use tools like ChatGPT. In addition, when predictive modeling is performed in various fields such as research and industrial sites, this predictive modeling, as a form of AI, plays an important role in healthcare, fraud detection, and bankruptcy prediction (Taha & Malebary, 2020; Moscato, Picariello & Sperlí, 2021 ; Park et al., 2021).
In line with this trend, we have already developed a DeepSHAP-based deep neural network (DNN) model (Davagdorj 2021) with feature selection techniques to build an explainable decision support system, shown in Figure 1. Therefore, it can be used not only by vulnerable groups and the elderly but also by the general public and we describe the XAI Framework using (Davagdorj 2021).

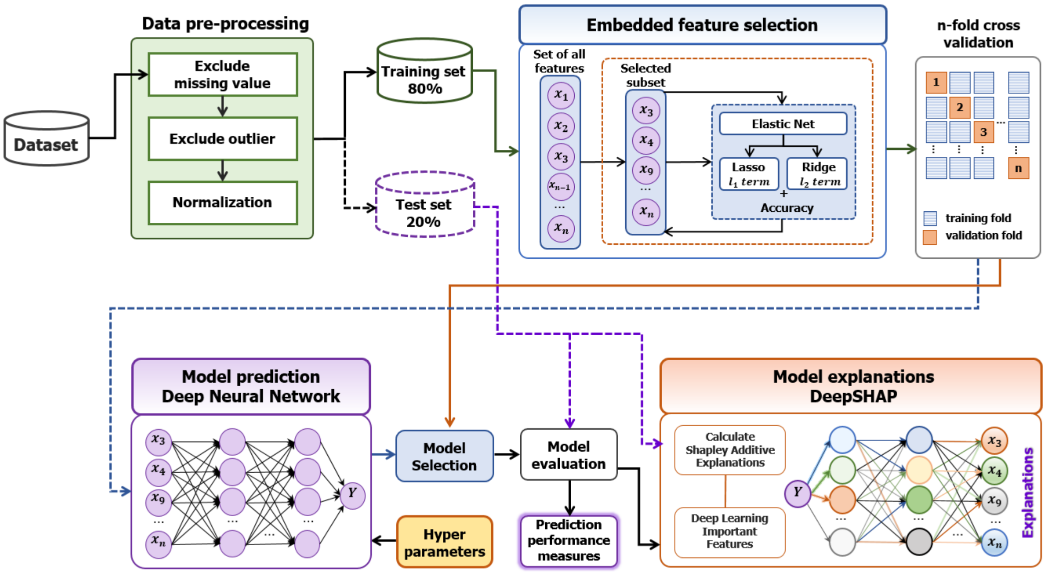

Figure 오류! 지정한 스타일은 사용되지 않습니다.. DeepSHAP based explainable deep learning framework (Davagdorj 2021)

The DeepSHAP Framework consists of four components which are data pre-processing, embedded feature selection, Deep Neural Network classifier, and model explanation DeepSHAP. The first is a data processing component which makes cleaned data and generates representative features. A data cleaning and embedded feature selection technique generates in the second component. The third component is not only to do the Deep Neural Network classifier but also to tune. Finally, the fourth component 3 is to provide the model explanation, the proposed framework's components are as shown in Figure 1.

Discussion: Clinicians struggle to interpret these decisions in deep learning due to the black-box nature of many real-world applications (Carvalho et al., 2019; Lauritsen et al., 2020; Elshawi et al., 2019). Most complex prediction model-based decision support systems are black boxes, and despite their good prediction accuracy, they have limitations in explaining predictions at the global and local levels.

We introduce a conversation between a professional doctor and a non-professional patient to facilitate the reader's understanding. Here, the patients are general people. A solution has been presented to the problem using an artificial intelligence technique that can be explained in this study, and for this method, we used the DeepSHAP-based deep neural network framework that we developed. The future challenges remain not only local problems but also problems applied to global problems to be used in the real field.

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