A Multi-Label Classification Framework for Cancer

Markian Jaworsky (u1101991)

Supervisors:
Principal supervisor Xiaohui Tao
Associate supervisors Jianming Yong, Ji Zhang, Lei Pan (External), Shiva Pokhrel (External)

School of Mathematics, Physics, and Computing, University of Southern Queensland, Australia

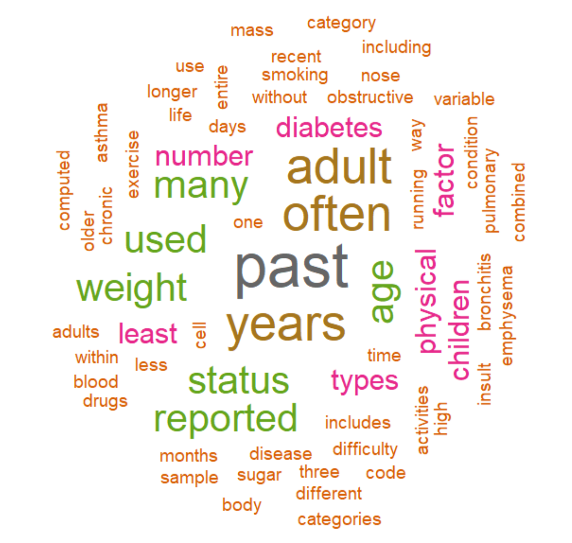
A presentation partially fulfil the requirements for the conformation of PhD candidature, August 22, 2022

Introduction

- A range of risk factors can be used as predictor variables in the likelihood of developing chronic illness.
- With awareness, patients can adapt their lifestyle in order to improve their chances of longer term survival.
- Risk factors can be categorized as being lifestyle, environmental or biomedical and can change over time.

Introduction

- Word cloud of text frequency variance between smoking and non-smoking lung cancer patients.

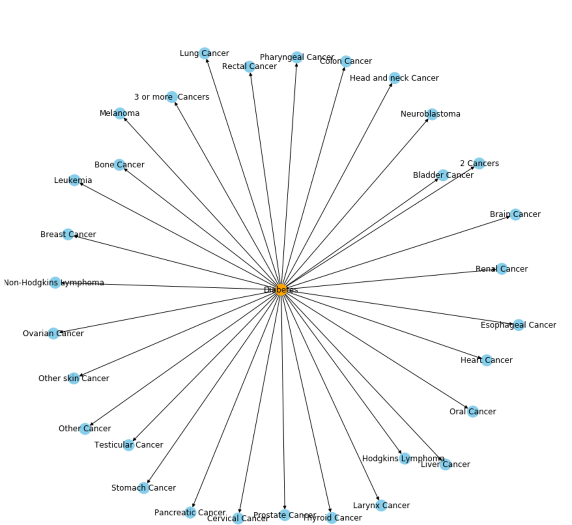


Introduction - Key Research Approach Change

- Most studies are typically focused on single disease datasets, however, to ensure that health advice is generalized and contemporary, the features that can predict the likelihood of many diseases can improve health advice effectiveness, when considering the point of view of the patient.
- 6 cancers correlate with diabetes according to the 2020 study of Wang *et al.* [1], suggesting that the cause of many cancers can be simplified to a combination of DNA damage and inflammation.
- Predictor variables with a 1-to-many cancer relationship can improve health advice of predictor variables with 1-to-1 relationships.

Research Scope - Goal

- A Framework for Handling the Data Challenges in the Multi-Label Classification of Multiple Cancer subtypes.
    - Providing current and evidental health advice.



Research Scope - Problem

- Individual diseases have individual data patterns, in order to predict multiple diseases, we must be able to overcome the many data challenges that can occur.

Research Scope - Questions

- How can we introduce innovation in the identification of data patterns in the classification of cancer subtypes?
- Using agile methodology how do we develop a new framework for the construction of predictive models of multiple cancers, and multiple cancer occurrences?

Research Scope - Objectives

- Develop a robust approach to using health surveys for the construction of predictive models of multiple chronic illnesses.
- Identify the optimum subset of health survey predictor variables to classify the largest subset of multiple cancer subtypes.

Research Scope - Limitations and Assumptions

- This study is focused on the technical challenges of data, the topic of data privacy is outside the scope of the reviewed literature.

Research Scope - Expected Research Outcome 1

- A subset of predictor variables that can be robustly used to predict a level of risk in multiple cancer subtypes.

Research Scope - Expected Research Outcome 2

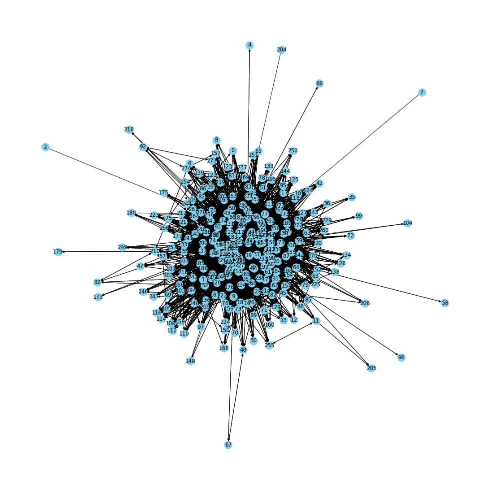
- A Framework for Handling the Data Challenges in the Multi-Label Classification of Multiple Chronic Illnesses.

Research Concept - Knowledge Graphs

- Our review of knowledge graph studies indicates that most research depends on the manual selection of articles to be used in constructing a knowledge graph.
- By identifying a complete source of knowledge we can automate the construction of a complete knowledge graph.
- Using a knowledge-based method to select features gives a predictive model assurance against detecting spurious correlations.

Research Scope - Contribution 1

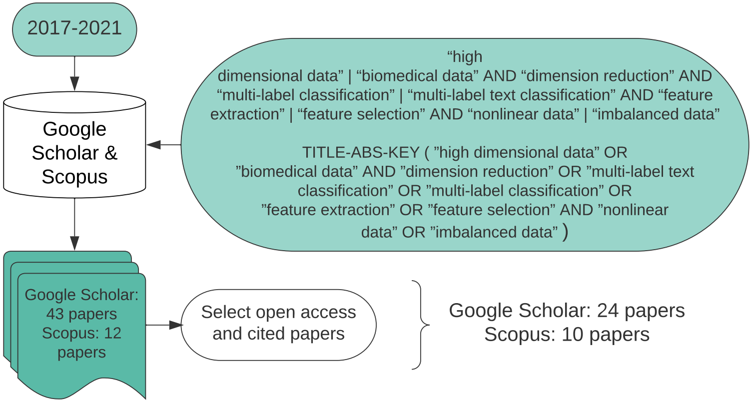
- Novel automated chapter ranking significance-based knowledge graph to identify inter-feature relations.
- Our automation uses the 26 chapters of WHO ICD.



Research Scope - Potential Contribution 2

- Further improve contribution 1 with prioritization of linear features over nonlinear.
- 2020 BRFSS Health Survey consists of 279 questions, of which 240 (86%) have nonlinear properties. Eg. Yes, No, Unsure.
- Only 39 (13%) questions can be considered to have linear variable answers. Eg. age, height, weight.

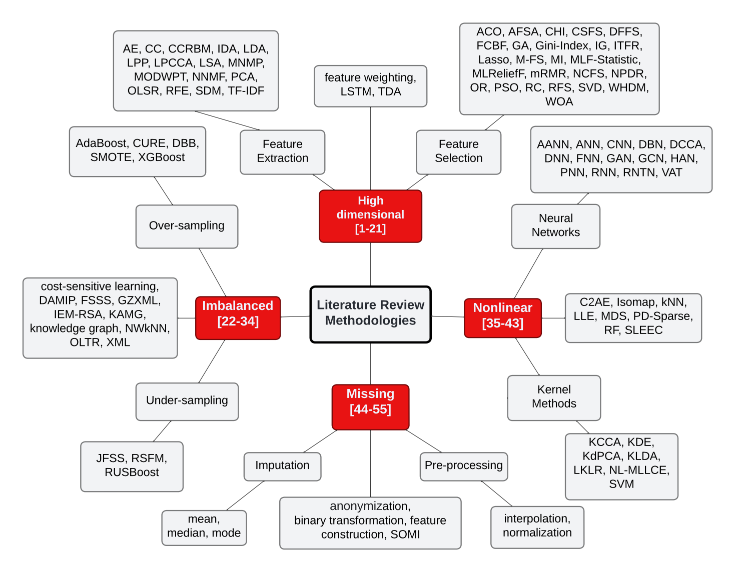
Literature Review - Scope



Literature Review - Data Challenges

- High Dimensional Datasets [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]
- Imbalanced Class Datasets [23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35]
- Multiple and Nonlinear Datasets [36, 37, 38, 39, 40, 41, 42, 43, 44]
- Datasets with Missing and Erroneous Values [45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56]

Literature Review

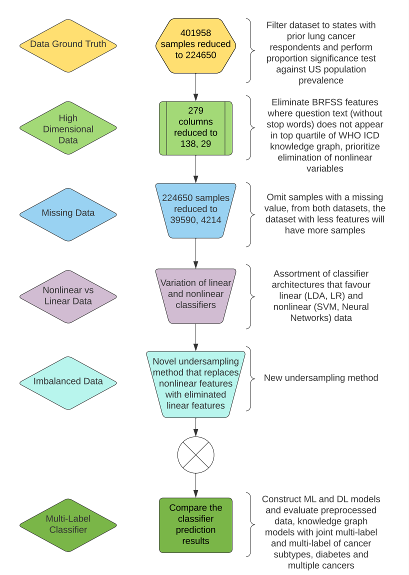


- There is not an existing single widely-adopted framework for uncovering data patterns to support the construction of multi-label chronic illness classifier.

Literature Review

- Therefore we are unable to satisfactorily state that RQ1 is adequately supported and proposed to conduct further research in order to answer RQ2.

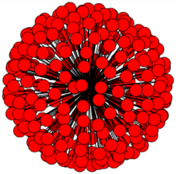
Research Design - Data Preparation



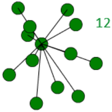
Research Design - Goal

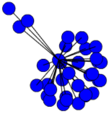
- Reproducible health survey analysis and predictive model construction

Research Design



Research Design:
Find the subset of predictor variables and algorithm that best classifies the largest subset of response variables





Research Design - Health Survey Classifiers

- We validate our general health advice by testing our feature selected dataset with the baseline dataset using these classifiers
- AdaBoost [57]
- K-nearest neighbours [57, 58]
- Linear Discriminant Analysis [59]
- Logistic Regression [57, 58]
- Multinomial Naive Bayes [57]
- Random Forest [57, 58]
- RUSBoost [57]
- Support Vector Machine [57]
- TensorFlow Convolutional Neural Networks [57]

Research Design - Parameter Tuning Optimization

- To be both optimal and reproducible, a tuning strategy is required
- Hyperopt [60, 61]
- Grid Search [62]
- ULMfit [63]

Research Design - Evaluation Metrics

- Macro Average F1-Score [15, 19, 18, 12, 50, 23, 27, 30, 26, 44, 42, 52, 53, 9, 64, 65, 62, 66, 55, 67, 31, 68, 48, 69, 49, 70, 71, 72, 73, 8, 74, 75, 76, 77, 78]
- Precision at Top K (P@k) [18, 40, 41, 79, 80, 81, 82, 32, 64, 33, 35, 83, 84, 85, 61, 86, 74, 77, 87]

Research Design - Dataset

- The United States CDC make available an anonymized annual Behavioral Risk Factor Surveillance System (BRFSS) survey data, which is free to the public domain and may be copied and distributed without permission.

From: Garvin, William S. (CDC/DDNID/NCCDPHP/DPH) <wsg1@cdc.gov>
Sent: 03 September 2021 23:02
To: Markian Jaworsky <Markian.Jaworsky@usq.edu.au>
Cc: Barrett, Drue H. (CDC/DDPHSS/OS/OSI) <dhb1@cdc.gov>
Subject: RE: Question on statement of CDC BRFSS Annual Questionnaire Data Ethics Approval

Dear Markian,

The Behavioral Risk Factor Surveillance System (BRFSS) is approved by US Office of Management and Budget (OMB) to collect data from the US general population under OMB Control number 0920-1061.

The CDC Human Research Protection Office has determined that this research activity (BRFSS data collection) remains exempt under 45 CFR 46.101(b)(2).

The BRFSS is a state based survey conducted in partnership with the participating state-health departments. A common core questionnaire and standardized optional modules are approved by the states and CDC programs each year. The state health departments implement the survey and oversee the ongoing data collection for their state, whether through a contracted data collector or in-house data collection. The states and data collectors have institutional review boards which review state-specific questionnaire content and determine what is applicable for inclusion in the BRFSS for a given state. The questionnaire and basic BRFSS data collection protocol are covered in the BRFSS Overview documentation released with the public use data set each year on the BRFSS website.

Hopefully this provides the information needed for explanation of the approval process of the BRFSS.

If you have additional questions or concerns please let us know.

Thank you,

Bill Garvin
Survey Operations
Population Health Surveillance Branch
Division of Population Health
National Center for Chronic Disease Prevention and Health Promotion
Centers for Disease Control and Prevention
(770) 488-4621

Research Design - Baseline Dataset

- The baseline dataset to be used first applies a filter of the geographical state of the respondent, states eliminated from the dataset have been identified by searching through prior years of surveys and deselecting states with no lung cancer candidates.
- In order to establish a dataset that is representative of the ground truth, the BRFSS annual survey can be filtered by states until an insignificant proportion of lung cancer, a chronic illness with a high prevalence amongst both male and female patients, such that it is comparable to the prevalence of lung cancer in the population of the USA.

Research Plan - Phase 1

- Knowledge Graph-Based Feature Selection for Multi-Label Classification on Health Survey Data

Research Plan - Phase 2

- Automated Knowledge Graph Construction for Healthcare Domain

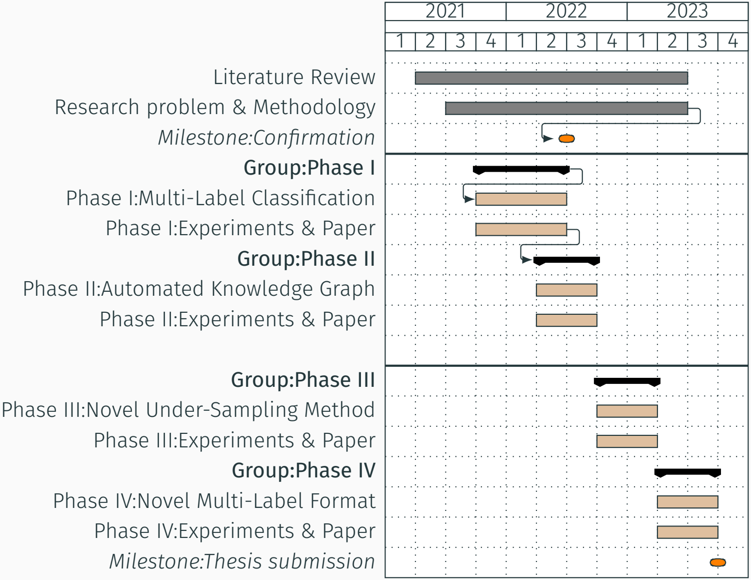
Research Plan - Phase 3

- Nonlinear with Linear Feature Replacement in Multi-Label Classification

Research Plan - Phase 4

- Construct a Multi-Label format which best classifies cancer subtypes

Timeline - Gantt Chart



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Timeline - Dissemination plan

- Confirmation of Candidature Draft Submission: 02/08/2022
- Science Direct Artificial Intelligence in Medicine Submission: 30/04/2023

Progress To Date

- Biomedical Engineering Review IEEE Submission: 25/04/2022
- IEEE International Conference on Data Mining (ICDM 2022) Submission: 11/06/2022
- Springer International Conference on Health Information Systems Acceptance: 16/08/2022

Other Issues - Ethics Approval

- USQ HREC ID: H21REA222
- Approval date: 15/10/2021
- Expiry date: 15/10/2024
- USQ HREC status: Approved

Other Issues - Publication Acceptance

- Part-time study
- Publication acceptance time

Conclusion 1

- Imbalanced class datasets require training sets to have balanced class data, or appropriate metrics to assess the precision of minority class predictions.
- Features with missing values can still be transformed into meaningful information, even in a binary format.

Conclusion 2

- The widely adopted oversampling method SMOTE only supports single label data samples, as such an ensemble of linear, nonlinear, and majority class undersampling multi-label classifiers can provide the best coverage for identifying and predicting true positive minority class samples.
- It was also observed that the usage of linear variables can be more valuable than nonlinear when a dataset has imbalanced classes.

Conclusion 3

- We can automate the construction of a knowledge graph using a Wilcox rank significance test and in order to assist the selection of features that contain the highest and lowest levels of inter-feature relations, using a knowledge base such as the WHO ICD.

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Thanks

Questions?

Markian Jaworsky
Markian.Jaworsky@usq.edu.au