

Chronic Pain Challenge: A Statistical Machine-learning Method for Chronic Pain Assessment

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ABSTRACT

Aim: The objective of Chronic Pain Challenge project is designing and construction of a machine-learning system to calculate the dynamic changes to the chronic pain risk score of an individual based on various weighted health behaviors.

Materials and methods: The visual analog scale (VAS) and Oswestry Disability Index (ODI) ratings of 218 subjects were studied for dynamic changes based on three weighted health behaviors, physical exercise, nutrition, and depression in order to predict their individual and cumulative impact on severity of chronic pain. The predictive function was used to produce confidence and prediction intervals for the calculation of new VAS and ODI scores using supervised and unsupervised machine-learning algorithms and R programming language for statistical computation.

Results: This 9 months research study resulted in the development of innovative design and construction of a machine-learning program that accurately predicted the changes to standardized tests, such as VAS and ODI based on weighted values for depression score (DS), nutrition score (NS) and physical activity score (PAS). The testing of both extreme and moderate ranges of health behavior values in a variety of subjects and comparison against simple weightage confirmed the accuracy and validity of the program.

Conclusion: Chronic Pain Challenge program is a valid and accurate method in predicting chronic pain risk of an individual based on the engagement in various health behaviors. The Chronic Pain Challenge program can predict and prevent progression of chronic pain and disability by global education and empowerment, thereby disrupting the current health care model with the emerging and accelerating technology.

Clinical significance: The Chronic Pain Challenge program is an innovative statistical machine-learning program for chronic pain predictability based on individual's health behavior patterns.

Keywords: Algorithm, Chronic pain, Health behaviors, Health risk, Health statistics, Machine learning, Pain risk.

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INTRODUCTION

Chronic pain is a major social and economic burden around the world. Globally, 20% of adults suffer from pain and 10% are newly diagnosed with chronic pain each year.¹ Pain can be acute or chronic, continuous or intermittent, nociceptive or neuropathic, or any combination thereof. Although there are several risk factors for chronic pain, the main determinants are mental and physical stress at work,^{2,3} socioeconomic status,⁴ rurality,⁵ occupational status,⁶ race,^{7,8} and education.⁹ These risk factors are preventable to a large extent and if identified and corrected in a timely fashion can lead to prevention of chronic pain and disability.

Developments in the field of genetics, information technologies, and nanotechnology are enforcing a more individualized approach to health care. People are living longer due to scientific advances in understanding of the etiology of diseases, improvements in diagnostic techniques, and sophistication of treatment protocols. However, in order to build healthy communities, the key is to focus on prevention and early intervention before the onset of chronic illness. Chronic pain due to its profound impact on the social and economic structure of a community warrants attention as an immediate public health priority.

Prevention of chronic pain necessitates the use of a pain measurement tool that can accurately identify the effect of health and behavioral interventions in people. Applying this tool to accurately predict the risk of developing chronic pain lacking healthy behaviors or vice versa can serve as a powerful tool in prevention of or treatment at an early stage of chronic pain before its multidimensional impact sets in. There are some aspects of lifestyle education that are practiced by primary care physicians and health coaches, but there is no universal paradigm accepted for chronic pain prevention and management.

In USA, Center for Medicare and Medicaid services has developed a risk adjustment system and has assigned a risk score to a particular patient based on their age, gender, and presence or absence of chronic disease.¹⁰ This system assigns a single "Health Risk Score" to a patient

and lacks the dynamic fluidity of changes in this score based on changes in health and wellness behaviors. As noted in the case of heart disease, poor nutritional habits, minimal exercise routine, and stress can significantly impact the risk of worsening heart disease. Unfortunately, there is no system currently in place for chronic. There is an immediate need for a mind shift of all stakeholders to take on the challenge of global pain care from treatment to prevention.

Recognizing this need, our project focuses on a machine-learning system that tracks the dynamic changes to chronic pain and disability scores of an individual based on their engagement in positive or negative health behaviors according to assigned individualized weightage.

MATERIALS AND METHODS

Our methodology aims at adapting the dynamic interaction of various health behaviors in providing an accurate real-time risk score for a subject. The computer algorithm designates weightage to each health behavior according to its importance in development or progression of chronic pain.

Although there are several health factors for the chronic pain, such as stress, socioeconomic status, occupation, obesity, smoking, lack of physical activity, unhealthy diet, we have identified nutrition (diet), physical activity (exercise), and depression (stress) as the most impactful in this respect based on the information obtained from the previously known studies.¹¹⁻¹³

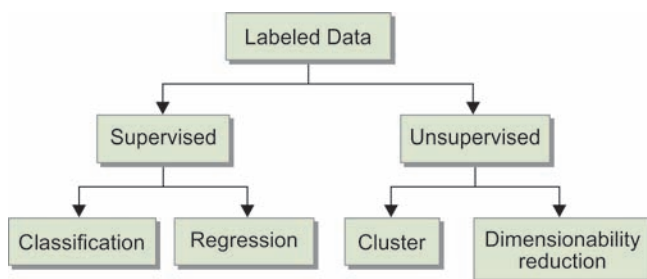
The nutrition health profile of an individual is evaluated via the Mini Nutritional Assessment (MNA-SF). The MNA is a short, valid nutritional screening tool that contains assessment questions related to nutritional and health conditions, independence, quality of life, cognition, mobility, and subjective health.¹⁴

The Borg rating of perceived exertion (RPE) is a way of measuring physical activity intensity levels.¹⁵ Perceived exertion is based on the physical sensations a person experiences during physical activity, including increased heart rate, increased respiration or breathing rate, increased sweating, and muscle fatigue.

The psychological risk of the individual is measured by PHQ-9, which is a reliable and valid measure of depression and a common clinical and research tool.¹⁶

Supervised and unsupervised machine-learning algorithms were considered to estimate chronic pain scores respectively (Flow Chart 1). Broadly speaking, supervised statistical learning involves building a statistical model for predicting an output based on one or more inputs while with unsupervised statistical learning, there are inputs but no supervising output; nevertheless, they help in learning relationships and structure.

Flow Chart 1: Statistical machine-learning methods via supervised/unsupervised algorithms



Linear regression and LASSO were considered for regression supervised learning and SVM, KNN, and CART were considered for classification supervised learning. The unsupervised learning algorithms can be further subclassified into cluster analysis and dimensionality reduction, and K-mean, PCA, and ICA algorithms were considered as part of this project.

Baseline Data

We started with data for 218 subjects with their visual analog scale (VAS) score and Oswestry Disability Index (ODI) score. This number (n) of 218 subjects was noted to be statistically significant for the validation of the results.

We looked at typical values for depression score (DS), nutrition score (NS), and physical activity score (PAS) and randomly assigned in the values to each subject. The ranges for depression, nutrition, and physical activity were based on how these were typically measured in a clinical setting (Table 1).

An initial weightage was assigned to different values of depression, nutrition, and physical activity. Tables 2 to 4 show the initial weightage that was assigned to depression, physical activity, and nutrition.

Table 1: Recording of subject name, identifiers, and scores of various categories

Name	DOB	VAS	ODI	DS	NS	PAS
Jane Doe	01/01/11	7	35	9	7	13
John Doe	02/02/22	5	22	10	6	6

Table 2: Depression measurement by PHQ-9 and weightage assignment

Score	Diagnosis	Weightage (%)
5–9	Minimal symptoms	0
10–14	Minor depression	5
15 or greater	Major depression	10

Table 3: Nutrition scores via the MNA-SF and weightage assignment

Score	Diagnosis	Weightage (%)
0–7 points	Malnourished	10
8–11	At risk of malnutrition	5
12–14	Normal nutritional	0

Table 4: Physical activity scores via Borg RPE and weightage assignment

Score	Interpretation	Weightage (%)
<6	No exertion	10
7–9	Extremely light	5
10–11	Light	0
12–16	Somewhat hard	-5
17–20	Maximal exertion	-10

RESULTS

The data was loaded in R and the coefficients for calculating the modified VAS (mVAS) and ODI (mODI) were recorded as depicted in Figures 1 and 2.

The predict function was used to produce confidence, and prediction intervals for the prediction of mVAS and mODI for given values of NS, DS, and PAS are shown in Figures 3 and 4.

In the example above, a subject with VAS pain score of 7 and another one with ODI score of 15 were taken and information for the subject’s mVAS and mODI scores were

```
> library(MASS)
> lm.fit=lm(mVAS~DS+NS+PAS+VAS,data=Auto)
> summary(lm.fit)

Call:
lm(formula = mVAS ~ DS + NS + PAS + VAS, data = Auto)

Residuals:
    Min       1Q   Median       3Q      Max
-1.2943 -0.4394 -0.1123  0.4177  1.6520

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  4.993130   0.161270   30.96 <2e-16 ***
DS            0.132920   0.006258   21.24 <2e-16 ***
NS           -0.184335   0.010210   -18.05 <2e-16 ***
PAS          -0.273724   0.007356   -37.21 <2e-16 ***
VAS           1.009293   0.013020   77.52 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5885 on 213 degrees of freedom
Multiple R-squared:  0.9746, Adjusted R-squared:  0.9742
F-statistic: 2046 on 4 and 213 DF, p-value: < 2.2e-16
```

Fig. 1: R program demonstrating the mVAS score

examined by varying the DS, PAS and NS scores. The variation in the modified score results were in line with the level of depression, physical activity, and nutrition according to their respective weightage. In some cases, the values went past the normal ranges of VAS and ODI, especially in subjects with high initial VAS or ODI, when combined with either high depression and/or low scores of nutrition or physical activity.

Results were calculated for all subjects taking their initial VAS and ODI scores and applying varying degrees of DS, NS and PAS scores along with the assigned weightage parameter for each health behavior to obtain mVAS and mODI scores. These results were then put through accuracy testing to ensure that the modified scores were indeed in line with the expected outcome.

DISCUSSION

In USA, more than 75% of health care spending is on people with chronic conditions. About one-fourth of people with chronic conditions have one or more daily

```
> library(MASS)
> lm.fit=lm(mODS~DS+NS+PAS+ODS,data=Auto)
> summary(lm.fit)

Call:
lm(formula = mODS ~ DS + NS + PAS + ODS, data = Auto)

Residuals:
    Min       1Q   Median       3Q      Max
-7.6056 -2.2384 -0.3902  2.2240  8.1380

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 26.55432   0.85285   31.14 <2e-16 ***
DS            0.62344   0.03208   19.43 <2e-16 ***
NS           -0.88662   0.05258  -16.86 <2e-16 ***
PAS          -1.44506   0.03788  -38.15 <2e-16 ***
ODS           0.98850   0.01540   64.20 <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.041 on 213 degrees of freedom
Multiple R-squared:  0.9677, Adjusted R-squared:  0.9671
F-statistic: 1596 on 4 and 213 DF, p-value: < 2.2e-16
```

Fig. 2: R program demonstrating the mODI score

```
> predict(lm.fit,data.frame(DS=20,NS=15,VAS=7,PAS=5), interval="confidence")
      fit      lwr      upr
1 10.58293 10.37707 10.7888
> predict(lm.fit,data.frame(DS=8,NS=6,VAS=7,PAS=11), interval="confidence")
      fit      lwr      upr
1 9.004565 8.893066 9.116064
> predict(lm.fit,data.frame(DS=8,NS=14,VAS=7,PAS=18), interval="confidence")
      fit      lwr      upr
1 5.613815 5.411487 5.816142
>
```

Fig. 3: Predictive accuracy testing data for mVAS

```
>
> predict(lm.fit,data.frame(DS=20,NS=15,ODS=15,PAS=5), interval="confidence")
      fit      lwr      upr
1 33.32605 32.20832 34.44379
> predict(lm.fit,data.frame(DS=8,NS=6,ODS=15,PAS=11), interval="confidence")
      fit      lwr      upr
1 25.15398 24.50407 25.80388
> predict(lm.fit,data.frame(DS=8,NS=14,ODS=15,PAS=18), interval="confidence")
      fit      lwr      upr
1 7.945648 6.857563 9.033732
> |
```

Fig. 4: Predictive accuracy testing data for mODI



activity limitations. The statistical figures are not much different in rest of the world. Although chronic diseases are among the most common and costly of all health problems, they are also among the most preventable. Chronic disease prevention, to be most effective, must occur in multiple sectors and across individuals' entire lifespan. For this, one needs to implement more comprehensive, outcome-drive, and individual centric-risk predictive machine analytic models that are actively monitored and managed by individuals themselves.

Chronic pain is a multidimensional experience that affects an individual in multiple complex ways and intertwines deeply with their financial, social, emotional interactions with family and community. There are several risk factors for the development of chronic pain. The intensity, location, and number of sites of pain have been attributed to severe chronic pain.¹⁷⁻¹⁹ Some of the other nonmodifiable risk factors include age, sex, socioeconomic, cultural, history of trauma, or abuse and genetics. Awareness of these factors is important in order to aggressively reinforce healthy lifestyle to offset some of the inevitable risk in these individuals.

Other factors, such as depression and anxiety have not only shown to be strong predictors of chronic pain but also are associated with poor prognosis.²⁰ These are preventable as are several others described here. There is evidence in the literature that comorbidities even as unrelated as ischemic heart disease contribute to the development of chronic pain,²¹ thereby reinforcing the importance of integrated care and managing an individual as a "whole." Obesity, in particular, has shown a string correlation as a risk factor for chronic pain. This may be related to lack of physical exercise, presence of comorbidities, and overall poor health status.²² Change in lifestyle with physical exercise specifically aerobic and strengthening exercise training for fibromyalgia²³ and walking have demonstrated a positive effect in patients with lower back pain.²⁴

Healthy diet and exercise have been associated with improved pain. Appropriate nutritional strategy has shown significant impact in preventing and treating metabolic and cardiovascular diseases. Some studies have demonstrated positive effects of omega-3 on morning stiffness and joint pain associated with rheumatoid arthritis or inflammatory bowel disease.²⁵ Some other foods have been studied to be pro-inflammatory and therefore not recommended for chronic pain patients. There is evidence now that reducing polyamine-containing foodstuffs may reduce hyperalgesia,²⁶ intake of alpha-lipoic acid administered intravenously at a dosage of 600mg/day over a period of 3 weeks and vitamin E may decrease pain associated with diabetic neuropathy.²⁷ In addition, there is some preliminary evidence to show

that medically supervised modified fasting, 300 kCal/day for 1 to 3 weeks could be useful to enhance mood in chronic pain patients.²⁸

Given the strong literature support for physical exercise, good nutrition, and mental health, it is necessary that we develop strategies to track risk predisposition of an individual and incorporate healthy behaviors to intervene in their chronic pain course. Our machine-learning program allows us to demonstrate the changes in an individual's risk score with their choice of lifestyle behaviors, which can serve as a very positive educational and reinforcement tool.

Our results are in line with the expected changes in the pain and disability score based on the sliding scale assigned to the three health behaviors. We used simulation of multiple variable parameters in order to keep the approach simple, cost-effective, and time efficient. Having established the plentitude and accuracy of the algorithm, we are now ready to study it in human subjects for clinical validation. This can be somewhat challenging, given the limitations associated with any pain clinical study, such as variations in the intensity and nature of pain, subjective nature of VAS and ODI reporting, and challenges around data documentation and collection.

Some other risk factors, such as socioeconomic status, access to health care, geographical location, social support structure, are also very important in determining predisposition to chronic pain in an individual and are commonly underestimated. From the data set perspective, more detailed analysis with inclusion of these additional risk factors is important in order to make a complete and accurate assessment of the total risk for chronic pain and disability development in an individual. As the subject data becomes more voluminous and more variables get added to the analysis, more comprehensive and advanced machine-learning tools will be necessary to make meaningful analysis and interpretations.

The need for the shift in policy from the treatment of diseases to a preventative approach in addressing the risk determinants of health has been proposed in the past. However, this concept has never been applied to chronic pain. Our effort is the first ever in introducing the concept of machine-learning methods in risk stratification and measurement in chronic pain.

CONCLUSION

Statistical machine-learning programs can be applied for prevention and treatment of chronic pain in a variety of ways. Specific algorithms can be applied to identify at risk population, weightage of individual risk factors, changes in risk scores of developing pain based on health behaviors, analysis of disease outcomes and disease prevention, and health care economics to project costs associated

with pain prevention and treatment. Paradigm shift in the health care model is imperative in order to take on the global challenge of disrupting the current health care model of treatment with prevention using emerging and accelerating technology.

CLINICAL SIGNIFICANCE

The chronic pain machine-learning program is an innovative statistical machine-learning program for chronic pain predictability based on individual's health behavior patterns.

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