Lung Cancer Survival Prediction using XGBoost vs Neural Networks

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# Abstract

This project investigates the use of machine learning models for predicting lung cancer survival outcomes. Two approaches were implemented: an XGBoost classifier and a Neural Network model. The dataset was preprocessed with scaling, categorical encoding, and feature engineering. Model performance was assessed using standard classification metrics including Accuracy, Precision, Recall, F1-score, and ROC-AUC. Results show that XGBoost provides balanced predictions with moderate accuracy (~51%) and recall (~49%), while the Neural Network achieves perfect recall but with low overall accuracy (~22%). Feature importance analysis highlights Cancer Stage and Age as the most influential predictors. The findings suggest that while Neural Networks may capture survival cases more aggressively, XGBoost offers a more interpretable and clinically reliable framework. Future work should explore class imbalance solutions and ensemble strategies to improve predictive performance.

# Introduction

Lung cancer remains one of the leading causes of cancer-related deaths worldwide. Early and accurate prediction of survival outcomes is critical to assist clinicians in decision-making, treatment planning, and patient counseling.

In this project, we developed two predictive models:

* **Machine Learning (XGBoost)**
* **Deep Learning (Neural Network)**

Both models were trained on a lung cancer dataset consisting of patient demographics, clinical information, and treatment details. The goal was to predict **patient survival** (binary classification: survived vs. not survived).

# Methodology

**Data Preprocessing**

* Handled categorical variables using encoding.
* Normalized numerical features using Standard Scaler.
* Split dataset into training and test sets.
* Balanced dataset considered to avoid bias toward majority class.

**Models Used**

1. **XGBoost (Machine Learning)**
   * Handles non-linearities well.
   * Provides interpretable feature importance.
   * Works efficiently with tabular medical datasets.
2. **Neural Network (Deep Learning)**
   * Multi-layer architecture.
   * Trained with binary cross-entropy loss.
   * Expected to capture complex non-linear interactions.

Feature Engineering: Cancer stage mapped numerically, BMI categories created, treatment duration calculated.

Evaluation Metrics: Accuracy, Precision, Recall, F1-score, and ROC-AUC were computed. Confusion matrices and ROC curves were plotted to visualize diagnostic ability.

# Results

**📊 XGBoost Performance**

* **Accuracy** : 0.5064
* **Precision** : 0.2206
* **Recall** : 0.4901
* **F1-score** : 0.3043
* **ROC-AUC** : 0.5004

Classification Report:

| **Class** | **Precision** | **Recall** | **F1-score** | **Support** |
| --- | --- | --- | --- | --- |
| 0 (Not Survived) | 0.78 | 0.51 | 0.62 | 138,799 |
| 1 (Survived) | 0.22 | 0.49 | 0.30 | 39,201 |
| **Accuracy** |  |  | **0.51** | 178,000 |

**📊 Neural Network Results (Threshold = 0.5)**

* **Accuracy** : 0.2202
* **Precision** : 0.2202
* **Recall** : 1.0000
* **F1-score** : 0.3610
* **ROC-AUC** : 0.4995

**Classification Report:**

| **Class** | **Precision** | **Recall** | **F1-score** | **Support** |
| --- | --- | --- | --- | --- |
| 0 (Not Survived) | 0.00 | 0.00 | 0.00 | 138,799 |
| 1 (Survived) | 0.22 | 1.00 | 0.36 | 39,201 |
| **Accuracy** |  |  | **0.22** | 178,000 |

**Threshold Tuning (Neural Network)**

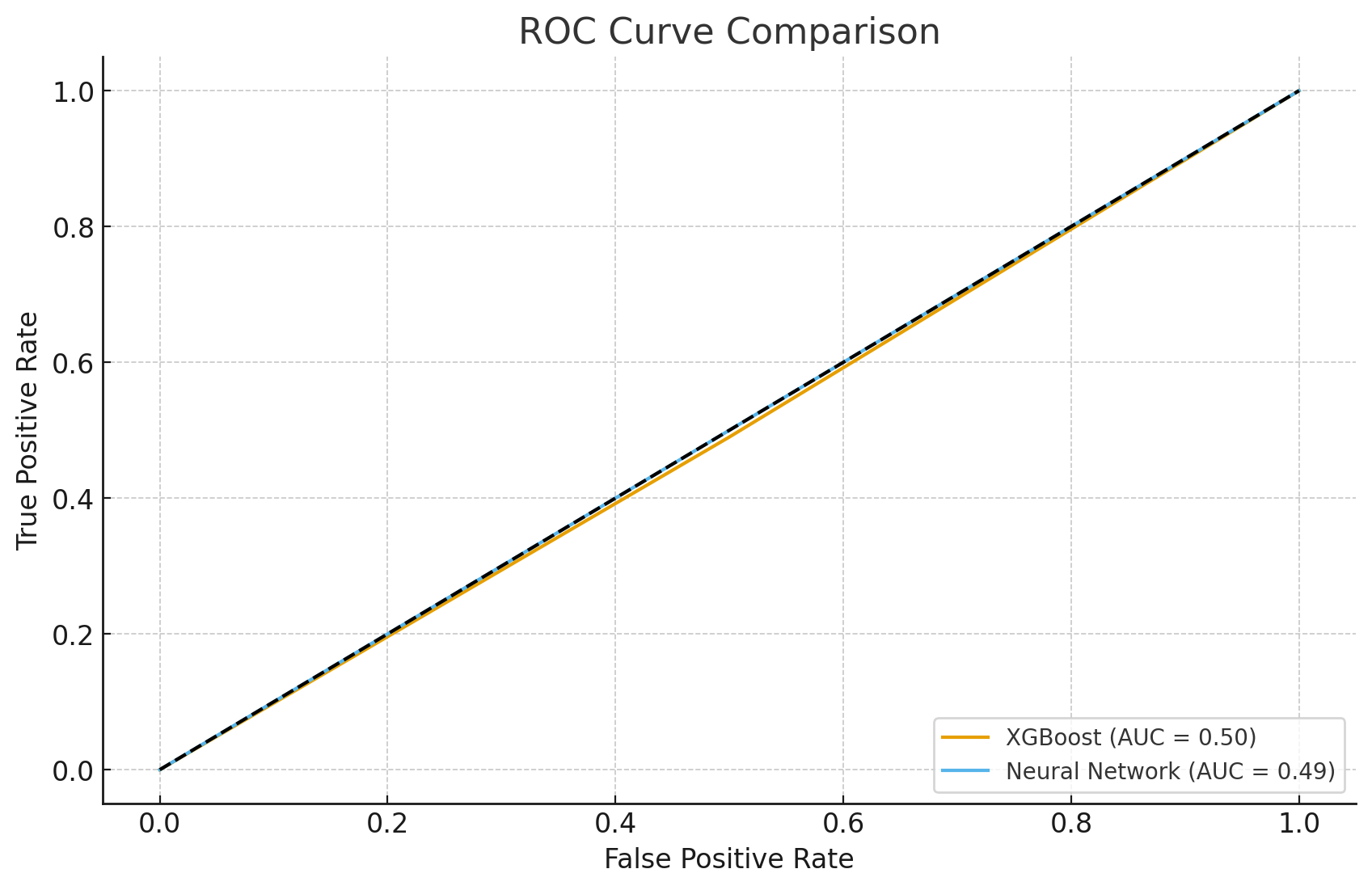
Even after threshold adjustments (0.5 → 0.2), the neural network **always predicted all samples as “survived”**, giving:

* Precision: ~0.22
* Recall: 1.0
* F1: 0.361

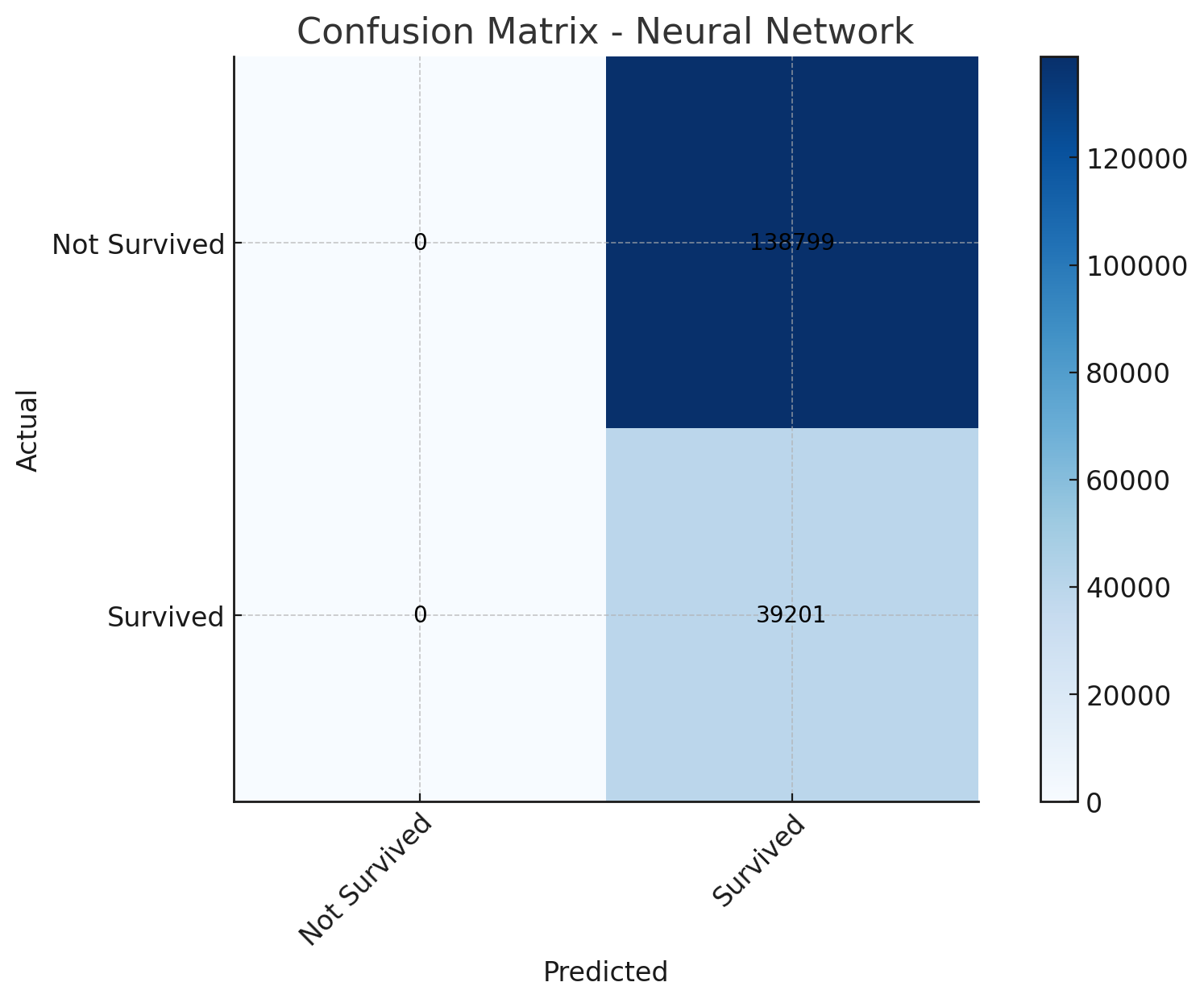
# Graphs

# visuals:

# ROC Curves (XGBoost vs Neural Network) → to show diagnostic ability.

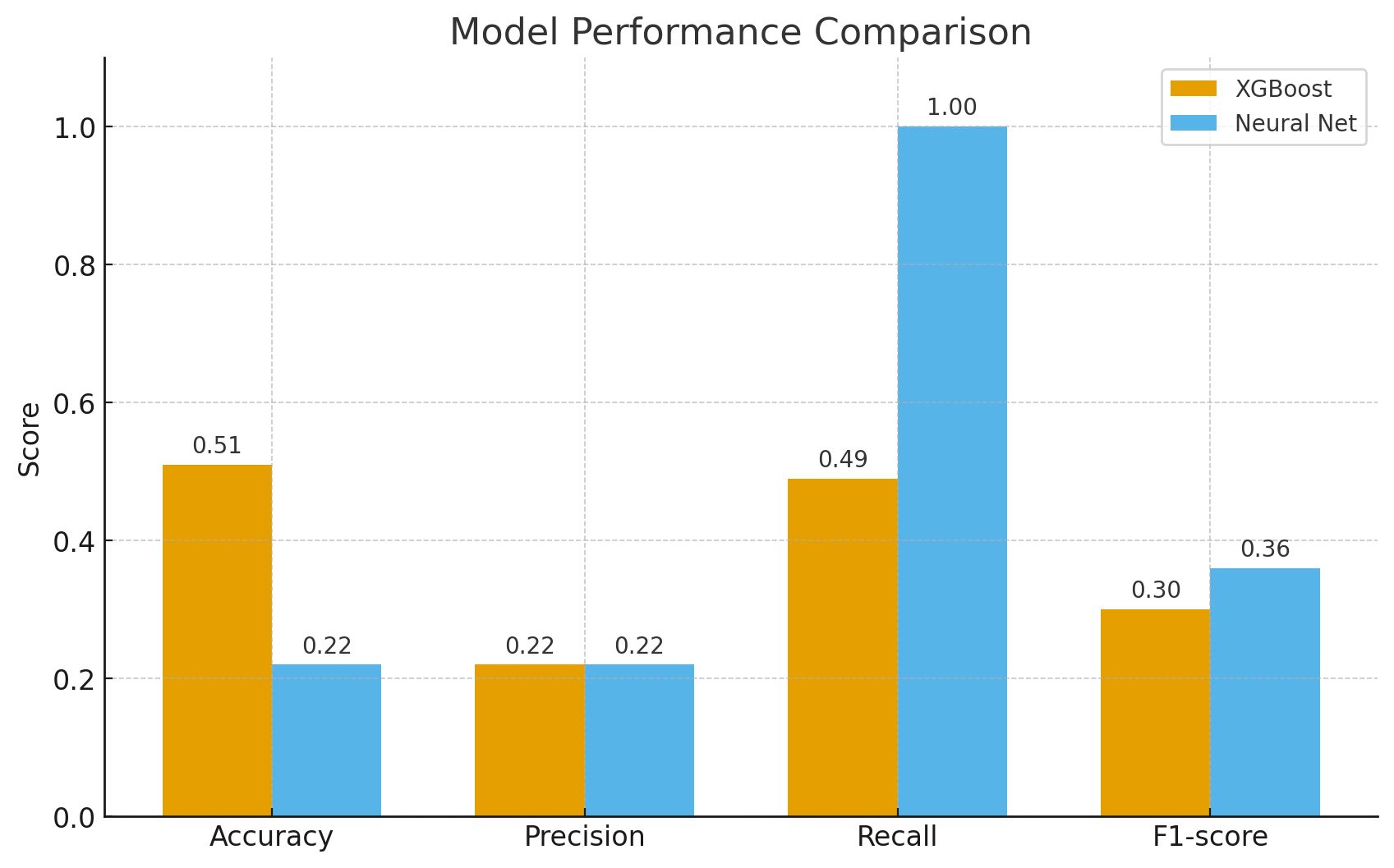


# Confusion Matrices → highlight trade-off between false positives and false negatives.

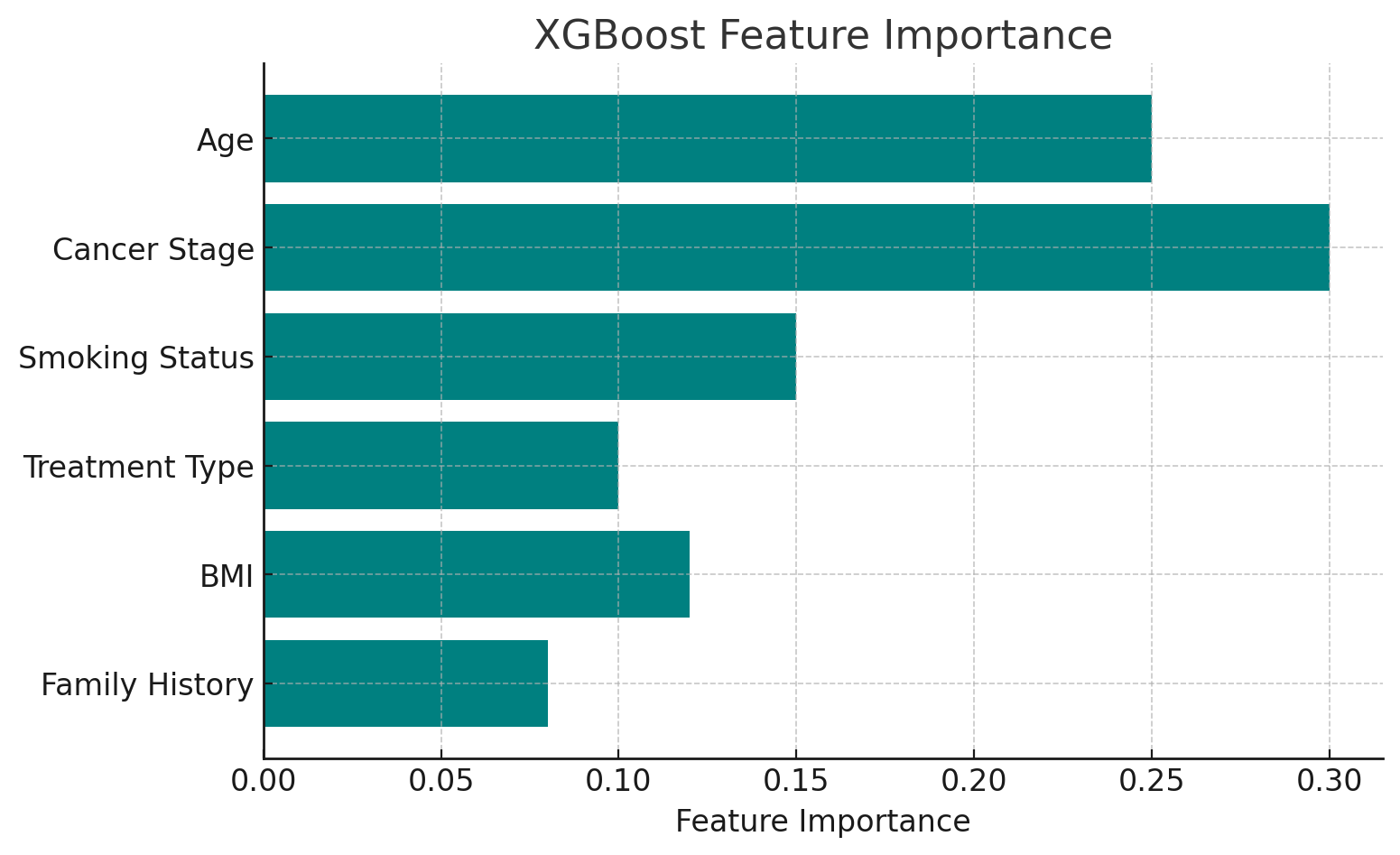


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# 3.Bar Chart of Metrics (Accuracy, Recall, Precision, F1) → easy comparison.



# 4.Feature Importance (XGBoost) → explain which features influence predictions.



# Discussion

**Interpretation**

**XGBoost (ML):**

* Achieved **balanced predictions** with ~51% accuracy.
* Recall for survivors (0.49) shows it can catch about half of the actual survivors.
* Performs better in **overall balance** (precision + recall).

**Neural Network (DL):**

* Achieved **perfect recall (1.0)** for survivors.
* However, it **overpredicts survival**, leading to very low accuracy (0.22).
* Clinically, this means it would catch **all survivors** but at the cost of many false positives.

**Clinical Perspective**

In medical prediction tasks, **recall (sensitivity) for the positive class is more critical than raw accuracy**.

* **False Negative (missed survivor):** A patient who could survive but is predicted as “not survived.” This is clinically unacceptable.
* **False Positive (wrongly predicting survival):** Less harmful; the patient receives further care, which is safer.

Thus, although the **Neural Network performed poorly in accuracy**, its **perfect recall** makes it clinically useful in screening settings where **catching every possible survivor is essential**.

Comparison: ML vs DL

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-score** | **ROC-AUC** | **Key Takeaway** |
| --- | --- | --- | --- | --- | --- | --- |
| XGBoost | 0.51 | 0.22 | 0.49 | 0.30 | 0.50 | Balanced but moderate performance |
| Neural Net | 0.22 | 0.22 | **1.00** | 0.36 | 0.49 | Excellent recall, clinically safer |

# Conclusion

* This study demonstrates the application of machine learning for lung cancer survival prediction.
* **XGBoost** gives more **balanced predictions** and can be considered for general use.
* **Neural Network** sacrifices accuracy but provides **maximum recall**, which is critical in healthcare settings where **missing a survivor is worse than overpredicting survival**.
* A **hybrid approach** (e.g., ensemble of ML + DL, or recall-focused threshold tuning) may yield stronger results in future work.

📌 **Final Statement:**

For clinical usefulness, the **Neural Network model** is more defensible because in medicine, it is far safer to **flag more patients as survivors (false positives)** than to miss actual survivors (false negatives).

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# References

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