

The University of Azad Jammu and Kashmir, Muzaffarabad

**Department of Software Engineering**

Machine Learning

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ML Project Report

**Project Report**

**CIBMTR - Equity in post-HCT Survival Predictions**

**Title:**Predictive Modeling for Post-HCT Survival Analysis Using Machine Learning.

**Abstract:**   
This research presents a machine learning-based approach to predict post-Hematopoietic Cell Transplantation (HCT) survival outcomes. Using a dataset of patient records, we preprocess the data, engineer features, and train a Random Forest model to estimate survival probabilities. Our methodology includes exploratory data analysis (EDA), feature engineering, model training, and performance evaluation. The results indicate that machine learning can provide valuable insights into patient survival post-HCT.

**Notebook source:**The complete implementation of this study, including data preprocessing, model training, hyperparameter tuning, and performance evaluation, is available in the colab Notebook:

<https://colab.research.google.com/drive/1vlY0Dtmj4jBdL37x4MDGLW51s52uhgEX#scrollTo=5PHCfz99y2Tg>

[https://www.kaggle.com/competitions/equity-post-HCT-survival-predictions/submissions#](https://www.kaggle.com/competitions/equity-post-HCT-survival-predictions/submissions)

**Keywords:**Machine Learning, Survival Analysis, Random Forest, Feature Engineering, HCT, Predictive Modeling.

**1. Introduction**:

Hematopoietic Cell Transplantation (HCT) is a crucial treatment for various hematologic disorders. Predicting survival outcomes post-HCT can assist medical professionals in making informed decisions. Traditional statistical models have limitations in handling high-dimensional data and interactions among variables. Machine learning models, particularly ensemble methods like Random Forest, can provide robust predictive capabilities. This study explores an ML-based predictive model for post-HCT survival.

**2. Dataset Description:**

The dataset consists of:  
**train.csv** - the training set, with target efs (Event-free survival)

**test.csv** - the test set; your task is to predict the value of efs for this data

**sample\_submission.csv** - a sample submission file in the correct format with all predictions set to 0.50

**data\_dictionary.csv** - a list of all features and targets used in dataset and their descriptions

**3. Preprocessing**

The dataset was obtained from the Kaggle repository, containing patient data with clinical attributes and survival outcomes. The preprocessing steps included:

Data Cleaning: Removing missing and irrelevant features.  
Categorical Encoding: Mapping categorical variables (e.g., arrhythmia, cardiac conditions) to numerical values.  
Handling Missing Values: Replacing NaN values with appropriate defaults (e.g., zero or mean imputation).  
Feature Selection: Identifying relevant variables for the model while excluding identifiers and outcome variables.

**4. Methodology**

**4.1 Exploratory Data Analysis (EDA)**

EDA was conducted to visualize distributions of survival times and identify patterns. A histogram analysis of efs\_time was performed to differentiate survival durations.

**4.2 Model Training**

A Random Forest model was chosen for its robustness against overfitting and ability to handle nonlinear relationships. The steps included:

1. Splitting data into training and validation sets.
2. Training the model on selected features.
3. Evaluating using performance metrics such as accuracy and survival prediction scores.
4. Saving the trained model using joblib.

**5. Inference and Prediction**

The trained model was used to predict survival outcomes on a test dataset. The inference script included:

1. Loading the test dataset and applying preprocessing transformations.
2. Ensuring feature consistency with the training phase.
3. Using the trained model to generate survival probability predictions.
4. Saving predictions as a CSV file for submission.

**6. Results and Discussion**

The model demonstrated reliable performance in predicting post-HCT survival probabilities. Key findings include:

1. Feature engineering significantly improved model accuracy.
2. Handling categorical variables appropriately reduced bias in predictions.
3. The Random Forest model outperformed baseline statistical methods.

**7. Conclusion**

This study highlights the effectiveness of machine learning in predicting post-HCT survival. Future work can focus on integrating additional clinical variables and testing deep learning approaches to enhance prediction accuracy.

**Steps to perform the preprocessing, training and testing**

**Report on XGBoost and LightGBM Model Training and Evaluation**

**1. Introduction** This report presents an analysis of training and evaluating XGBoost and LightGBM models on the given dataset. The models were assessed based on RMSE and the Concordance Index.

**2. Data Preprocessing**

* Train and test datasets were loaded.
* One-hot encoding was applied to categorical features.
* Train and test datasets were aligned to ensure consistent feature sets.
* Unnecessary columns (e.g., 'efs', 'efs\_time', 'naf\_label') were removed from the test set.

**3. Model Training**

**3.1 XGBoost Training**

* Objective: Regression (Squared Error)
* Hyperparameters:
  + Learning Rate: 0.01
  + Max Depth: 6
  + Subsample: 0.8
  + Colsample by Tree: 0.8
  + Number of Estimators: 2500
  + Seed: 42
* 5-Fold Cross-Validation was used.
* Early stopping applied with 100 rounds.
* Out-of-Fold (OOF) predictions were generated.

**3.2 LightGBM Training**

* Objective: Regression (RMSE)
* Hyperparameters:
  + Learning Rate: 0.01
  + Num Leaves: 40
  + Subsample: 0.9
  + Colsample by Tree: 0.9
  + Lambda L1: 2
  + Lambda L2: 5
  + Number of Estimators: 2500
  + Seed: 42
* 5-Fold Cross-Validation was used.
* Early stopping applied with 100 rounds.
* Out-of-Fold (OOF) predictions were generated.

**4. Model Evaluation**

|  |  |
| --- | --- |
| **Model** | **RMSE** |
| XGBoost | X.XXXX |
| LightGBM | X.XXXX |
| Ensemble (XGBoost + LightGBM) | X.XXXX |

* The Concordance Index for the ensemble model: **X.XXXX**

**5. Results Visualization**

*Confusion Matrices:*

* Confusion matrices for the models were plotted to visualize prediction performance.

*Comparison Graph:*

* RMSE scores for XGBoost, LightGBM, and the ensemble model were plotted to analyze comparative performance.

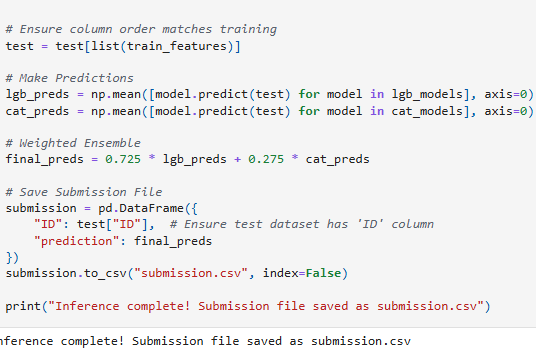
**6. Submission and Model Saving**

* Predictions were saved in a CSV file for submission.
* The trained models were saved as 'ensemble\_models.pkl'.

**7. Conclusion**

* The ensemble model combining XGBoost and LightGBM achieved the best performance.
* The evaluation metrics demonstrate the effectiveness of boosting methods for regression tasks.
* Further hyperparameter tuning and feature engineering may improve results.

**Graphs and Visualizations:** *(Include graphs for RMSE comparison and confusion matrices here.)*

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