



Mahatma Gandhi Institute of Technology

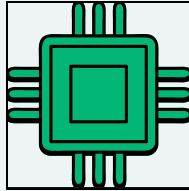


FACULTY COORDINATOR

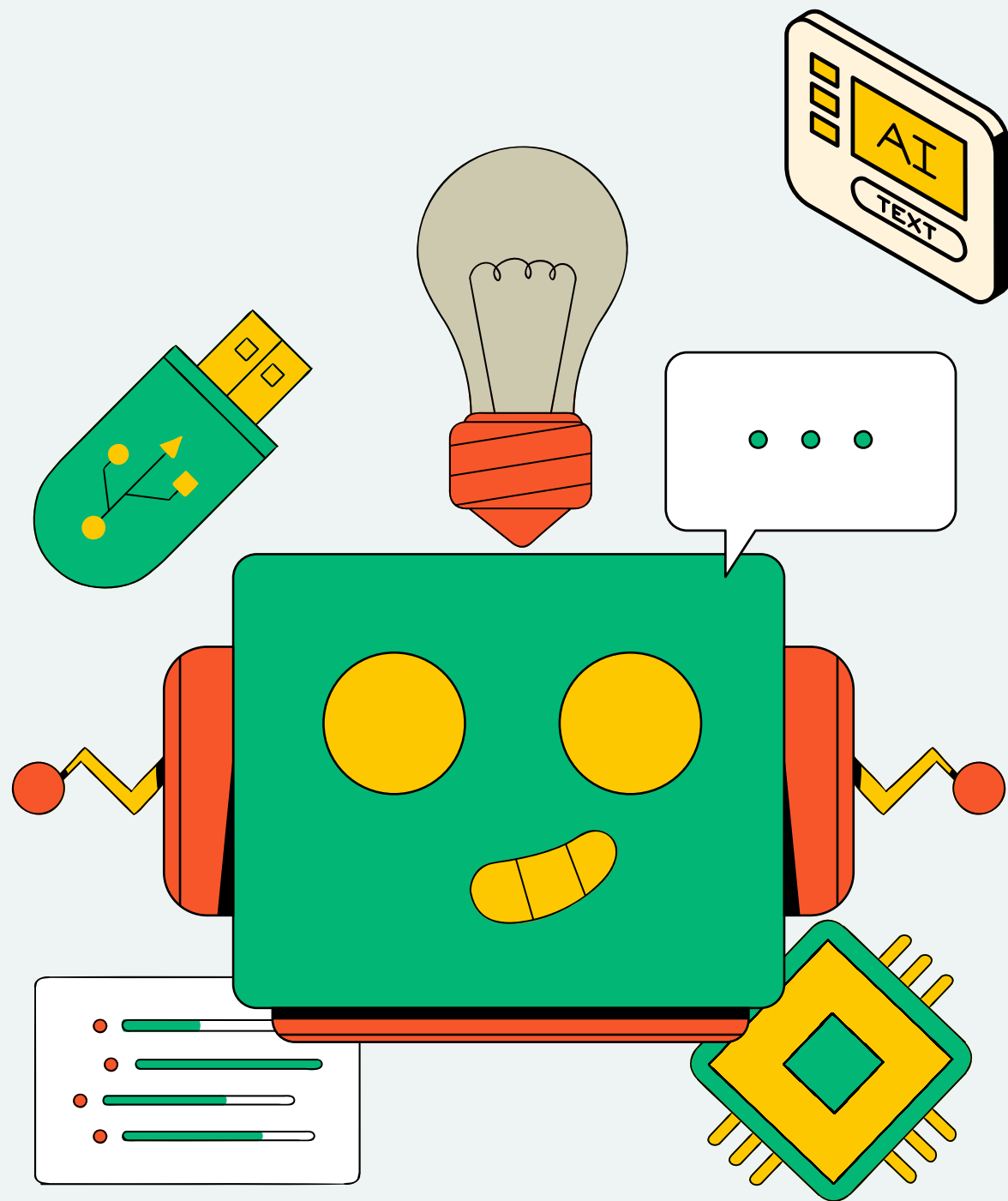
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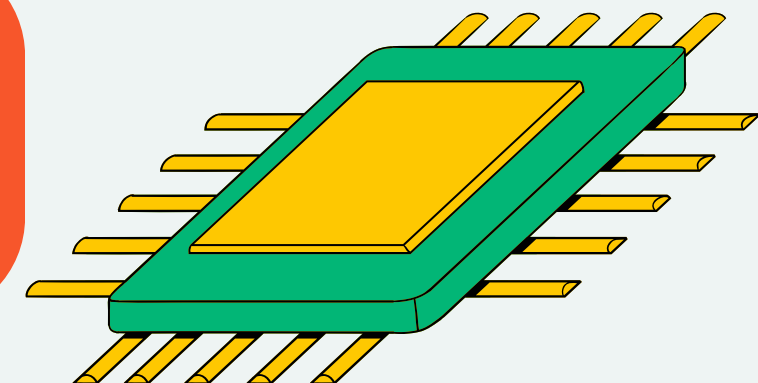
POST-HCT SURVIVAL PREDICTIONS

MACHINE LEARNING

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PRESENTATION OUTLINE

- ABSTRACT
- LITERATURE REVIEW
- FLOWCHART (ACTIVITY DIAGRAM)
- SEQUENCE DIAGRAM
- SYSTEM ARCHITECTURE
- USE CASE DIAGRAM
- CLASS DIAGRAM




ABSTRACT

PROBLEM STATEMENT:
Existing HCT survival prediction models fail to account for racial and medical disparities, leading to biased and less accurate predictions.

PROPOSED SOLUTION: An ensemble model combining XGBoost and CatBoost to improve survival predictions for HCT patients. This approach leverages gradient boosting techniques to handle both numerical and categorical clinical variables efficiently. The ensemble is trained on a synthetic survival dataset and evaluated using the Stratified Concordance Index (C-Index) to ensure fairness across racial groups.



LITERATURE REVIEW

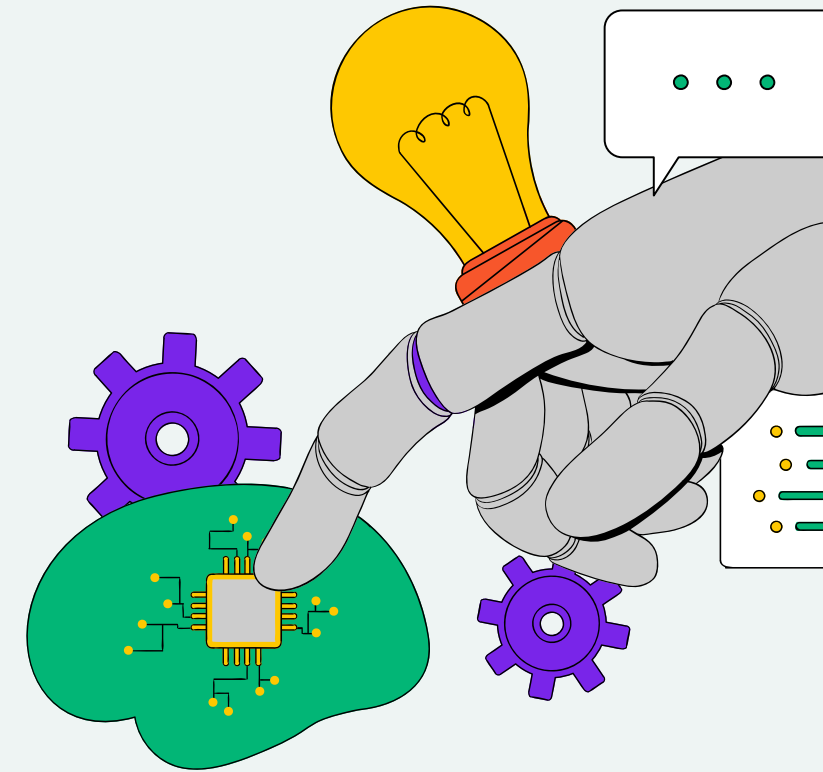
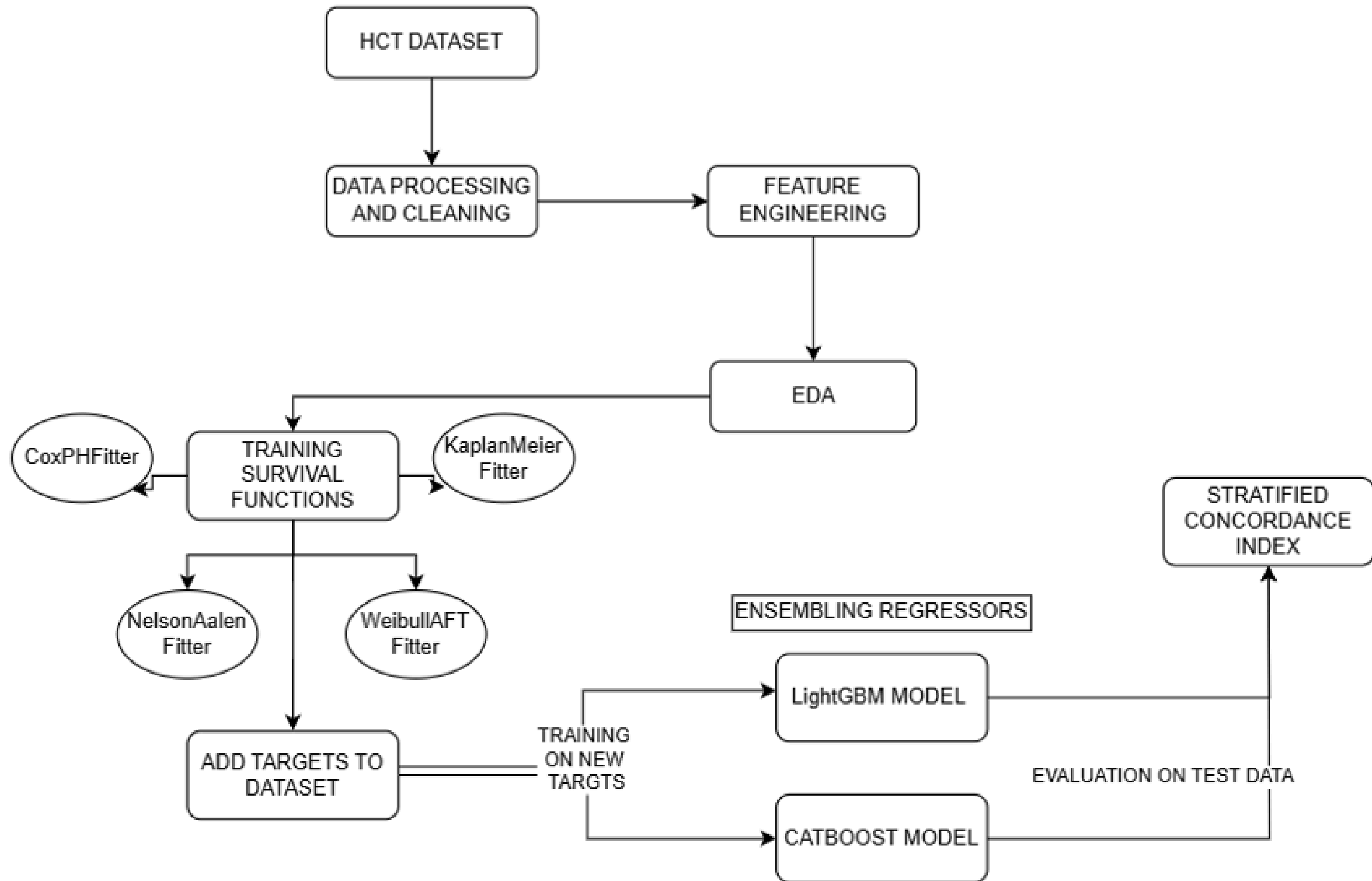
| Author | Title | Year | Methodology/ concept used/summary | Merits | Demerits |
|-----------------------------------|--|------|--|--|---|
| Gonca Buyrukoğlu | Survival Analysis in Breast Cancer: Evaluating Ensemble Learning Techniques for Prediction | 2024 | Evaluates Cox PH, Random Survival Forest, and Conditional Inference Forest for breast cancer survival prediction. | RSF and Cforest outperform Cox PH, improving predictive accuracy. | Limited to two specific datasets. |
| Hussam Alawneh, Ahmad Hasasneh | Survival Prediction of Children After Bone Marrow Transplant Using Machine Learning Algorithms | 2024 | Uses ML models (RF,XGBoost, AdaBoost, etc.) to predict pediatric bone marrow transplant survival. | Achieves 97.37% accuracy using feature selection and hyperparameter tuning. | Does not account for time- dependent covariates.  |

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|---|---|-------------|--|---|--|
| <p>Hamed Shourabizadeh, Dionne M. Aleman, Louis-Martin Rousseau, Arjun D. Law, Auro Viswabandya, Fotios V. Michelis</p> | <p>Machine Learning for the Prediction of Survival Post-Allogeneic Hematopoietic Cell Transplantation: A Single-Center Experience</p> | <p>2023</p> | <p>Investigates ML models for HCT survival prediction using 2,697 patient records. RF achieved the best AUC of 0.71.</p> | <p>Identifies significant clinical predictors for survival stratification.</p> | <p>Limited to a single-center dataset, requiring external validation.</p> |
| <p>Yaroslav Tolstyak etal.</p> | <p>The Ensembles of Machine Learning Methods for Survival Predicting After Kidney Transplantation</p> | <p>2021</p> | <p>Applies ensemble ML models and Kaplan-Meier estimation to predict kidney transplant survival.</p> | <p>Uses multiple feature selection techniques for better predictive accuracy.</p> | <p>Limited dataset generalizability, requiring further validation.</p> <div></div> |

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|-------------------------------|---|------|---|---|---|
| Jennifer Clarke, Mike West | Bayesian Weibull Tree Models for Survival Analysis of Clinico- Genomic Data | 2007 | Uses Bayesian Weibull tree models for survival prediction via recursive partitioning. | Integrates genomic and clinical data effectively for personalized predictions. | Computationally intensive and requires domain expertise. |
|-------------------------------|---|------|---|---|---|



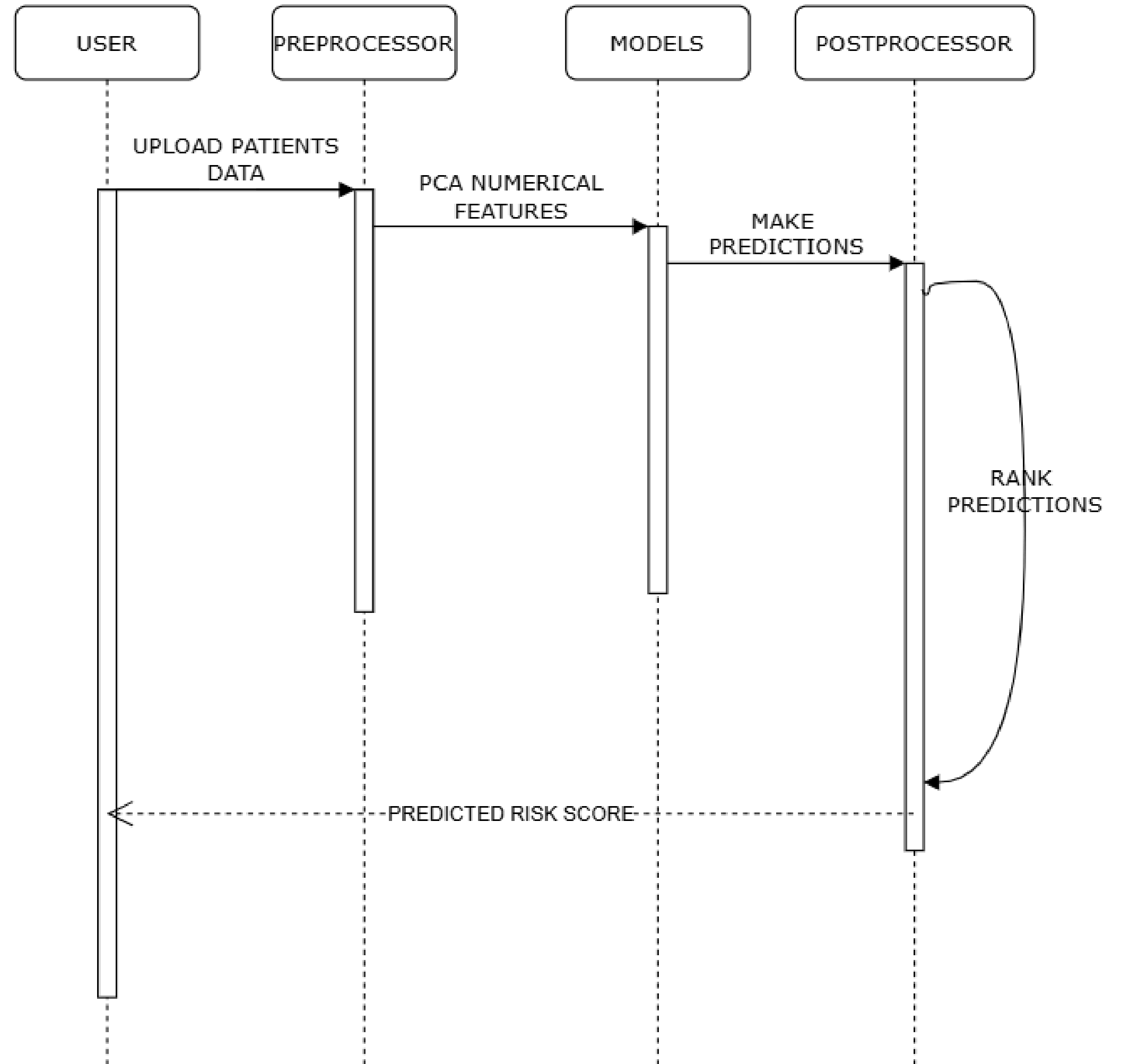
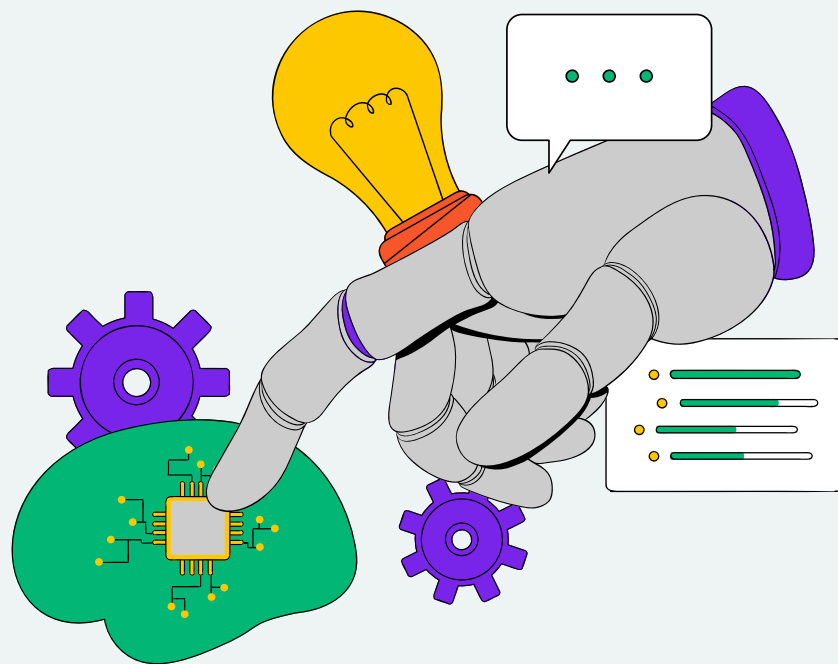
FLOWCHART (ACTIVITY DIAGRAM)



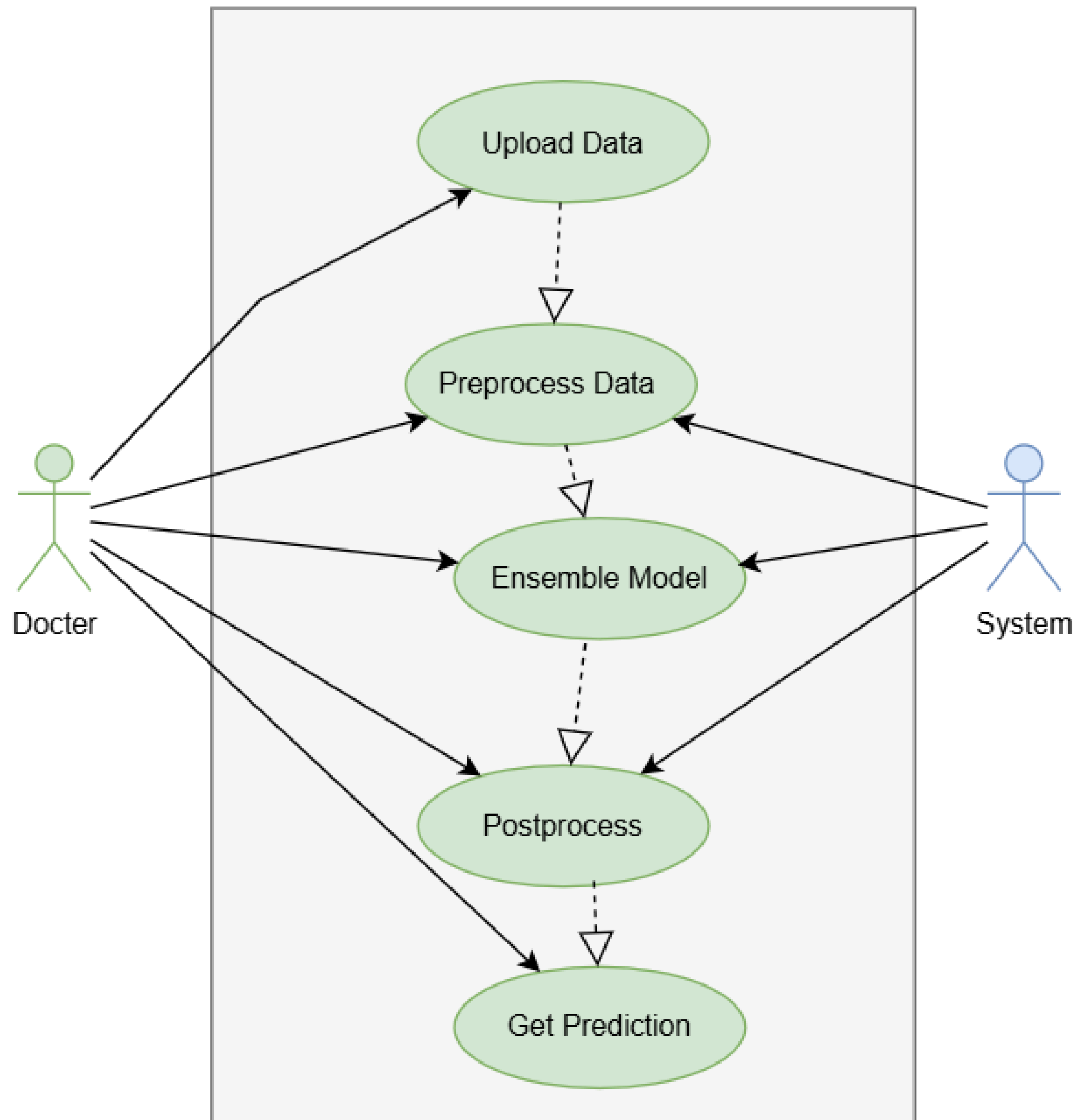
SEQUENCE DIAGRAM

COMPONENTS:

- USER
- PREPROCESSOR
- ENSEMBLED MODELS
- POSTPROCESSOR



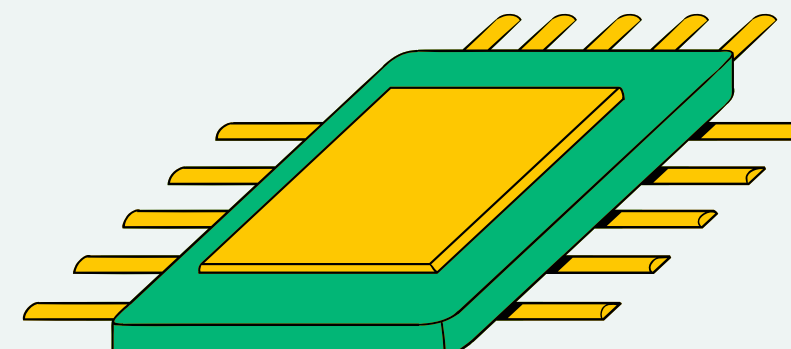
USE CASE DIAGRAM



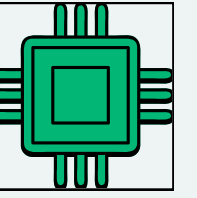
USE CASE DIAGRAM

ACTIONS:

- **UPLOAD DATA**
- **PREPROCESS:** Normalize and PCA to numerical Data.
- **ENSEMBLED MODELS:** XgBoostRegressor and CatBoostRegressor
- **POSTPROCESSOR:** Rank Outputs and apply weights.



CLASS DIAGRAM



CLASS DIAGRAM

