

Deep learning analysis of NIS database on Anterior Cervical Discectomy and Fusion comorbidity complications

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INTRODUCTION: An increasingly more common treatment for cervical degenerative diseases is Anterior cervical discectomy and fusion (ACDF). This treatment has an almost 8-fold increase in usage among all patients with a cervical degenerative disease – increasing to 28-fold in patients above 65 years old. This popularity may be attributed to the fact that studies have shown that ACDF results in good clinical outcomes and fusion rates and is a cost-effective procedure. However, this popularity and these studies have resulted in ACDF being performed on older and sicker patients. As popularity of ACDF as a surgical technique increases, more patients are exposed to intraoperative and postoperative complications after ACDF which are associated with worse outcomes as well as an increased burden on the healthcare system. Deep learning algorithms are powerful tools that can be used to analyze large sets of data and uncover patterns that may be difficult to uncover through traditional means. Traditional statistical analyses are limited in number of factors that can be simultaneously analyzed. To overcome this, a deep learning algorithm can be used to elucidate relationships that may be more complex. Using this to understand complication rates for ACDF may help uncover trends and details that may not be obvious.

METHODS: The National (Nationwide) Inpatient Sample from 2017 was used as the dataset to train the deep learning neural network model on. This dataset was filtered to include all patients that were surgically treated with ACDF using ICD-10 code 0RG20A0 for Fusion of 2 or more Cervical Vertebral Joints with Interbody Fusion Device, Anterior Approach, Anterior Column, Open Approach resulting in 5723 patients with 2829 (48.2%) female and 3039 (51.8%) male. The deep learning model was constructed using IBM SPSS Program (Armonk, NY) Multilayer Perceptron function with multiple hidden layers and a hyperbolic tangent. The input factors include: Elective versus non-elective admission, indicator of sex, race (uniform), median household income national quartile for patient ZIP code, all comorbidities, age, number of diagnoses, number of procedures and length of stay. The output factors include: Refined DRG: Risk of Mortality Subclass and Severity of Illness Subclass which are categorized 1 through 4. For severity of illness, 1 is minor loss of function, 2 is moderate loss of function, 3 is major loss of function, and 4 is extreme loss of function. For risk of mortality, 1 is minor likelihood of dying, 2 is moderate likelihood of dying, 3 is major likelihood of dying, 4 is extreme likelihood of dying. The model was trained and tested using a standard split of 70% data for training and 30% of the data for testing – specifically 3824 (70.4%) of samples were used for training and was tested on 1610 (29.6%) of samples. Using these variables from the NIS database, the deep learning model will output how important each input variable is for calculating the output relative to each other with the most important variable being 100%. The ROC curve shows the rate in which the neural network will correctly identify a piece of data for the dataset. An ROC of 0.5 indicates that the model cannot discriminate the data with any reliability, 0.7 to 0.8 is considered acceptable, 0.8 to 0.9 is considered excellent, and anything above is considered exceptional. Length of Stay was used as a validation measure to ensure that the model works as this is a well-established retrospective measure that is correlated to complication rate.

RESULTS SECTION: To validate the model, the ROC for the output variable: "all patient Refined DRG: Severity of Illness Subclass" was determined to be 0.846, 0.792, 0.876, 0.806 for classification 1, 2, 3, 4 respectively (Figure 1). For the output variable: "all patient Refined DRG: Risk of Mortality Subclass" was determined to be 0.812, 0.724, 0.836, 0.936 for classification 1, 2, 3, 4 respectively (Figure 2). All variables above 10% independent variable importance are shown in Figure 3. The most important variable was the length of stay (100%), followed by number of diagnoses (82.3%), age in years at admission (43.6%), congestive heart failure (31.3%), diabetes with chronic complications (30.5%), number of procedures (25.9%), race (21.8%), renal failure (20.8%), valvular disease (14.3%), obesity (14.1%), drug abuse (12.3%), fluid and electrolyte disorders (11.7%), paralysis (11.6%), coagulopathy (10.7%), liver disease (10.6%), alcohol abuse (10.6%), and pulmonary circulation disease (10.1%) (Figure 3).

DISCUSSION: The output for DRG: Severity of Illness is excellent except for all classification 2 which is just under the cutoff for being acceptable. The DRG: Risk of mortality model is extremely good at classifying patients as a 4, is excellent at classifying patients as 1 and 3, and acceptable at classifying patients as 1 and 2. Based on these classifications, the factors that have the highest contribution to predicting if a patient has a high risk of mortality or if they will have a high severity of illness are described in the results below. Length of stay has the largest contribution which may be expected since it is well-characterized that illnesses with increased severity, mortality rates, and complication rates are all correlated with longer lengths of stay. Other factors include the number of procedures performed and age of the patient, which is also an expected outcome. However, the other results highlight an interesting relationship where certain comorbidities have a significantly greater substantial effect on outcomes for patients than others. Congestive heart failure and diabetes have twice the impact on mortality and severity of illness as other comorbidities. Limitations of this study are its retrospective nature as well as the limited data set. While this deep learning neural network was learned from the NIS database in 2017, more data could have been compiled to give the model more training data.

SIGNIFICANCE/CLINICAL RELEVANCE: (1-2 sentences): Awareness of the correlation between an individual’s demographics and comorbidities can help influence perioperative and intraoperative management and risk assessment for certain patients. Understanding an individual’s risk for ACDF is important to consider when determining if the risk of operation outweighs the potential benefit especially in complex situations where patients may have multiple comorbidities in which surgery does not improve quality of life.

IMAGES AND TABLES:

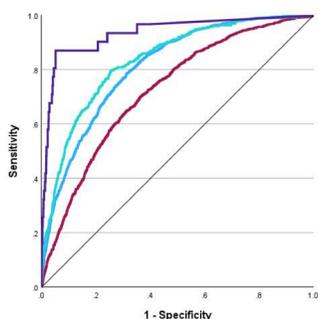


Figure 1. ROC curve for the dependent variable: "all patient Refined DRG: Severity of Illness Subclass" which are categorized 1 through 4. For severity of illness, 1 is minor loss of function, 2 is moderate loss of function, 3 is major loss of function, and 4 is extreme loss of function.

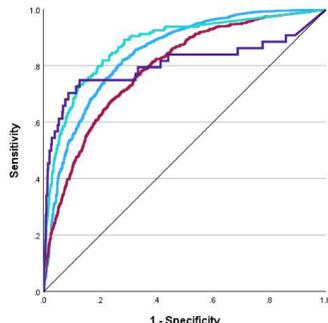


Figure 2. ROC curve for the dependent variable: "all patient Refined DRG: Risk of Mortality Subclass" which are categorized 1 through 4. For risk of mortality, 1 is minor likelihood of dying, 2 is moderate likelihood of dying, 3 is major likelihood of dying, 4 is extreme likelihood of dying.

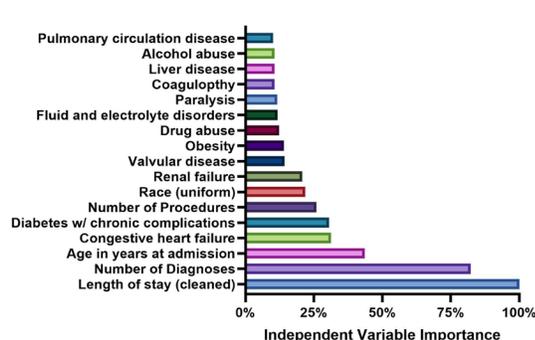


Figure 3. Independent variable importance output by the deep learning neural network normalized such that the variable of highest importance = 100%. Variables under 10% of independent importance were not included.