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Modeling Survival Outcomes in Eye Cancer Patients Using Advanced Statistical and Machine Learning Approaches

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Abstract: Although uncommon, eye cancers present a serious threat to both vision and overall survival. These malignancies include retinoblastoma, uveal melanoma, and primary intraocular lymphoma. This study employs advanced survival-analysis techniques to explore prognostic factors and to model patient outcomes using data from 5,000 clinical cases. The Kaplan–Meier estimator, Cox proportional-hazards regression, and Random Survival Forest algorithms were applied to estimate survival probabilities and compare model performance. Key determinants of survival included age, tumor stage, gender, and specific genetic markers. Machine-learning models demonstrated superior predictive accuracy relative to traditional methods, suggesting significant potential for individualized prognosis and therapy planning. The findings highlight the value of combining classical statistics with ensemble learning to enhance ocular-oncology analytics and improve patient-specific care strategies.

Keywords: eye cancer, survival analysis, Kaplan–Meier, Cox proportional hazards, Random Survival Forest, prognostic modeling, ocular oncology.

I. INTRODUCTION

Ocular malignancies, though relatively rare, are clinically significant due to their impact on both visual function and life expectancy (He et al., 2022). The major intraocular cancers—retinoblastoma, uveal melanoma, and intraocular lymphoma—vary in etiology, genetics, and therapeutic response. Prognosis typically depends on patient age, tumor characteristics, and molecular profile (Stålhammar, 2022).

Recent developments in computational statistics and machine learning have enabled improved survival prediction, facilitating more personalized treatment strategies (Huang et al., 2025). Despite these advances, existing models often overlook complex nonlinear interactions among prognostic variables. The present study integrates classical survival-analysis approaches with ensemble learning to identify the most influential predictors of eye-cancer survival and to enhance prognostic accuracy.

II. OBJECTIVES

- 1) To analyze survival patterns among patients diagnosed with eye cancer.
- 2) To determine key prognostic variables influencing patient outcomes.
- 3) To compare the predictive power of traditional statistical models and machine-learning techniques.
- 4) To develop an integrated model for individualized survival estimation.

III. PROBLEM STATEMENT

Conventional prognostic tools in ocular oncology frequently show limited accuracy and seldom incorporate higher-order relationships between clinical and molecular features. There is therefore a need for robust, data-driven approaches that can manage censored data and population heterogeneity to yield reliable and interpretable survival predictions (Uno et al., 2011).

IV. METHODOLOGY

A. Data Collection and Preprocessing

A retrospective dataset comprising 5,000 patient records was obtained from clinical archives. Each record included demographic details, tumor characteristics, and relevant genetic information. Data cleaning and coding were conducted, and missing values were imputed using multivariate techniques to preserve statistical validity.

B. Statistical and Machine-Learning Methods

- 1) Kaplan–Meier Estimation: The Kaplan–Meier method (Kaplan & Meier, 1958) was used to estimate survival probabilities. Curves were generated for subgroups defined by age, cancer type, and stage to visualize differences in median survival times.
- 2) Cox Proportional-Hazards Model: A multivariate Cox regression (Cox, 1972) assessed the influence of demographic and clinical variables—including age, sex, tumor stage, and genetic markers—on survival. Proportional-hazards assumptions were verified through Schoenfeld residual analysis.
- 3) Random Survival Forest (RSF): To capture nonlinear relationships, a Random Survival Forest model (Ishwaran et al., 2008) was trained using 1,000 trees. Model validation employed five-fold cross-validation, and predictive performance was quantified using the concordance index (C-index) and Brier score.

C. Model Evaluation

Performance was compared across models using the C-index, log-rank tests, and Brier scores (Harrell et al., 1982). Higher C-index values indicated superior discriminative capacity, while lower Brier scores reflected more accurate predictions.

V. RESULTS

Kaplan–Meier curves demonstrated significant variation in median survival across cancer types; patients with retinoblastoma exhibited the longest survival durations. The Cox model identified age, tumor stage, and genetic markers as statistically significant predictors ($p < 0.05$).

The RSF model achieved a C-index = 0.896, surpassing the Cox model (≈ 0.85), thereby confirming the advantage of ensemble methods in handling high-dimensional and heterogeneous data. Variable-importance analysis ranked age, tumor stage, and genetic features as the strongest determinants of survival. Notably, certain genetic variants appeared to exert a protective influence, a finding warranting further genomic investigation.

VI. CONCLUSION

This study confirms that advanced survival-analysis techniques can substantially improve prognostic modeling in ocular oncology. The Random Survival Forest model produced the most accurate survival estimates, supporting its application in personalized treatment planning. Future research should aim to integrate molecular-omics data and validate predictive models across diverse demographic populations to enhance generalizability and clinical adoption.

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