Multi-context path-aware graph convolutional neural network learning for health risk prediction

Dhanasekaran K[1], *Sudhakar K*[2]

[1] Lincoln University College (LUC),47301, Petaling Jaya, Selangor Darul Ehsan, Malaysia; [2] Department of Artificial Intelligence and Data Science, Nitte Meenakshi Institute of Technology (NMIT), Nitte (Deemed-to-be University), Bengaluru, Karnataka, India

jcedhana16@gmail.com

Abstract: Existing works on graph convolutional neural network learning methods for health risk prediction indicate that there are limitations due to a lack of multimodal fusion using text, Electronic Health Records (EHR), lifestyle data and Internet of Things (IoT) data. Other limitations include the use of heterogeneous graph neural networks, absence of path-aware graph reasoning, and weak patient-similarity modeling. Moreover, the class imbalance was not adequately addressed. Few studies apply focal loss optimization for mental-health risk prediction, and there are limited multiclass risk prediction methods with classes such as Low, Moderate, High, and Critical. To address these limitations, we propose a multi-context path-aware graph convolutional neural network learning approach that utilizes BERT and GCNN for health risk prediction. This research enhances the performance of health risk prediction specifically for patients with mental health issues.

Keywords: deep learning; health risk prediction; graph convolutional neural network; mental health; path-aware reasoning.

Introduction

The rapid development of digital technologies has created new opportunities for context-aware health-risk prediction. Conventional physiological data analytics provide valuable information about patients' physical condition, and social media text classification can provide information about emotions, behavioral aspects, symptoms, lifestyle patterns, and psychological states. Integrating these heterogeneous data is particularly important because health risk is not determined by a single physiological variable. It requires analysis of data including the interaction of physiological conditions, symptoms, lifestyle patterns, emotional states, and social relationships. Therefore, an effective health-risk prediction should perform multimodal data analytics, considering the relationships among the entities present in that information.

The proposed Multi-Context Path-Aware Graph Convolutional Neural Network (MC-PA-GCNN) builds a heterogeneous relationship graph that represents four important relationships such as patient–patient, patient–symptom, patient–lifestyle, and patient–disease. Patient–patient edges are used to capture similarities or associations between individuals. Patient–symptom edges represent observed symptoms. Patient–lifestyle edges are used to represent lifestyle-related characteristics, and patient–disease edges capture disease associations or clinically relevant disease information. This structure enables the model to analyze health information from multiple contexts rather than treating all features independently.

Related work

Machine learning classifiers can provide more effective early detection and assessments of mental health. Recent works have suggested that machine learning algorithms such as decision trees, support vector machines, Bayesian learning, and neural networks provide the most accurate prediction model for psychological issues such as stress, depression, and anxiety among university students [1].

Advanced machine learning models could enhance text generation to forecast mental well-being. Nevertheless, studies on mental well-being based on classification techniques among samples in the Asian population are scarce. A few research studies also reported that random forest- or decision tree-based methods were some of the best techniques to forecast mental health [2].

The recent advancements provide the possibility of applying the classification approach to achieve the fast and objective diagnosis of mental conditions such as bipolar disorder [3], posttraumatic stress disorder [4]. The ability to accurately extract fine-grained emotions from everyday narratives enables automated psychological screening [5]. Labib et al. [6] combines multi-head attention and ensemble techniques into RoBERTa-based models to improve performance on datasets like SemEval-2018 and GoEmotions.

Baek et al. [7] have proposed the multiple regression-based ContextDNN to predict the risk of depression. This existing method uses contextual information which includes surrounding conditions and time, and supply it to a neural network. Furthermore, it creates neural networks and associates the individually learned neural networks via the regression mechanism. Thus, it provides a way to predict latent situations that influence mental health. However, this approach is limited by a dependent variable. In practice, since there are multiple dependent variables, it is necessary to consider all of them. Clustering analysis is used to classify similar data into multiple groups. It has no predefined class labels.

Key Contribution

- This study presents an analysis of existing works on mental health risk prediction.
- This study proposes a Multi-Context Path-Aware Graph Convolutional Neural Network (MC-PA-GCNN) for health-risk prediction.
- The graphical representation of relationships enables the model to analyse health information from multiple contexts rather than treating all features independently.

Method, Experiments and Results

Let us consider that the patient data be P={p_1,p_2,...,p_n }, Health Issues are represented by H={h_1,h_2,...,h_m }, Lifestyle Data be L={l_1,l_2,...,l_k}, and Social Media Data be S={s_1,s_2,...,s_t}. We construct a graph G=(V,E), where Nodes represent patients, symptoms, diseases, and lifestyles, and Edges represent interactions and similarities. The proposed method introduces a robust and accurate BERT-GCNN with Multi-context representation, path-aware graph convolutional learning, and focal loss optimization, for predicting health risks. Figure 1 shows the architecture of the proposed BERT-GCNN method.

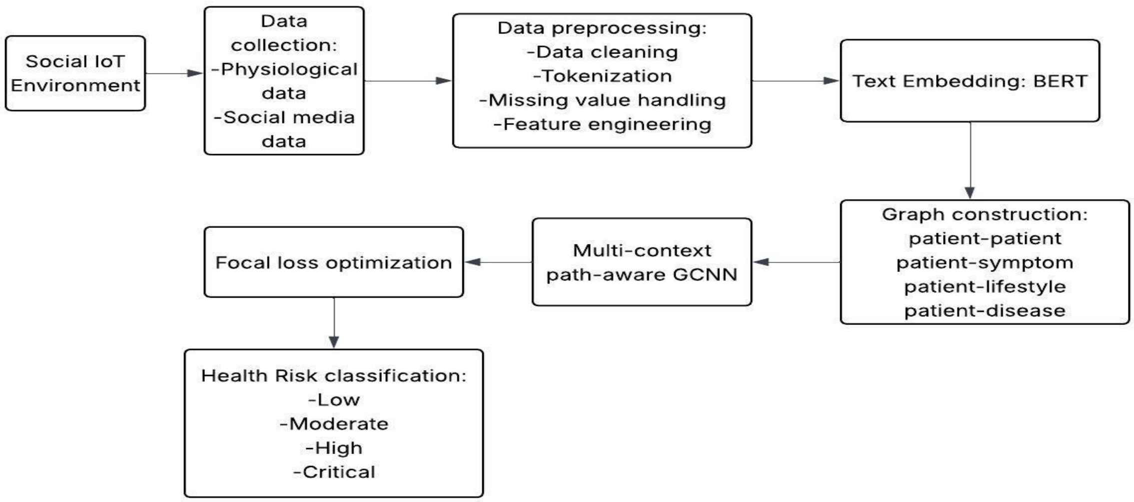

Figure. 1 Architecture of the proposed method

The Dataset consists of patient features, health issues data, and social media features. The physiological data is captured from the survey responses, and the social media data is generated from GoEmotions dataset. Tables 1, and 2 provide essential features from the dataset.

Table 1. Patient-related features

Table 1. Health issues-related features

Disease
Depression
Anxiety
PTSD (Post-traumatic stress disorder)
Diabetes
Hypertension
Obesity

Table 2. Social Media Features

Feature
Sentiment
Emotion
Negativity
Isolation Index

Stress Keywords
Sleep Complaints
Health Discussions

The proposed Multi-Context Path-Aware Graph Convolutional Neural Network (MC-PA-GCNN) include five major stages: (1) multimodal data preprocessing, (2) BERT-based text representation, (3) feature engineering with multimodal fusion, (4) multi-context graph representation and path-aware graph learning, and (5) health-risk classification. The overall objective is to learn a patient representation incorporating physiological characteristics, contextual information, symptoms, lifestyle patterns, disease associations, and relationships between selected pairs of features.

Let the patient be pi, xi{phys} represent physiological features, and xi{text} denote social-media text. NLP is applied to work with social media features. The patient is also associated with symptoms, lifestyle characteristics, and specific disease information. The proposed model learns a mapping, that is, [f(xi{phys},xi{text},G)→Yi], where G denotes the heterogeneous multimodal graph.

Data Preprocessing

A systematic preprocessing pipeline is applied before model training to enhance the quality of data and ensure compatibility between the physiological features and textual modalities. Data Cleaning, Missing-Value Handling, Tokenization, and Feature Engineering

BERT-Based Text Embedding

This technique captures semantic context from social-media text using BERT. The text embedding captures contextual information about emotional expressions, symptoms, lifestyle-related patterns, and other health-related patterns. Thus, expressions with similar words but different contextual meanings receive different representations. This addresses the inability of traditional machine-learning models to effectively capture semantic context.

Multimodal Feature Representation

The physiological representation hi{phys} is generated from the physiological attributes after feature engineering. The fused representation provides a patient-level embedding that contains complementary information from physiological observations and social-media-derived semantic/emotional information. Symptom, lifestyle, and disease attributes are retained separately for graph construction so that their relationships with patients can be explicitly modeled rather than being completely absorbed into a single feature vector.

Multi-Context Graph Construction

A heterogeneous graph G=(V,E), is constructed to model relationships among patients and health-related entities. The graph contains four principal relationships: (a) Patient–patient relationships (G{PP}) (b) Patient–symptom relationships (G{PS}) (c) Patient–lifestyle relationships (G{PL(d) Patient–disease relationships (G{PD}).

Experimental analysis

The proposed MC-PA-GCNN was evaluated on the GoEmotions-based data to perform multimodal health-risk prediction task. The dataset was prepared by combining physiological patient information with social-media-textual and emotional information. The model predicts health-risk levels according to four major categories, which include Low, Moderate, High, and Critical.

The experimental settings use Python 3.11, PyTorch 2.3, Transformers 4.x, PyTorch Geometric, and the scikit-learn package. A 13th Gen Intel Core i5-1335U processor operating at 1300 MHz with 10 cores and 12 logical processors, 16 GB RAM, and the specified TPU accelerator were used to conduct the experiment. The model was used a batch size of 32 and for 100 epochs. AdamW optimizer was employed with a learning rate of 1*10-4, and a dropout rate of 0.3 to improve generalization. The relationship structures on the graph enable the proposed model to exploit relationships that are not available in the feature-based classification models.

Conclusions

This study proposed a Multi-Context Path-Aware Graph Convolutional Neural Network (MC-PA-GCNN) for multimodal health-risk prediction using GoEmotions-based data. The framework combines physiological patient information and BERT-created semantic and emotional representations from a social media dataset. The proposed model predicts health risks at four risk levels, which include Low, Moderate, High, and Critical.

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