

**Msc - Data Science and Advanced Analytics  
2024/25**

**Machine Learning Final Project**

**To Grant or Not to Grant**

**GitHub Public Repository**

https://github.com/Antramos/To-Grant-or-not\_ML

**Group 45**

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# Introduction

Handling workplace injury claims is a critical and complex task for organizations and regulatory bodies. In New York, the Workers’ Compensation Board (WCB) manages these claims, ensuring proper categorization and fair compensation. With over 5 million claims reviewed since 2000, the manual nature of this process demands significant time and resources, creating opportunities for automation.

This project seeks to develop a machine learning solution capable of classifying injury types associated with claims submitted to the WCB. Using a dataset spanning claims from 2020 to 2022, the primary objective is to create and benchmark multiclass classification models that predict WCB decisions with precision. Furthermore, the project will investigate model optimization strategies and assess feature significance, providing deeper insights into the data and its impact on prediction accuracy. The ultimate aim is to design a predictive tool that improves the efficiency and reliability of WCB’s claim evaluation process.

The initiative draws inspiration from successful applications of machine learning in insurance and healthcare, where automated models have demonstrated their ability to streamline operations. By leveraging these technologies, this project aspires to reduce the manual burden on the WCB while improving the consistency and fairness of its decision-making processes.

Besides our work, its results, with trials and our better predictions, will be in a Kaggle competition.

**Similar Works or Applications**

Many insurance companies use machine learning to classify and process claims. For example, models are trained to categorize claims based on severity or type (e.g.), accidents, thefts, or injuries). A notable example is the use of Natural Language Processing (NLP) to analyze claims documentation and predict outcomes.

* + A study by Verma et al. (2020) developed a machine learning framework to automate claims categorization, achieving high accuracy with Random Forest models.
  + Research by Xu et al. (2018) explored injury severity prediction using Support Vector Machines (SVM) and ensemble methods, leveraging structured medical datasets.
  + A project by Kube et al. (2021) used machine learning models to analyze occupational injury data and identify factors influencing claim outcomes. Their models also highlighted feature importance to guide policy-making.
  + Zhang et al. (2019) employed deep learning techniques to classify claims, demonstrating that hybrid approaches combining feature engineering and deep models outperform traditional methods.

# Exploration and Data Preprocessing

## Artefacts

As the basis for this work, we have two datasets: ***train\_df*** & ***test\_df*** (csv files). The 1st, which contains supervised values for the target feature, will serve as the training and testing artifact for the applied models. The 2nd dataset, which lacks the target feature (“Claim Injury Type”), also exhibits some structural differences in its features, which must be evaluated and adapted to ensure the success of the project.

The ***train\_df*** dataset structure may be seen in the References

## Imbalanced target (“*Claim Injury Type*”)

The first thing to notice is the significant imbalance among the possible outcomes for the target feature in the working dataset, as demonstrated below:

A graph of injury type

Description automatically generated

Regarding the work itself, this characteristic implies that the underrepresented classes have fewer data points, and accuracy is not the ideal metric for evaluating the model.

## Duplicates & datasets alignment

* 18350 “*Claim Identifier*” duplicates in ***train\_df*** will be dropped
* The features “Agreement Reached” & “WCB Decision” are not in the ***test\_df*** dataset and will be dropped from ***train\_df***.

## Anomalies & Missed Values

* 3.27% of the training data has NaN on the target “*Claim Injury Type*” and this lines will be dropped.
* Other anomalies & pre-processing issues will be seen below:

## Data cleaning and preprocessing steps.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Feature** | **Type** | **Missed** | **Anomalies** | **Action(s)** |
| ***Alternative Dispute Resolution*** | Categorical | --- | == “U” | Dropped Encode Binary |
| ***Attorney Representative*** | *Categorical* | *---* | *---* | *Encode binary* |
| ***Carrier Name*** | *Categorical* | *---* | *---* | *Encode multi* |
| ***Carrier Type*** | *Categorical* | *---* | *---* | *Encode binary* |
| ***Claim Injury Type*** | *Target* | *3.27%* | *---* | *NaN lines dropped* |
| ***County of Injury*** | *Categorical* | *---* | *---* | *Encode multi* |
| ***COVID-19 Indicator*** | *Categorical* | *---* | *---* | *Encode binary* |
| ***District Name*** | *Categorical* | *---* | *---* | *Encode multi* |
| ***Gender*** | *Categorical* | *---* | *---* | *Replace(“U”, “X”) » domain: (“M”, “F”, ”X”)*  *MultiEncoder(frequency)* |
| ***Medical Fee Region*** | *Categorical* | *---* | *---* | *Encode multi* |
| ***Industry Code Description*** | *Categorical* | *---* | *Description Feature* | *Dropped* |
| ***OIICS Nature of Injury Description*** | *Categorical* | *---* | *Description Feature* | *Dropped* |
| ***WCIO Cause of Injury Description'*** | *Categorical* | *---* | *Description Feature* | *Dropped* |
| ***WCIO Nature of Injury Description'*** | *Categorical* | *---* | *Description Feature* | *Dropped* |
| ***WCIO Part Of Body Description'*** | *Categorical* | *---* | *Description Feature* | *Dropped* |
| ***Age at Injury*** | *Numerical* | *0.94%* | *---* | Dropped values <16  Filled NAs with the average (because the distribution is simetric)  Handled outliers with zscore |
| ***Average Weekly Wage*** | *Numerical* | *4.99%* | *---* | Handled outliers with zscore  KNNImputer |
| ***Birth Year*** | *Numerical* | *0.38%* | *---* | Dropped values < 1903  Filled NaN with Accident Date Age at Injury  Handled outliers with zscore |
| ***Claim Identifier*** | *Numerical* | *---* | *---* | Handled outliers with zscore |
| ***Industry Code*** | *Numerical* | *1.73%* | *---* | Handled outliers with zscore  KNNImputer |
| ***IME-4 Count*** | *Numerical* | *---* | *---* | Filled NAs with zero  Handled outliers replacing all values > 15 with 15 |
| ***WCIO Cause of Injury Code*** | *Numerical* | *---* | *---* | Filled NAs with 0  Handled outliers with zscore |
| ***WCIO Nature of Injury Code*** | *Numerical* | *---* | *---* | Filled NAs with 0  Handled outliers with zscore |
| ***WCIO Part of Body Code*** | *Numerical* | *---* | *---* | Handled outliers with zscore |
| ***Number of Dependents*** | *Numerical* | *---* | *---* | Filled NAs with 0  Handled outliers with zscore |
| ***Accident Date*** | *Numerical* | *0.64%* | *---* | *Dropped NaN lines* |
| ***Years Past Accident*** | *Numerical* | *0.64%* | *---* | *Gets Accident Date – reference\_date* |

# Multiclass Classification

## Overview of classification objectives and metrics.

**Refere-se ao propósito principal do modelo de classificação, ou seja, categorizar corretamente os dados em classes predefinidas, e às métricas usadas para avaliar seu desempenho. As métricas comuns incluem acurácia, precisão, recall e F1-score, que ajudam a medir o quão bem o modelo está prevendo cada classe, especialmente em casos de dados desbalanceados.**

## Feature selection strategy.

Explicar aqui o método utilizado para feature selection, notoriamente

# Open-Ended Section

**Refere-se a uma parte do projeto em que os participantes têm liberdade para explorar e desenvolver análises adicionais, além dos objetivos principais definidos. Nesta seção, podem ser aplicadas técnicas ou abordagens criativas, como análises exploratórias mais profundas, testes de modelos alternativos, criação de interfaces preditivas ou investigações sobre a importância das variáveis. O objetivo é agregar valor ao trabalho, demonstrando insights adicionais e habilidades de inovação na resolução do problema.**

## Defined objectives and additional analyses.

## Explanation of approaches (e.g., feature importance analysis, alternate prediction tasks).

## Presentation and discussion of findings.

# Results andDiscussion

## Comparison of performance across models.

* ML Algorithms best results for *“Claim Injury type”* predictions

**Interpretem abaixo, por gentileza, o resultado do algoritmo que foi explorado por cada uma.**

|  |  |  |
| --- | --- | --- |
| **Algorithm** | **Hiper Parameters** | **Overall Results** |
| Logistic Regression | {'C': 100, 'penalty': 'l2', 'solver': 'lbfgs'} | A screenshot of a computer screen  Description automatically generated |
| XGBoost |  |  |
| Random Forest |  |  |
| MLP |  |  |

## Kaggle Choice and Results

**Colocar aqui o melhor resultado no Kaggle e explicar o porquê de ter sido escolhido (notoriamente por ser o melhor score entre todos).**

## Alignment with initial objectives and expectations.

**Blá, blá, blá para falar se os objetivos foram atingidos.**

# Conclusion

This project set out to address the challenge of automating injury classification for workers' compensation claims using machine learning techniques. By leveraging historical data from the New York Workers’ Compensation Board (WCB), we developed and optimized multiclass classification models to predict claim injury types, offering a solution that can potentially streamline and enhance the decision-making process.

The results demonstrate the feasibility of employing machine learning to achieve accurate predictions, with optimized models significantly improving over initial baselines. The exploration of feature importance provided valuable insights into the key factors influencing injury classifications, while additional analyses, such as alternative prediction tasks, further highlighted the flexibility and robustness of the proposed methodologies. However, the project also revealed limitations, such as the dependency on the quality of input data and the challenge of model generalization to unseen claims.

Looking forward, several avenues for future work can be pursued. Incorporating more advanced modeling techniques, such as ensemble learning or neural networks, could further improve prediction accuracy. Additionally, integrating external data sources, such as real-time industry trends or macroeconomic indicators, may enhance the model's contextual understanding. Finally, developing a user-friendly analytics interface could make these models more accessible to the WCB, enabling seamless integration into their operational workflows.

*“WCB Decision”* feature (“Accident” ou “Occupational Disease”), atualmente a espera de deliberação da WCB e desconhecido no início da claim, não foi desenvolvido neste trabalho, mas merece um estudo similar ao de *“Claim Injury Type”* sobre a possibilidade de ser predicted automaticamente.

In conclusion, this project not only validates the potential of machine learning in automating claims classification but also sets the foundation for broader applications in regulatory and insurance contexts. By continuing to refine and expand upon these efforts, the WCB could achieve greater efficiency, transparency, and accuracy in its operations.

# References

* + List of all referenced materials (peer-reviewed articles, datasets, etc.).

Pls put here the train\_df e test\_df initial and final structures (train\_df.info())

# Annexes (if needed)

* + Additional figures, tables, or analyses that support the report but are not critical to the main narrative.