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Laser-tissue interactions: A comparative analysis on synthetic and realistic datasets using machine learning and deep neural network techniques

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Abstract

In recent years, the use of lasers has increased in many applications, including highly sensitive applications such as tissue lasers. These applications require high precision due to their direct interaction with biological tissue. They also require a thorough understanding of the physical properties of the laser and its effects on biological tissue. Understanding laser parameters, selecting the most important and influential parameters, and developing a system capable of evaluating the classification process are essential to ensure the most appropriate use of lasers in clinical applications. This study presents a new, high-quality dataset, publicly available to researchers, divided into two parts: the synthetic dataset, which simulates ideal laser conditions, and the realistic dataset, which simulates realistic laser conditions in terms of some noise. The dataset, both synthetic and realistic, contains many important properties of laser-tissue interactions, such as wavelength, pulse duration, thermal conductivity, and other features. The features are classified relative to the laser beam to select the best and most effective features for the tissue using XGBoost and SHAP before being used with classifiers. The dataset provided high accuracy when evaluated using six different classifiers: three modern classifiers and three traditional classifiers. This study aims to present a comprehensive workflow, from data generation to results acquisition and analysis.

Keywords: Deep Learning; Deep Neural Network; Feature Selection; Laser-Tissue Interactions; Machine Learning

1. Introduction

The interaction of lasers with tissues and the introduction of lasers into clinical medicine and dentistry have been among the most discussed topics of the last two decades, with the increasing use of lasers in various applications, including highly sensitive applications, such as tissue interaction and even in the detection and treatment of cancer cells [1].

In this type of research, it is crucial to consider the optical and physical properties of lasers and biological tissues. Understanding the basic concepts of both tissue biology and laser physics ensures optimal therapeutic results.

Tissues constantly interact with light, and light helps stimulate tissues to create many important elements for the body, such as melanin production or vitamin D synthesis [2].

Lasers are one of the light sources, specifically monochromatic light sources, which emit a single, predetermined wavelength. Wavelength is one of the most important characteristics of lasers when working with biological tissues. Wavelength affects the distance the laser can penetrate into tissue, which absorbs the wavelength by special photoreceptors (chromophores) such as hemoglobin, oxyhemoglobin, and melanin [3].

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Tissues exhibit different responses to the type of laser beam they receive and to the parameters that affect it, such as wavelength, pulse duration, energy density, thermal conductivity, flux, and the beam pattern. Therefore, this study ensures that all of these parameters are accurately captured in a new dataset that has been created and made publicly available to researchers [4]. The dataset, which was created entirely synthetically using Python, contains two parts. The first is the synthetic dataset, which simulates a laser under ideal conditions, without any distortion or noise, which is unlikely in real-life applications. However, it was created for comparison with the second dataset, the realistic dataset. In the realistic dataset, noise was added at certain rates to ensure that the radiation was similar to that of laser beams in practical experiments, ensuring the quality of the models being tested.

All features were initially tested using XGBoost and SHAP for both datasets, to analyze the importance of each feature for the classification process and to analyze the reasons for the differences in values between the two datasets using XGBoost and SHAP.

To evaluate the results, six models were used: three state-of-the-art models (XGBoost, deep neural network, and LightGBM), and three traditional models (Random Forest, Support Vector Machines, and Logistic Regression). A large number of models were tested to compare the new models with models that have demonstrated high accuracy in previous research, as well as to ensure the accuracy of the dataset when used with different modeling methods.

2. Literature Review

With the proliferation of lasers, especially in recent years, and their penetration into many fields, research has increased on their interaction with materials and objects, including tissues, which are highly complex and sensitive.

Years ago, specifically in 1989, studies began examining the effects of monochromatic visible light on tissues and cells. It was observed that exposure to this monochromatic light enhances metabolic processes in cells depending on the wavelength and intensity of the monochromatic light [5]. These effects of lasers on cells have become evident in numerous other studies, which have demonstrated various cell responses to laser radiation, such as increased mast cell numbers and degranulation [6], and enhanced procollagen production in human dermal fibroblast cell cultures [7].

Many other studies have also examined the effect of parameters on tissues, such as the study on the speed of thermal ablation using lasers on chicken and pig tissues. However, the problem was the limited data used during the experiments [6].

The problem of limited data sets persisted in many other studies, where lasers of various power levels were used to evaluate burn depth in the tissues of several animals, such as cows and chickens. Although the study yielded significant results, the limited laboratory data used limited the possibility of replicating the experiment by other researchers [8].

Recent studies have also demonstrated the possibility of using artificial intelligence to distinguish tissue types using ultrasound waves. The study achieved good accuracy rates, but it also suffered from a limited data set, as the study did not provide a large, reliable database [9].

The AI revolution has produced numerous new laser datasets, and researchers have begun to create datasets that can be used in AI applications. One such dataset contains 2,000 laser images created using simulation systems [10].

These experiments and other studies that have used various techniques, such as optical tomography, sensitive infrared imaging, and tissue optical property estimation techniques, have primarily suffered from the lack of high-quality, open-source datasets. This study attempts to address this by providing a high-quality dataset that has been tested using several classification models, as demonstrated by the results [4, 11-13].

3. Research Methodology

This section presents the steps and methods used in this research, starting with the method of creating the dataset of both types, the ideal in the first case and the realistic in the second case, and the methods used to evaluate this model.

3.1. Dataset Creation

The first step is to create a high-quality dataset for model selection. Therefore, two versions of the dataset were created: the first is a synthetic dataset, simulating ideal conditions, and the second is a realistic dataset, simulating realistic experimental conditions. This way, the models will be fully tested and compared under all conditions.

The two datasets are generated using specialized mathematical functions for laser beam data generation. They contain the same parameters, such as wavelength and pulse duration. The difference between the two datasets is that the first is a synthetic dataset, simulating ideal conditions, while the second is a realistic dataset, with some noise and distortion added to it. 5% of the labels were inverted to simulate natural human error. After creating the two datasets, they are processed and split into equal training and test sets to ensure a balanced distribution of data during the evaluation process. Table 1 shows a sample of the data from the two datasets, the synthetic and realistic.

Table 1 A sample of the data from the two datasets, the synthetic and realistic

Dataset Type	Wavelength (nm)	Pulse Duration (ns)	Energy Density (J/cm^2)	Absorption coefficient (cm^{-1})	Thermal Conductivity (W/(m·K))	Fluence ($J/cm^2/ns$)	Beam Profile	Success
synthetic	623.4	2.17	12.8	6.34	1.92	5.90	0.214	1
Realistic	615.7 (±1.2%)	2.31 (±3.1%)	13.1 (±2.4%)	6.28 (±0.9%)	1.85 (±1.8%)	5.67	0.221	1
synthetic	892.1	0.87	8.4	8.15	3.67	9.66	0.108	0
Realistic	904.5 (±1.5%)	0.92 (±5.7%)	8.1 (±3.6%)	7.98 (±1.3%)	3.72 (±1.3%)	8.80	0.116	0

3.2. Model Evaluation

The next stage is testing the generated datasets using several new and traditional machine learning models. The first classifier is XGBoost, which uses a five-class crossover to ensure highly accurate feature selection and achieve the desired results. In parallel with XGBoost, LightGBM is used, which trains the model using the same data used with XGBoost. The two classifiers are then combined using a majority voting system to form a hybrid system that leverages the strengths of both classifiers. Deep neural network techniques are also used, as neural networks have a high capacity to handle numerical data, such as the one found in the dataset we created, and to select features with high accuracy. In addition to these techniques, traditional classifiers were used to provide high classifier diversity and to provide a solid baseline for comparison with existing research. Random forests, support vector machines, and logistic regression were used. Table 2 shows the parameters used for all classifiers.

Table 2 Parameters used for all Classifiers

Classifier	Parameter	Value
XGBoost	Learning Rate	0.01 to 0.3
	Max Depth	3 to 10
	Gamma	0.0 to 0.2
	Number of Estimators	50 to 300
	Subsample	0.5 to 1.0
Deep Neural Network	Optimizer	Adam optimizer (learning rate = 0.005)
	Epochs	30
	Batch Size	32
	Neurons	256 neurons (initial dense layer), 128 (second dense layer), 64 and 32 (Subsequent layers)
	Activation	ReLU activation

	Regularization	L2 regularization (λ = 0.01)
	Dropout Layer	Rate = 0.3
LightGBM	Number of Estimators	300
	Learning Rate	0.05
	Max Depth	7
	Random State	42
Random Forest	Number of Estimators	200
	Maximum depth	10
Support Vector Machines	Kernel	RBF
	Gamma	scale
Logistic Regression	Maximum Iteration	500

After all classifiers have completed their work, the results are augmented by combining the unwound predictions with the original features for meta-learning to evaluate performance (via confusion matrices and F1-scores). This process helps select the best classifier by determining the best F1-score value. This model, fully illustrated in Figure 1, is expected to improve the classifier selection process and increase the accuracy of laser-tissue interactions.

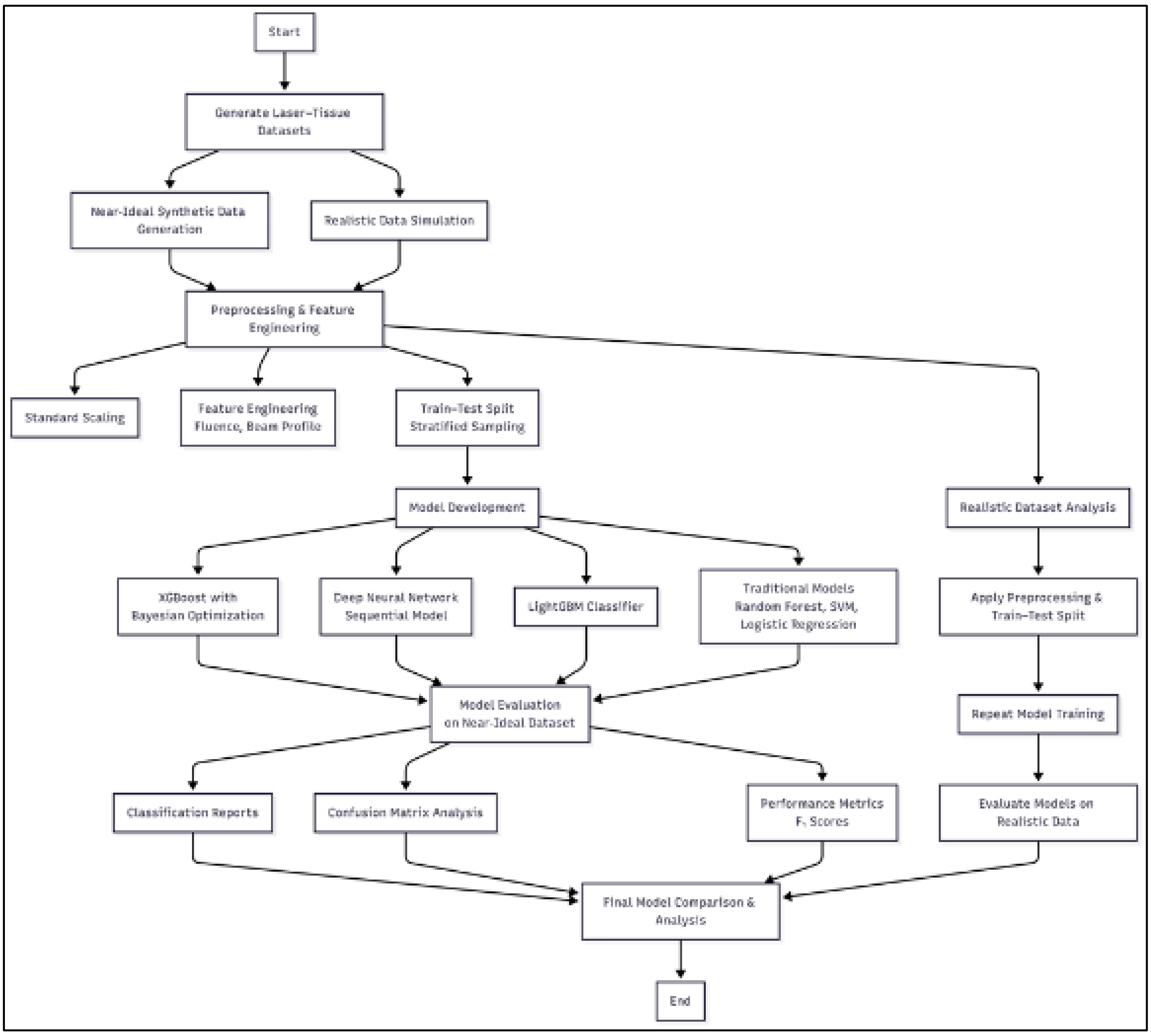

Figure 1 Proposed Model Diagram

4. Results and Discussion

This chapter details the results in terms of the performance of selecting the most important features from a synthetic and realistic dataset, then applying the techniques to both datasets and analyzing the results.

4.1. Synthetic and Realistic Datasets Features Importance

Since the generated dataset contains many parameters, it is important to analyze these features before proceeding to the actual evaluation of the dataset or model. This analysis will reveal important observations and conclusions about the laser-tissue interaction process. It should be remembered that this study deals directly with real tissue, so feature analysis will contribute to greater accuracy when conducting experiments under realistic experimental conditions.

Table 3 shows the standardized importance metrics. Thermal conductivity appears to be the most important feature in the SHAP-based analysis, with a standardized importance of 1 in both datasets. However, its importance in the XGBoost-based analysis yields different results: ≈0.39 in the synthetic dataset and ≈0.71 in the realistic dataset.

Table 3 Features Importance using XGBoost and SHAP

Feature	XGBoost - Synthetic	SHAP - Synthetic	XGBoost - Realistic	SHAP - Realistic
Thermal conductivity	0.388722	1.000000	0.705475	1.000000
Pulse duration	0.301435	0.906396	0.596496	0.626760
Absorption coefficient	0.316498	0.777739	0.603215	0.787267
Energy density	0.436423	0.398320	0.361968	0.414773
fluence	1.000000	0.261683	1.000000	0.645585
wavelength	0.018235	0.024720	0.107013	0.104520
Beam profile	0.019014	0.013957	0.144913	0.153100

In the case of thermal conductivity, we can consider the utility of the feature measured by SHAP to be more significant, as thermal conductivity is a very important factor in the laser-tissue interaction process, as it can cause tissue damage if the threshold for reasonable thermal conductivity is exceeded. Other features, such as fluence, demonstrated significant importance in the segmentation decision process. Fluence showed a high standardized importance in the XGBoost-based analysis, reaching 1 for both datasets. However, its importance in the SHAP-based analysis showed a discrepancy, reaching ≈0.65 for the synthetic dataset and decreasing to ≈0.26 when noise was added to the realistic dataset. This relatively large difference in importance suggests that relying on thermal conductivity as the primary feature may be more effective.

Pulse duration showed inconsistent results, with its importance decreasing in the SHAP-based analysis under realistic conditions, while its importance doubled in the XGBoost-based analysis under the same realistic conditions. This illustrates the difference between the usefulness of features in tree segmentation (used in XGBoost) and their actual predictive impact (used in SHAP).

The absorption coefficient feature showed consistent results across both datasets, confirming its importance as an important feature that is not significantly affected by noise, like other features.

The power density appears stable in the SHAP-based analysis but decreases significantly in the XGBoost-based analysis. Despite this discrepancy, it can be confirmed that power density is one of the most important features physically. However, this decrease may be due to its linear relationship with the results, which makes it less valuable for tree segmentation under noise.

The fluence effect shows the greatest discrepancy in the results. Despite the good results in the XGBoost-based analysis, where the value reached 1 for both datasets, the importance in the SHAP-based analysis is significantly lower, reflecting an overreliance on geometric features in the tree models.

Wavelength and beam profile appeared as the least important features among all features in both datasets, consistent with theoretical predictions for near-infrared laser systems.

4.2. Performance on the Synthetic Dataset

All results were tested and performance evaluated on the synthetic dataset in the first case, where all techniques demonstrated excellent predictive results due to the quality of the data. Table 4 shows the results of all classifiers on the synthetic dataset.

Table 4 Model Performance on the synthetic Dataset

Model	F1 Score
XGBoost	0.9930
Deep Neural Network	0.9803
LightGBM	0.9923
Random Forest	0.9854
SVM	0.9898
Logistic Regression	0.9526

In general, the newer classifiers demonstrated higher and more consistent results, with the XGBoost model achieving the highest F1 score of 0.9930, slightly ahead of LightGBM, which achieved a similar F1 score of 0.9923. The deep neural network model also demonstrated excellent results, albeit slightly lower than previous techniques, achieving an F1 score of 0.9803.

Traditional classification techniques demonstrated impressive results, with Random Forest, SVM, and Logistic Regression achieving F1 scores of 0.9854, 0.9898, and 0.9526, respectively. Figure 2 shows the confusion matrix for each model. The matrices show high power for all classification models, with the majority of misclassifications being limited to the borderline cases, giving all models high reliability and accuracy.

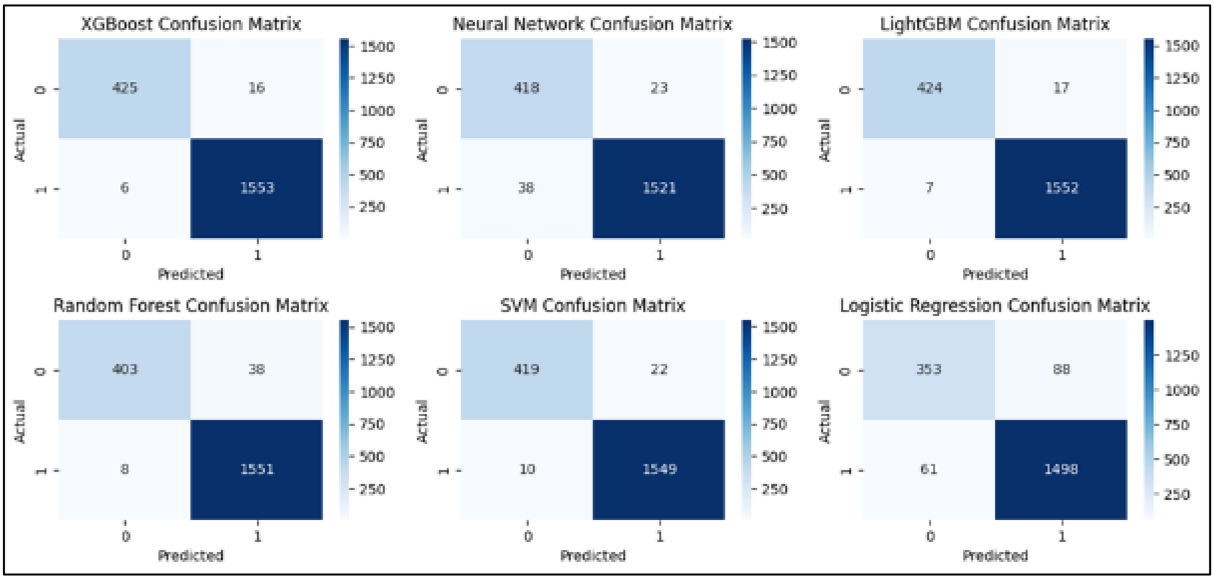

Figure 2 Confusion Matrices for the synthetic dataset models

4.3. Performance on the Realistic Dataset

The real test of the classifiers is with a realistic dataset, a dataset that mimics real-world data in terms of noise and interference. Table 5 shows the results of the classifiers on the realistic dataset. The classifiers performed well, although their results were slightly lower than those of the synthetic dataset, which is expected due to the addition of noise and interference.

Table 5 Model Performance on the Realistic Dataset

Model	F1 Score
XGBoost	0.9371
Deep Neural Network	0.9341
LightGBM	0.9330
Random Forest	0.9314
SVM	0.9393
Logistic Regression	0.9156

In general, the newer classifiers demonstrated higher and more consistent results in average, with the XGBoost model achieving the second highest F1 score of 0.9371, slightly ahead of deep neural network, which achieved a similar F1 score of 0.9341. The LightGBM model also demonstrated excellent results, albeit slightly lower than previous techniques, achieving an F1 score of 0. 9330.

Traditional classification techniques demonstrated impressive results, with Random Forest, SVM (the higher result), and Logistic Regression achieving F1 scores of 0.9314, 0.9393, and 0.9156, respectively.

Figure 2 shows the confusion matrix for each model. The matrices show high power for all classification models, with the majority of misclassifications being limited to the borderline cases, giving all models high reliability and accuracy.

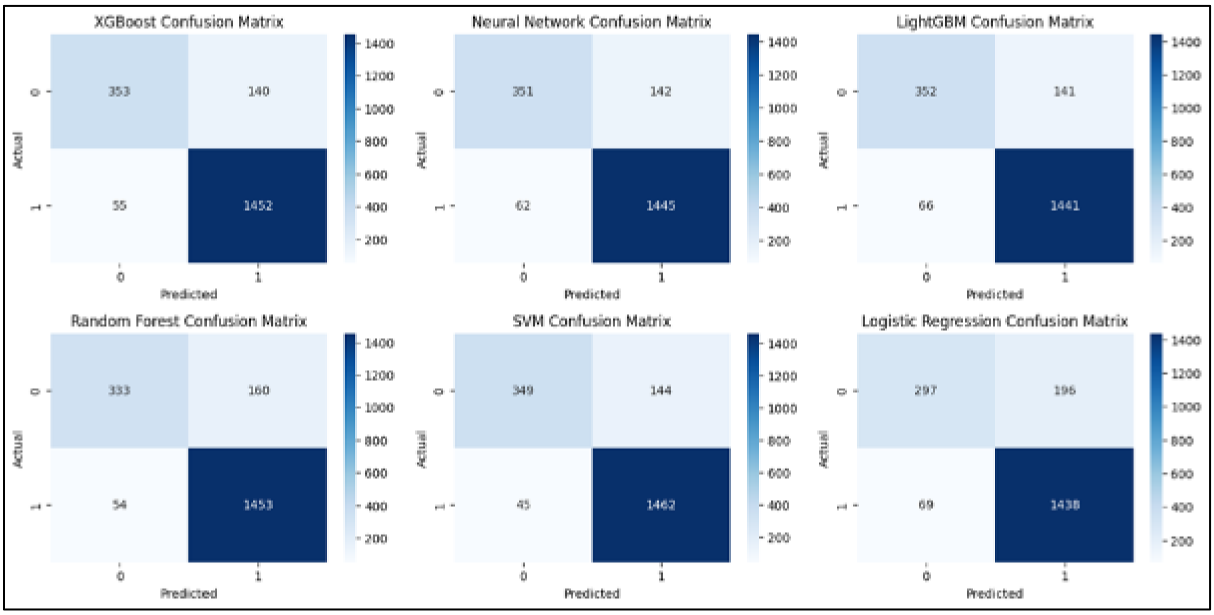

Figure 3 Confusion matrices for the realistic dataset models

5. Conclusion

The results demonstrated the high ability of the selected classification models to classify laser beams generated in new datasets and made them publicly available to researchers. This improved the laser-tissue interaction process and provided a highly accurate and safe alternative, especially since laser-tissue interaction is a sensitive process.

This study presented two datasets: the first was a synthetic dataset representing ideal laser conditions, while the second was a realistic dataset, which simulated realistic laser conditions in terms of noise and interference. This provided a comprehensive analysis for combining design models in terms of handling both synthetic and realistic data.

Six models were used, ranging from modern classification models, XGBoost, LightGBM, and a deep neural network. Three traditional classification models were also used: Random Forest, SVM, and Logistic Regression. Modern techniques demonstrated significant superiority overall, with two of the top three models with both synthetic and realistic data being from modern classification models. The only classifier among traditional classification models that achieved comparable results to modern classification models was SVM, which was among the top three classification techniques with both datasets.

This study provides two new datasets that can be directly used in many machine learning techniques that require high-resolution datasets. Both datasets, and the results they demonstrated with the six models used, demonstrated high quality, providing promising avenues for future research and potential clinical applications that require direct laser-tissue interaction.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

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