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# Decision tree-based methodology to select a proper approach for wart treatment

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ABSTRACT

The human papillomaviruses (HPVs) can be responsible for various types of benign tumors called warts. Although warts can grow on all parts of the human body, common warts and plantar warts (as the most prevalent warts) grow principally on the hands and feet soles, respectively. Different treatment approaches such as cryotherapy and immunotherapy can be used to conquer the disease. However, the best healing method should be selected based on the patient circumstances. This study employs the classification and regression tree (CART) algorithm to develop accurate predictive models capable of analyzing the response of patients having common and/or plantar warts to the cryotherapy and/or immunotherapy methods. To develop a CART classifier for the cryotherapy method, independent parameters including the age and gender of patient, number of warts, type of wart, surface area of warts, and the time elapsed before treatment are used. In the case of immunotherapy, in addition to the above-mentioned variables, the induration diameter of the initial test is also considered. The error analysis reveals that the implemented CART models provide the highest achievable accuracy for the application of interest. Moreover, the proposed decision tree-based models are simple to use and more reliable, in contrast to the literature models that are mainly originated from the fuzzy rule-based method. Hence, the models introduced in this study can assist both patients and physicians save cost/time and improve the quality of healing operation.

## 1. Introduction

As a broad category of deoxyribonucleic acid (DNA) viruses, human papillomaviruses (HPVs) can induce diseases such as cervical, anal, vulvar, and vaginal cancers. Until now, at least 150 various HPVs have been discovered in human DNA [1]. Although the HPV vaccine was introduced in 2006 as the primary prevention of HPV-related diseases, the rates of HPV vaccination are still low [2]. In addition, HPVs are responsible for benign proliferations, called warts, on the body skin [3]. It is believed that the cutaneous warts are mainly caused by some alpha-PV types (HPV2, HPV3, HPV10, HPV27, and HPV57), gamma-PV types (HPV4, HPV60, and HPV65), and mu-PV types (HPV1 and HPV63) [4–12]. A number of research studies found that the racial factor has a significant impact on the rate of warts, since its rate is lower in African-Americans than in Caucasians [13–15]. In an annual family practice, 6% of school children and 2% of general people were known to have warts [16].

There are different types of warts including flat wart, plantar wart, common wart, filiform wart, mosaic wart, subungual wart, butcher's wart, endophytic wart, and myrmecia wart. The plantar and common warts are predominant among them [17]. Generally, the plantar warts are initiated on the foot/toes bottom and the common warts are found on the feet and hands. 70% of the cutaneous warts are known to be common warts. About 65% of untreated common warts will disappear within two years [18]. The spontaneous disappearance rate of plantar warts without treatment is between 65% and 78% [19]. Depending on the sensitivity of the patient and the anatomic location of plantar warts, they can be either painful or non-painful [20]. The medical reports show that patients, who have never had a wart, have a lower risk to be affected by warts, compared to those who have had plantar or common warts previously [21–24].

To overcome warts, there are several treatment approaches: destructive methods, immunotherapy, antimitotic drugs, and other available methodologies (e.g., duct tape, garlic extract, sinecatechins, and local hyperthermia). Surgical excision, cryotherapy, laser therapy, electro-surgery, and curettage are categorized as the destructive methods. It should be mentioned that the topical chemotherapy including bichloroacetic or trichloroacetic, salicylic acid, podophyline,

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cantharidin, and 5-flurouracil is also considered as a conventional destructive treatment method [18]. Based on a study conducted by Kassis et al. [25], it was concluded that continuous ultrasound has no healing effect while struggling with wart disease. In the immunotherapy, the humoral and/or cellular immune responses are elicited by using drugs such as imiquimod, zinc sulfate, diphenylcyclopropenone, and cimetidine [26]. However, none of them are well-tolerated and high efficient [27]. Indeed, the therapeutic approaches can eliminate the symptoms and signs of warts. This is due to the fact that HPVs have no cure [20]. It was found that plantar warts and common warts are different in responding to the treatment [28]. Hence, it was believed that the cure for warts needs to be individualized [18]. According to the previous studies, the success rate of the known methods applied for common wart treatment varies from 32% to 93% [29,30].

Cryotherapy is one of the most utilized treatment methods for warts. Although the cryotherapy is painful, and it has side effects, it is inexpensive and easy to employ. In this method, the liquid nitrogen is directly applied to warts for 10–20 s [26]. The mechanism of the cryotherapy technique is still unknown. However, it seems that the freezing operation results in local irritation and consequently, an immune response is stimulated [26]. To achieve satisfactory results, the procedure should be repeated every 2–3 weeks. According to a study by Bourke et al. [31], the healing rate of the cryotherapy, repeated every three weeks, for warts on hands was between 30% and 70% after three months. Other studies showed that warts treated with the cryotherapy and/or salicylic acid have a 60%–80% success rate [32–34]. This destructive approach causes blistering as it causes damages to the skin and it is painful. Moreover, there are risks of hyperpigmentation, hypopigmentation, and scarring with the cryotherapy [26].

As another wart treatment method, immunotherapy does not suffer from most disadvantages associated with the cryotherapy [17]. In this approach, a skin test antigen is injected into a lesion with the aim of inducing a T-cell-mediated, immunological response. In contrast to other available strategies for wart treatment, the immunotherapy has the potential to result in a generalized immune response to the virus [35]. The key mechanism of this method is linked to a delayed-type (or type IV) hypersensitivity reaction [21]. For the first time, Lewis [36] reported the use of immunotherapy with dinitrochlorobenzene (DNCB) for common warts in 1973. Due to the mutagenic nature of DNCB, it is not utilized in the clinical setting anymore [36]. The non-mutagenic substance, known as diphencyprone (DCP), can be used for the immunotherapy. Buckley et al. [37] investigated the warts treated with solutions of DCP over eight years.

For the purpose of improving the diagnosis in the medical science, implementation of machine learning and data mining approaches can be beneficial in terms of prediction accuracy and time (and cost) aspect. Several studies reported in the literature introduce the application of predictive methods/algorithms for diagnosis and treatment selection of skin-related diseases. For example, Parikh and Shah [38] employed the support vector machine method combined with the polynomial, radial basis function, linear, t-student, and inverse multi-quadratic kernels for classification of skin diseases including fungal infection, bacterial infection, scabies, and eczema. The datasets employed in their study have been obtained from an Indian hospital. An accuracy of about 95% was attained in their study. In another research investigation, El Bachir Menai and Altayash [39] used a decision tree-based method for diagnosis of erythemato-squamous disease in dermatology. Their proposed approach led to a 95% precision. In addition, there are a number of research works in the open sources that have implemented a variety of connectionist tools to investigate treatment of the melanoma (a category of skin cancers) in terms of classification and diagnosis ways [40–45].

Khozeimeh et al. [17] proposed a fuzzy rule-based methodology to study the effectiveness of cryotherapy and immunotherapy methods for treatment of common and/or plantar warts. Using the databases provided by Khozeimeh et al. [17], Akben [46] applied the ID3 algorithm to develop classification models for wart treatment selection. The developed ID3 models were then employed to create the fuzzy informative images. In another study, Khatri et al. [47] utilized the J48 algorithm in combination with the genetic programming for the same application of interest where they used the same databases as well. Guo et al. [48] employed a deep convolution neural network discriminator for differentiating between the seborrheic keratosis and flat warts. Guimarães et al. [49] utilized the fuzzy neural network method to improve the prediction capability of the expert system for the immunotherapy approach. For two commonly employed cryogens; namely nitrous oxide probes and liquid nitrogen spray, Mercer and Tyson [50] performed a mathematical modeling approach to find a relationship between the tissue freezing zone and freezing time.

Decision trees (DTs), as a type of supervised machine learning and data mining approaches, are capable of conducting the regression and/or classification problems. There are several forms of DTs including classification and regression tree (CART), ID3, C5, and C4.5 to develop a DT-based model. In 2017, CART methodology was employed to forecast the carbon dioxide solubility in ionic liquids [51]. In another study [52], a CART-based model was presented to model the equilibrium carbon dioxide loading capacity of sodium Glycinate. In the context of classification problem, DT classification was implemented for predicting the soil drainage classes in Denmark [53].

To the best of our knowledge, there no research studies in the literature that use CART-based methods for selection of the best approach for wart removal. The primary objective of the present work is to introduce simple-to-employ and accurate decision tree (DT)-based models that can be used by physicians to select the best treatment method for common and/or plantar warts. To attain this goal, the CART algorithm is utilized for the development of efficient classifiers. Dividing the desired database iteratively, CART leads to a homogenous classification of the target/dependent parameter. One of the main advantages of the strategy proposed in this study over other algorithms is that the designed CART-based models can be visualized through an understandable manner. Indeed, there is no need for medical experts to obtain mathematical and computational information regarding the classification methodology. Hence, the visualized tree-based models can be effectively used by medical experts/doctors for the prediction purposes.

The remainder of the current research study consists of four main sections: Section 2 briefly describes the CART algorithm and the theory behind it. In Section 3, the classifier development procedure is explained. Then, the results achieved in this work are presented and discussed in Section 4. Finally, the conclusions are drawn in Section 5.

## 2. Decision tree learning

Similar to other machine learning and intelligence approaches such as artificial neural networks, support vector machines, and adaptive neuro-fuzzy inference systems, the decision trees (DTs) technique is able to solve regression and classification problems. Highlighting one important characteristic of DTs, the DT learning is known to be computationally inexpensive. Furthermore, no assumptions are needed concerning the predictors' parameters distribution. The DTs approach is also robust in handling the missing data points [54–56].

As a decision support method, the DTs method employs a tree-like model that can be visualized. Fig. 1 demonstrates a simple decision tree. The depicted tree is designed for a hypothetical analysis that has $X = (X_1, X_2)$ as a vector of two independent variables. As can be observed from Fig. 1, the target (dependent parameter) can be estimated through four internal nodes and five leaves. In this approach, $T_i$ and $L_i$ are the threshold values of the leaf. According to the decision tree presented in Fig. 1, the tree development is performed from the top to the down. At the beginning, the magnitude of $X_1$ is compared to a threshold value. If the value of $X_1$ is higher than the value of $T_1$, the right branch, i.e. NO, is selected for the remaining steps to obtain the

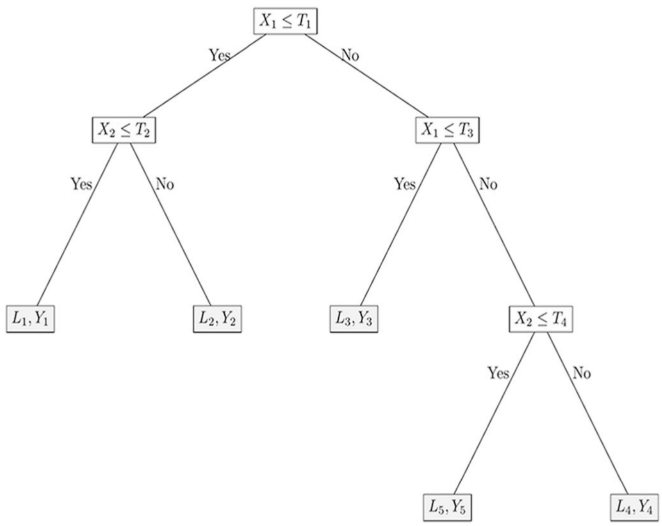


**Fig. 1.** A typical decision tree (adapted from Ref. [62]).

final result. Otherwise, the left branch should be chosen.

There are a number of algorithms suggested in the literature to develop decision tree-based regressors or classifiers. A few of the well-known algorithms include iterative Dichotomiser 3 (ID3) [55], C4.5 (developed as a successor of the ID3 learning algorithm) [57], fuzzy ID3 [58], and CART [59]. In the regression and classification applications, DTs technique offers distinct advantages. For example, the DTs model is easy to interpret and also to visualize. Indeed, compared to black-box models such as artificial neural networks, DTs models can be demonstrated in a graphical form. However, there are some disadvantages associated with DTs. One of the main drawbacks of DTs is their limitation for estimating continuous values in the context of regression analysis. Furthermore, for both classification and regression tasks, the structure of the created tree might be complicated due to the presence of many branches. The structure of DTs is highly dependent on the data introduced for modeling. In other words, variations in the dataset will change the structure of the tree. Hence, DTs methods might be variable and unstable.

Over the years, the classical CART algorithm has remained as a commonly utilized decision tree. This is mainly due to the nature of this effective methodology [51,60]. Indeed, the CART model is fast to create, and it applies to both the quantitative and qualitative data. In this study, the CART method is used to develop tree-based classifiers for the application of interest. To develop a CART model, the recursive binary splitting is used. For regression problems, the squared residentials minimization algorithm is preferred to be employed for the splitting. In the case of classification analysis, splitting rules such as Twoing and Gini may be applied. In this research, the Gini splitting rule is utilized. To determine the importance of each feature in the collected databases, the strategy of Gini permutations/measurements is also applied. Consider that the $n_k$ samples' fraction from $k = \{0, 1\}$ category out of all the samples at the node $\tau$ is expressed as follows:

$$p_k = n_k/n \tag{1}$$

In Equation (1), $p$ refers to the probability of having a specific data class in a branch of the DT (node $\tau$). The following equation presents the mathematical expression for the Gini impurity, $i(\tau)$:

$$i(\tau) = 1 - \sum_k {p_k}^2 \tag{2}$$

If the node has only one single class, the equation output becomes zero that is the best value for the impurity. For a two-class problem (class 0 and class 1), $i(\tau)$ is calculated as follows [61]:

$$i(\tau) = 1 - {p_1}^2 - {p_0}^2 \tag{3}$$

As the samples are separated and sent to sub-nodes $\tau_1$ and $\tau_2$, the Gini impurity changes. To define the reduction amount of $i(\tau)$, as a result of separating and sending the samples to sub-nodes $\tau_1$ and $\tau_2$ by a threshold $t_\theta$ on feature $\theta$, the following expression can be used [61]:

$$\Delta i(\tau) = i(\tau) - p_l i(\tau_l) - p_r i(\tau_2) \tag{4}$$

Depending on the applied setting (when creating a tree), the ideal strategy is to make enough branches until each branch has a Gini impurity of zero.

Conducting a proper/systematic search over all the available features at the node, the pair $\{\theta, t_\theta\}$ that leads to a maximal $\Delta i$ is obtained. After this stage, the algorithm records and accumulates a decrease in $i(\tau)$ for all the nodes (individually for all features). If we have a random forest of CARTs instead of a single CART, the Gini importance is calculated using the following expression [61]:

$$I_G(\theta) = \sum_T \sum_\tau \Delta i_\theta(\tau, T) \tag{5}$$

in which, $I_G(\theta)$ resembles the Gini importance and $T$ denotes the number of trees in the model. The Gini importance indicates how often a specific feature $\theta$ is employed for a split, and how important its general discriminative value is for the classification analysis of the objective function.

## 3. Model development

### 3.1. Databases

To develop classifiers to study the applicability of the immunotherapy and cryotherapy (as wart treatment approaches), two different databases reported in the literature [17] are employed. The databanks have been gathered in Ghaem Hospital's dermatology clinic (Mashhad, Iran), in the time period of January 2013 to February 2015, from the patients affected by common and/or plantar warts. It is believed that these two categories of warts are the most widespread warts. The detailed procedure to obtain the information on the types and treatment ways of warts for the model development can be found elsewhere [17].

Using one of the databases, six vital parameters including the age and gender of the patients, number of warts, type of warts, surface area of warts, and the time elapsed before treatment are recorded to demonstrate the patient response to the cryotherapy method. The second database has seven variables to investigate the responses of the patients to the immunotherapy treatment. Both databases have six variables in common. However, the induration diameter of the initial test is also considered as a key parameter for the immunotherapy approach. Eqs. (6) and (7) mathematically represent the independent variables to study the responses of patients to the cryotherapy and immunotherapy methods, respectively.

$$\text{RESPONSE}_{\text{cryotherapy}} = f(\text{Age, Sex, time, number of warts, type of warts, and area of warts}) \tag{6}$$

$$\text{RESPONSE}_{\text{immunotherapy}} = f(\text{Age, Sex, time, number of warts, type of warts, area of warts, and induration diameter}) \tag{7}$$

More information/data such as ranges of the independent parameters existing in the databases are given in Table 1 and Table 2.

### 3.2. General step

To construct the robust classifiers based on the CART algorithm for selecting the appropriate wart treatment method, each collected database is randomly divided into two distinct categories; namely training dataset and testing dataset. Since there is no universal rule for allocations of data points to the training and testing phases, the trial and error

**Table 1**
Information of patients treated with the immunotherapy strategy.

| Independent parameter | Value/type |
|---|---|
| Gender | 49 women and 41 men |
| Age (year) | 15–56 |
| Time elapsed before treatment (month) | 0–12 |
| Number of warts | 1–19 |
| Types of warts | 47 common, 22 plantar, and 21 both the common and plantar |
| Surface area of the warts ($mm^2$) | 6–900 |
| Induration diameter of initial test (mm) | 5–70 |

**Table 2**
Information/data of patients treated with the cryotherapy method.

| Independent parameter | Value/type |
|---|---|
| Gender | 43 women and 47 men |
| Age (year) | 15–67 |
| Time elapsed before treatment (month) | 0–12 |
| Number of warts | 1–12 |
| Types of warts | 54 common, 9 plantar, and 27 both the common and plantar |
| Surface area of the warts ($mm^2$) | 4–750 |

procedure can be utilized for this task. Normally, 80–90% of the data points are used for the model training [63–66]. Using 90% of the wart dataset, it is found that the CART model can provide satisfactory results.

In our study, the training dataset consists of 90% of the used databank. The remaining 10% of the data points are labelled as the test samples. This is due to the fact that the random separation of data results in a more reliable (and generalized) model. Indeed, the classifier model can be created by employing the data points allocated for the training phase of the CART model proposed in this study. Once the model was built, it can be assessed in terms of accuracy using the unseen data points, i.e. the testing dataset.

### 3.3. Classifier development

This study utilizes the CART algorithm to introduce rigorous classifiers for the proper selection of the wart treatment approach. The

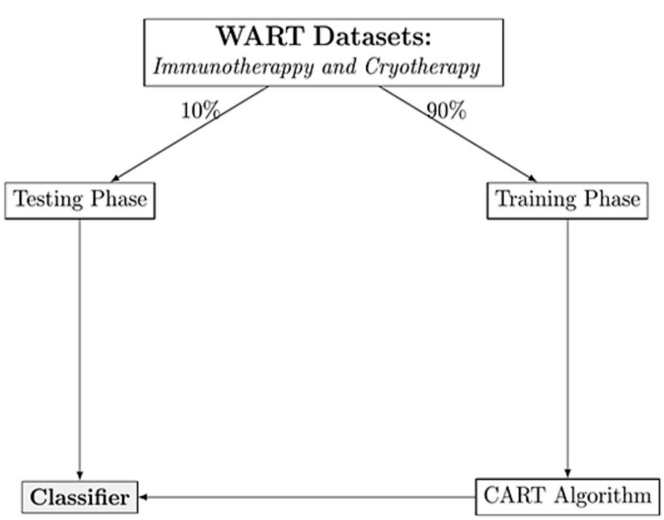


**Fig. 2.** Schematic of the procedure for model development to select the appropriate wart treatment method.

model development procedure is graphically represented in Fig. 2. To build a tree-based model on the foundation of the CART method, two influencing parameters including the number of features and the maximum depth of the tree need to be defined. The maximum depth of the CART refers to the maximum length among the existing paths that joins a root of the tree to a leaf.

The number of independent variables determines the number of features. The databank for the cryotherapy method consists of six independent parameters. In the case of immunotherapy methodology, there are seven independent parameters in the corresponding database. Since there is no universal rule to obtain the optimal CART maximum depth, a trial and error procedure is used. To start the procedure, the initial CART depth is supposed to be three. Eventually, it is found that the optimum values of the CART maximum depth are 10 and 8 for the immunotherapy and cryotherapy cases, respectively. Fig. 3 demonstrates the developed CART classifier to investigate the effectiveness of the immunotherapy technique for wart treatment. The CART model proposed for the cryotherapy method is depicted in Fig. 4. The high-quality version of Figs. 3 and 4 is also included in Appendix A.

## 4. Results and discussion

### 4.1. Accuracy assessment

In the case of classification problems, the accuracy only indicates the correct classification. This parameter considers equal costs for misclassification. Considering the unequal costs of decisions, the confusion matrix can be utilized to determine the specificity, sensitivity, and accuracy. Furthermore, statistical parameters such as mean squared error (MSE) and absolute average deviation (AAD) are normally used when the values of continuous variables are predicted [63–66]. Most classification problems are binary variable (Correct/False and Yes/No).

As shown in Figs. 3 and 4, the proposed CART classifiers provide easy-to-use and rigorous graphical models to evaluate the success of cryotherapy and immunotherapy in treating the common and/or plantar warts. Assessing the capability of the proposed classifiers, appropriate statistical parameters such as classification accuracy (ACC), sensitivity or true positive rate (TPR), and specificity or true negative rate (TNR) are utilized. The corresponding formulas for ACC, TPR, and TNV (in percentage) are listed below through Eqs. (8)–(10), respectively.

$$ACC = \frac{tn + tp}{tp + fp + fn + tn} \times 100 \tag{8}$$

$$TPR = \frac{tp}{tp + fn} \times 100 \tag{9}$$

$$TNR = \frac{tn}{tn + fp} \times 100 \tag{10}$$

where *fp*, *fn*, *tn*, and *tp* stand for the false positive, false negative, true negative, and true positive, respectively.

The statistical analysis reveals that the outcomes obtained from the presented CART models are in excellent agreement with the existing real data. Indeed, both the CART models developed for the cryotherapy and immunotherapy methods are able to forecast the patient response to the treatment without any error. In other words, the values of ACC, TPR, and TNV for the proposed CART models are equal to 100% for the both training and testing phases.

### 4.2. Comparison with other available techniques

In 2017, Khozeimeh et al. [17] employed a fuzzy rule-based framework to select a proper method for wart treatment. Recently, Akben [46] and Khatri et al. [47] utilized DT-based algorithms for the development of classification models with a capability for selecting the best

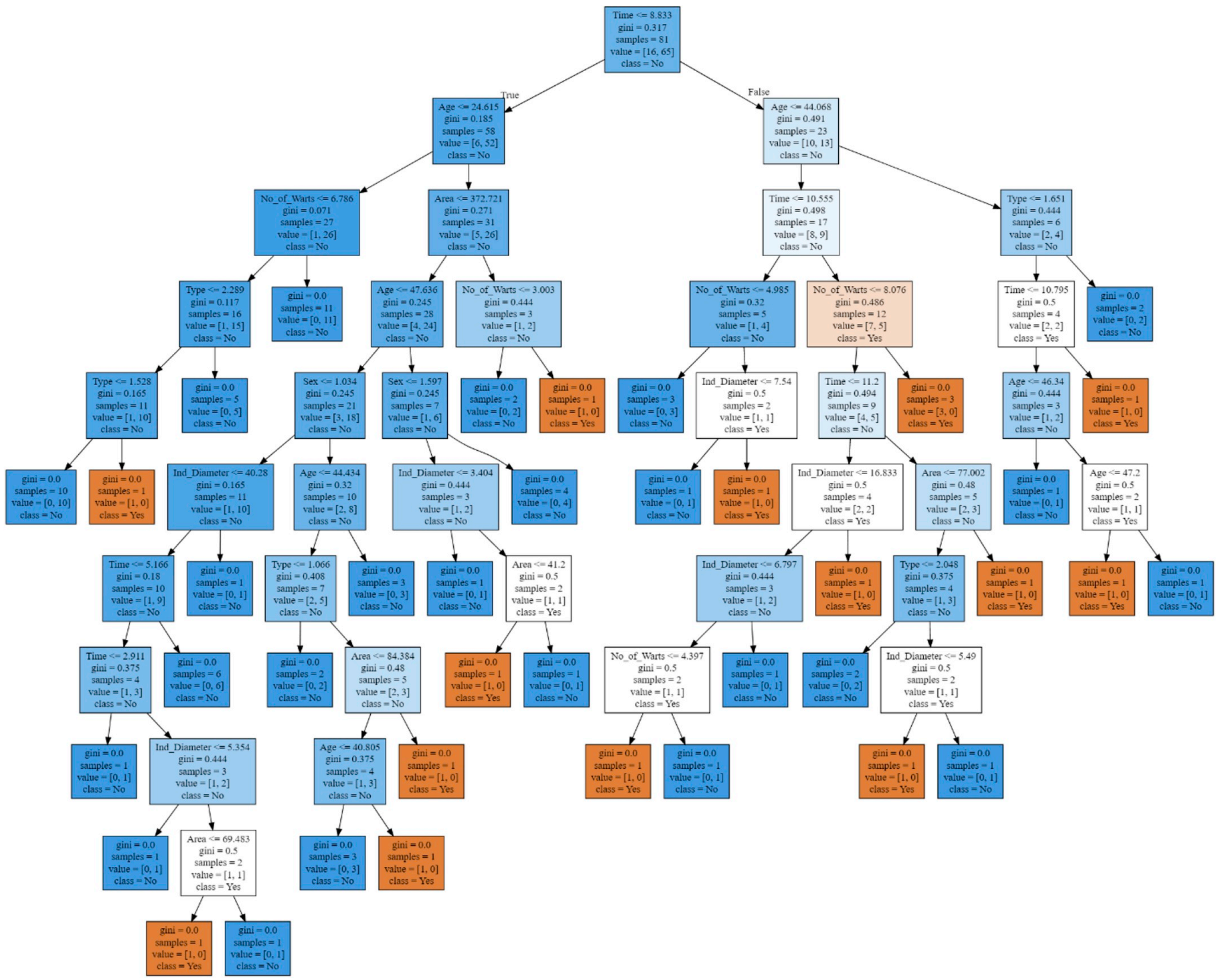


**Fig. 3.** The developed CART approach to study the effectiveness of the immunotherapy technique for wart treatment.

approach for wart treatment. Furthermore, Khatri et al. [47] evaluated the classification capability of several methods including support vector machine (SVM), k-nearest neighbors (KNN), random forest (RF), naïve Bayes (NB), logistic regression (LR), linear discriminant (LD), bagged trees (BaT), and boosted trees (BoT). It should be mentioned that all the previous studies discussed in the current research work have used the same databanks to introduce the classification strategies. To evaluate the robustness of the model proposed in this study for selecting the most effective wart treatment technique, the previous research investigations that employed the same databases, but different predictive approaches, are chosen for the comparison purposes.

For the immunotherapy technique, Table 3 summarizes a comparison between the proposed CART model and the available models (in the literature) in terms of sensitivity (TPR), specificity (TNR) as well as the accuracy. As it is evident from Table 3, the decision tree-based models outperform the previous models introduced for the immunotherapy case. In addition, the BoT and LD models exhibit the weakest results with an accuracy rate of 78.9% for the immunotherapy scenario. Fig. 5 illustrates a graphical method to compare the accuracies of our new CART models and the models available in the open sources.

Correspondingly, Table 4 compares the classification performance of the introduced CART model for the cryotherapy case to that of the above-mentioned literature models. Similar to the immunotherapy case, the results tabulated in Table 4 exhibit the superiority of the suggested CART model over the previous models for the cryotherapy treatment methodology. For the cryotherapy case, the fuzzy rule-based strategy [17] achieved 80% accuracy, which is the lowest amongst the available literature models. The performance of the literature models as well as our CART model in terms of precision is graphically presented in Fig. 6.

Comparing the results of the proposed CART models with the outcomes of the models suggested by Khozeimeh et al. [17], Akben [46], and Khatri et al. [47] reveals the supremacy of the decision tree-based techniques over the literature models for selection of the best approach for wart treatment. Beside the accuracy, the CART models provide a simple-to-use framework to select the proper treatment method without any calculator or computer assistance, while the fuzzy rule-based models appear to be appreciably sophisticated where the computational procedure might be complicated. As a result, the predictive models proposed in this study is more reliable and applicable than other literature models for medical experts. In other words, since there is no need to have knowledge and theoretical background about mathematical expressions or machine learning fundamentals, the proposed tree-based models can be simply utilized by medical experts/doctors before implementing a treatment procedure. Generally, employing this type of classification techniques in the health and medical sectors leads to

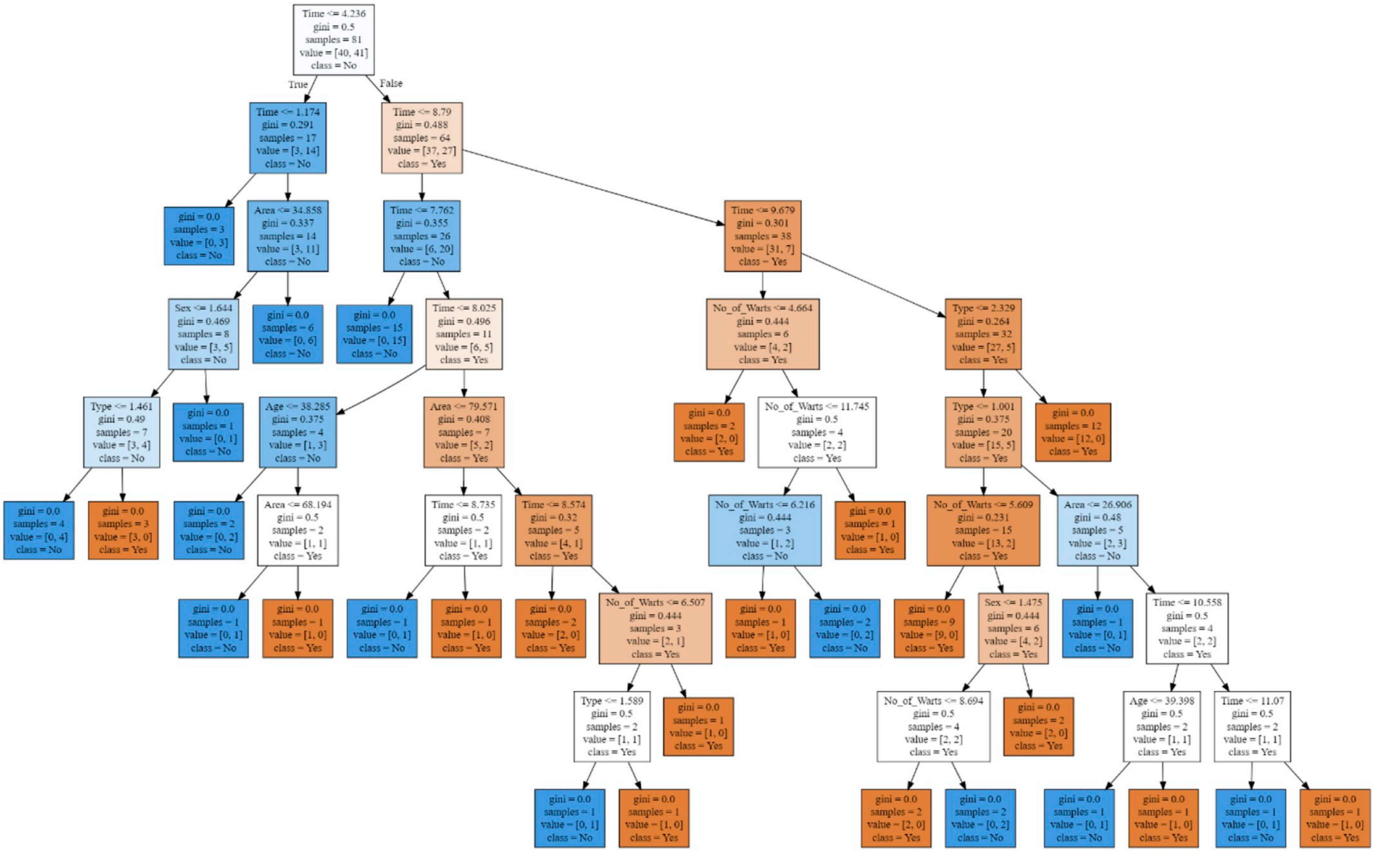

**Fig. 4.** The introduced CART model to examine the effectiveness of the cryotherapy method for wart treatment.

**Table 3**
Comparison between the performance of the proposed CART model and the literature models for immunotherapy case based on statistical analysis.

| Model | Assessment parameter | | |
|---|---|---|---|
| | ACC | TPR | TNR |
| CART (this work) | 100 | 100 | 100 |
| Fuzzy rule-based [17] | 83.3 | 87.0 | 71.0 |
| J48 [47] | 82.2 | 82.2 | 56.7 |
| GA-J48 [47] | 96.7 | 96.7 | 91.4 |
| ID3 [46] | 90.0 | 97.2 | 63.2 |
| SVM [46] | 87.8 | * | * |
| KNN [46] | 87.8 | * | * |
| LR [46] | 83.3 | * | * |
| LD [46] | 78.9 | * | * |
| NB [46] | 87.8 | * | * |
| RF [46] | 80.0 | * | * |
| BaT [46] | 80.0 | * | * |
| BoT [46] | 78.9 | * | * |

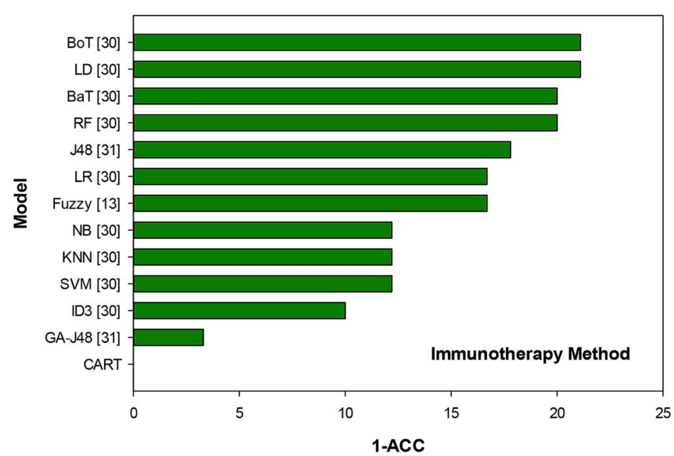


**Fig. 5.** Graphical comparison of the proposed CART model with the literature models for the immunotherapy method.

higher success rates in diagnosis and treatment of various diseases so that they decrease the associated expenses and time required for the corresponding medical operations.

### *4.3. Feature importance*

The importance of each independent parameter involved in the development of the CART classifiers for the immunotherapy dataset is depicted in Fig. 7. As seen in Fig. 7, the most important feature, to realize whether the immunotherapy is a proper treatment method or not, is the time elapsed before performing the treatment. This feature has 22.7% importance in the construction of the CART model. The outcome of the study conducted by Khozeimeh et al. [17] is in agreement with this research finding as Khozeimeh et al. [17] concluded that the time elapsed before accomplishing the immunotherapy has the highest effectiveness. Also, gender of the patient, with only 2% influence on the CART structure development, has the least significance among the contributing factors. Although the literature [17] claimed

**Table 4**
Values of statistical parameters for the proposed CART model and the literature models for cryotherapy case based on comparison between predictions and real data.

| Model | Assessment parameter | | |
|---|---|---|---|
| | ACC | TPR | TNR |
| CART (this work) | 100 | 100 | 100 |
| Fuzzy rule-based [17] | 80.0 | 82.0 | 77.0 |
| J48 [47] | 93.3 | 93.3 | 93.9 |
| GA-J48 [47] | 98.9 | 98.9 | 87.0 |
| ID3 [46] | 94.4 | 89.6 | 100 |
| SVM [46] | 90.0 | * | * |
| KNN [46] | 88.9 | * | * |
| LR [46] | 86.7 | * | * |
| LD [46] | 87.8 | * | * |
| NB [46] | 85.6 | * | * |
| RF [46] | 92.2 | * | * |
| BaT [46] | 92.2 | * | * |
| BoT [46] | 82.2 | * | * |

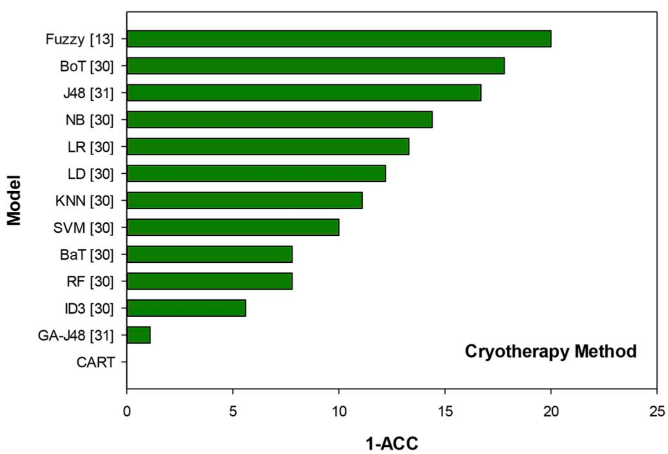


**Fig. 6.** Comparison of performance of the proposed CART model with that of the previous models for the cryotherapy scenario.

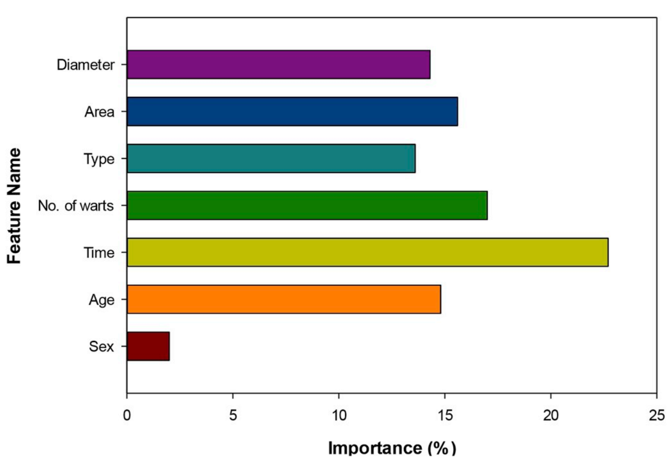


**Fig. 7.** Relative significance of the features involved in the CART model for immunotherapy approach.

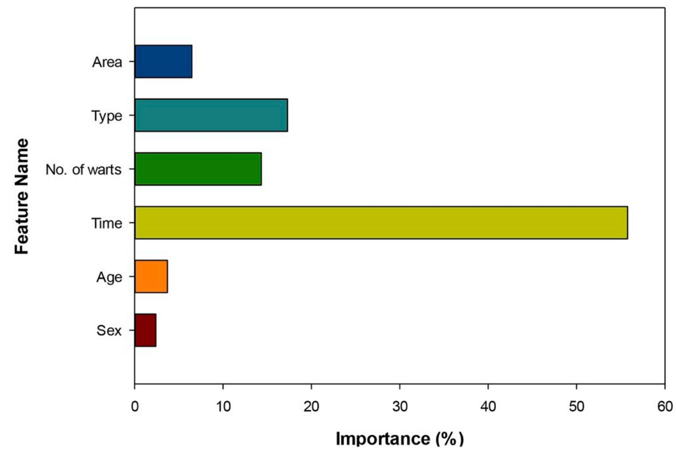


**Fig. 8.** Feature importance plot of the CART model suggested for the cryotherapy method.

that the gender of patient has a low effectiveness in the immunotherapy case, the lowest impact is associated with the number of warts based on their research study. Other features including the induration diameter of initial test, age of the patient, number of warts, type of warts, and the surface area of the warts have almost the same significance in the decision tree creation process.

Fig. 8 describes the relative importance of the features employed to develop the CART model for assessment of the effectiveness of the cryotherapy method. Similar to the immunotherapy case, the most important variable in the CART development process is the time elapsed before starting a treatment. It is worth noting that this parameter is more important than other features of the database all together such that it has a 55.77% significance in the CART model development for the cryotherapy method. However, the lowest importance for this database belongs to the gender of the patient. The results obtained by Khozeimeh et al. [17] showed that the gender has the minimum importance when the patient is treated by the cryotherapy, which is the same as the finding of the current study. However, based on the methodology employed by Khozeimeh et al. [17], the highest relative rank was given to the age of patients, which is in contradiction with the outcome of the present study.

## 5. Conclusions

In the current study, CART methodology is employed to develop robust classifiers to choose a proper treatment approach (cryotherapy or immunotherapy) for common and/or plantar warts. The performance of the developed tree-based classifiers is compared to that of the methodologies available in the literature in terms of reliability and prediction accuracy. Outcomes of the introduced CART models reveal an excellent performance for both cryotherapy and immunotherapy approaches so that the ACC, TPR, and TNR are found to be 100%. On the other hand, the literature models for the cryotherapy case lead to ACC, TPR, and TNR ranging from 80.0% to 98.9%, 82.0%–98.9%, and 77.0%–100%, respectively. For the immunotherapy case, the magnitudes of ACC, TPR, and TNR are between 78.9% and 96.7%, 82.2%–97.2%, and 56.7–91.4%, correspondingly. Furthermore, the proposed models appear in a graphical form and can be easily employed in an understandable manner. Hence, it can be concluded that no model can rival the proposed CART models in terms of both accuracy and simplicity of implementation. By obtaining further information from various groups of patients, it is possible to present more efficient (and generalized) decision tree-based models that can be more practical for different cases. It is recommended to incorporate effective hybrid and ensemble methodologies (e.g., genetic algorithm and particle swarm optimization) into the CART algorithm for future studies. Implementation of hybrid/ensemble methods might further simplify (and improve) the structure of the tree-based models developed for wart treatment.

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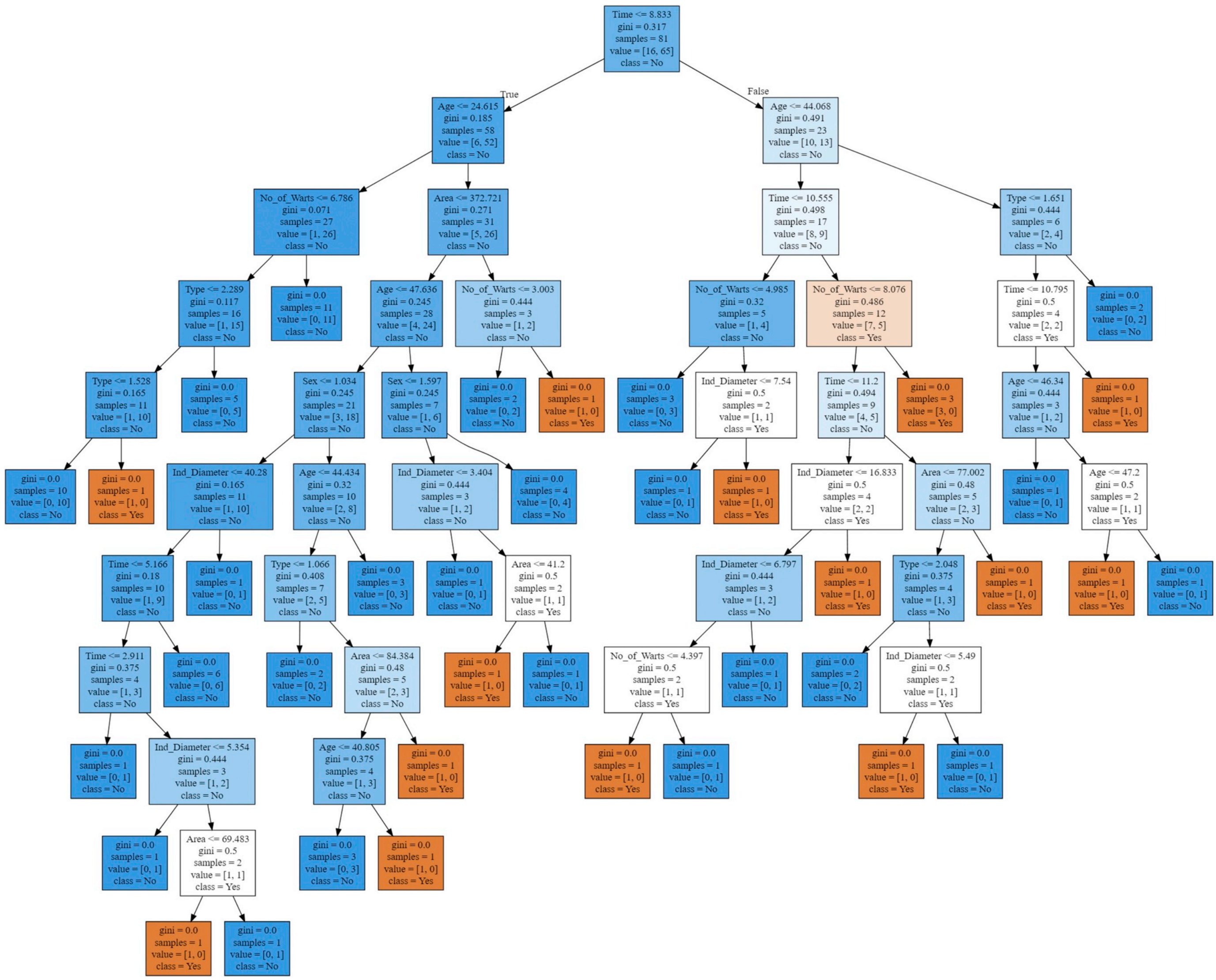
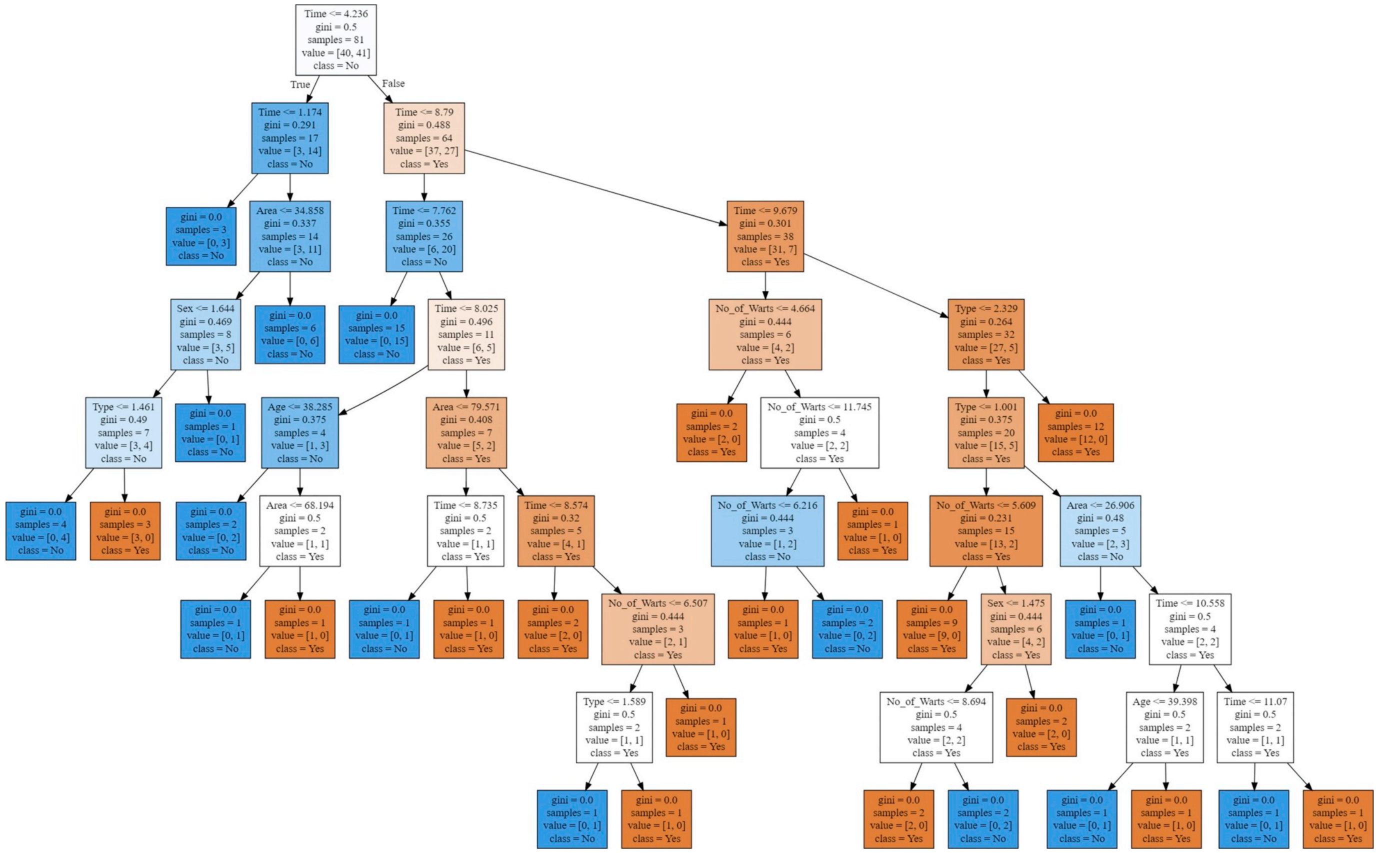
## Appendix A

The high-quality version of Figs. 3 and 4 is given in this document.




**FigA1.** A better version of Fig. 3.




**FigA2.** Fig. 4 presented in a higher quality.

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