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Adopting Machine Learning to Automatically Identify a Suitable Surgery Type for Refractive Error Patients

Mustafa Ali Malla[a,b*], Omar Hussien Al-Beak[a,b], Duaa Mowafaq Hameed[a,b,] Marwa Mawfaq Mohamedsheet Al-Hatab[a], Raid Rafi Omar Al-Nima[a], Mohammed Sabah Jarjees[a] & Khalil A. K. Al-Maqsood[b]

[a]*Technical Engineering College, Northern Technical University, Iraq*

[b]*Directorate of Ninawa Health, Ministry of Health, Iraq*

[*]*Corresponding author: mustafa.ali@ntu.edu.iq*

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ABSTRACT

Refractive error is a visual impairment that arises when the ocular anatomy hinders the proper focusing of light onto the retina, the light-sensitive tissue layer located at the posterior region of the eye. This condition poses difficulties in achieving clear vision. Refractive error stands as the prevailing kind of visual impairment. The objective of this study is to classify two surgical approaches utilized in the treatment of refractive defects. Two commonly performed refractive surgeries are Photo-Refractive Keratectomy (PRK) and Laser-Assisted In-Situ Keratomileusis (LASIK). Artificial Intelligence (AI) encompasses a specific branch known as Machine Learning (ML), which is the focal point of this investigation. ML is dedicated to the advancement and use of algorithms that possess the capacity to acquire knowledge from data and enhance their predictive capabilities without explicit programming. The present study employs sophisticated ML methods to classify different types of refractive defect surgeries using a dataset of 124 samples obtained from Al-Rabee Hospital in Iraq, specifically focusing on corneal topography data. Two ML approaches, namely K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN), are employed to predict the kind of refractive defect surgery. The findings produced from the experiment demonstrated an accuracy rate of 90.32% for the KNN algorithm and a perfect accuracy rate of 100% for the ANN algorithm. Additionally, the KNN algorithm exhibited a sensitivity of 90% and a specificity of 90.54%. The study's findings indicate that the ANN classifier outperforms the KNN classifier.

Keywords: Refractive error; classification; k-nearest neighbor; artificial neural network

INTRODUCTION

The process of automating the development of analytical models is commonly referred to as Machine Learning (ML) in the field of data analysis. ML is a subfield of Artificial Intelligence (AI) predicated on the notion that machines possess the capacity to acquire knowledge from data, discern patterns, and render decisions autonomously, therefore obviating the need for human intervention. In contemporary clinical care, the field of ML has gained significant traction within the broader domain of AI research. This surge in popularity may be attributed to ML's remarkable precision in managing extensive datasets, aptitude for constructing statistical prediction models, and capability to estimate novel data instances. Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Least Absolute Shrinkage and Selection Operator (LASSO) are among the often-employed techniques in the field of ML(Caixinha and Nunes 2017). Nevertheless, previous ML models have been perceived as opaque entities due to their lack of clear articulation of knowledge (Yu et al. 2018). Human experts have the ability to provide reasons in a manner that is distinct from their non-human counterparts. The concept of explainable AI is now being introduced inside the domain of medicine. By offering consumers a comprehensible model that enables them to make justifiable judgments and verify the proper operation of the model (Adadi and Berrada 2018). Several medical fields, including ophthalmology (Akkara and Kuriakose 2019), radiology(Hosny et al. 2018) , (Al-Hatab et al. 2022), dermatology (Hogarty et al. 2020), pathology (Colling et al. 2019), pediatrics (Liang et al. 2019), gynecology (Desai 2018), oncology (Rattan et al. 2019), endocrinology (Gubbi et al. 2019), and cardiology (Johnson et al. 2018), have actively adopted AI advancements. In the past decade, significant advancements have been made in the field of refractive surgery, leading to the successful improvement of patients' overall quality of life. The cornea, located at the front of the eye, is a transparent, spherical structure that may be modified by various surgical interventions to enhance or alter the eye's focusing capabilities. Refractive surgery is a non-invasive method for correcting or enhancing visual acuity, which does not need surgical intervention. During several surgical procedures, it is possible to implant a lens into the eye (Abdelghany and Alio 2014). Figure 1. Presents the block diagram illustrating the process of automatically identifying the type of surgery.

The motivation of this study is to develop and verify the efficacy of a ML algorithm in the automated identification of an appropriate surgical procedure, specifically Laser-Assisted In-Situ Keratomileusis (LASIK) or Photo-Refractive Keratectomy (PRK), for patients with refractive errors. This approach aims to alleviate the burdensome and time-consuming process of manually selecting the treatment type, which also requires specialized expertise.

The primary contributions and originality of this work are as follows:

1. The present study focuses on the invention, implementation, and testing of an algorithm specifically developed for the automated selection of surgical types as a clinical decision support.
2. The utilization of ML algorithms is employed to develop a surgical selection methodology based on corneal metrics, including flat keratometry, steep keratometry, pachymetry (corneal thickness), and visual acuity assessment.

The remainder of this paper is organized as follows. Section 2 of this paper provides a comprehensive review of the existing literature pertaining to refractive surgery. Section 3 of this research provides a comprehensive overview of the materials and methods employed, encompassing the assessment and validation of performance. Section 4 presents the findings, concurrently. Finally, section 5 provides an analysis of the findings and discusses the resulting debates and conclusions.

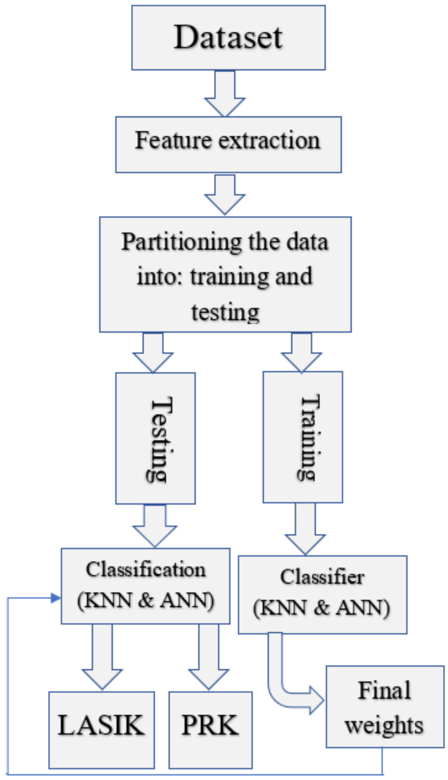


FIGURE 1. The proposed sketch for the required processing stages in this study.

RELATED LITERATURE SURVEY

This study is extension to previous several work where it considers the identification of corneal refractive surgery patients. In 2020, T. K. Yoo *et al.* developed a multiclass ML model that selects the laser surgery option including laser epithelial keratomileusis LASEK or (PRK), LASIK and small incision lenticule extraction (SMILE) on the expert level, multiclass XGBoost model was used and exhibited an accuracy of 81.0% and 78.9% when tested on the internal and external validation datasets, respectively (Yoo et al. 2020). In 2019, T. K. Yoo *et al*. proposed identification of candidate patients for corneal refractive surgery. This study applied ML to patients how may or may not be suitable for surgery (Yoo et al. 2019). In 2019, Kim T. *et al.* investigated the refractive surgery procedures. This work discussed the surgery types in-depth (Kim et al. 2019). In 2019, Malik S. *et al*. introduced a study that aimed to develop a general framework for recording diagnostic data so that ML can be more accurate and reliable by considering multiple features and to facilitate prediction of eye disease diagnosis like cornea based on symptoms using ML algorithms. Used algorithms included Decision Tree (DT), RF, Naive Bayes and ANN. The RF and DT algorithms' prediction rate is more than 90% as compared to more complex methods like ANN(Malik et al. 2019). In 2017, Fageeri S. *et al.* In his paper, intelligent ML algorithms are used to classify the type of an eye disease. Three ML techniques are during the investigation, which are Naïve Bayesian, SVM, and J48 DT. The obtained result showed that J48 classifier with 98.75% accuracy outperforms both Naïve Bayesian as well as SVM (Fageeri et al. 2017). In 2014, Torricelli *et al.* introduce 1067 refractive surgery candidates for LASIK and PRK which enrolled in the study, to evaluate exclusion criteria for patients who were not offered refractive surgery. Refractive surgery was performed in 657 (61.6%) patients, and 410 (38.4%) of all screened patients did not have refractive surgery. Abnormal corneal topography and low, or insufficient, corneal thickness remain the most common exclusion factors for corneal refractive surgery (Torricelli et al. 2014). In 2009, Wilson S. *et al.* presented the refractive surgery options with advantage and indications recommending an optimal option after carefully reviewing patient data (Ambrósio and Wilson 2003). This work aims to further explore the topic of refractive surgery by investigating the most appropriate form of surgery for applicants via the use of sophisticated ML algorithms. This study builds upon past research in the field.

METHODOLOGY

FEATURE EXTRACTION

A set of six features is extracted from each sample, which play a crucial role in determining the type of surgery. These features were manually recorded in an Excel datasheet and include age, flat keratometry (K1), steep keratometry (K2), Central Corneal Thickness (CCT), Sphere, and Cylinder or Astigmatism. Figure 2. Presents the flow charts for both K-Nearest Neighbor (KNN) and ANN describing complete proposed work, algorithm, dataset information.

The Pentacam device (McAlinden et al. 2011) was utilized to execute all the features mentioned earlier. Subjective measurements of sphere and cylinder were conducted, along with the utilization of multiple Auto Refractometers (AR)(Stoor et al. 2015)(Shneor et al. 2012). Two distinct classes represented the resulting outcome: 0 for LASIK and 1 for PRK. The appropriate surgical technique, namely LASIK or PRK, is accomplished by utilizing KNN and ANN algorithms, which analyses the characteristics provided in a real dataset.

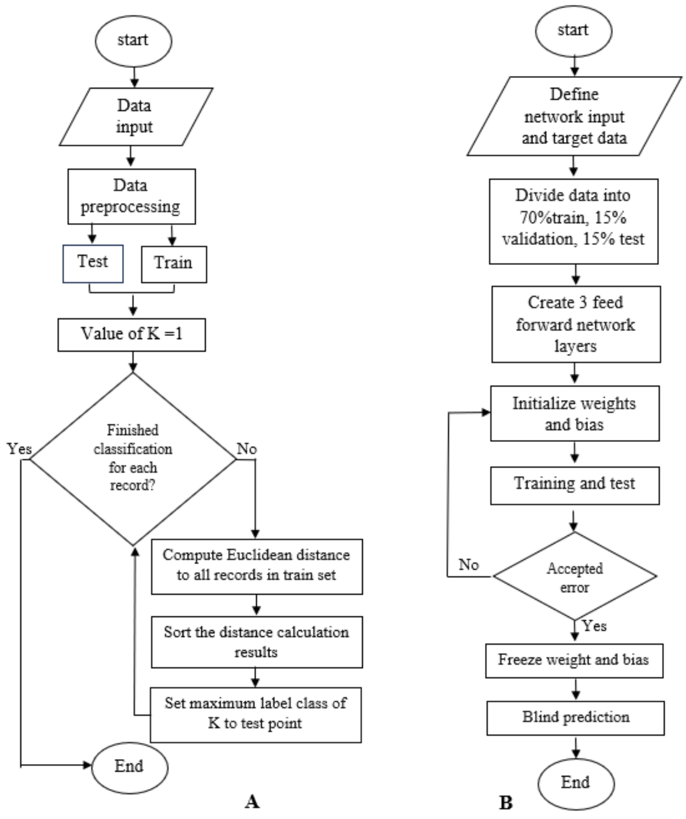


FIGURE 2. Presents the flow charts for both: (A) KNN and (B) ANN

CLASSIFICATION MODELS

The KNN algorithm employs proximity as a non-parametric methodology for classifying or predicting the grouping of an individual data point. The supervised learning approach is considered one of the most straightforward ML algorithms. This is attributed to its focus on the concept that points with similarities tend to be located close to each other. The approach is commonly employed for classification purposes and may also be utilized for regression or classification issues, (Mahesh 2018) as seen in Figure 3. Euclidean distance is elucidated using Equation (1) to compute the distance between two data points and Figure 4. Clearly describe the concept of Euclidean distance. A specific query data point is categorized by utilizing the Euclidean distance in conjunction with the categorized neighbor samples. The resulting equation is utilized to identify the nearest class to the requested data point. The parameter k in the KNN approach determines the number of neighbors that will be considered in the process of obtaining the final outcome.

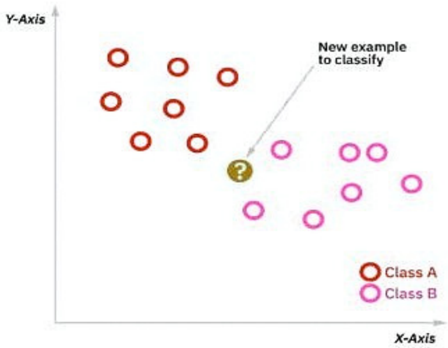


FIGURE 3. Simplified description of KNN algorithm

$$y = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

where: x_1, y_1 represent position of point A coordinate on system, and x_2, y_2 represent position of point B coordinate. An ANN is a computational model that draws inspiration from the structure and functioning of biological neural networks, such as the human brain. The primary component of this paradigm is the unique structure of information processing, which involves the utilization of several closely related processing neurons that collaborate to handle a given issue. Similar to human beings, ANNs acquire abilities through the process of learning from external sources. An ANN is specifically constructed for a particular purpose, such as data categorization or pattern detection. Learning in biological systems is a consequence of synaptic changes occurring between neurons. The aforementioned statement holds true for ANNs as well (Maind and Wankar 2014). Figure 5. Illustrates a simple representation of a neural network. Bias is included in the computation of the ANN by including it as a component of the weighted sum of the inputs, as shown in Equation (2).

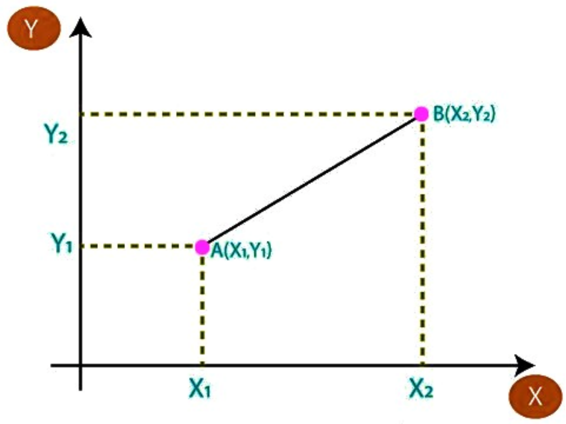


FIGURE 4. Description of **Euclidean distance between two points.**

$$y = \sum_{i=1}^{n} w_i * x_i + b \tag{2}$$

where: w_i represents the weight, x_i represent the input and b is bias.

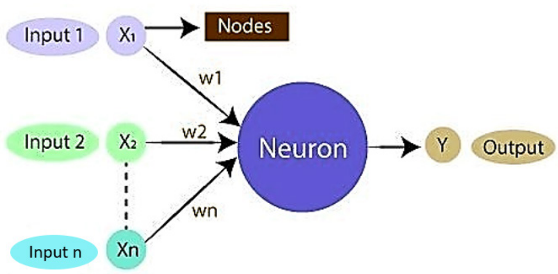


FIGURE 5. Simple neural network architecture with clarifications.

In this study, the classification is done using the two proposed methods of KNN and ANN. In KNN classifier, finding the effective K value is the goal of the method, the classification is performed with 30 folds cross-validation and number of neighbors (k value) is 1 with a dataset of 124 sample and 6 features. The project continues with an ANN of a three-layers feed-forward network. Sigmoid function is considered, because it is a non-linear function, the output of this unit would also be non-linear for the weighted sum of the inputs ensuring that a neuron's output would always fall between zero and one, it is used in the hidden layer which defined in Equation (3) (Jamel Ban and Khammas 2012). SoftMax function describes the relative probabilities for each class in the output layer, where it is utilized. The number of neurons in each layer is represented as follows, the neurons in the input layer are 6 which reflects the number of features in the dataset (6 features), the output layer matches the number of classes in this case 2 class is used, and the one hidden layer uses two thirds or seventy to ninety percent of the input layer's neurons' total number (Karsoliya 2012).

$$\sigma(y) = \frac{1}{1 + e^{-y}} \tag{3}$$

where: y is weighted sum of the inputs including the bias as defined in Equation (2). With the ANN classifier the dataset is auto divided as follow:

1. Training: its data are used by the learning algorithm and the weights then adjusted based on its inaccuracy.
2. Validation: when network generalization reaches a certain point (stops improving), validation data are utilized to determine when training should be stopped.
3. Testing, it's data that have no effect on training and provide an independent measure of network performance during and after training.

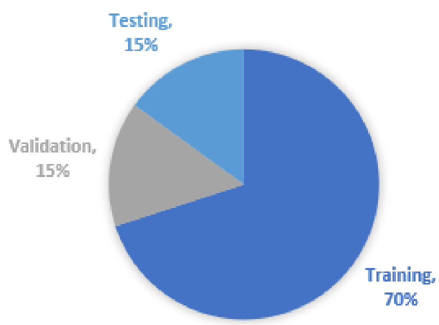


FIGURE 6. The division percentages of dataset in employed ANN classifier

RESULTS AND DISCUSSION

DATASET DESCRIPTION

This study utilizes a medical dataset obtained from the Ophthalmic unit in Al-Rabee hospital, Iraq. The dataset consists of 124 samples, each containing six features: age, K1, K2, CCT, Sphere, and Cylinder (Astigmatism). These features were collected from patients exhibiting one or more types of refractive defects, including myopia (nearsightedness) and hyperopia (farsightedness). Myopia causes distant objects to appear blurry, while hyperopia results in blurred vision of nearby objects. Presbyopia poses difficulties for those in the middle-aged and older demographic when attempting to focus on objects in close proximity, whilst astigmatism can cause nearby and distant objects to look blurred or distorted.

OBTAINED RESULTS

The obtained results are of the mentioned real dataset for refractive error patients and where the classification happened according to its features.

In order to present the performance of each classifier of them; KNN and ANN we must present the result of each one regarding to Accuracy (Acc.), Training Time (TT), sensitivity and specificity.

In case of Acc, and TT, the highest Acc. obtained is 90.3% with TT of 1.792 seconds in the case of KNN with 30 folds cross validation. The Acc. means model has attained 90.3% right predictions in respect to total number of samples. In other words, Acc. represents true predicted LASIK patients (45 samples) and true predicted PRK patients (67 samples) divided by total number of samples as shown in Confusion matrix for KNN in Figure (8) and the Acc. is specified in Equation (4).

While the 30 folds of cross validation refers to the dividing the dataset into 30 folds so 124 samples divided by 30 will be resulted in ≈ 4 sample in each fold, then only one sample is selected to test the model and the rest are employed for training in each fold. Then the process is iterated by choosing a different test set and training sets until all samples are used. Any other number of folds used for training gives a lower value for Acc. as shown in Table 1. So, in this paper the highest Acc. is adopted at 30 folds.

Moreover, the Acc. was 100% with TT of ≈ 0 sec. In the case of the ANN classifier, the Acc. means the model has attained 100% correct predictions with respect to the total number of samples. Acc. represents actual predicted LASIK patients (50 samples) and true predicted PRK patients (74 samples) divided by the total number of samples (124), and the Acc. is specified in Equation (4).

$$Acc = \frac{TP + TN}{total\ number\ of\ samples} \tag{4}$$

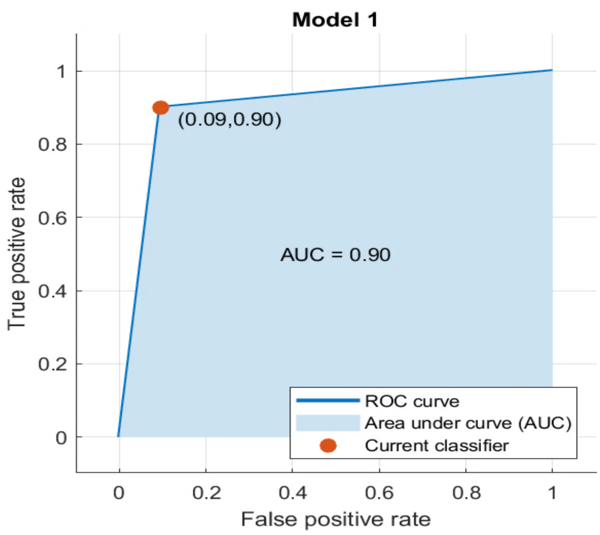
TABLE 1. Number of folds in cross validation against accuracy using KNN classifier.

No. of folds	Accuracy using KNN
26	87.9%
28	88.7%
30	90.3%
34	88.7%

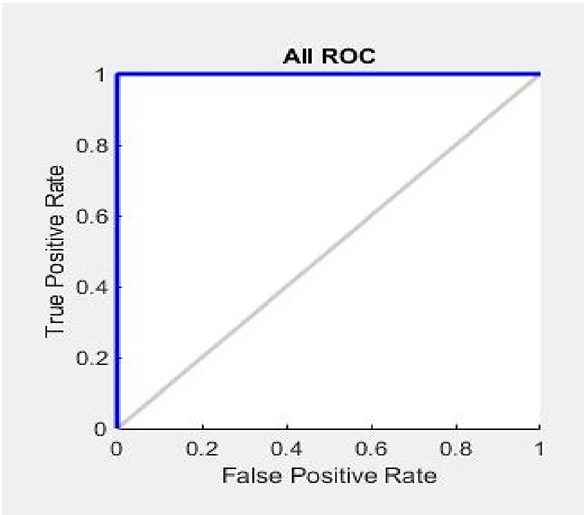
All the testing and training of classifiers are done using a computer with the following specifications: Lenovo-brand laptop with 8 GB of DRAM DDR3, an Intel core (TM) i3 processor clocked at 2.5 GHz and 0.5TB HDD hard drive.

In addition to Acc. and TT, the sensitivity and specificity must also be defined to evaluate the performance of each classifier, where sensitivity tells what proportion of LASIK has got properly classified patients, True Positive Rate (TPR) can be calculated using Equation (5) (Trevethan 2017), where properly classified LASIK patients are divided by total number of LASIK patients, 90% of sensitivity is obtained in the case of KNN classifier. While specificity tells what proportion of PRK has got properly classified patients, True Negative Rate (TNR) is calculated using Equation (6) (Trevethan 2017), where properly classified PRK patients are divided by total number of PRK patients, 90.54% of specificity is resulted in the case of KNN classifier. 100% of sensitivity and specificity have been recorded for the ANN classifier, in other words, all LASIK patients (50 samples) and PRK patients (74 samples) where properly classified. Figure 7. Shows the Receiver Operator Characteristic (ROC) curve and the Area Under Curve (AUC), which measures how well a classifier can distinguish between different classes(Fawcett 2006), with 0.90 AUC for KNN classifier and 1 AUC for ANN classifier. A ROC curve is constructed by plotting the TPR against the false positive rate (FPR). The TPR is the proportion of observations that were correctly predicted to be positive (properly predicted LASIK samples) out of all positive observations as in Equation (5). Similarly, the FPR is the proportion of observations that are incorrectly predicted to be positive (not properly predicted PRK samples) out of all negative observations as in Equation (7).

While our recommended model for surgical type identification is ANN, it is important to note that we did not incorporate cross-validation into our evaluation process. The omission of cross-validation was a strategic decision based on the characteristics of our dataset and the specific requirements of the surgical classification task. Our focus has been on demonstrating the accuracy and reliability of the ANN model through extensive testing and rigorous performance assessment, which we believe aligns well with the objectives of our research.



KNN classifier



ANN classifier

FIGURE 7. The ROC curve for KNN and ANN classifiers

$$Acc = \frac{TP + TN}{total\ number\ of\ samples} \quad (4)$$

$$sensitivity = TP/(TP + FN) \quad (5)$$

$$specificity = TN/(TN + FP) \quad (6)$$

$$false\ positive\ rate = FP/(TN + FP) \quad (7)$$

where: TP is True Positives (TP) properly predicted LASIK samples, FN is False Negative (FN) not properly predicted LASIK samples, TN is True Negative (TN) properly predicted PRK samples and FP is False Positive (FP) not properly predicted PRK samples.

All these variable values can be reported by the confusion matrix (for KNN classifier) as shown in Figure 8. While Figure 9. Is a chart for calculated Acc., sensitivity and specificity for both classifiers (KNN and ANN) using Equations (4), (5) and (6).

The only previous published study related to this work investigated multiclass ML (XGBoost) model to classify patients into four categories PRK, LASIK, SMILE, and contraindication groups. With a 10-fold cross-validation in the training dataset with the synthetic minority oversampling technique (SMOTE) process reached a performance of 82.1%(Yoo et al. 2020). This paper classified patients into two categories PRK and LASIK where the eye center which data collected from have only these two options of surgery and with 124 cases achieved 100% acc. using ANN network.

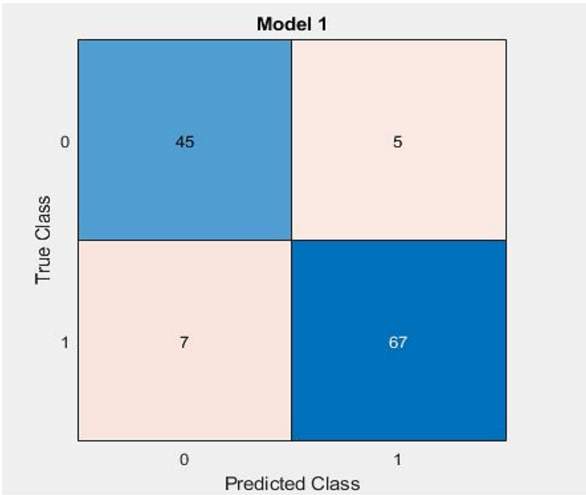


FIGURE 8. Confusion matrix for KNN, where TP at the top-left corner, FP at the bottom-left corner, FN at the top-right corner and TN at the bottom-right corner.

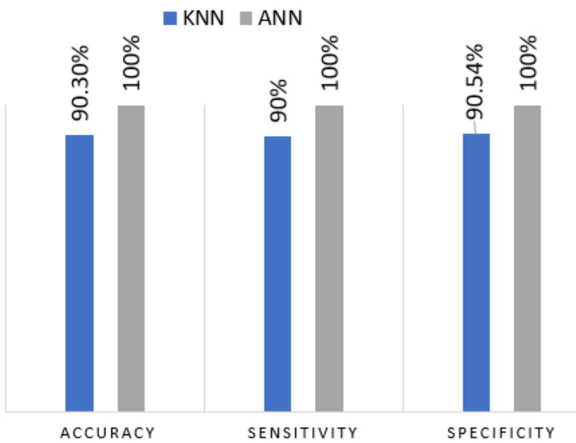


FIGURE 9. The Acc., sensitivity and specificity for both KNN and ANN

CONCLUSION

In summary, this study undertook thorough process of data collection and analysis, with a specific focus on authentic datasets from potential patients undergoing refractive surgical procedures, namely PRK and LASIK. An appropriate laser surgery strategy for refractive correction is an important issue to decrease postoperative complications. Prior to surgery an expert decides on the surgery option based on a patient's condition. The proposed model provided a surgical option on the expert level based on a clinical decision database. These candidates were categorized using KNN and ANN algorithms, utilizing the dataset's available features. The study successfully achieved the accurate identification of the most suitable surgical procedure for patients with refractive errors, reducing the need for extensive human intervention in the decision-making process and to assist in less risky clinical decision. This approach offers potential benefits in terms of time and effort savings for medical professionals and stakeholders operating within this domain. To the best of the authors' knowledge, this is the second study to select the corneal refractive surgery option using AI.

It's essential to acknowledge certain limitations of this research, notably the dataset's size, which was constrained due to the recent establishment of the refractive surgery center and limited computational resources. To address these limitations, future work should consider diverse datasets with variations in type, size, and variables. For example, the inclusion of additional features, such as the degree of eye dryness, could be explored before implementing ML methods in this domain, potentially with the support of high-performance computing resources.

While the findings indicate the exceptional performance of the ANN algorithm in classification, it's important to note that the numerical analysis details are not presented in this conclusion. Nonetheless, this study lays the groundwork for the promising application of ML in enhancing surgical procedure selection in refractive surgery.

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DECLARATION OF COMPETING INTEREST

None

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