Wrightington, Wigan and Leigh NHS Foundation Trust

Lancaster University

Predicting ICU Transfers: A Machine Learning Approach to Early Identification of Critical Patients

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Introduction and Motivation

Brief overview of the problem:

•30% of mortality at WWL NHS Trust linked to missed diagnoses of rapidly deteriorating patients

•Need for early and accurate prediction of ICU transfers

Importance of predicting ICU transfers:

•Reduce care requirements and associated costs

•Improve patient outcomes

•Enhance hospital resource management

Current limitations of NEWS2 score:

•Does not capture complex interactions between patient variables

•Misses some patients who deteriorate rapidly

Key Objectives

- Develop a predictive model to accurately forecast ICU transfers using machine learning techniques.
- Address the challenge of class imbalance in ICU transfer data to improve model performance.
- Identify the most important features that contribute to ICU transfer predictions for better clinical decision-making.

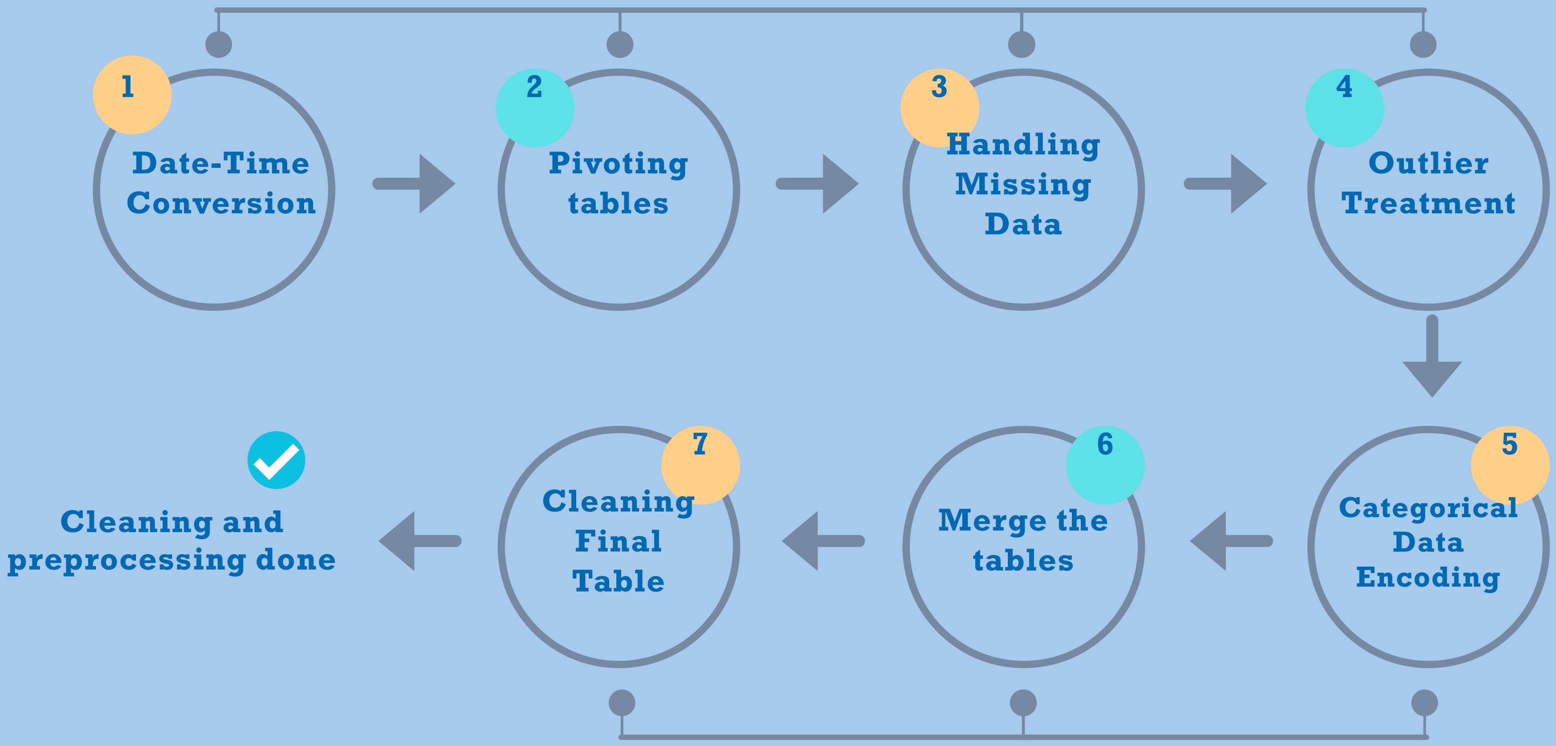
Dataset Overview

1. Target Dataset • Patient admission and outcome data
2. Observe Dataset • Patient vital signs and NEWS2 components
3. Diagnostic Dataset • Results of various diagnostic tests

Data Characteristics:

- Time span: Jan 2019 - May 2024
- 73,628 unique patients all aged 18+

Simplified steps for Preprocessing



Date-Time Conversion and Pivoting tables

1.Date-Time Conversion • Converted AdmitDtm and Obs_dtm to datetime format • Used pandas' to_datetime() function • Applied 'errors='coerce'' to handle inconsistencies • Enabled accurate time-based calculations and filtering

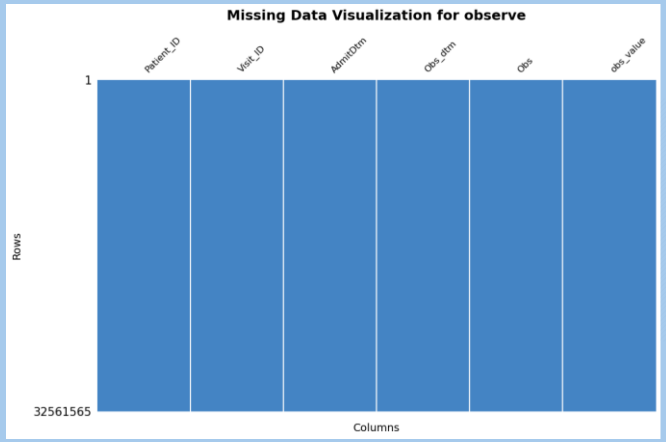
2.Data Restructuring (Pivoting) • Transformed data into wide-format table • Each row: unique combination of Patient ID, Visit ID, AdmitDtm, Obs_dtm • Results became columns

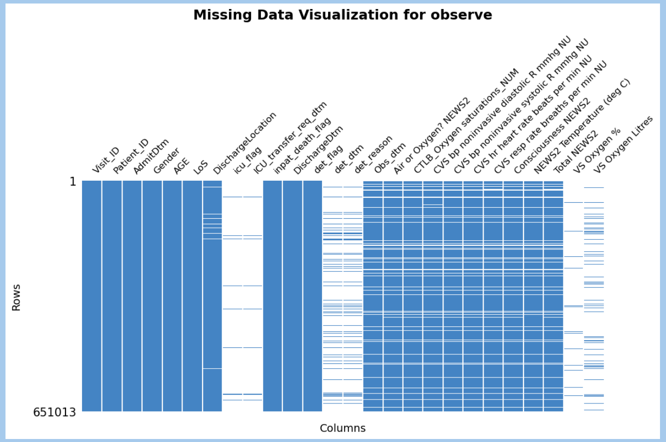
Key Benefits:

•Improved data consistency

•Enhanced time-based analysis capabilities

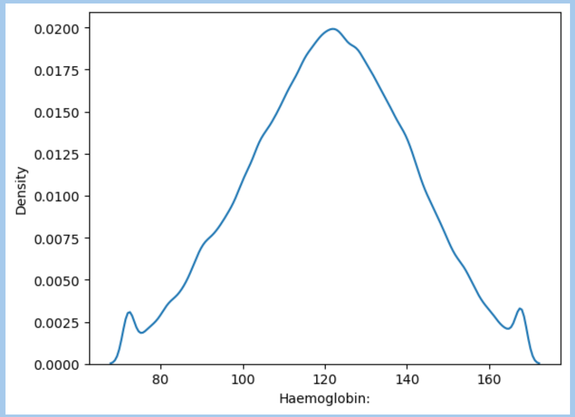
•Optimized format for a model as each unique test will become a feature





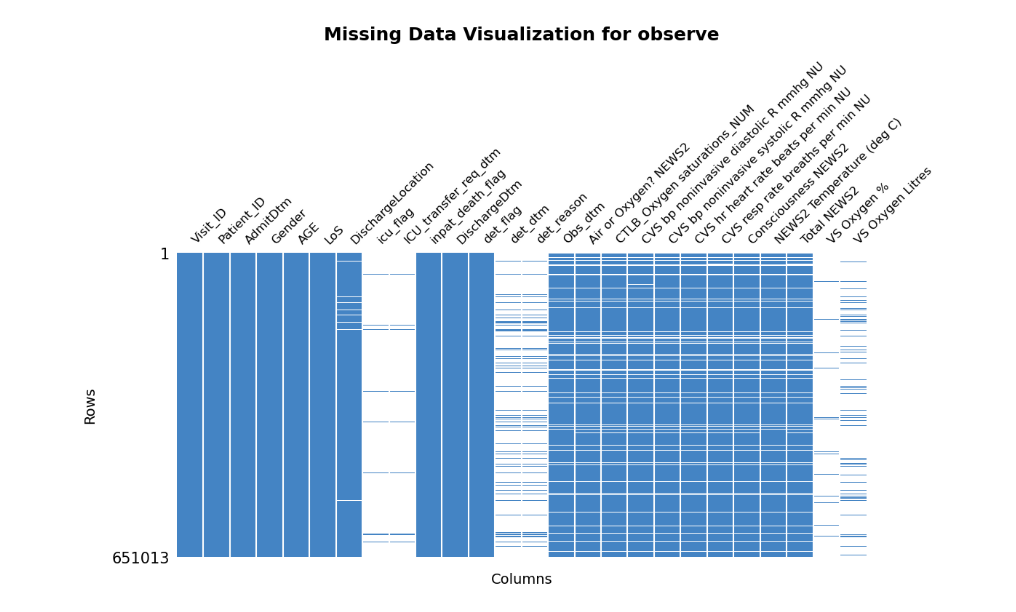
Outlier Treatment and Categorical Data Encoding

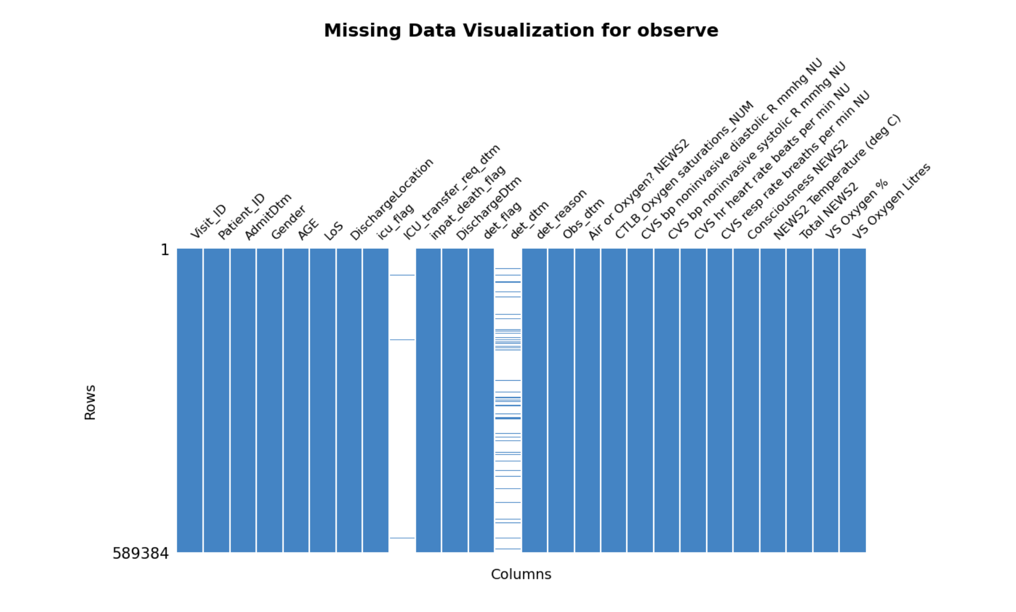
1. Outlier Treatment: Winsorization • Applied to numerical columns • Replaced values below 1st and above 99th percentiles • Balanced approach: preserves data structure while reducing outlier impact • Suitable for medical data: retains potentially significant extreme values Benefits: • Maintains data distribution • Preserves clinically relevant information • Improves model resilience to extreme values
2. Categorical Data Encoding • Used scikit-learn's LabelEncoder for 'Gender' variable • Transformed categorical data into numerical format Importance: • Enables inclusion of categorical variables in models • Preserves categorical information in a model-compatible format



Handling Missing Data

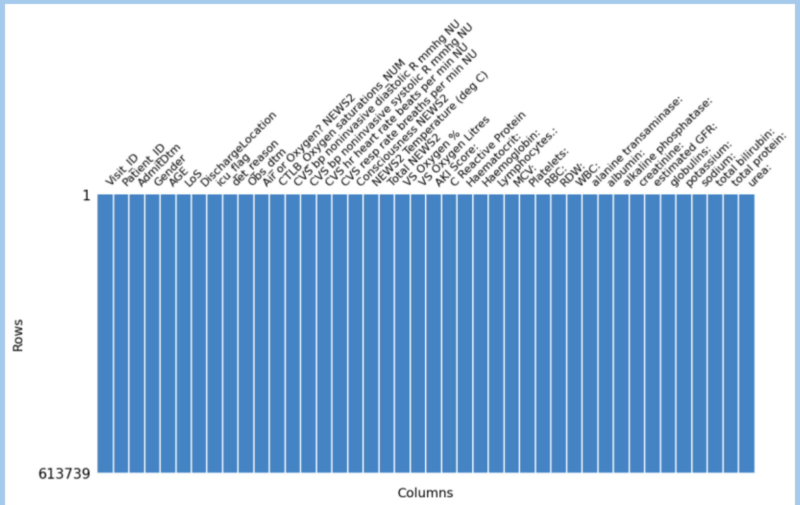
- Data Filtering: Removed rows missing critical timestamp data .
- Imputation: Applied forward and backward filling for time-series data, and iterative imputation to estimate remaining missing values.
- Duplicate and Threshold Filtering: Removed duplicate rows and filtered rows with more than 16 missing values.
- Data Validation: Validated binary variables, corrected outliers, capped percentages, and ensured all values were clinically possible.





Data Combination and Final Preprocessing

1. Data Integration • Merged observation and diagnostic datasets • Aligned datetime fields across datasets • Performed outer join for comprehensive patient view
2. Handling Missing Data • Conducted thorough missing value analysis • Applied forward/backward filling for time-series data • Used IterativeImputer for remaining missing values
3. Data Cleaning • Removed rows with missing crucial timestamps • Filtered out rows with excessive missing values • Eliminated duplicate entries
4. Preventing Data Leakage • Removed post-event variables (e.g., DischargeDtm, ICU_transfer_req_dtm)
5. Data Validation and Correction • Ensured correct data types and value ranges • Rounded scores and counts to whole numbers • Removed impossible values (e.g., negative bilirubin)



Feature Selection and Data Preparation

Feature Selection

- Included: • Patient demographics • Vital signs • Diagnostic test results
- Excluded to Prevent Data Leakage: • Identifiers (e.g., Visit ID, Patient ID) • Future information (e.g., DischargeDtm, ICU_transfer_req_dtm) • Redundant information (e.g., AdmitDtm)

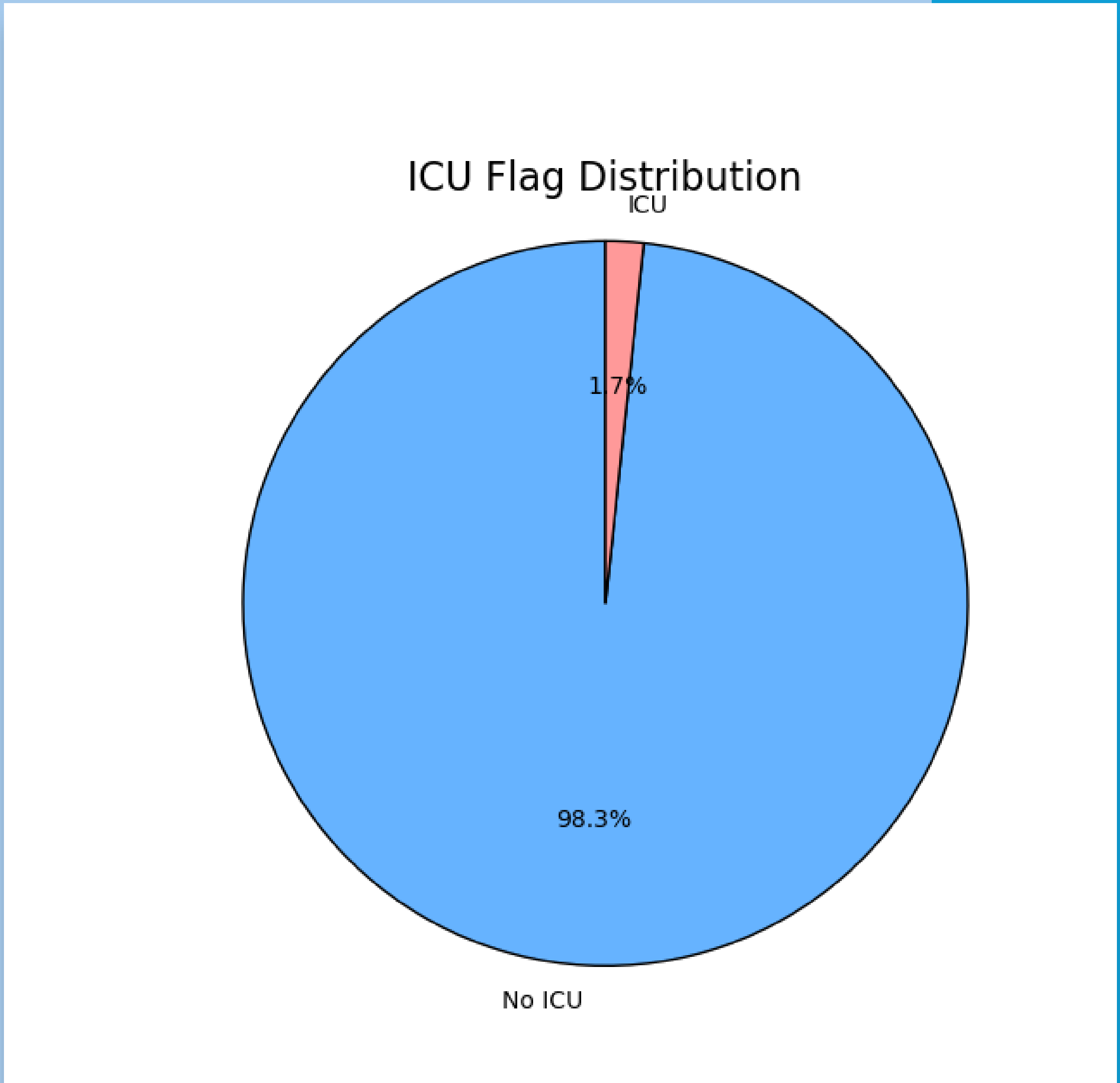
1. Target Variable • 'icu_flag': Binary indicator of ICU transfer
2. Data Type Consistency • Ensured appropriate data types for all features • Encoded categorical variable gender as mentioned before

Key Principles:

- Exclusion of post-event information
- Focus on real-time available data
- Prevention of overfitting and data leakage to maintain the integrity of predictive task

Class Imbalance

- Only 1.7% of patients required ICU transfer, highlighting a major class imbalance.
- Imbalance makes models biased toward predicting "No ICU" (98.3% majority).
- To improve predictions, various balancing techniques need to be tested



Addressing Class Imbalance

Techniques Explored:

1. Oversampling Methods • **SMOTE**: Creates synthetic minority examples • **ADASYN**: Focuses on samples near decision boundary • **Random Over-Sampling**: Duplicates minority samples
2. Undersampling Methods • **Random Under-Sampling**: Removes majority samples • **Tomek Links**: Removes noisy majority samples • **Edited Nearest Neighbors (ENN)**: Cleans both classes • **Near Miss**: Keeps relevant majority samples
3. Combination Method • **SMOTE + Random Under-Sampling**

Rationale for Multiple Techniques:

- Different methods suit various aspects of imbalance
- Allows comparison of effectiveness in ICU transfer prediction

Model Selection

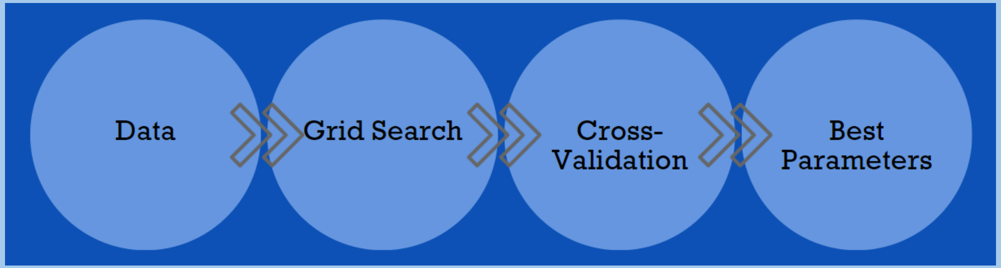
Model Selection: Random Forest and XGBoost

1. Random Forest • Ensemble method: Combines multiple decision trees • Handles non-linear relationships in medical data • Built-in feature importance rankings • Resistant to outliers and noisy data • Good generalization, reduced overfitting
2. XGBoost • Superior predictive power in various ML tasks • Captures complex, non-linear relationships • Provides feature importance rankings • Handles missing data internally • High performance crucial for medical predictions
3. Combined Strengths • Leverages two different ensemble approaches • Creates a comprehensive predictive framework • Enhances overall predictive capability for ICU transfers

Key Benefits of Using Both: • Robust performance across different data characteristics • Complementary strengths for complex medical data • Increased confidence in predictions through model comparison

Hyper Parameter Tuning

1. Importance of Hyperparameter Tuning
    - Optimizes model performance for specific datasets
    - Addresses overfitting:
    - Prevents models from memorizing training data
    - Improves generalization to unseen data



2. Methodology
    1. Utilized sklearn's GridSearchCV which:
    2. Systematically works through multiple combinations of parameter tunes
    3. Trains and evaluates a model for each combination •
    4. Implemented 3-fold cross-validation:
    5. Helps in assessing model performance consistency
    6. Optimized for F1-score

3. Tuned Parameters
    - Random Forest: • n_estimators • min_samples_split • min_samples_leaf • max_features • bootstrap
    - XGBoost: • n_estimators • learning_rate • subsample • colsample_bytree • scale_pos_weight

Temporal Split and Model Validation

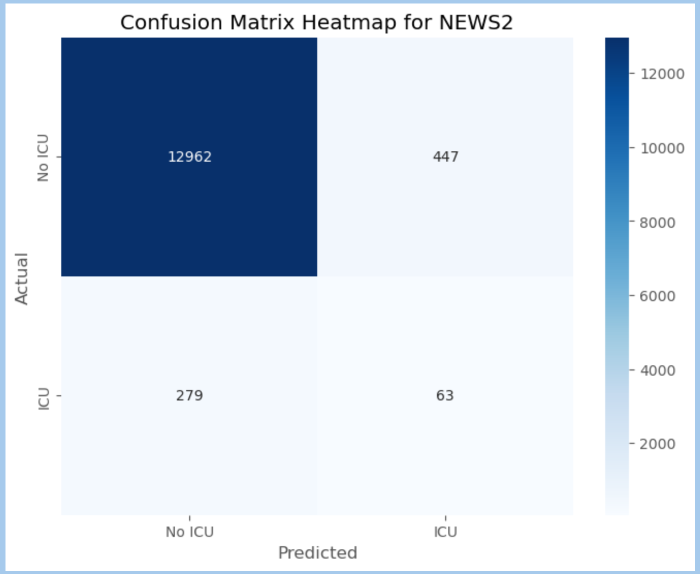
1. Data Split • Training and Initial Testing: Data before April 1, 2024 • Validation Set: Data from April 1, 2024 onwards
2. Model Validation • All models evaluated on post-April 2024 validation set • Includes:
    1. Baseline model
    2. Models with different imbalance handling techniques
3. Rationale • Simulates real-world application • Trains on historical data, predicts on future unseen data • Tests model performance in practical scenarios

Key Benefits:

- Realistic assessment of model generalization
- Avoids data leakage from future to past
- Evaluates model's ability to handle temporal shifts in data

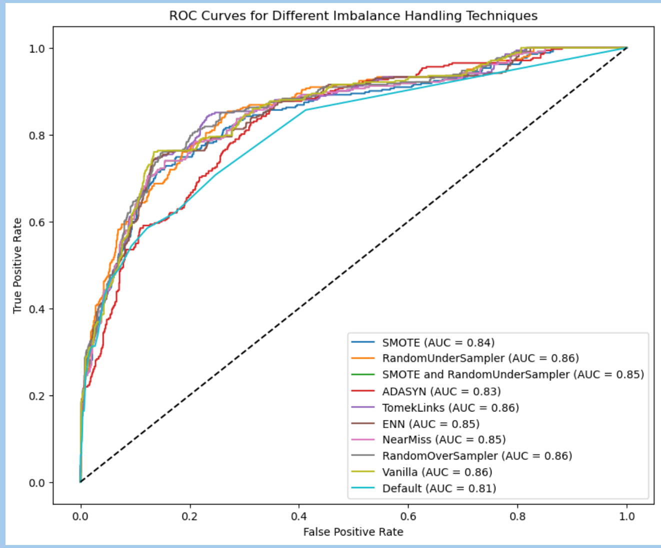
Performance of Total NEWS2 Score

Performance Metrics:
•Precision: 0.12
•Recall: 0.18
•F1-score: 0.15
Interpretation:
•Only 12% of patients flagged for ICU transfer actually required it
•NEWS2 captured only 18% of patients who truly needed ICU transfer
•High number of false positives and false negatives indicates significant room for improvement, which our model aims to address

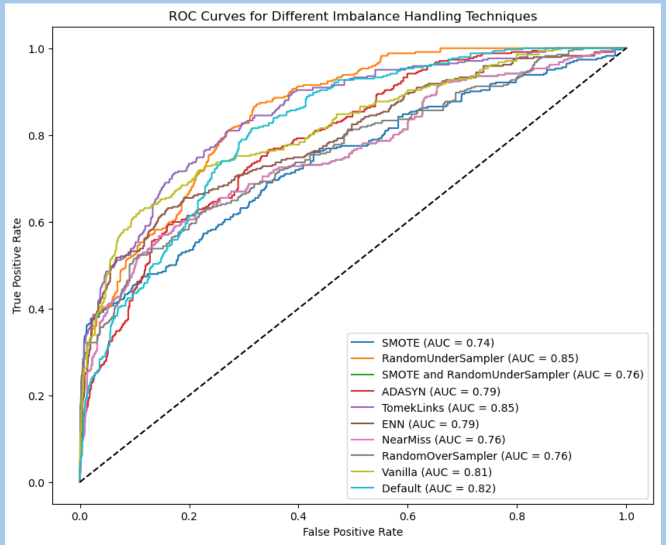


ROC Curve Analysis: Random Forest vs. XGBoost

- **Random Forest** shows more **consistent performance** across different imbalance handling techniques, with AUC values clustering between **0.83 and 0.86**.
- **XGBoost** results are more varied, with AUC values ranging from **0.74 to 0.85**.
- Techniques like **RandomUnderSampler** and **TomekLinks** perform well with both models, but **Random Forest** offers a **more stable ROC** across techniques.



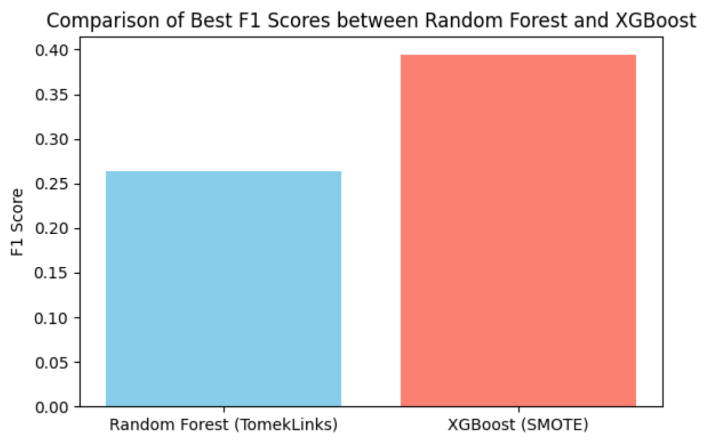
Random Forest



XGBoost

F1-Score and Best Performing Model

- While ROC curves show that Random Forest consistently performed better, we chose the F1-score as our primary metric.
- The F1-score was selected to balance precision (avoiding unnecessary ICU transfers) and recall (capturing patients in need of ICU care)
- The best results were achieved using XGBoost with SMOTE and Random Forest with TomekLinks.
- **XGBoost with SMOTE** delivered the highest F1 score, making it the most effective model



Feature Importance Analysis: Default XGBoost vs SHAP

Key Observations:

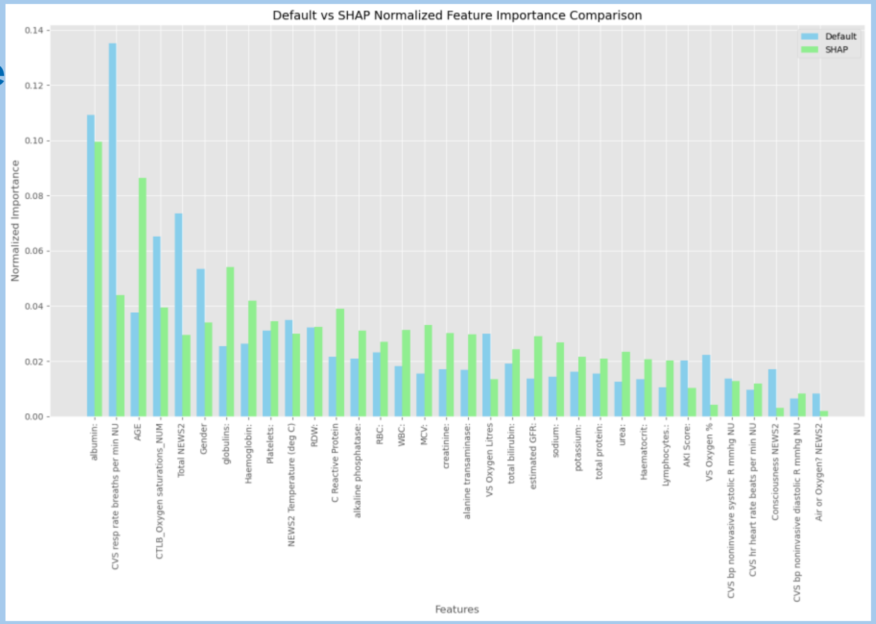
- Both methods agree on high importance of albumin levels
- SHAP assigns higher importance to age (AGE)
- Default method emphasizes oxygen-related features more

Preference for SHAP Method:

- Grounded in cooperative game theory
- Accounts for feature interactions
- Captures complex, non-linear relationships

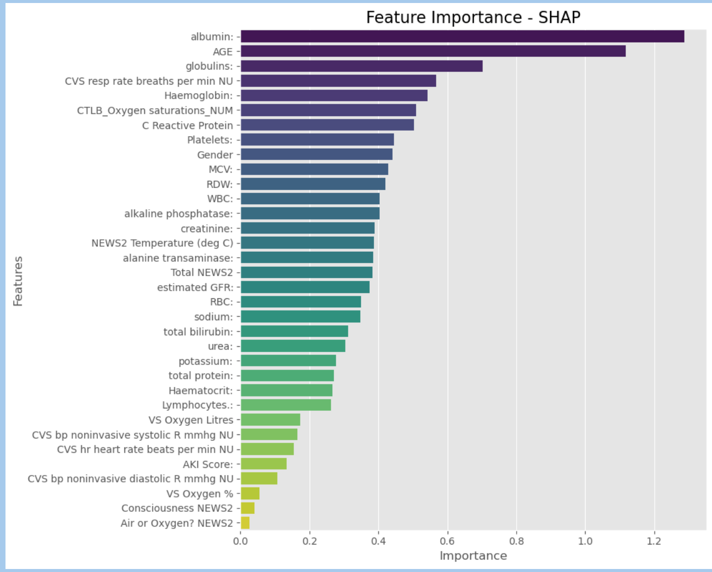
Implications:

- Albumin levels are crucial predictors across methods
- Age may have more complex impact than initially thought
- Oxygen-related features' importance varies by method



Feature Importance Insights

- Key Features: albumin, age and globulin are the top predictors.
- SHAP Analysis: SHAP reveals the non-linear impact of features like age, which ranks higher than in traditional methods.
- Balanced Data: Vital signs and lab values both play crucial roles in ICU transfer predictions.
- Clinical Relevance: Combining easily measurable bedside data with lab results provides a balanced and actionable model for ICU transfer predictions.



Limitations and Ethical Considerations

Limitations:

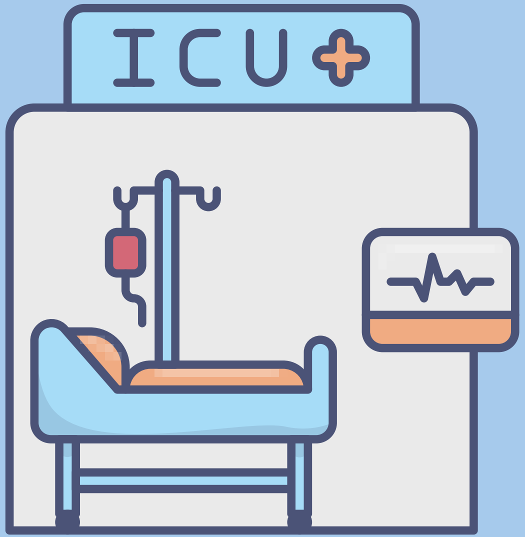
1. Data Constraints • F1 score of 0.39 indicates room for improvement • Lack of doctors' diagnostic notes in dataset • Need for more complex clinical decision-making data
2. Validation Needs • Further testing required on data from other hospitals • Live hospital data testing needed
3. Implementation Challenges • Integration into existing workflows and IT systems

Ethical Considerations:

1. Model Transparency • Accessible documentation of architecture and decision-making
2. Fairness • Regular audits to prevent discriminatory predictions
3. Human Oversight • Model should complement, not replace clinical judgment • Training for healthcare providers on model use and limitations
4. Data Privacy • Adherence to UK data protection regulations • Robust anonymization measures
5. Accountability • Clear framework for model-influenced decisions
6. Patient Communication • Transparent information about model's role in care

Future Work

1. Incorporate Doctors' Diagnostic Notes • Use natural language processing to extract insights • Capture important observations not in structured data
2. Collaborate with Healthcare Professionals • Discuss significant features identified by the model • Refine data collection based on clinical expertise • Recommend frequency of measurements for key indicators
3. Explore Alternative Modeling Approaches • Investigate time-series analysis • Capture progression of patient conditions over time
4. Expand Data Collection • Include a wider range of hospitals • Improve model generalizability • Account for variations in patient populations and resources
5. Enhance Model Interpretability • Develop more intuitive ways to present model predictions • Create user-friendly interfaces for clinical staff



Final Remarks

Key Achievements:

- XGBoost with SMOTE outperformed NEWS2 in ICU transfer prediction
- Addressed class imbalance effectively
- Enhanced model interpretability using SHAP

Potential Impact:

- Improved critical care management
- Optimized resource allocation
- New insights for patient monitoring and risk assessment

This study serves as a stepping stone towards enhancing patient care through ethically implemented, data-driven decision support systems in ICU predictive modeling.

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