Prospect – Senior Design Project Report

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Summary of project:

Prospect was designed as a model solution to determining patients risk of opioid addiction using machine learning. There was no means of making an evaluation of patient risk that didn't use machine learning to gauge weather or not a patient was at risk of addiction. cliexa created proprietary algorithm that determined a patients risk based on the self-reported patient metrics alone using a basic calculation. We were then asked to help develop a model that incorporates machine learning in order to make a more accurate estimation of risk of addiction.

Initially our team used the SOAPP-14 to determine a patients risk but, as we worked more with this metric, we discovered a percentage of error that this metric had for true-positive cases. Our team eventually decided to go with using the proprietary algorithms output as our truth data for our algorithm to learn from. In order to model the problem of 7 dimensions classifying down to one dimension we had to scale the patient metrics to the same weighted ranges. These ranges for some went as high as 70 and as low as 0. Some metrics for the patients were not always filled in and as such had no weight in the final calculation for this machine learning algorithm.

SOAPP® Cutoff Score	Sensitivity	Specificity	Positive Predictive Value	Negative Predictive Value	Positive Likelihood Ratio	Negative Likelihood Ration
Score 7 or above	.91	.69	.71	.90	2.94	.13
Score 8 or above	.86	.73	.75	.86	3.19	.19
Score 9 or above	.77	.80	.77	.80	3.90	.28

Table 1 Effectiveness of the SOAPP® [1]

In terms of Risk of opioid addiction, the *positive predictive value* is expressed as the following ratio:

$$\frac{\text{proportion of all those screened who are addicts and have a positive screening test}}{\text{proportion of all those screened who have a positive screening test.}}$$

[2]

Having more consistency in our patient metrics would have definitely given our algorithm a steadier stream of data to learn on. As it was, the data is collected from patients in intervals and at the patient's discretion. Some of the metrics are not needed for one patient but another patient may need them. To this extent the problem was hard to model and drove a need for a robust algorithm that can pick up outlying trends that still have a significant weight in the overall classification.

The other goal our algorithm needed to accomplish was to classify the patient's collective metrics into a risk assessment. This was the fine-tuning part of the project. The way in which the basic

algorithm classifies data was designed for the user to have some flexibility. It allowed them to make some slight change in their method of evaluating patients and gave them some liberty to tweak the algorithm. This could be based on the client that did not agree with particular assessments or a client who wanted stricter levels.

In the end, after researching a while we decided to implement a deep neural network. We designed the network to accommodate changes in how the basic algorithm was designed and to accommodate changes in how the final classification was made. This allowed the end user to determine the the best version of the proprietary algorithm as the truth data for the neural network as well as fine tuning the algorithm for use case scenarios. To interpret and classify the data efficiently we narrowed the output of the neural network to values between 0 – 2 approximately. This reclassification enabled the network to have more accuracy and less mean squared error.

Accuracy of Neural Network Algorithm:

Prior to final classification our algorithm is performing as designed with an average accuracy of 90%. this accuracy is based on the training size, diversity of the training data, and how well our model matches the data being passed through it.

```
527/527 [==============================] - 0s 374us/sample - loss: 0.0186 - acc: 0.9127
      Id      Phq9      Gad7  Dast10     Audit  Ace       Pdi  Cssrs  Calculated Risk  Predicted Risk
0      1  0.423077  0.714286     0.3  0.033333  0.6  0.642857    0.0                1        1.015510
1      2  0.192308  0.285714     0.1  0.000000  0.5  0.542857    0.0                1        1.002512
2      3  0.653846  0.619048     0.2  0.000000  0.0  0.000000    0.0                1        0.970266
3      4  0.576923  0.285714     0.1  0.000000  0.4  0.000000    0.0                1        0.988852
4      5  0.461538  0.428571     0.0  0.033333  0.2  0.714286    0.0                1        0.963937
..   ...       ...       ...     ...       ...  ...       ...    ...              ...             ...
522  525  0.692308  0.714286     0.1  0.233333  0.0  0.500000    0.0                1        0.987845
523  526  0.384615  0.523810     0.2  0.000000  0.4  0.000000    0.2                1        0.963987
524  527  0.384615  0.523810     0.1  0.000000  0.9  0.000000    0.0                1        0.974703
525  528  0.000000  0.619048     0.2  0.000000  0.0  0.000000    0.0                0        0.057067
526  529  0.576923  0.714286     0.1  0.000000  0.5  0.771429    0.6                2        1.603452

[527 rows x 10 columns]
Mean Squared Error:  [0.018637996119229686, 0.91271347]
Cliexa@Prospect:/opt/Cliexa/prospect/neuralNet$
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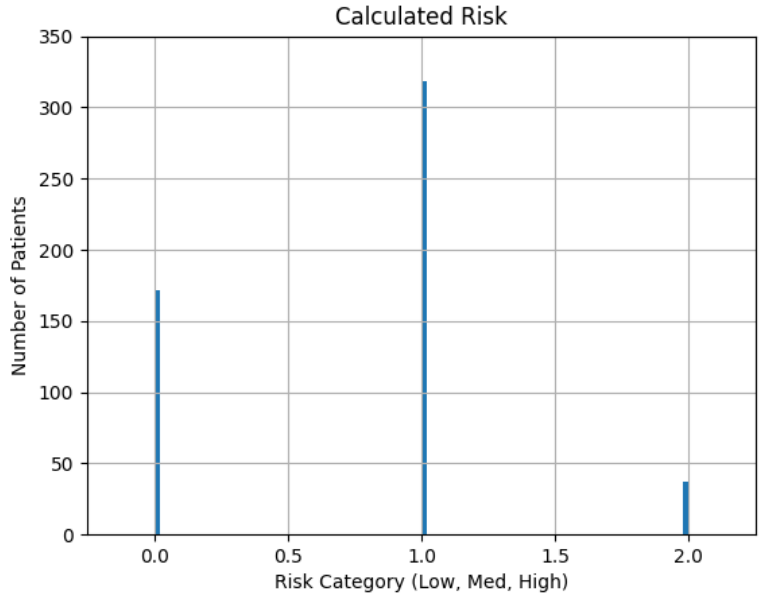
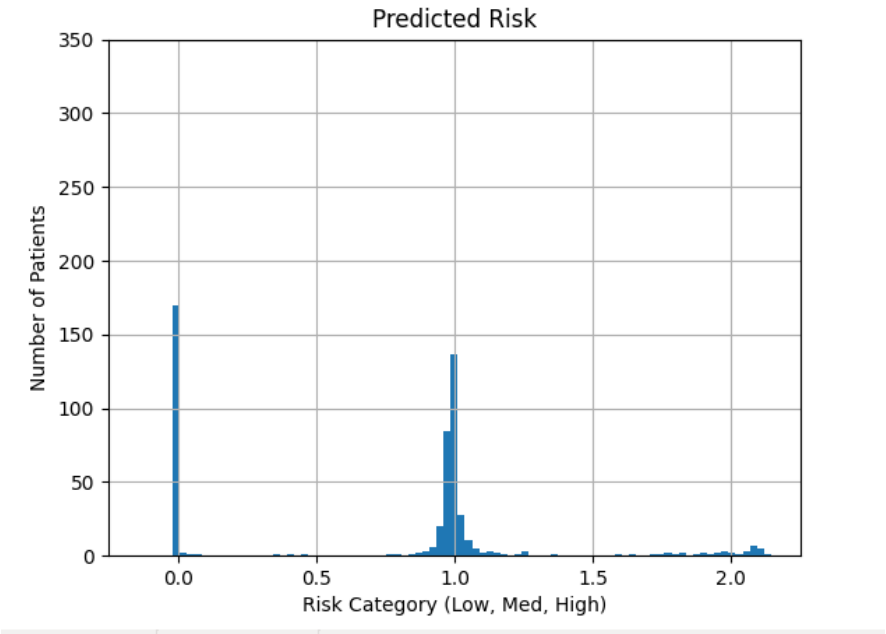


Above we have the calculated risk that is based on the proprietary algorithm. This is the risk assessment that cliexa's algorithm calculated and that our neural network is predicting. Below is our

algorithm's predicted risk. Its output is similar to a clustering algorithms output in that we are classifying and clustering for different groups of risk categories.



We spent a decent amount of time working on figuring out what activation functions to use and what model of a network gave the best accuracy. There was a lot of trial and error involved as well. In the end we went with a RELU activation function and designed our network to have about a three-to-one ratio on the size of each subsequent middle layer. We stayed consistent with this as any activation functions other than the RELU caused degradation in classification and our performance diminished.

This project demonstrated the possibility of using machine learning in medicine as a means of classifying patients. It is important to note that the model that is built will affect the outcomes of the results. Ensuring that there is a diverse set of data when the model is being trained will help the model to identify various patient categories more aptly. In terms of the records being used for the model, we were given some data that was patient data that had been cleaned so as to not be traceable to current patients.

<u>Metrics used in network:</u>

1. PHQ-9: Quality of Life
   9 Question form with scoring ranges from 1-27 with depression levels.
2. GAD-7: General Anxiety Disorder
   7 Question form with scoring ranges from 1-21 with anxiety levels.
3. DAST-10: Drug Abuse Screening Test
   10 Question form with scoring ranges from 1-10 with drug abuse levels.
4. AUDIT: Alcohol Use Disorders Identification Test
   10 Question form with scoring ranges from 1-40 with alcohol abuse levels.
5. PDI: Pain Disability Index
   10 Question form with scoring ranges from 1-70 to determine a patient's experience of pain.
6. C-SSRS: Columbia-Suicide Severity Rating Scale
   7 Question form to detect suicidal ideation and behaviors with 1-25 scoring.

7. ACE: Adverse Childhood Events
   10 Question form with scoring ranges from 1-10 determining patient's adverse childhood events.

Metric proposed for truth data

SOAPP-14: Screener and Opioid Assessment for Patients with Pain
A tool used by clinicians to determine how much monitoring a patient being prescribed opioids will need. It is a questionnaire of 14 questions with a total score range of 1-56 (7 and above indicating that someone is most likely an opioid addict).

Works Cited

[1] Anon. New Hampshire Medical Society. Retrieved October 12, 2019 from [1] Anon. New Hampshire Medical Society. Retrieved October 12, 2019 from https://www.nhms.org/sites/default/files/Pdfs/SOAPP-14.pdf

[2] Anon. Newcastle University School of Mathematics, Statistics and Physics. Retrieved October 12, 2019 from http://www.mas.ncl.ac.uk/~njnsm/medfac/MBBS/handout.pdf