A Comparison of Machine Learning Algorithms to Predict Social Determinants of Health

Abstract

The circumstances in the places where individuals are born, live, study, work, play, worship, and age impact a wide range of health, functional, and quality-of-life outcomes and hazards. In this research, we employ data mining, machine learning (ML) techniques, and neural network (NN) methodologies to predict social determinants of health. For this research, we used the CITI Program dataset. The collection includes information on 673 patients, their none unique class features and **BARRIERS** that's target attributes. Several alternative machine learning methods were examined to construct prediction models for our categorization utilizing SDH data. The results demonstrated that the ideal machine learning methodology, as measured by predictive precision, recall, and F-measure score, differed depending on the classification algorithm, implying that a method for creating predictive models from SDH data is effective. The best models for each categorization and label obtained prediction accuracies of 30–90%, showing that the methodology has the potential to supplement conventional methods for categorizing Social Determinants of Health. We developed the NN model with a different hidden layer with different threshold and discovered that the NN with one and hidden layer and BinaryRelevance GaussianNB delivered the highest percent accuracy.

Keywords

Machine learning (**ML**), Data Mining, Neural Network (**NN**), K-fold Cross Validation, Accuracy, Precision, Recall, F-Measure, Social Determinants of Health (**SDH**), BinaryRelevance GaussianNB(**BR_GN**), BinaryRelevance KNeighborsClassifier (**BR_KN**), BinaryRelevance RandomForestClassifier (**BR_RF**), ClassifierChain GaussianNB (**CC_NB**), ClassifierChain KNeighborsClassifier (**CC_KN**), ClassifierChain RandomForestClassifier (**CC_RF**), OneVsRestClassifier GaussianNB (**OVR_NB**), OneVsRestClassifier KNeighborsClassifier (**OVR_KN**), and OneVsRestClassifier RandomForestClassifier (**OVR_RF**).

1. Introduction

The non-medical elements that influence health outcomes are known as social determinants of health (SDH). They are the circumstances in which people are born, grow, work, live, and age, as well as the larger set of factors and institutions that shape daily life conditions. Economic policies and systems, development objectives, social norms, social policies, and political systems are examples of these forces and systems.

The SDH have a significant impact on health disparities, which are inequitable and preventable variations in health status found within and between nations. Health and sickness follow a social gradient in nations of all income levels: the lower the socioeconomic position, the poorer the health.

Data mining and machine learning have been emerging, dependable, and supportive technologies in the medical arena. The data mining approach is used to preprocess and pick important characteristics from our data, while the machine learning method aids in the automation of SDH prediction.

Data mining and machine learning algorithms can help identify the hidden pattern of data using the cutting-edge method; hence, a reliable accuracy decision is possible. Data Mining is a process where several techniques are involved, including machine learning, statistics, and database system to discover a pattern from the massive amount of dataset [1]. According to Nvidia: Machine learning uses various algorithms to learn from the parsed data and make predictions [2].

2. Methods

2.1. Data, feature, and software tool

There are 673 patients in the dataset, each with their own set of seven unique features. The properties of this dataset are described in Table 1. Seven factors used to predict SDH are Age, Language, Birth, Zip Code, Nearest cancer center, Kilometers to nearest cancer center, Duration to nearest cancer center, and Outcomes. The Seven class properties are treated as independent/feature variables, whereas the 'outcomes' attribute is treated as a dependent or target variable. The 'outcomes' SDH target attribute is made up of 93 labels, each of which is a binary value with a value of 0 indicating no label and 1 indicating label. We employed data mining and machine learning techniques in our study to predict whether or not a patient had a label. For the performance analysis of the SDH dataset, we employed the Python programming language and data mining technique with python. Data preparation, classification, visualization, and feature selection are all available in python. All including Neural Network is coded in the Python programming language and implemented in the Visual Studio integrated development environment.

Table 1. The attributes of SDH dataset.

Attribute	Description	Type
PDAGE	Age (years).	NUMERIC
PDLANG	Main Language spoken	STRING
PDBIRTH	Country of Origin/Heritage	STRING
PDZIP	Current zip code of the person	STRING
ZIPCODE _TO_NEAREST CANCER CENTER	Nearest cancer center zip code	STRING
KM_ TO_NEAREST CANCER CENTER	Distance to Nearest cancer center	NUMERIC
DURATION_ TO_NEAREST CANCER CENTER	Duration to Nearest cancer center	NUMERIC
BARRIES	Target Attribute	ARRAY

2.2. Data preprocessing

Preprocessing aids in the transformation of data so that a more accurate machine learning model may be generated. To enhance data quality, preprocessing performs a variety of activities such as, filling missing values, data normalization/standardization, and feature selection. The collection contains 673 samples

2.2.1 Missing value identification

We found the missing values in the datasets using Excel, as shown in Table 2.

[Table 2]. The number of missing values in SDH dataset.

Attribute	No of Missing values
PDAGE	1
PDLANG	1
PDBIRTH	2
PDZIP	6
NEAREST CANCER CENTER	6
KM_ TO_NEAREST CANCER CENTER	6
DURATION_ TO_NEAREST CANCER CENTER	6

2.2.2 Feature Selection

Pearson's correlation approach is a well-known method for determining the most important attributes/features. This approach calculates the correlation coefficient, which is related to the output and input qualities. The value of the coefficient remains between 0 and 1. A significant correlation is shown by a value above or below 0.5, whereas no correlation is indicated by a value of zero. [Table 3] shows the results of using the correlation filter to find the correlation coefficient. For relevant qualities, we chose a cut-off of 0.2. As a result, the seven most important input attributes are AGE, PDLANG, BIRTH, ZIP, Nearest hospital, Nearest cancer center, Km to nearest cancer center, Duration to nearest cancer center and Nearest cancer center zip.

Table 3. The correlation between input and output attributes.

Attribute	Correlation coefficient
PDAGE	0.694993
PDLANG	0.311131

PDBIRTH	0.309027
PDZIP	0.581835
NEAREST CANCER CENTER	0.359098
KM_ TO_NEAREST CANCER CENTER	0.254201
DURATION_ TO_NEAREST CANCER CENTER	0.219211

2.2.4 MultiLabelBinarizer

We use a Multilabelbinarizer to turn the labels into individual columns because your target property was in an array form. [Table 4] shows how it works. This means that if the rows have similar labels, there will be 1 and 0 if not in the columns. You can encode many labels per instance with Multilabelbinarizer. You might create a DataFrame with this array and the encoded classes to translate the resultant array.

Table 4. How MultiLabelBinarizer works

Target	A	B	C	D
[A,C]	1	0	1	0
[C,D]	0	0	1	1
[A,B,D]	1	1	0	1

2.2.3 Normalization

We did feature scaling by Normalization the data to have a data from 0 and 1 range, which increased the calculation performance of the method. We have 666 samples/instances after preprocessing and handling missing and none values.

2.3. Dataset train and test method/ Evaluation Strategy

The dataset is ready to train and test after it has been cleaned and preprocessed. To test the performance of the multiple machine learning models, we utilized K-fold cross-validation and the 80 percent /20 percent train/test splitting approach individually. The train/split approach divides the dataset into training and testing sets at random. The data is separated into K folds in the K cross-validation approach. Validation/testing is done with one fold, and training is done with the remaining K-folds. The technique will be repeated until each and every K fold is a test set. The average of all recorded Kth test scores is used to assess performance.

2.4. Design and implementation of classification model

Basically, there are three methods to solve a multi-label classification problem, namely: Problem Transformation, Adapted Algorithm and Ensemble Approaches. In this study we used Problem Transformation method and different ML classification techniques such as BinaryRelevance, ClassifierChain, OneVsRestClassifier, and neural network are used to investigate the SDH (CNN). For the CNN algorithm, we utilized Kth value = 10. Figure 7 and 8 depicts the proposed model diagram.

2.4.1 BinaryRelevance model implementation

This is the most basic strategy, in which each label is treated as a distinct single-class classification issue. Let's look at an example, as given below. We have the following data set, where X is the independent characteristic and Y is the target variable. This problem is divided into four separate single class classification problems in binary relevance.

X	Y_1	Y_2	Y_3	Y_4
$x^{(1)}$	0	1	1	0
$x^{(2)}$	1	0	0	0
$x^{(3)}$	0	1	0	0
$x^{(4)}$	1	0	0	1
$x^{(5)}$	0	0	0	1

X	Y_1
$x^{(1)}$	0
$x^{(2)}$	1
$x^{(3)}$	0
$x^{(4)}$	1
$x^{(5)}$	0

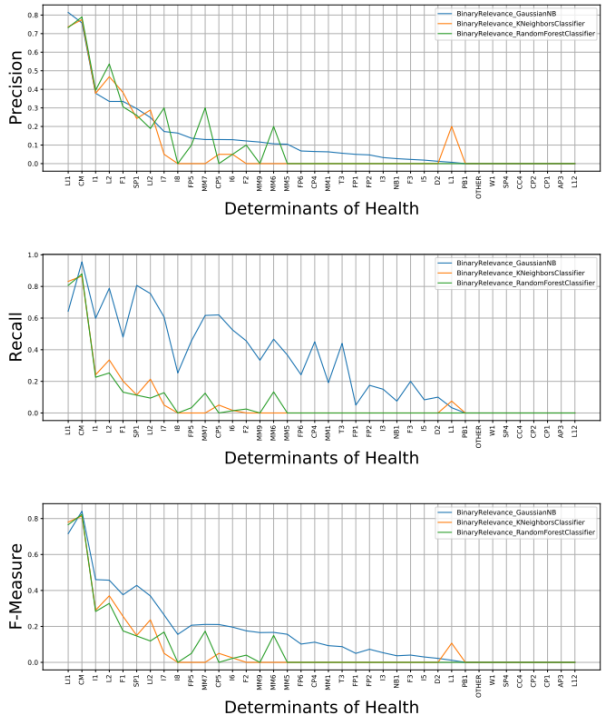
X	Y_2
$x^{(1)}$	1
$x^{(2)}$	0
$x^{(3)}$	1
$x^{(4)}$	0
$x^{(5)}$	0

X	Y_3
$x^{(1)}$	1
$x^{(2)}$	0
$x^{(3)}$	0
$x^{(4)}$	0
$x^{(5)}$	0

X	Y_4
$x^{(1)}$	0
$x^{(2)}$	0
$x^{(3)}$	0
$x^{(4)}$	1
$x^{(5)}$	1

[Fig 1] -How BinaryRelevance Works

We deploy three binary relevance model with three different classifications. We implemented the BinaryRelevance with GaussianNB, KNeighborsClassifier, and RandomForest. and the results are compared.



[Fig 2] Binary Relevance Comparisons

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2.4.2 ClassifierChain model implementation

The initial classifier is trained only on the input data, and each subsequent classifier is trained on the input space as well as all previous classifiers in the chain. [Fig3]

X	y1
x1	0
x2	1
x3	0

Classifier 1

X	y1	y2
x1	0	1
x2	1	0
x3	0	1

Classifier 2

X	y1	y2	y3
x1	0	1	1
x2	1	0	0
x3	0	1	0

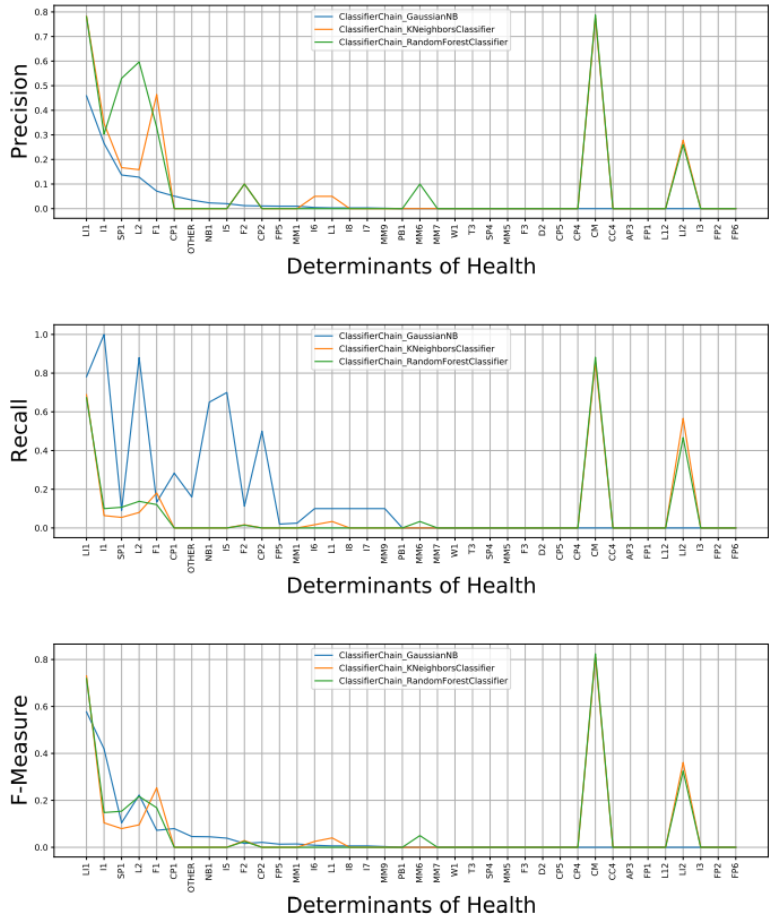
Classifier 3

X	y1	y2	y3	y4
x1	0	1	1	0
x2	1	0	0	0
x3	0	1	0	0

Classifier 4

[Fig 3] -How ClassifierChain Works

We deploy three binary relevance model with three different classifications. We implemented the ClassifierChain with GaussianNB, KNeighborsClassifier, and RandomForest. and the results are compared.



[Fig 4] -ClassifierChain Comaprisons

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2.4.3 OneVsRestClassifier model implementation

This technique, often known as one-vs-all, consists of fitting one classifier per class. The class is fitted against all the other classes for each classifier.

X	Y1	Y2	Y3	Y4
x1	0	1	1	1
x2	0	0	1	1
x3	1	0	1	0

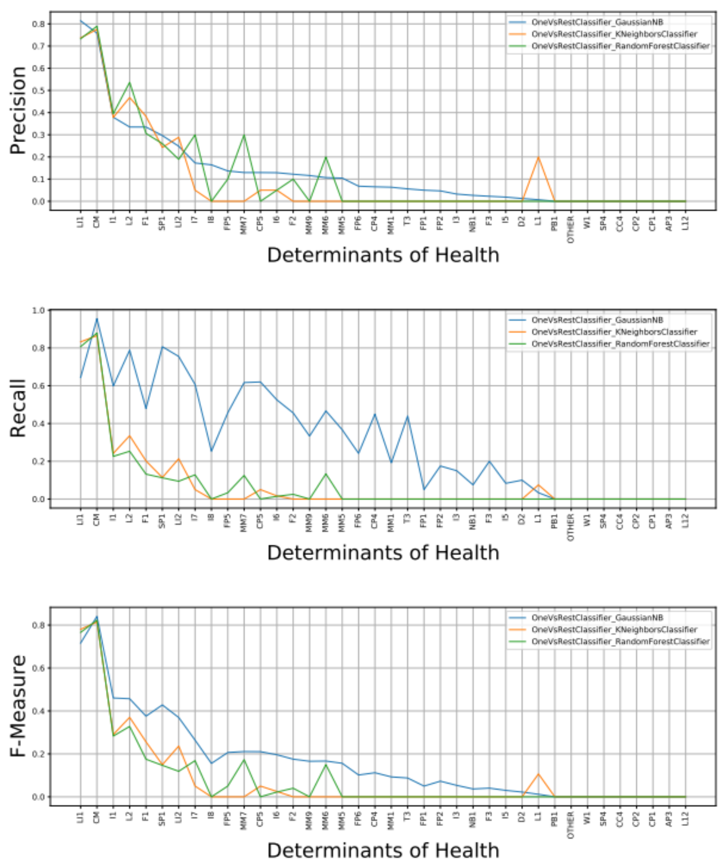
X	Y1	Y2	Y3	Y4
x1	0	1	1	1
x2	0	0	1	1
x3	1	0	1	0

X	Y1	Y2	Y3	Y4
x1	0	1	1	1
x2	0	0	1	1
x3	1	0	1	0

X	Y1	Y2	Y3	Y4
x1	0	1	1	1
x2	0	0	1	1
x3	1	0	1	0

[Fig 5] -How OneVsRestClassifier Works

We deploy three binary relevance model with three different classifications. We implemented the OneVsRestClassifier with GaussianNB, KNeighborsClassifier, SVC, and RandomForest. and the results are compared.



[Fig 6] OneVsRestClassifier Comaprisons

[Download : Download PDF with more info (30KB)]

2.4.4 Neural network model implementation

We created two separate neural network models with different hidden layer depths. The neural network was implemented with hidden layers 1 and 2, 3 different thresholds and 512 epochs, and the results were compared. The activation function in the hidden layer of CNN processes the weighted sum of input. In our research, we used sigmoid and RELU activation functions. The neural network models were created using the Keras and TensorFlow libraries. A Sequential class from the Keras library was utilized. The 'Outcomes' attribute contains the target variables. During the backpropagation procedure of CNN, the optimizer is necessary to reduce the output error. As an optimizer, we used rmsprop (Root Mean Square Propagation). The learning rate is a parameter in an optimization algorithm that controls the weight adjustment with respect to loss gradient. We used different learning rates to find an effective one. From the scikit-learn library, we used the train_test_split function to perform the train/test splitting task. We also used the K-Fold cross_val_score function from the scikit_learn library for the K-fold cross-validation task.

2.4.4.1 Developing a NN model with one hidden layer

We began by creating a neural network that included one hidden layer in addition to the input and output layers. As there are seven features, we designated the input layer as having seven neurons. Max pooling, batch normalization, a dropout layer, and a RELU activation function are all included in the hidden layer. There are 93 neurons in the output layer, with a sigmoid activation function. In Fig. 5, the model summary of NN with one hidden layer is shown.

Layer (type)	Output Shape
conv1d (Conv1D)	(None, 5, 128)
max_pooling1d (MaxPooling1D)	(None, 5, 128)
batch_normalization (BatchNo	(None, 5, 128)
dropout (Dropout)	(None, 5, 128)
flatten (Flatten)	(None, 640)
dense (Dense)	(None, 93)

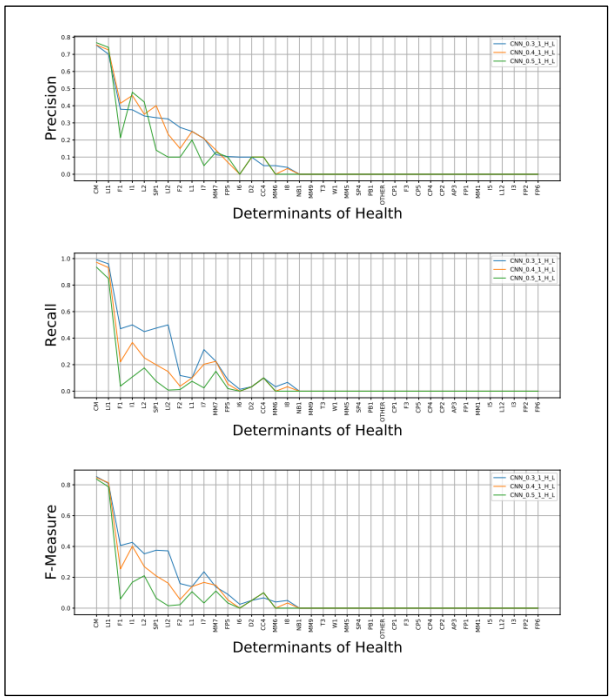
[Fig 7] – CNN One Hidden Layer

2.4.4.2 Developing a NN model with two hidden layers

We've created a NN model with one hidden layer that has the same input shape, neurons, and activation function as NN. The second layer has a hidden layer with 26 neurons and an output layer with 93 neurons with a sigmoid activation function, similar to the NN with one layer. In Fig. 6, the model summary of NN with two hidden layers is shown.

Layer (type)	Output Shape
conv1d (Conv1D)	(None, 5, 128)
max_pooling1d (MaxPooling1D)	(None, 5, 128)
batch_normalization (BatchNo	(None, 5, 128)
dropout (Dropout)	(None, 5, 128)
conv1d_1 (Conv1D)	(None, 3, 32)
flatten (Flatten)	(None, 96)
dense (Dense)	(None, 93)

[Fig 8] – CNN Two Hidden Layers



[Fig 9] – CNN One Hidden Layer Results
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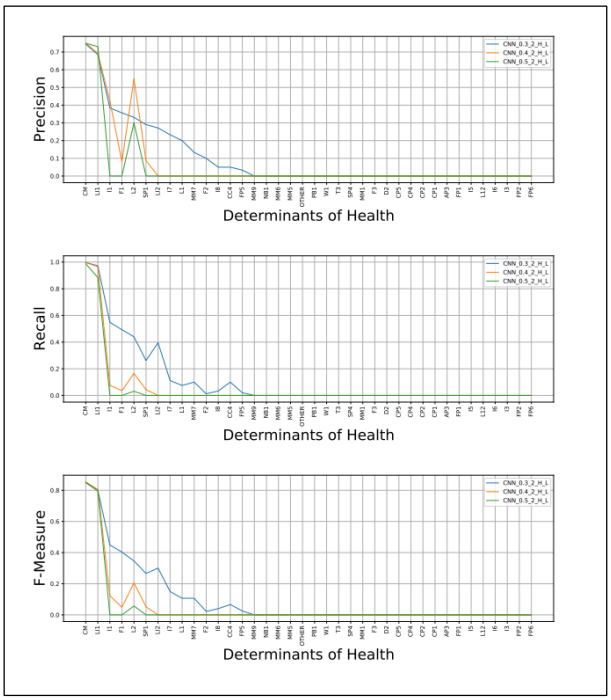

[Fig 10] – CNN Two Hidden Layers Results
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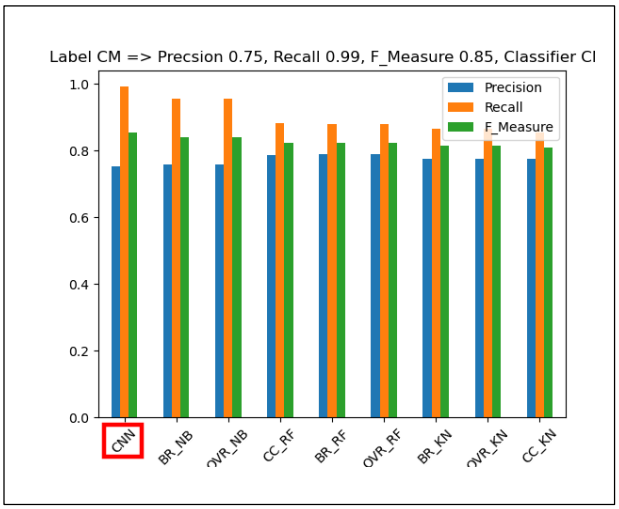
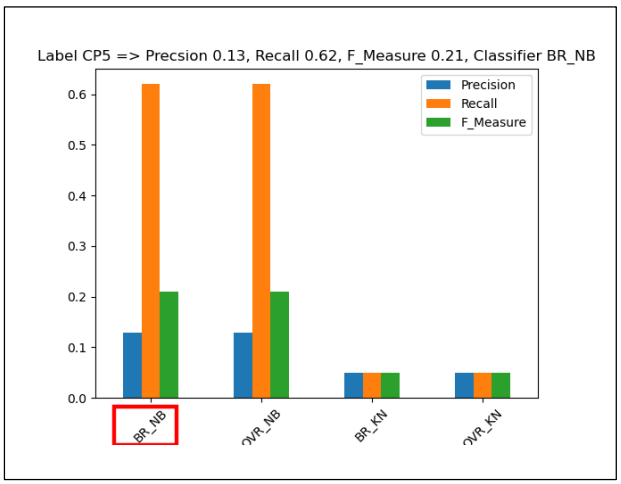
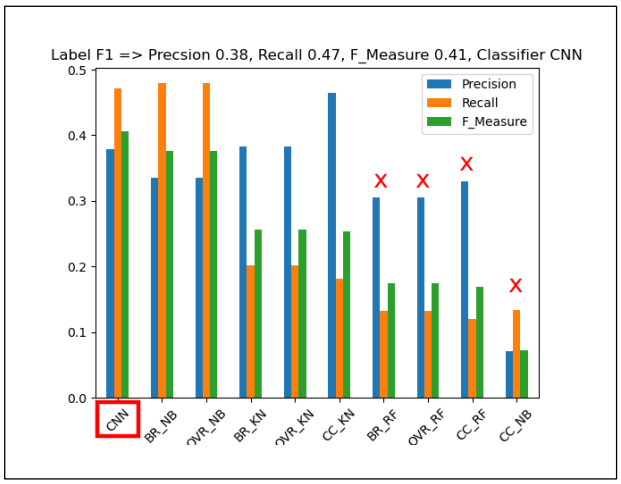
3. Results and discussion

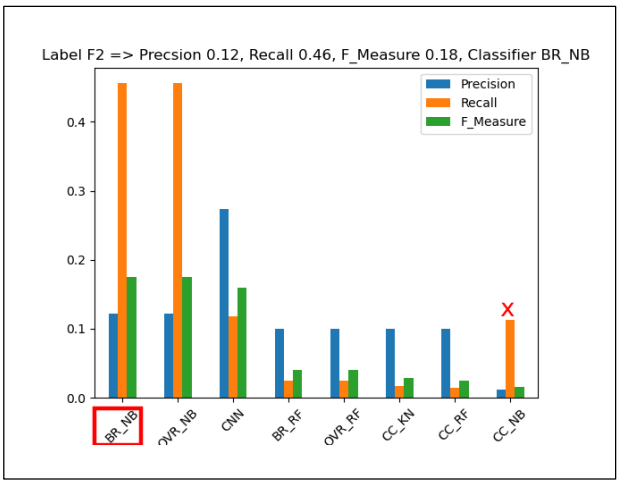
3.1. Results for ML method BinaryRelevance, ClassifierChain, OneVsRest on all Barries

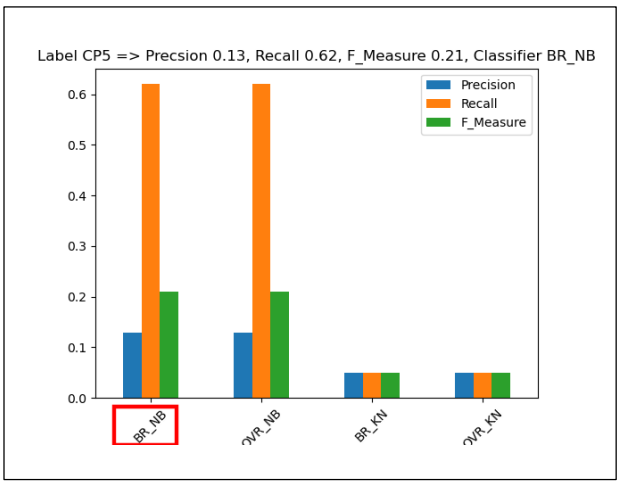
For every Box represents a label or Barrier the classifier in red yields the best accuracy, classifiers with a (X) above the bar statistically significantly worse (p<0.5)

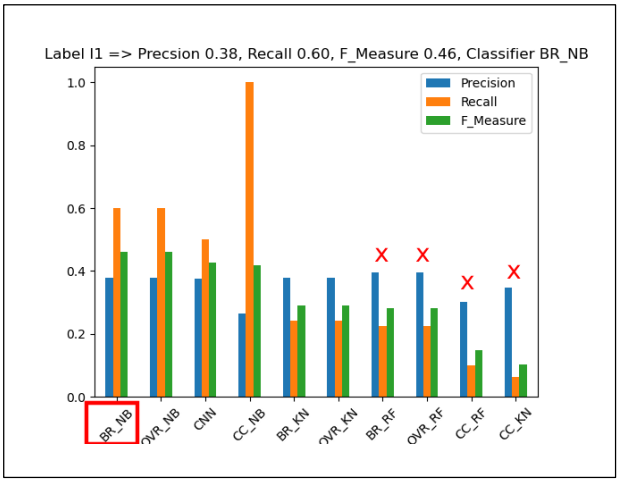


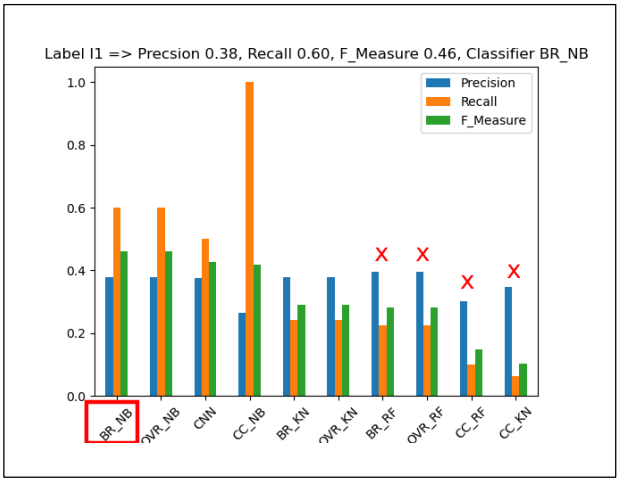








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BR_KN
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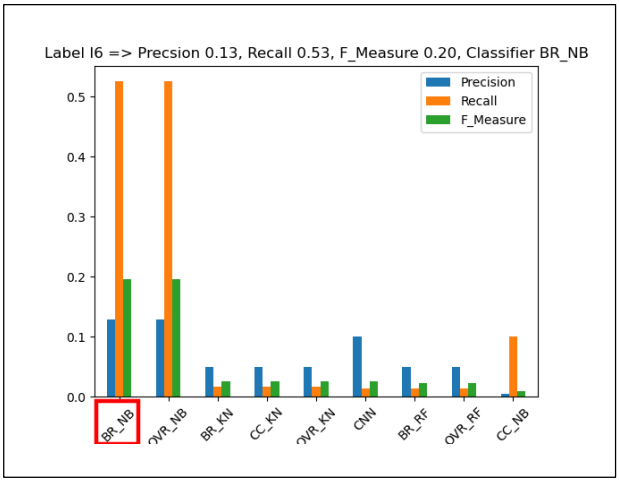
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CNN
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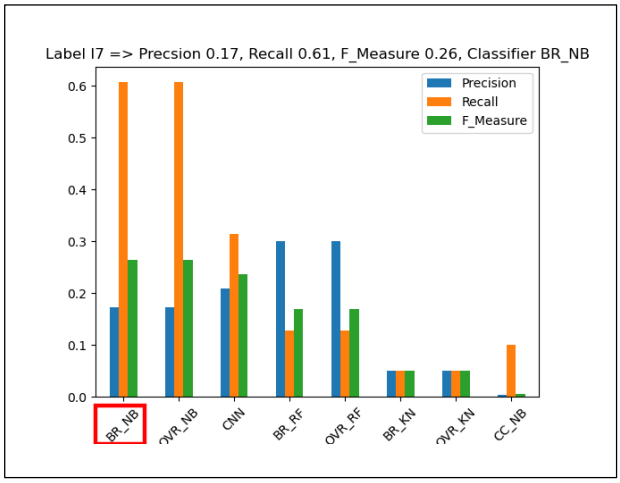
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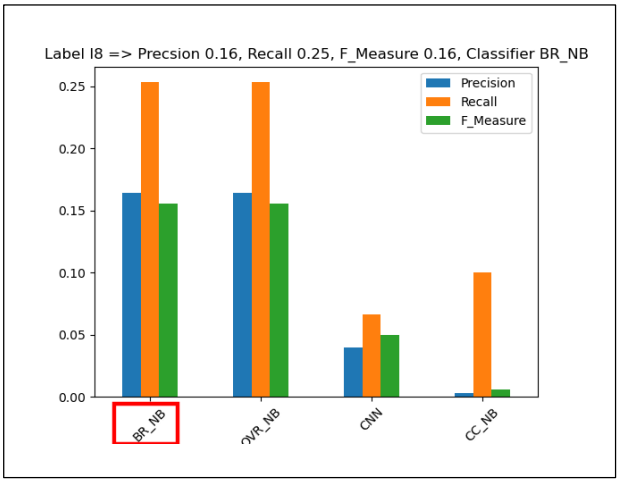
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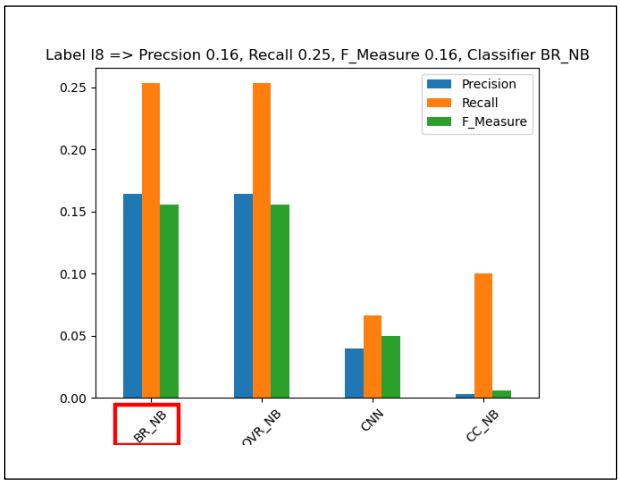
Recall
F_Measure
BR_NB
OVR_NB
CNN
CC_NB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Recall
F_Measure
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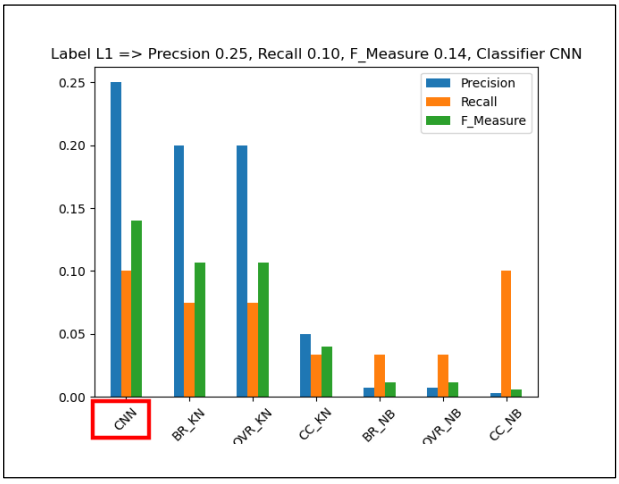
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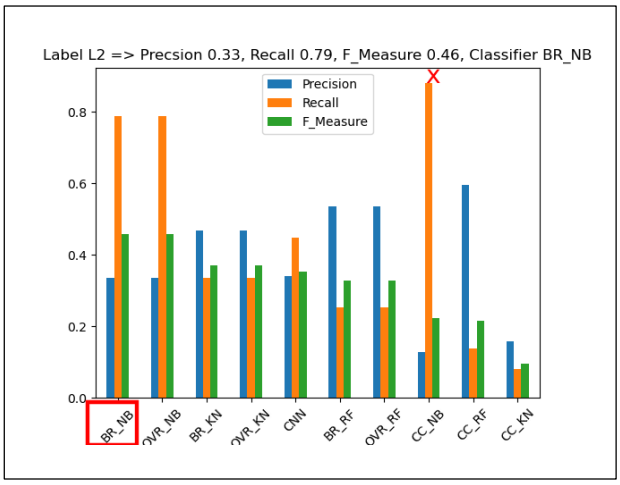
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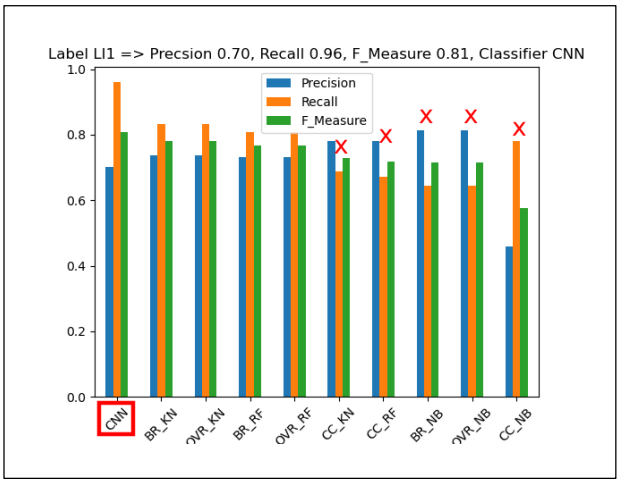
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Recall
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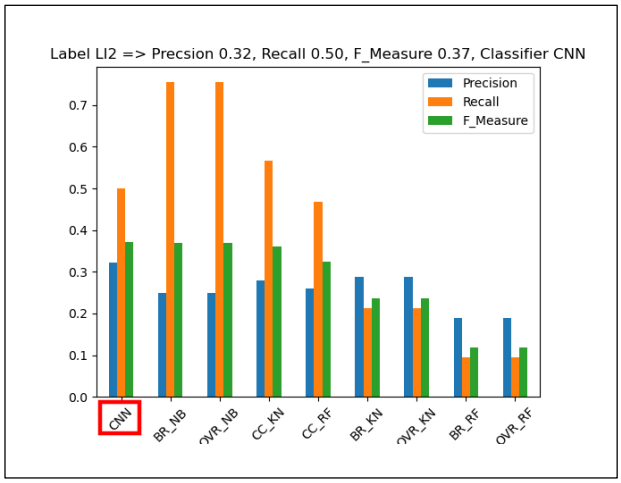
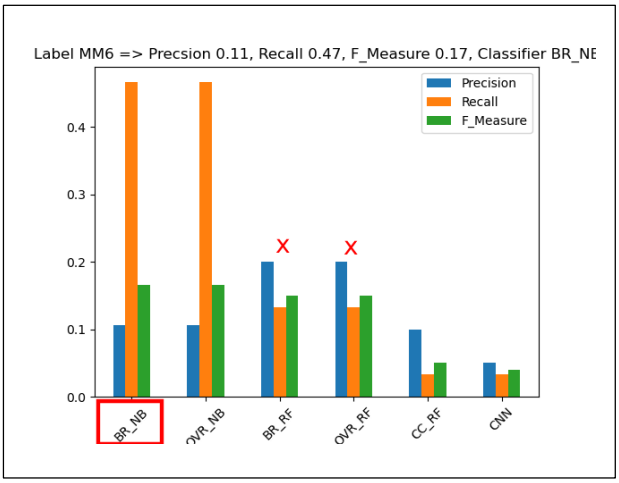
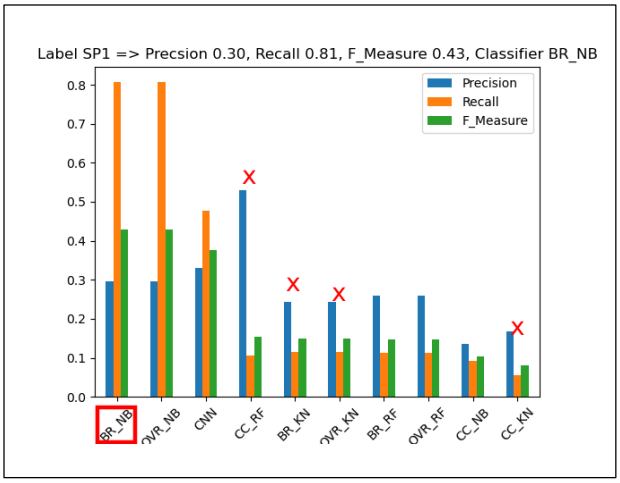
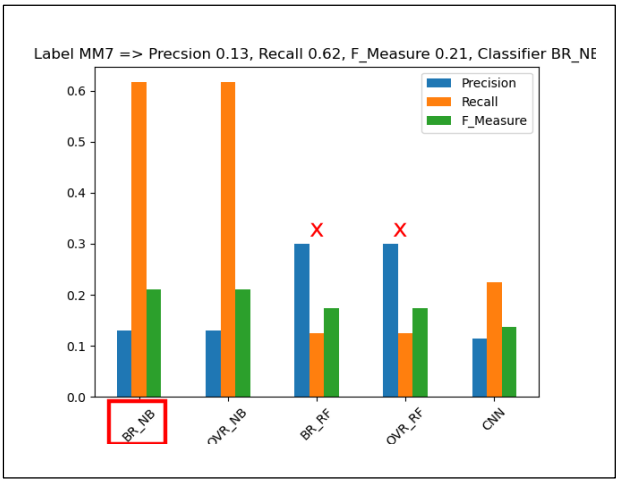
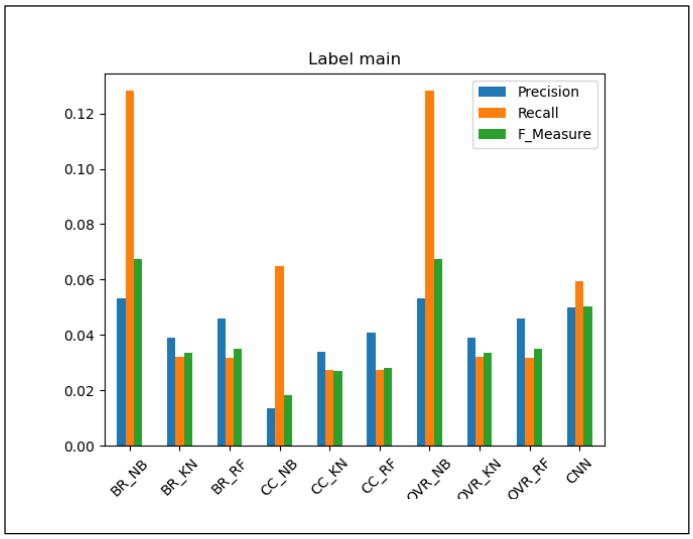








3.2. Results for ML method Binary Relevance, ClassifierChain, OneVsRest on all Barries



Conclusion

According to research, social determinants of health can have a greater impact on health than health treatment or lifestyle choices. Numerous research imply that SDH is responsible for 30-55 percent of health outcomes. Furthermore, estimations reveal that industries other than health contribute more to population health outcomes than the health sector.

Addressing SDH appropriately is fundamental for improving health and reducing longstanding inequities in health, which requires action by all sectors and civil society.

Utilizing Python, we preprocessed the data. In the CITI Program dataset, we employed seven input features (PDBIRTH, PDLANG, PDZIP, Km to nearest cancer center, Duration to nearest cancer center, Nearest cancer center zip, and Nearest cancer center zip) and 93 output features (outcomes). On the CITY Program dataset, we employed multiple machine learning methods to predict SDH, including BinaryRelevance(GaussianNB), BinaryRelevance((KNeighborsClassifier), BinaryRelevance((RandomForestClassifier), ClassifierChain(GaussianNB), ClassifierChain(KNeighborsClassifier), ClassifierChain(RandomForestClassifier), OneVsRestClassifier(GaussianNB), OneVsRestClassifier(KNeighborsClassifier), OneVsRestClassifier(RandomForestClassifier), and OneVsRestClassifier(SVC), and assessed the performance on various measures. or some metrics, such as precision, recall, and F-measure, all models produce positive outcomes. We also used the NN model to predict SDH in the CITY Program dataset. With varied thresholds and 512 epochs, we employed the 1, 2 hidden layers in the neural network model, which had a good score among our constructed models for SDH. The NN with one hidden layer and BinaryRelevance(GaussianNB), are the most efficient and promising of all the presented models for evaluating SDH, with an accuracy rate greater than 50 for most of the barrier

References

[1] What's the Difference Between Artificial Intelligence, Machine Learning and Deep Learning? https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/.

[2] Multi-Label Classification https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/

[3] Multi-Label Classification https://www.analyticsvidhya.com/blog/2017/08/introduction-to-multi-label-classification/

[4] Using neural networks for data mining https://www.sciencedirect.com/science/article/abs/pii/S0167739X97000228

[5] CNN Keras with cross validation
https://www.kaggle.com/franklemuchahary/basic-cnn-keras-with-cross-validation

[6] Multi-Class Text Classification with Scikit-Learn
https://towardsdatascience.com/multi-class-text-classification-with-scikit-learn-12f1e60e0a9f

[7] Multi-Label Classification with Deep Learning
https://machinelearningmastery.com/multi-label-classification-with-deep-learning/

[8] Multi-Label Classification of Satellite Photos of the Amazon Rainforest
https://machinelearningmastery.com/how-to-develop-a-convolutional-neural-network-to-classify-satellite-photos-of-the-amazon-rainforest/

[9] Machine learning approaches to the social determinants of health in the health and retirement study
https://www.sciencedirect.com/science/article/pii/S2352827317302331