AGENDA

1 <u>Introduction</u>

<u>Methodology</u>

<u>Exploratory Analysis</u>

<u> Preprocessing</u>

<u> Modelling</u>

6 Results

INTRODUCTION

Adult Census Dataset

The Adult census data is a dataset containing information on individuals in the United States, including their demographic and socio-economic characteristics, and whether their income is above or below \$50,000 per year.

Problem Statement

Can we predict an individual's income based on their characteristics?

Objectives

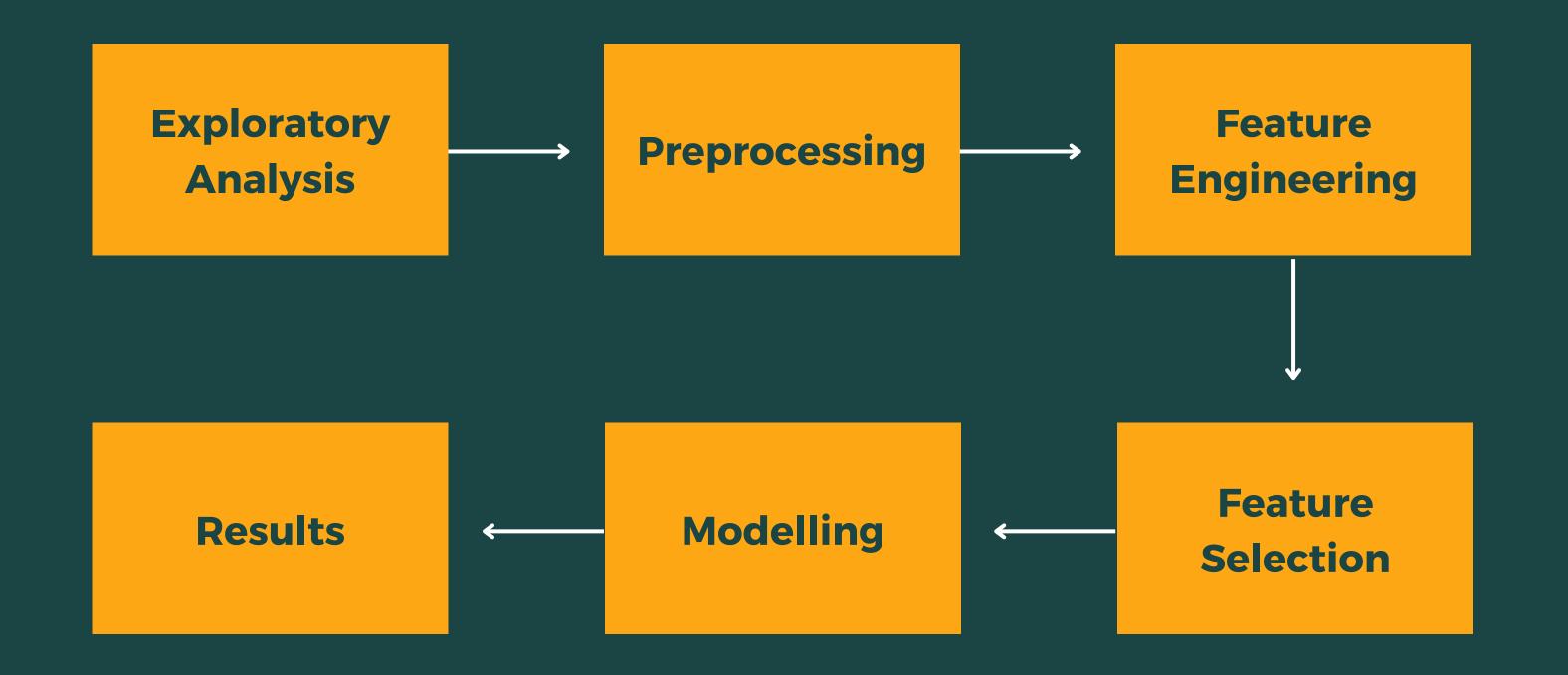
It is significant because it can help researchers better understand the factors that contribute to income inequality in Society.

Solution

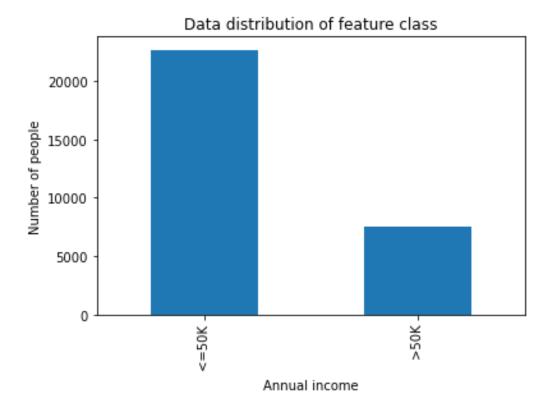
Demonstrate an effective methodology for predicting income from the Adult census data and provide insights into contributing factors.



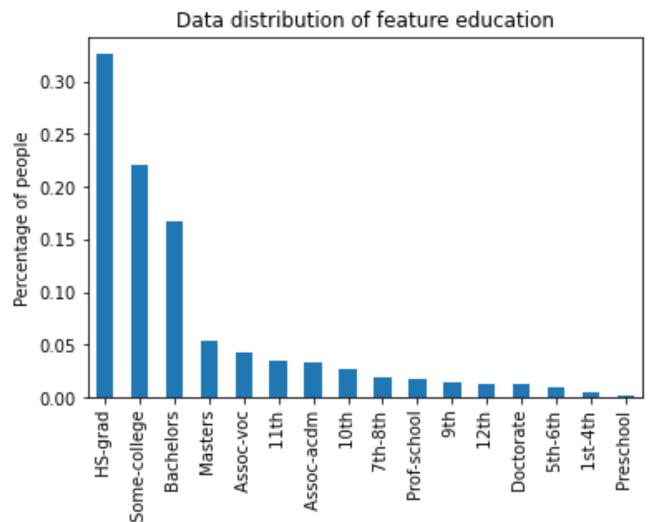
METHODOLOGY

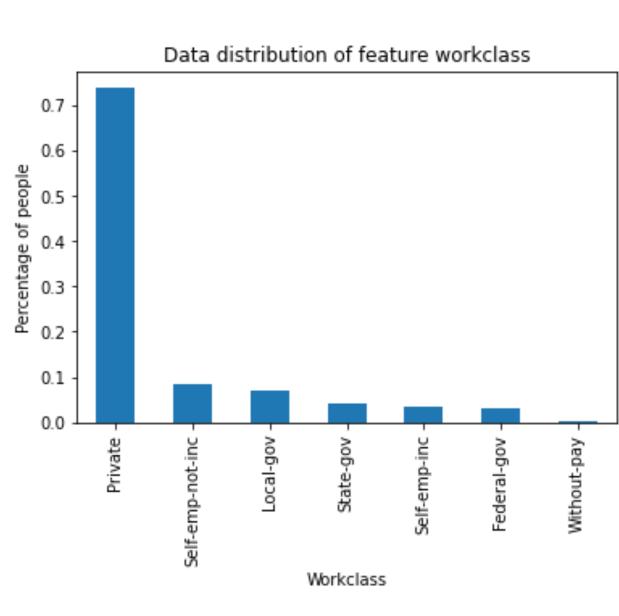


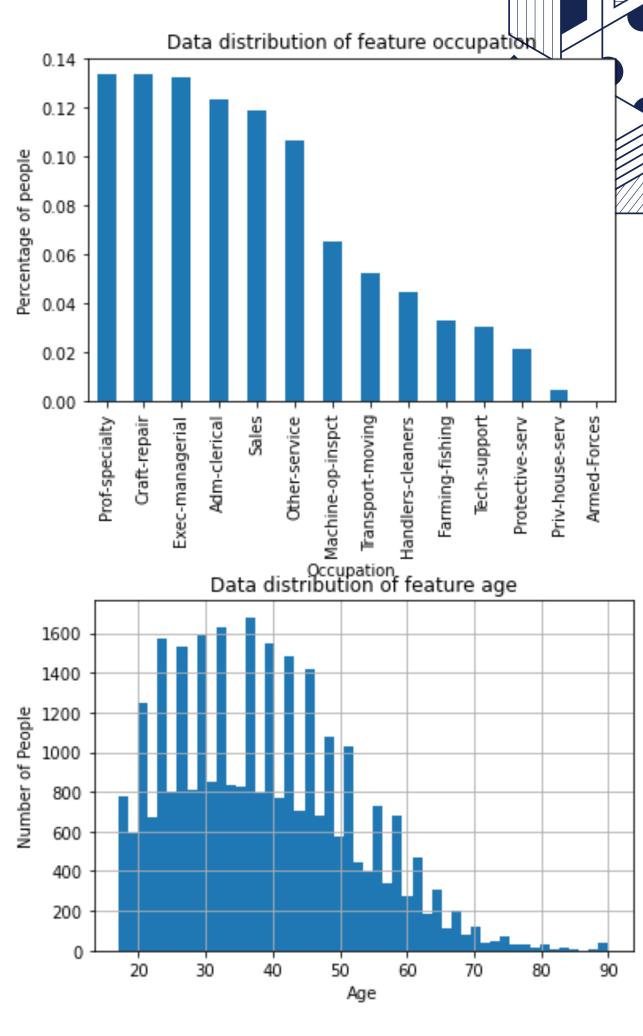
EXPLORATORY ANALYSIS



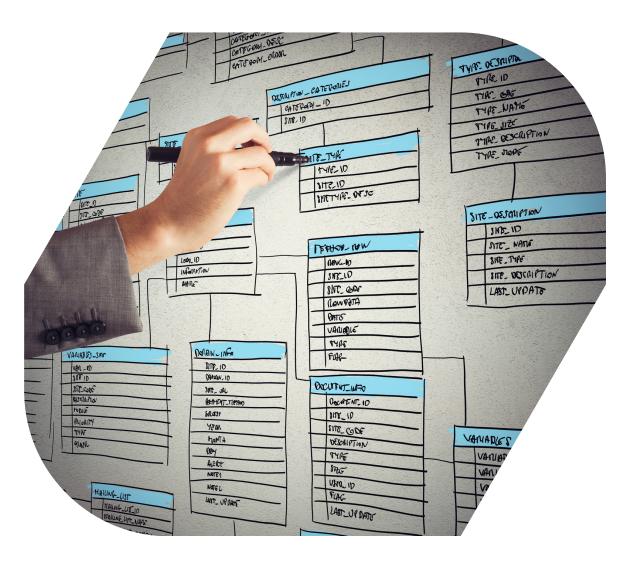
IMBALANCED CLASSES IN ADULT CENSUS DATA







PREPROCESSING



Handling Missing Values

Categorical Variables

Feature Engineering

Feature Selection

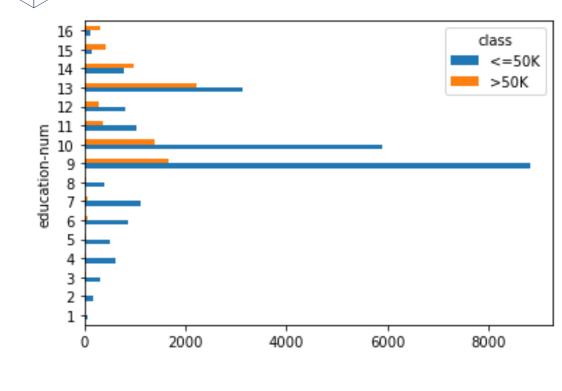
The Adult census data contains missing values, which need to be handled before the data can be analyzed. Rows with missing data were dropped and some redundant columns were dropped.

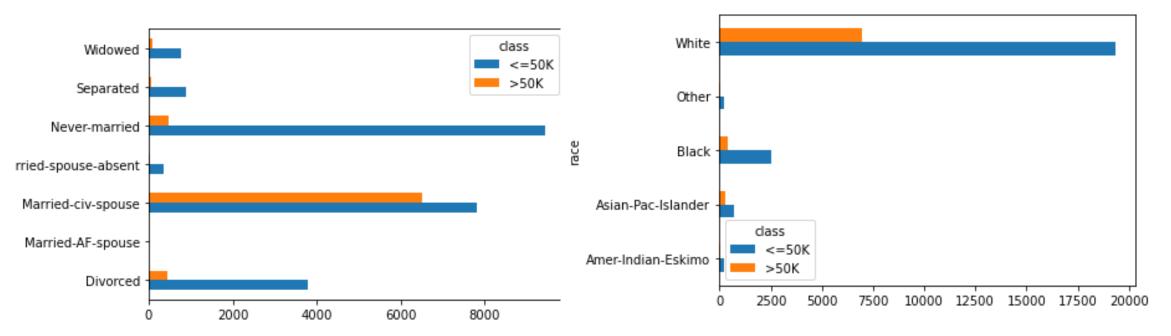
The Adult census data contains several categorical variables, such as race and occupation, that need to be converted into numerical variables before they can be used in predictive models. This can be done using techniques such as one-hot encoding or label encoding.

We modified some features in the data to reduce complexity and make more balanced

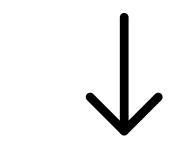
Some Algorithms such as Random Forest, Chi-square Feature Selection were done to select the most important features for the model.

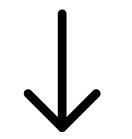
FEATURE ENGINEERING

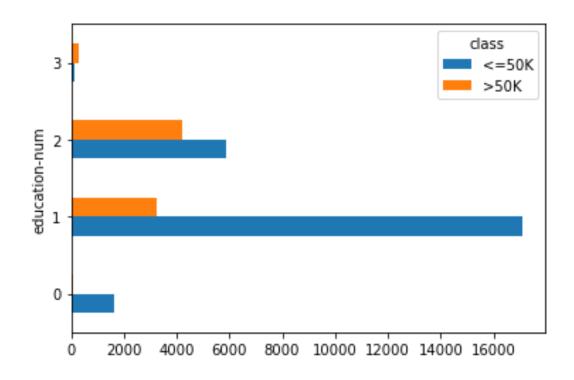


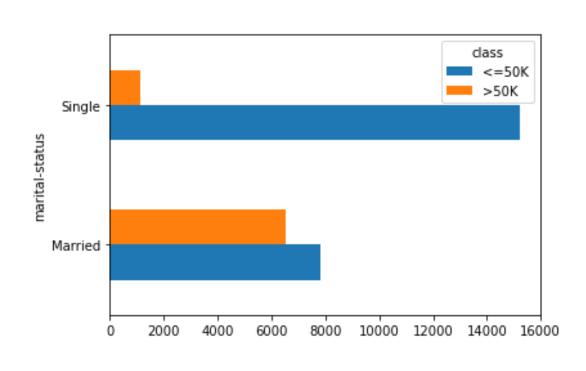


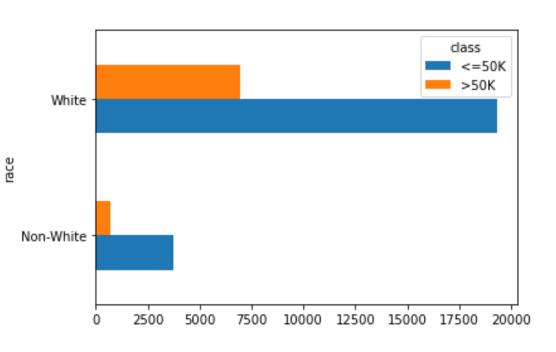






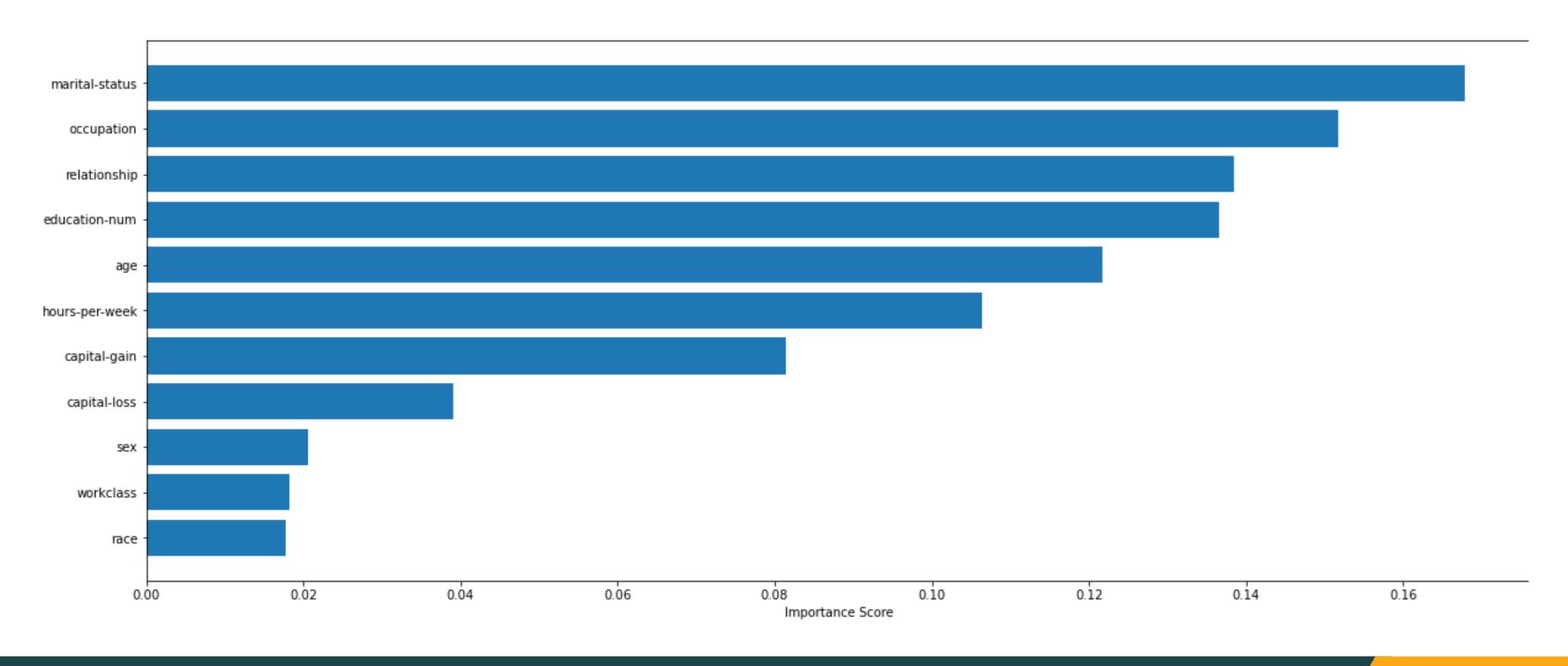






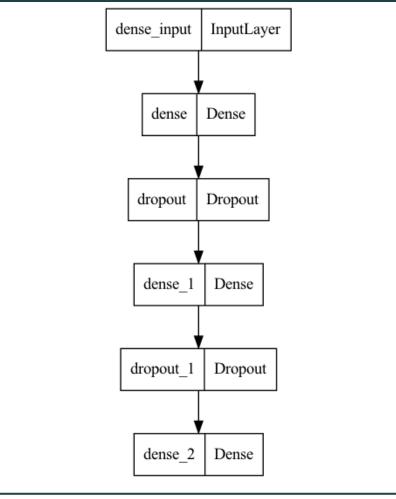
FEATURE SELECTION

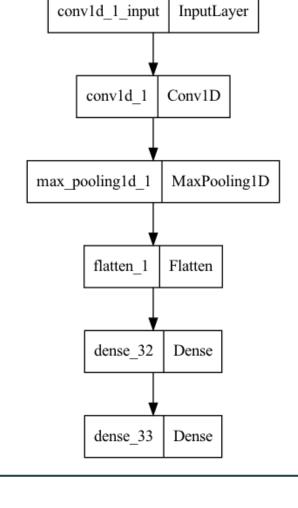
Based on the Random Forest feature importance tests, 3 common features with the least importance are sex, race, and work class.



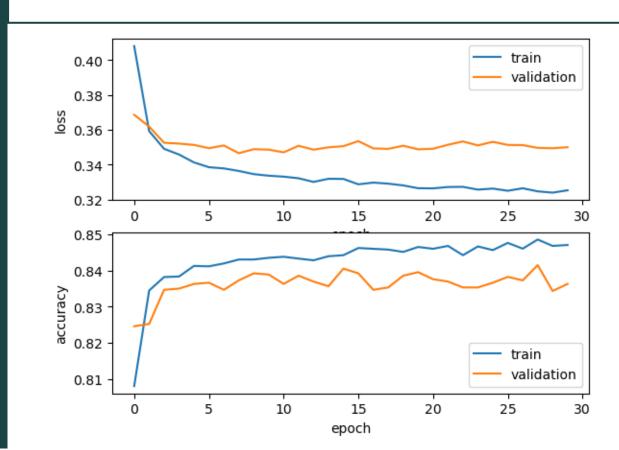
MODELLING

- Various neural network models were explored. DNN and CNN were the most common architectures.
- Model performance was evaluated using accuracy, roc-auc score, precision, recall, and F1 score.
- Models were optimized through hyperparameter tuning and feature selection.
- Models were trained using GPUs on Google Colab and Kaggle to utilize parallelisation.

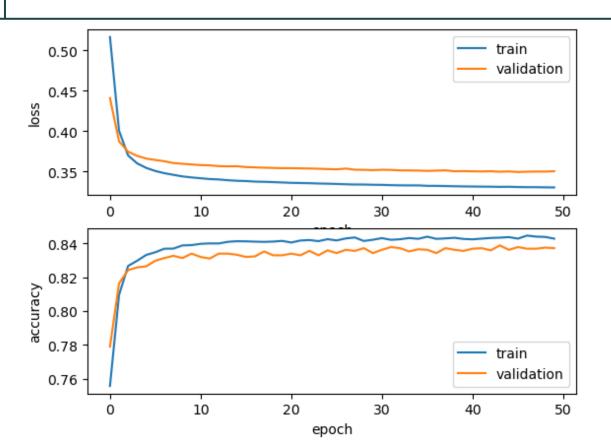




Dense Neural Network Architecture



Convolution Neural Network Architecture



RESULTS FOR IMBALANCED TRAINING SET

Default Threshold (0.5)

Best Threshold = 0.212586

Accuracy Score: 0.85

Precision: 0.71

Recall: 0.59

F1: 0.64

AUC: 0.75

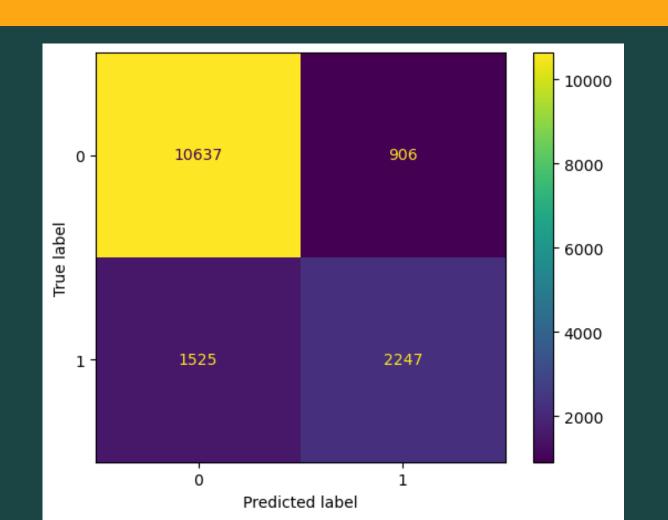
Accuracy Score: 0.78

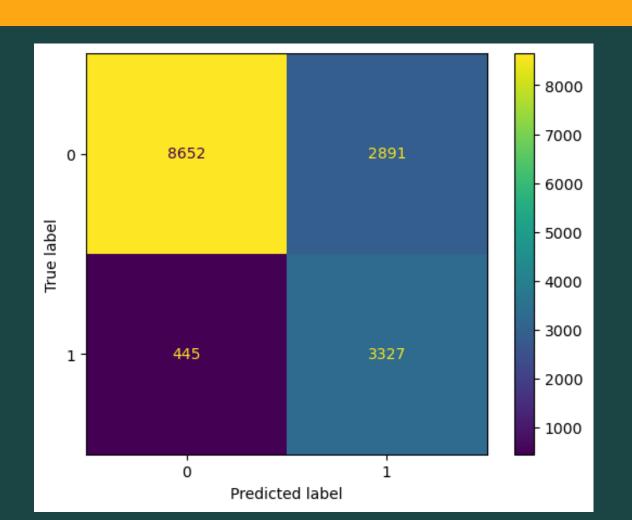
Precision: 0.53

Recall: 0.88

F1: 0.66

AUC: 0.81





RESULTS FOR OVERSAMPLED TRAINING SET

Default Threshold (0.5)

Best Threshold = 0.405082

Accuracy Score: 0.82

Precision: 0.61

Recall: 0.75

F1: 0.68

AUC: 0.80

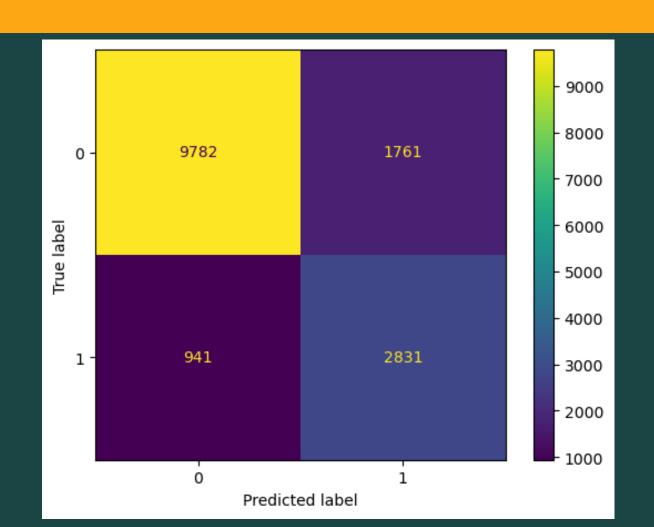


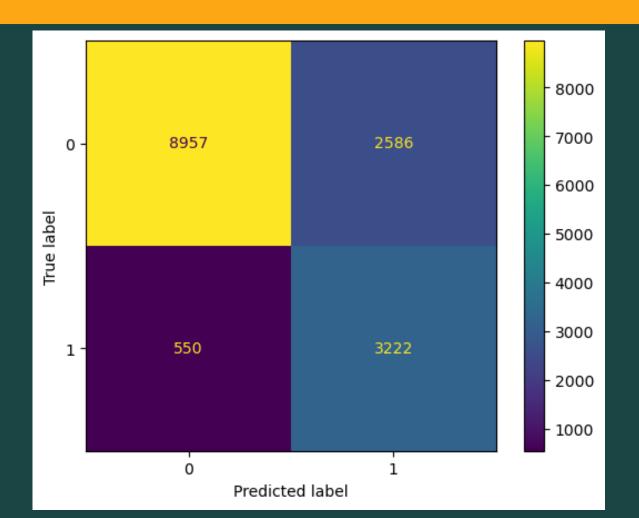
Precision: 0.55

Recall: 0.85

F1: 0.67

AUC: 0.82





CONCLUSION

Main Problem

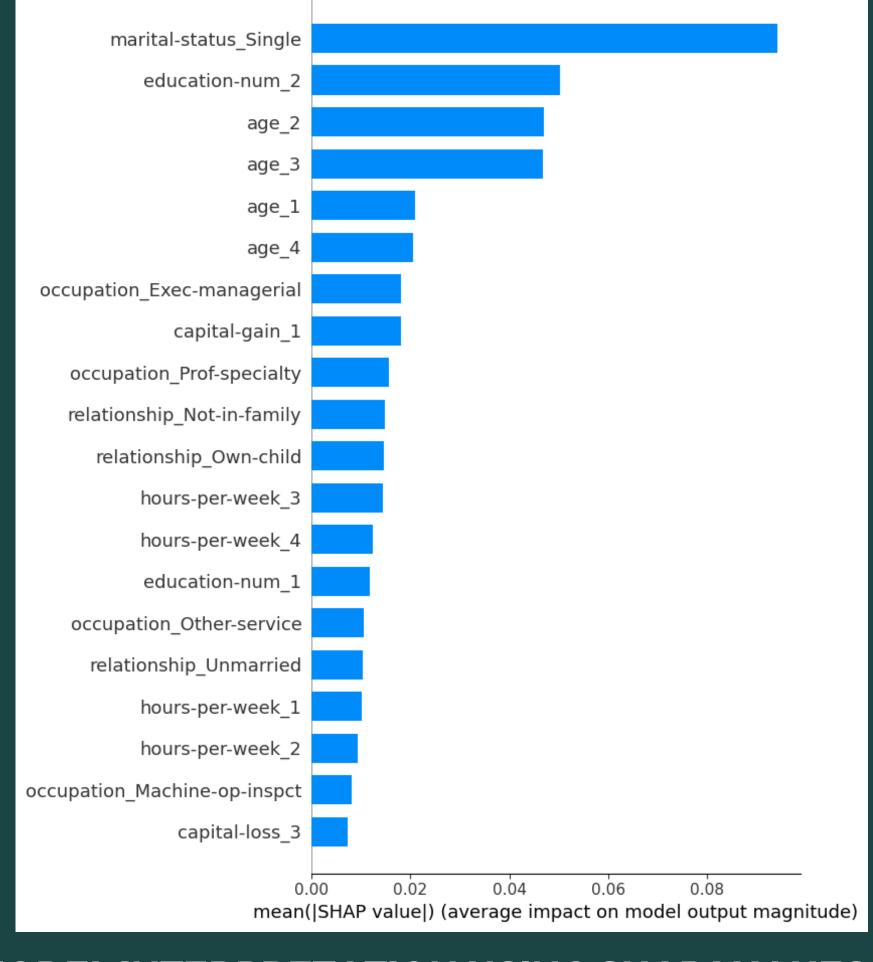
Can we predict an individual's income based on their characteristics?

Why is it important?

The factors that contribute to it can help us design policies to address income inequality.

Conclusion

We can observe that factors such as marital status, education, age and occupation are important in determining income.



MODEL INTERPRETATION USING SHAP VALUES