A Multi-Label Classification Framework for Cancer

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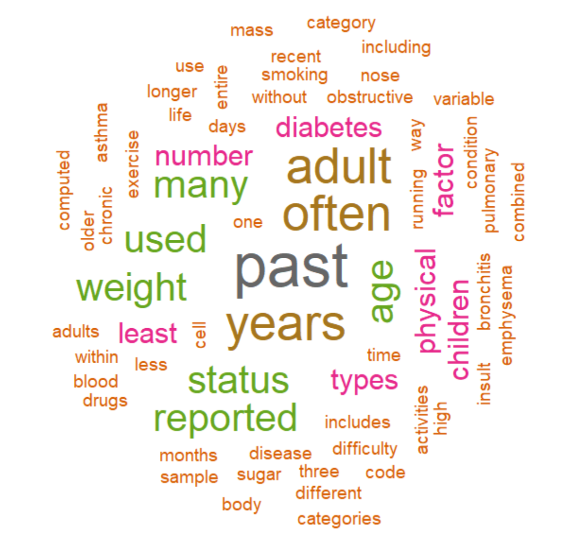
Introduction

- 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.

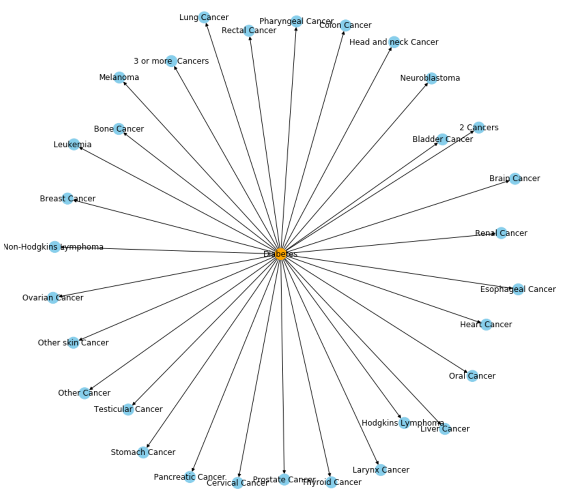
- Word cloud of text frequency variance between smoking and non-smoking lung cancer patients.



- Most studies are typically focused on single disease datasets, however, to live a truly healthy lifestyle, the features that can be used to predict the likelihood of many diseases is more useful.

Research Scope - Goal

- A Framework for Handling the Data Challenges in the Multi-Label Classification of Multiple Cancer subtypes.



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 and provide a framework for 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

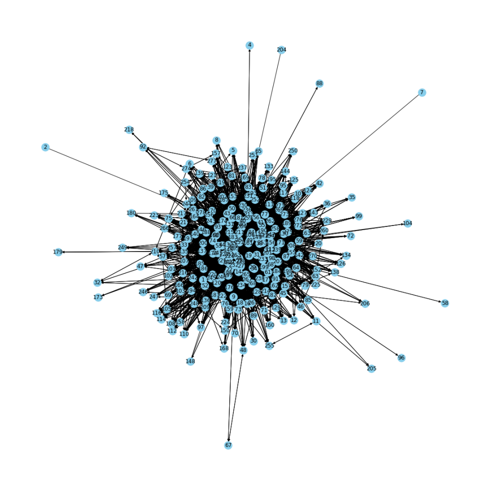
- A subset of predictor variables that can be robustly used to predict a level of risk in multiple cancer subtypes.

Research Scope - Expected Research Outcome 2

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

Research Scope - Potential Contribution 1

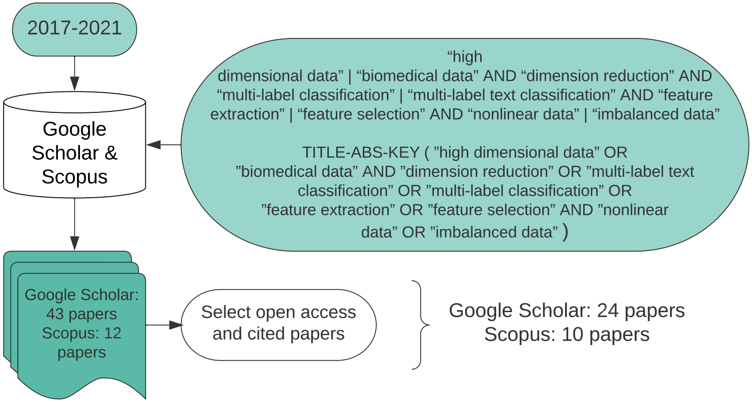
- Novel automated chapter ranking significance-based knowledge graph to identify inter-feature relations.
- Our automation uses the 26 chapters of WHO ICD.



Research Scope - Potential Contribution 2

- Novel majority class under-sampling method that replaces nonlinear features with eliminated linear features.

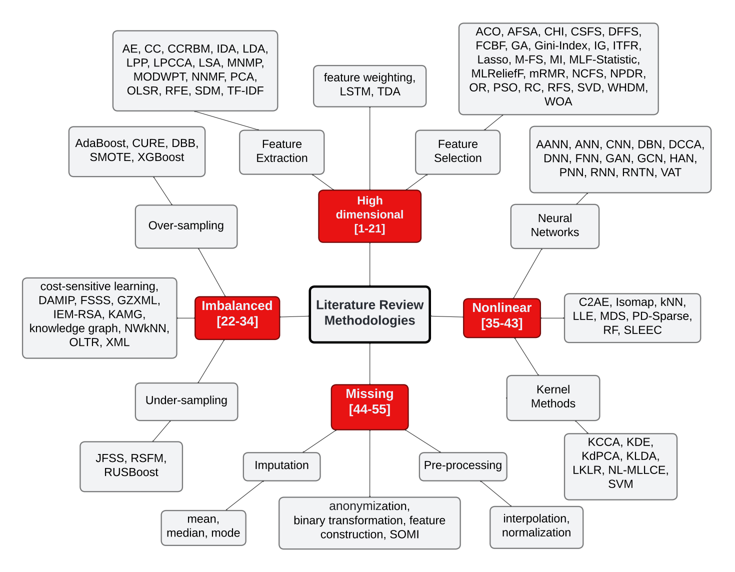
Literature Review - Scope



Literature Review - Data Challenges

- High Dimensional Datasets [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21]
- Imbalanced Class Datasets [22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34]
- Multiple and Nonlinear Datasets [35, 36, 37, 38, 39, 40, 41, 42, 43]
- Datasets with Missing and Erroneous Values [44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55]

Literature Review

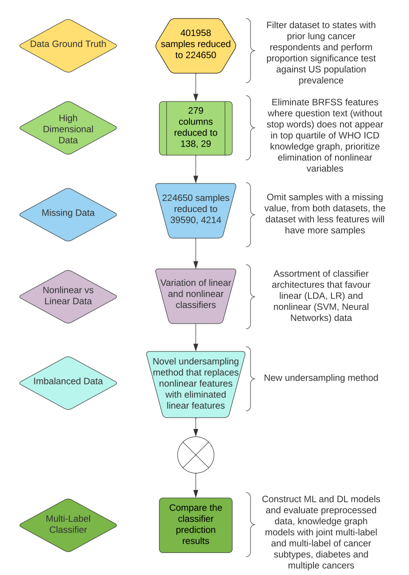


- There is not an existing single widely-adopted framework for uncovering data patterns to support the construction of multi-label chronic illness classifier.

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.

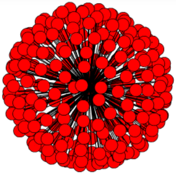
Research Design - Data Preparation



Research Design - Goal

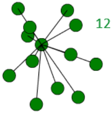
- Reproducible health survey analysis and predictive model construction

Research Design



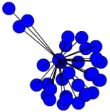
278 Health Survey Predictor Variable Candidates

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



12 ML/DL Algorithm Candidates

34 Health Survey Response Variable Candidates



Research Design - Health Survey Classifiers

- AdaBoost [56]
- K-nearest neighbours [56, 57]
- Linear Discriminant Analysis [58]
- Logistic Regression [56, 57]
- Multinomial Naive Bayes [56]
- Random Forest [56, 57]
- RUSBoost [56]
- Support Vector Machine [56]
- TensorFlow Convolutional Neural Networks [56]

Research Design - Parameter Tuning Optimization

- To be both optimal and reproducible, a strategy is required
- Hyperopt [59, 60]
- Grid Search [61]
- ULMfit [62]

Research Design - Evaluation Methods

- Macro Average F1-Score [14, 18, 17, 11, 49, 22, 26, 29, 25, 43, 41, 51, 52, 8, 63, 64, 61, 65, 54, 66, 30, 67, 47, 68, 48, 69, 70, 71, 72, 7, 73, 74, 75, 76, 77]
- Precision at Top K (P@k) [17, 39, 40, 78, 79, 80, 81, 31, 63, 32, 34, 82, 83, 84, 60, 85, 73, 76, 86]

Research Design - Dataset

- The United States CDC and Prevention make available an anonymized annual Behavioral Risk Factor Surveillance System (BRFSS) survey data from across all 50 US states from the years 1985 to 2020, which is free to the public domain and may be copied and distributed without permission.
- The annual surveys consist of between 100 to 454 questions which vary from year to year and up to half a million respondents complete the surveys each year, and is the world's largest annual health survey.

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

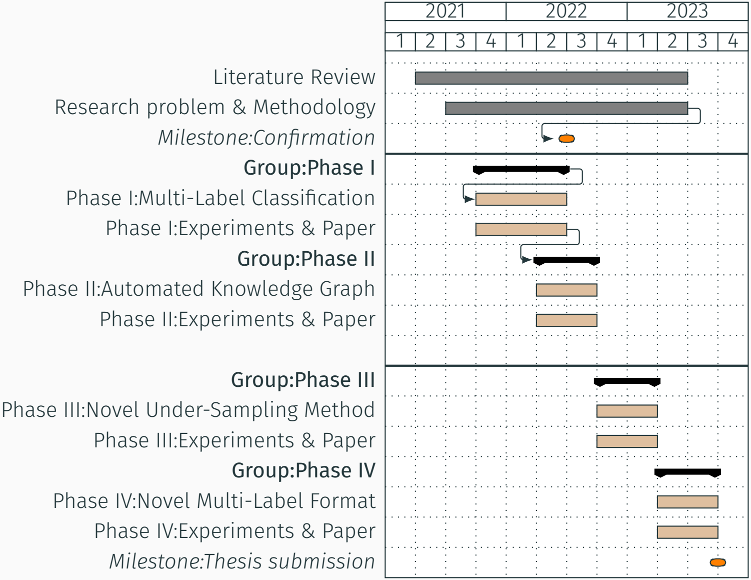
Research Plan - Phase 3

- 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



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 Submission: 02/07/2022

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

- 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?

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