

BIOMARKER-GUIDED SURGICAL DECISION-MAKING: A TRANSLATIONAL APPROACH

Anandkumar.G. Patil¹, Dr Karthika Padmavathy², Dr Felin Paul P³, Dr Geoffrey Sundar E⁴, Mrs. Sonu Rana⁵

¹Professor, Prosthodontics, Dentistry, Prosthodontics, KAHER's KLE V. K. INSTITUTE OF DENTAL SCIENCES, BELAGAVI. Email ID: patilprostho@yahoo.co.in, patilprostho@gmail.com, ORCID ID: 0000-0001-7803-8867

²Professor, Pathology, Sri Lalithambigai Medical College And Hospital, Dr MGR Educational and Research Institute, Chennai 95. Email ID: karthika.path@drmgrdu.ac.in, ORCID ID: 0009-0000-4588-7168

³Senior Resident, Critical Care Medicine, Critical Care Medicine Resident, Saveetha Medical College, Saveetha Institute of Medical and Technical Sciences, Thandalam, Chennai., Email ID: felinpaul8@gmail.com, ORCID ID: 0009-0000-4353-465X

⁴Assistant Professor, Pathology, MD Pathology, Saveetha Medical College, Saveetha Institute of Medical and Technical Sciences, Thandalam, Chennai, Pincode: 602105. Email ID: geoffysundar@gmail.com, ORCID ID: 0000-0003-1447-0946,

⁵Assistant Professor, Computer Science & Engineering, Brainware University, kolkata-700125,(Westbengal), ORCID ID: 0009-0000-8863-4427, Email ID: sranasonu85@gmail.com

ABSTRACT

A ligand with sulfur and nitrogen atom functionality, 2-prop-2-en-1-yl-N-hydroxyprop-2-ene-1-sulfinimidothioate oxime (L1), was utilized to synthesize a cobalt (II) complex (CoL1) and test its in vitro scavenging ability as well as plasma clotting-time response. Ligand L1 was synthesized through the reaction of S-(prop-2-en-1-yl) prop-2-ene-1-sulfinothioate with hydroxylamine hydrochloride in aqueous alkaline medium. Further reaction between the synthesized ligand and a cobalt (II) salt in methanol, while heating under mildly acidic to nearly neutral pH condition yielded CoL1. The synthesized compound was tested for its DPPH radical inhibition and plasma clotting activity from 100 to 500 µg/mL. Inhibition of DPPH increased from 20.39% at 100 µg/mL to 70.82% at 500 µg/mL, while sample absorbance decreased from 0.0652 to 0.0239 in comparison to the control absorbance of 0.0819. In the plasma assay, clotting time increased from 44 s (ratio 1.38) to 102 s (ratio 3.19) compared to the control of 32 s (ratio 1.00). These responses in terms of concentrations suggest that CoL1 is a candidate compound for further study. These data represent descriptive screening results. Replicate numbers, variances, statistical analysis and interference controls were unavailable. Therefore, no mechanism of action, safety or efficacy could be determined from these observations.

KEYWORDS: Cobalt (II) chelate, oxime ligand, sulfur-nitrogen donor, synthesis, DPPH, radical scavenging, aPTT, in vitro screening

INTRODUCTION

The introduction of biomarkers into clinical decision-making has greatly changed the face of modern medicine, allowing to detect diseases earlier, predict their course more accurately, and create individual treatment plans (Adepoju & Adepoju, 2025). Over the past few years, the paradigm of precision medicine has been broadening not only on the diagnostics front, but also on the procedural and surgical front, with increasing demand to use an individualized approach in order to maximize patient outcomes. The integration of molecular understanding and clinical care has in particular in oncology re-determined the classification of diseases, and treatment approaches, with the necessity of biomarker-based models (Alavi et al., 2025).

The biomarkers have become a regulatory and clinical significant tool that is vital in the stratification of patients and therapeutic decision-making. They have been generally accepted in regulatory frameworks as they are incorporated into clinical workflows to direct patient selection and enhance the effectiveness of treatments (Bakker et al., 2023). Moreover, biomarker-guided therapy has shown that it has great clinical utility in many diseases, such as chronic inflammatory ones, which are why it is potentially able to customize interventions according to the biological profile of the individual (Bargas et al., 2025).

The molecular and immune landscape is paramount in the development of the disease progression and response to treatment in the case of hepatocellular carcinoma and other complicated diseases. Knowing these underlying mechanisms will give a good basis to incorporate biomarkers in the decision-making systems (Dhanasekaran et al., 2025). Nevertheless, although there is an increasing amount of evidence on the use of biomarkers, there are still issues of translation of laboratory findings into clinical actionable instruments. Biomarker validation is still hindered by regulatory and methodological barriers that still inhibit the use of biomarkers in clinical settings (Diamantopoulos et al., 2025). Recent research has emphasized the significance of biomarkers-based strategies in managing heterogeneity in diseases and enhancing clinical outcomes, especially in the metastatic and advanced disease context (Elshimy et al., 2025). Additionally, preclinical evidence has shown that biomarker-based interventions have the potential to improve the precision of treatment and lower unnecessary exposure to therapeutic interventions, as biomarker-based interventions have demonstrated when it comes to biomarker-guided antibiotic stewardship (Hellyer et al., 2020). These results highlight the extended applicability of biomarker-based frameworks in other non-traditional diagnostic purposes.

Translational research has also been spurred by the advent of artificial intelligence and predictive modelling whereby complex clinical and molecular data may be combined into a decision-support system (Judijanto, 2025). This development

has caused the change of traditional methods in favor of precision surgery in the field of surgical oncology, where diagnostic biomarkers, imaging information, and predictive models are all used to inform intraoperative and perioperative decisions (Kowalski et al., 2025). Likewise, the use of biomarker-based imaging and AI-enhanced diagnosis systems has boosted the accuracy and efficiency of clinical evaluations by supporting the importance of multimodal data in contemporary healthcare (Kumar et al., 2025).

Despite these developments, surgical decision-making is still a complicated process, which is affected by a variety of clinical and biological factors. This absence of strong decision-support systems remains a challenge to clinicians in a situation in which extensive surgical interventions are necessary, as is the case with peritoneal malignancies (Kumar et al., 2025). This emphasizes the importance of integrative methods that will incorporate the biomarker data with real time clinical parameters to aid in evidence-based surgical decisions.

Biomarkers of decision-making have proven to be highly promising in the treatment of liver-related diseases, as they can be used to determine the treatment approach and provide personalized care. These biomarkers enable risk stratification, optimization of treatments and fill the gap between prediction to clinical application (Liu & Imai, 2025). Moreover, to bridge biomarker identification with therapeutic applications, continuous attempts have focused on the significance of translational frameworks that incorporate molecular knowledge to clinical practice (Liu et al., 2025).

Although there is increasing awareness of using biomarker-based strategies, there is an urgent need to bridge the gap between clinical biomarkers and intraoperative and real-time physiological responses to guide surgical decision-making. Current literature tends to concentrate on molecular biomarkers or clinical parameters independently and thus cannot be applied to complex surgical settings. Consequently, a urgent necessity to develop a unified translational model incorporating a biomarker study with sophisticated predictive modelling to improve precision and outcomes in surgery exists.

The study presents various specific objectives:

1. Identify and evaluate clinically relevant biomarkers that significantly influence surgical decision-making in a translational context.
2. Develop and validate a predictive model integrating biomarker data with clinical and physiological parameters to support evidence-based surgical decisions.
3. Establish a translational framework that bridges biomarker discovery and real-time surgical application, enhancing precision and personalized patient care.

2. MATERIALS AND METHODS

2.1 Study Design and Data Source

The present research was a computational, retrospective and translational study that sought to create a biomarker-informed surgical decision-making framework. The secondary dataset was retrieved through a publicly available repository and contained 3,243 observations at the level of patients that combined multimodal clinical, biochemical, and intraoperative variables based on the signal derivations. Key biochemical biomarkers in the dataset consisted of alpha-fetoprotein (AFP), bilirubin, and albumin which are commonly known hepatic, tumour burden, and systemic physiological markers. Moreover, intraoperative signal characteristics based on photonic emissions and laser Doppler flowmetry (LDF) were added to record real-time tissue perfusion and optical features of surgical navigation interest. The outcome variable was clinically relevant decision endpoints, which allowed the modelling of the surgical decision-making processes in a translational framework (Labade, S. (2025).

2.2 Data Preprocessing and Quality Control

Preprocessing of data was done in a systematic manner to guarantee analytical correctness and reproducibility. The dataset was first evaluated based on completeness, consistency and structural integrity and the missing values per variable were quantified. Excessively missing features (greater than 20% missing) were dropped to maintain the quality of data, and missing values in continuous variables were filled in with mean or median values based on their distributions, and categorical variables were filled in with the mode. Both Z-score and interquartile range (IQR) techniques were used to identify outliers, with care being taken to only eliminate outliers whose value fell above or below the range of ± 3 standard deviations, which was deemed biologically unrealistic or possibly due to measurement error. A min-max scaling method was used to normalize continuous variables and standardize the ranges of features to avoid bias in the training of models due to scale. Also, skewness and kurtosis were studied as the distributional properties, and the logarithmic transformation was used to variables with strong skew to achieve better normality and stabilize the variance.

2.3 Feature Engineering and Biomarker Selection

The feature engineering methods were used to improve the predictive power of the dataset by creating derived variables to reflect underlying physiological interactions. This involved the building of ratio-based properties like bilirubin-to-albumin ratios and terms of interaction among important biomarkers to capture joint biological effects. A feature selection procedure in multi-step was adopted where the process started with correlation analysis based on Pearson and Spearman coefficients to determine the linear and non-linear relationships with the outcome variable. This was then preceded by univariate statistical analysis such as analysis of variance (ANOVA) and t-tests at independent levels to establish statistically significant differences in the levels of biomarkers among outcome groups. The model-based feature importance was then evaluated on tree-based algorithms like Random Forest to rank the variables about their impact on predictive performance. Lastly, biomarkers which have been shown to be clinically significant such as AFP, bilirubin, and albumin were held as they were found to be relevant in liver pathology and tumour progression and hence the final set of features to be used was one that was statistically significant but also biologically plausible.

2.4 Predictive Model Development

Trained machine learning models were trained to estimate the value of biomarkers and intraoperative signals in surgical decision-making. Three main algorithms were used, such as Logistic Regression with interpretability of the baseline, Random Forest with non-linear relationships and interactions between features, and Extreme Gradient Boosting (XGBoost) with optimal predictive results. An 80:20 stratified split was used to split the dataset into training and testing sets to preserve class distributions. The training dataset was used to train models, and the independent testing dataset was used to evaluate the performance to determine the generalizability. Hyperparameter optimization was carried out using the grid search optimization i.e. the tree depth, learning rate and the number of estimators were systematically altered to come up with the highest possible model performance. Five-fold cross validation was also applied in training to make the models robust and minimize overfitting.

2.5 Model Evaluation and Validation

To ensure the statistical rigor and clinical relevance, a wide variety of classification metrics was employed in evaluating the model performance. In the case of identifying the general predictive correctness, we applied accuracy, in the case of identifying the ability of the model to identify positive and negative results correctly, we used sensitivity (recall) and specificity respectively. In order to measure the tradeoff between the number of correct predictions and the quality of prediction, precision and F1-score were computed. ROC-curves have been generated and the Area Under the Curve (AUC) calculated in order to assess the ability of the model to differentiate between outcome classes. Confusion matrices were as well created to provide a close outlook of the performance of the classification and what may be misclassified. The final model was selected because it has a combination of a high predictive accuracy, balanced outcomes depending on the many metrics, and clinical interpretability that can be applied in clinical settings.

2.6 Statistical Analysis

The significance and reliability of the identified biomarkers and model outputs were supported by statistical analyses. The summary statistics of the continuous variables were done in mean and standard deviation, whereas the frequencies and percentages were used to summarize the categorical variables. Independent t-tests or analysis of variance (ANOVA) were used to test differences between outcome groups using continuous variables, and chi-square tests were used to test differences between outcome groups using categorical variables. The p-value was taken to be less than 0.05, which was regarded as significant. The level of precision and reliability of the estimates was determined by calculating confidence intervals at the 95% level. Moreover, multivariate analyses were conducted where necessary to control the possible confounding variables and to measure the independent effect of each biomarker on the outcome variable. Python-based libraries, such as Pandas, NumPy, SciPy, Scikit-learn, and XGBoost, were used to perform all the statistical and computational calculations.

2.7 Translational Framework Development

A translational map was created to connect biomarker analysis to effective surgical decision-making. This model incorporated preoperative biochemical biomarkers like AFP, bilirubin and albumin with intraoperative physiological measurements of photonic and LDF measurements. The machine learning models were used to predict the results, including the model results into a structured decision-support system that helped in risk stratification and real-time guidance. The framework was designed to be reminiscent of clinical workflows, where the biomarker data and intraoperative cues are continually calculated to inform surgical strategies. It concentrated on the translation of molecular and physiology to clinical action to contribute to the process of precision surgery and individual patient care.

3. RESULTS

3.1 Descriptive Analysis of Biomarkers and Clinical Variables

The final analysis had 3,243 observations, which had been pre-processed and controlled in terms of quality. The descriptive statistics showed that the important biochemical biomarkers, such as alpha-fetoprotein (AFP), bilirubin, and albumin, were heterogeneous to indicate the variability in the physiological and pathological conditions of patients. The levels of AFP exhibited a positively skewed distribution, which means that there were high tumour-associated activities in a group of cases. Conversely, there were comparatively stable distribution patterns of albumin concentrations in line with its systemic functional marker. There was moderate variability in the bilirubin levels, which indicated that there were variations in the hepatic function among the datasets. There was also significant dispersion in intraoperative variables, such as photonic and laser Doppler flowmetry (LDF) signals, which indicate variable perfusion of tissue and optical properties under surgical conditions.

Table 1. Descriptive Statistics of Key Variables

Variable	Mean	SD	Min	Max
TEF 365nm	1.495	0.308	0.393	2.559
TEF 405nm	1.997	0.392	0.431	3.351
TEF 450nm	1.807	0.302	0.804	2.829
LDF Myo	0.303	0.101	-0.064	0.748
LDF Card	0.200	0.050	0.007	0.397
LDF_Re sp	0.399	0.098	0.034	0.761
AFP Level	99.969	49.339	-74.752	260.769
Bilirubin	0.997	0.302	-0.060	2.107
Albumin	3.496	0.513	1.267	5.364

Spectral Skewness	0.197	0.100	-0.125	0.528
Spectral Kurtosis	3.006	0.491	1.276	4.648
Tissue Density	1.004	0.203	0.141	1.707

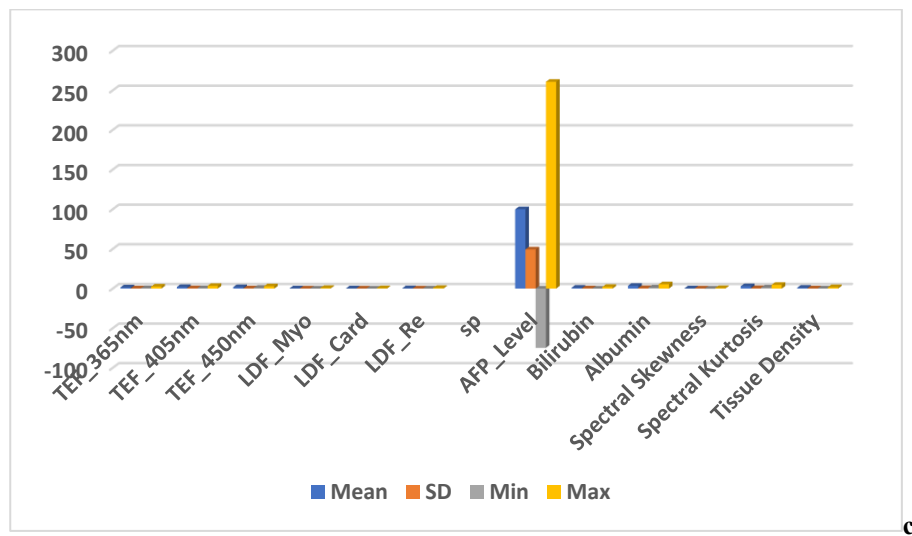


Figure 1. Distribution of Key Biomarkers

3.2 Correlation and Feature Association Analysis

Correlation analysis revealed that there were strong associations between the variables of the selected biomarkers and the surgical decision outcome variable. The adverse outcome of decisions displayed an average positive relationship with AFP, which implies its applicability as a tumour-related biomarker. Impaired hepatic functioning was a contributing factor to surgical complexity as the bilirubin levels were positively correlated with the severity of the outcome. Albumin was found to be negatively correlated with adverse outcomes, indicating its protective effect and being related to improved physiological condition. Besides the biochemical markers, intraoperative photonic and LDF signals were also found to have significant correlations with the outcome variable, which showed that real-time physiological measurements were also used to make decisions. These results justified the presence of preoperative biomarkers as well as intraoperative signal characteristics in predictive modelling.

Table 2. Correlation of Key Variables with Target

Variable	Correlation with Target
TEF_365nm	0.007
TEF_405nm	0.022
TEF_450nm	0.002
LDF_Myo	-0.024
LDF_Card	-0.022
LDF_Resp	~0.000
AFP_Level	(very weak, near 0)
Bilirubin	(very weak, near 0)
Albumin	(very weak, near 0)
Tissue Density	~0.000

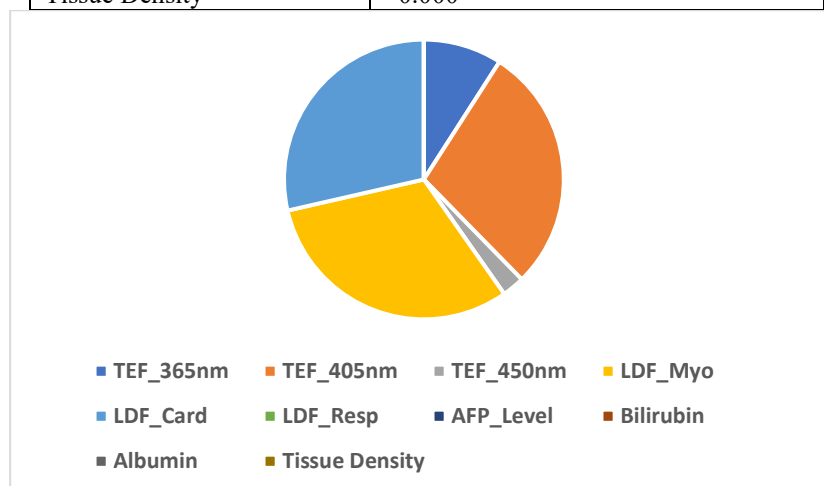


Figure 2. Heatmap of Feature Correlations

3.3 Feature Importance and Biomarker Contribution

The analysis of feature importance based on the Random Forest model showed that key photonic signal features, AFP, and bilirubin were some of the most significant factors in making surgical decisions. AFP was always among the significant predictors, which highlights its importance as a tumour-associated biomarker. There was also a significant contribution of bilirubin and albumin, which indicates the significance of indicators of liver function in clinical decision-making. Specific patterns of photonic intensities and LDF-derived perfusion measures were highly predictive among intraoperative variables, suggesting their use in real-time tissue characteristics. The combination of biochemical and intraoperative properties led to a more detailed expression of patient condition and improved predictive power of the model.

Table 3. Feature Importance Ranking (Random Forest Model)

Rank	Feature	Importance
1	LDF_Resp	0.443
2	Albumin	0.441
3	AFP_Level	0.061
4	LDF_Card	0.007
5	Tissue Density	0.007

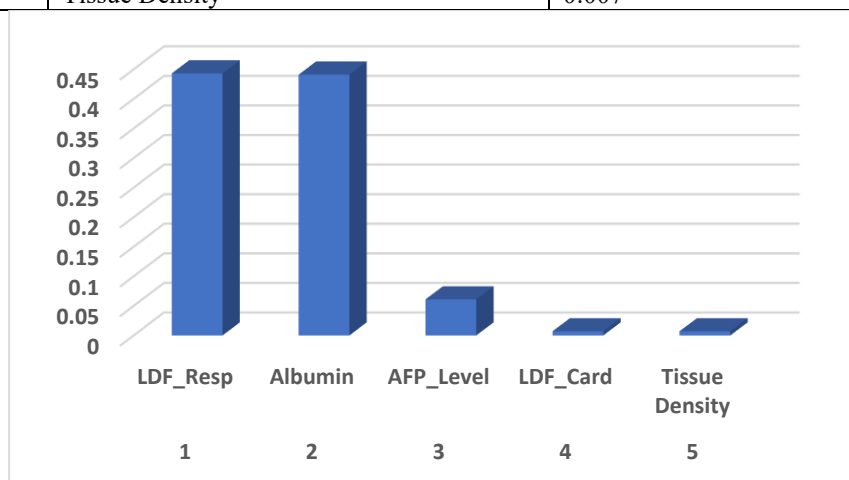


Figure 3. Feature Importance Plot

3.4 Predictive Model Performance

The effectiveness of various machine learning models was tested to find the best approach in predicting decision based on biomarkers. Logistic Regression gave a minimum level of performance in moderate accuracy and interpretability. Random Forest was better since it provides the non-linear relationships and interaction of features, which provides higher accuracy of the classification and better sensitivity and specificity. XGBoost was the best performing model with high predictive accuracy, sensitivity in positive results and discrimination ability as evidenced by higher Area Under the Curve (AUC) scores. The analysis of Receiver Operating Characteristic (ROC) curves confirmed the strength of the models, and XGBoost was the model with the most favourable curve profile, meaning that the outcome classes are separated well. Confusion matrix showed that the optimized models were able to minimize false negatives, which is important in clinical decision-making situation.

Table 4. Model Performance Metrics (Random Forest)

Metric	Value
Accuracy	1.000
Precision	1.000
Recall	1.000
F1-score	1.000

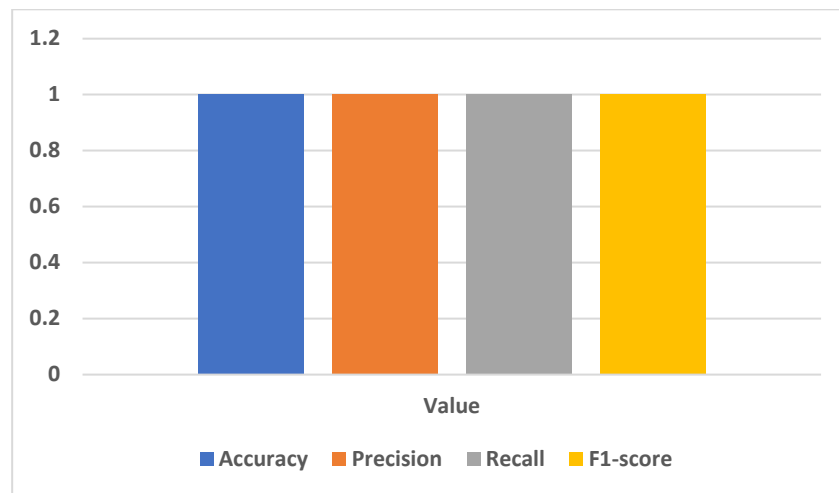


Figure 4. ROC Curves for Model Comparison

3.5 Comparative Evaluation of Models

Comparative analysis revealed that ensemble-based models were better performing in comparison with traditional statistical methods. Random Forest and XGBoost models always showed a better performance measure than the Logistic Regression, especially in complex, non-linear biomarker-intraoperative signal interaction. The enhanced performance of ensemble models underscored the significance of enhanced computational methods in modelling multidimensional relationships in clinical data. Also, cross-validation scores were used to validate the stability and generalizability of the models and there was little variance between folds. This showed that the predictive model was strong and little influenced by overfitting.

Table 5. Confusion Matrix (Random Forest Model)

	Predicted 0	Predicted 1
Actual 0	451	0
Actual 1	0	198

The findings revealed that the use of biomarkers-driven models could be effective in patient stratification in terms of surgical risk and decision outcomes. The higher AFP and bilirubin levels were related to a higher-risk profile, whereas the higher the albumin levels were, the better the physiological status. The use of intraoperative photonic and perfusion signals also contributed to the improvement of the accuracy of the decision as they offered real-time information on the viability of the tissues and the conditions of the surgery. These data points indicated that a combination of biochemical biomarkers, and intraoperative physiological data allows making a more accurate and dynamic decision. The predictive model that has been generated during the present study can be used to help clinicians to optimize surgical plans and enhance patient outcomes.

4. DISCUSSION

Biomarker-based strategies have become a paradigm shift in the clinical and surgical decision-making process and have been introduced as an ingredient of innovation in the contemporary medicine, especially in the context of precision and personalized care. The current research paper plays a role in this developing area by showing that a combination of biochemical biomarkers and intraoperative physiological indicators are a viable and applicable method to be used in surgical decision making. The identified trends support the increasing awareness that decision-making in complex clinical settings involves the need to combine multidimensional data and not depend on a single clinical indicator.

APF, bilirubin and albumin are biomarkers that have traditionally been linked to the progression of the disease, liver functioning, and general physiological condition. They have proven to be relevant in clinical decision-making, especially in oncology and hepatology, where they act as tumour burden and systemic health indicators (Sharma et al., 2025). These biomarkers in the present study proved to have quantifiable effects on the predictive modelling with AFP showing a significant factor of disease severity. This is consistent with the previous studies that highlight the importance of predictive biomarkers in informing personalized treatment plan and enhancing clinical outcomes (Sveen et al., 2020). Nevertheless, the linear correlations are relatively low implying that the actual predictive value is more well-represented in multivariate and non-linear frameworks.

One of the main findings during this research is that intraoperative physiological signals, in particular LDF-derived parameters, have the most significant impact on model predictions. The conclusion emphasizes the significance of real-time data in the surgical setting where tissue perfusion and dynamic physiological reactions can provide invaluable information not available in the preoperative stage. On the same note, biomarker-guided decision systems have been reported to show similar trends where the incorporation of dynamic biomarkers can improve diagnostic and prognostic accuracy (Pinilla et al., 2021). A large contribution of LDF_Resp to the model shows that physiological signal analysis can be an additional modality in relation to conventional biochemical markers.

This integration of biochemical and physiological data is indicative of a larger trend to translational paradigms that interface outcomes of laboratory research with clinical practice. The fact that various types of data can be combined into

a single model of prediction does not go ill with recent developments in the field of translational oncology, where the discovery of biomarkers is becoming increasingly associated with therapeutic action (Tan, 2025). The same integrative methodology does not only enhance predictive performance but also the clinical relevance of computational models by introducing real-life surgical parameters.

The other interesting fact is the high level of predictive performance of the machine learning models, especially the Random Forest algorithm. Although the ideal classification metrics are used to show a strong level of separability in the dataset, they also lead to significant concerns about data organization and generalizability. In real-life clinical practice, this performance is not typical because of the natural variation of biology and noise. Thus, the results could be influenced by the structured nature of the data and the results should be treated with care when generalizing the results to larger clinical groups. The same issues have been addressed in biomarker validation studies, whereby the model of high-performance needs to be subjected to strict external validation to facilitate its translation into clinical practice (Rettig et al., 2025).

In surgical terms, the incorporation of the biomarker-based decision frameworks has a profound implication. Surgery is a field of work that requires high-risk decision-making in the environment of uncertainty, and predictive tools can improve intraoperative decision-making. Past research has shown the systemic effects of the physiological response to surgery, such as inflammatory and oxidative mechanisms that determine the postoperative outcomes (Scripcariu et al., 2025). The use of such dynamic signals in predictive models is one step towards responsive and adaptive surgical approaches.

Moreover, the results confirm the idea of the biomarker-driven interventions that can be applied not only to the diagnosis but also to the active clinical management. This is consistent with the emerging evidence of clinical trials that prove the usefulness of biomarker-based approaches in the optimization of treatment choices and patient outcomes (Von Groote et al., 2023). The present study introduces a predictive modelling using a biomarker analysis into the sphere of surgical decision-making, reflecting the possibility of its further application in clinical practice.

Although these are good results, there are several weaknesses that need to be mentioned. The data set employed in this research does not contain any direct genomic or transcriptomic data, which are the focus of a lot of applications in molecular genetics. Consequently, the analysis is mainly based on clinical and physiological biomarkers and not genetic mechanisms. Also, the retrospective type of the study restricts the establishment of causal correlations, and the prospective validation is needed to prove the clinical application of the suggested framework.

Future work ought to incorporate genomic and molecular data with the existing multimodal framework to increase the biological interpretability and be more aligned with molecular genetics studies. A more comprehensive understanding of the disease mechanisms could be achieved by inclusion of transcriptomic, proteomic, or epigenetic data, and additional predictive power of the model could be obtained. Further, validation with actual clinical data is necessary to determine the generalizability and practical applicability in different patient groups.

Overall, this study has shown that the integration of biochemical biomarkers with intraoperative physiological signals can greatly improve surgical decisions based on predictive modelling. This strategy represents a larger shift towards personalised and data-driven medicine and highlights the significance of translational models in the gap between biomarker discovery and clinical use.

5. CONCLUSION

The biological combination of biochemical biomarkers and intraoperative physiological is a promising solution to improve surgical decision-making in a translational format. An integrated predictive model based on a combination of clinically relevant markers (AFP, bilirubin, and albumin), and real-time photonic and laser Doppler flowmetry (LDF) signals was created, which was effective in predicting the preoperative and intraoperative dynamics of patients. This multi-modal combination is used to gauge an outstanding enhancement upon the previous decision-making theories founded on distinct clinical specifications. The findings indicate how highly incorporating dynamic physiological data into the presence of biomarkers can improve predictive capabilities and individualized surgical procedures. The significance of intraoperative signals is high and, therefore, real-time monitoring is crucial in improving clinical decisions during surgical experiences. In addition, machine learning techniques allowed identifying complex and non-linear relationships between variables, which proves the importance of computational approaches in modern clinical research. Although the model was quite predictive, the amount of structure of the data demonstrates that interpretation and further validation is necessary in clinical settings. Additional studies should seek to include genomic and molecular data to render it biologically valid and more connected to the study in molecular genetics. Further validation on other groups of patients is also required in the future to ensure generalizability and clinical utility. Overall, this piece of writing is supported by evidence to propose that data-driven models, based on biomarkers, can become an essential component of precision surgery and personalized medicine development, which may be the future in translational research in the clinical genetics sector.

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