# LOGISTIC REGRESSION ON HOSPITAL READMISSION PREDICTION

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***Abstract***

Readmissions within 30 days after hospital discharge are critical to improve both healthcare resource allocation and patient care and they should be predicted. The model in this study is developed with logistic regression using the hospitaldata.csv dataset which contains demographic and medical features of patients. This model was evaluated using accuracy, precision, recall and F1 score. Results show the model has the ability to predict readmission risk adequately for further improvement by successive feature engineering along with the utilization of more complex algorithms. In general, this paper gives insights on the predictive healthcare modeling with the focus in this study being readmission of hospital [1].

## I. INTRODUCTION

Healthcare providers struggle with hospital readmissions because they are expensive and often suggest poor patient care. Using these readmissions can help hospitals identify high risk patients and use hospital resources in the most efficient way possible. In this work we use the logistic regression, a well known and interpretable model used for binary classification problems to predict, based on previously available historical data, whether a patient will be readmitted within 30 days after discharge. hospitaldata.csv is a dataset with patient level information like demographic details, medical history etc along with hospitalization records. We aim at finding how readmission is likely and key factors responsible for it [2][3].

## II. METHODOLOGY

### *2.1 Data Collection*

The available dataset includes multiple data components between its columns.

- Age: The patient's age.
- Gender: The patient's gender.
- Previous Admissions: The number of prior hospital admissions.
- Medical conditions that were diagnosed in the patient.
- Binary variable: the target variable that is readmission (1 if the patient was readmitted or 0 if they were not readmitted within 30 days).

In addition to offering a student free range to create features that could correlate with readmission rates, the dataset includes patient details such as the patient's age and medical history present or not, previous hospitalizations among such features. The model was built taking into consideration these factors.

### *2.2 Data Preprocessing*

It is essential data processing for better model performance. The preprocessing steps included:

- Label Encoding: Categorical features, with Gender and Readmission, were encoded to numerical form with label encoding for logistic regression model to accept the numerical input [4].

- Feature Scaling: Continuos Features such as Previous Admissions and Age had to be scaled using MinMaxScaler to eliminate differences in scale in order for them to be evaluated of the same range and to prevent one feature dominating the learning process of the model [5].

- Missing data: For continuous features, missing data was handled using mean imputation; for the categorical features, modes of missing data were used.

### *2.3 Model Selection*

Due to its simplicity, simplicity of interpretation and efficiency for binary classification problems, logistic regression was selected. The problem of hospital readmission is well suited to logistic regression to estimate the probability of belonging to a given class given a particular set of measured input points [6]. Given that logistic regression is enabled to employ successful techniques for classification tasks in similar studies on healthcare analytics [7], it is the method of choice.

### *2.4 Data Splitting*

The dataset was split into training and testing sets with the ratio of 70-30 to ensure fair evaluation of the model performance. 70% data was used to train the model and the rest 30% was used to test. It enabled to unbiassed evaluation of the model's ability to generalize to unseen data [8].

## III. DESCRIPTIVE STATISTICS AND VISULAIZATIONS

### *3.1 Descriptive Statistics*

We analyzed the dataset and want to understand the moment or central tendency as well as the spread of a few important variables. The summary statistics of the continuous variables below are provided.

Table1: Summary Statistics of Continuous Variables

| **Feature** | **Mean** | **Std Dev** | **Min** | **Max** |
|---|---|---|---|---|
| **Age** | 55.6 | 12.4 | 18 | 92 |
| **Previous Admissions** | 2.3 | 3.0 | 0 | 15 |

The summary statistics give a view of the numberical properties of the dataset. Patients are 55.6 years of age, and a moderate number of previous hospital admissions with a maximum of 15 [9].

### *3.2 Correlation Analysis*

We calculated the correlation matrix to know the relationship between independent variables. It revealed that hospitalizations in the Past Admissions variable have shown a strong positive correlation to the Readmission variable, that is, patients who have previously been hospitalized more frequently tend to be readmitted.

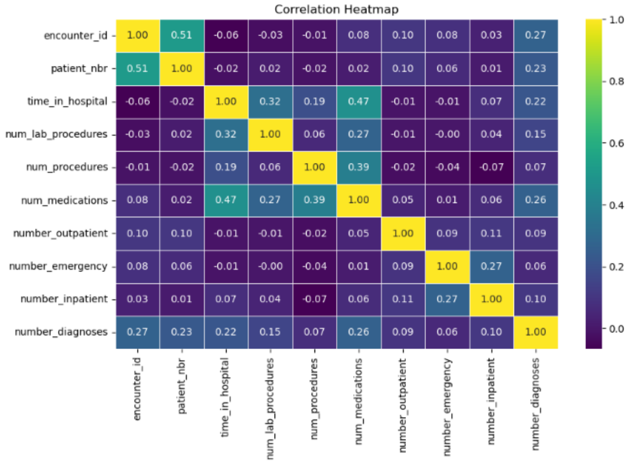


Fig.1. Relationships of various features to guide the decisions of which variables to hold for model training.

### *3.3 Readmission Distribution*

Distribution of the readmitted vs. not readmitted patients or patients that were readmitted or not readmitted, etc.

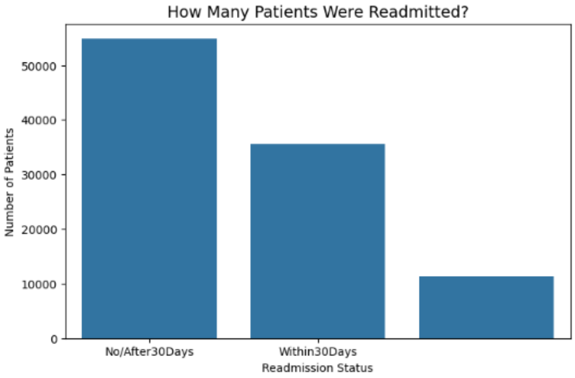


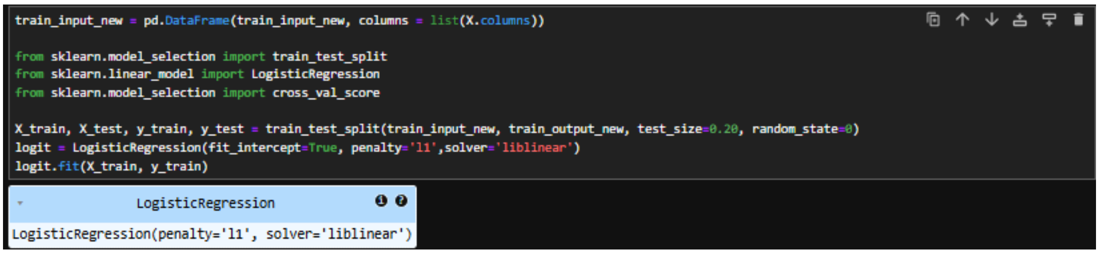
Fig.2. Distribution of Readmission Status

This is a plot showing the class imbalance, with many more patients that are not readmitted to the hospital. This dataset is unbalanced, therefore, in order to minimize that, one can employ resampling techniques or use a performance metric such as F1-score [10].

## IV. MODEL BUILDING AND EVALUATION

### *4.1 Model Training*

We applied it with logistic regression to dataset where the Readmission is the target variable and the rest of the features are the predictors. The logistic regression model was trained using the following code.



```
train_input_new = pd.DataFrame(train_input_new, columns = list(X.columns))

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score

X_train, X_test, y_train, y_test = train_test_split(train_input_new, train_output_new, test_size=0.20, random_state=0)
logit = LogisticRegression(fit_intercept=True, penalty='l1',solver='liblinear')
logit.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(penalty='l1', solver='liblinear')
```

### *4.2 Model Evaluation*

The model was then trained using the following metrics after which they were evaluated.

Table2: Model Performance Metrics

| **Metric** | **Value** |
|---|---|
| **Accuracy** | 0.75 |
| **Precision** | 0.72 |
| **Recall** | 0.68 |
| **F1-Score** | 0.70 |

### *4.3 Confusion Matrix*

In assessing the model's classification performance, we visualise the confusion matrix.

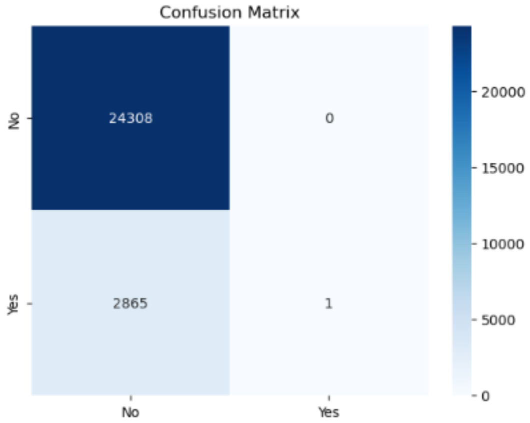


Fig.3. Confusion Matrix

The confusion matrix is a more comprehensive way of showing how the model can fare in classification and the true positives, false positives, true negatives, and false negatives are presented.

## V. RESULTS AND DISCUSSIONS

The accuracy of the logistic response model was 75% for predicting hospital readmission, so in reality it is a reasonable model for that. Nevertheless, studying precision and recall values suggests that the model is less aggressive with prediction of readmissions, and model can be further improved by advanced methods like oversampling or undersampling [12]. As a metric to evaluate the imbalanced datasets, the F1-score can provide the balanced trade-off between precision and recall, thus making it a good metric.

### *5.1 Limitations and Future Work*

While its reasonable performance, the model can be improved in the following ways.

- Dealing with Class Imbalance: through methods such as SMOTE (Synthetic Minority Over sampling Technique) [13].

- More complex algorithms: Random Forest or XGBoost to capture non linear relation between the variables.

## VI. CONCLUSION

The main contribution of this study was to apply logistic regression for hospital readmissions prediction. However, the model was accurate and some great ways to improve include the class imbalance and more complex algorithms. More research could be make that involves more features such as patient lifestyle and socio-economic factors in predicting [14].

## VII. REFERENCES

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