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Enhancing Medical Diagnosis Accuracy with an Adaptive Decision Tree Using Dynamic Thresholds and Intuitionistic Fuzzy Sets

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Abstract

Medical diagnosis is usually associated with uncertainty and vagueness, as well as inconsistent clinical information, which decreases the classification reliability. To surmount this problem, this research suggests that the Intuitionistic Fuzzy Adaptive Decision Tree (IF-ADT) that incorporates the dynamic threshold optimization method with intuitionistic fuzzy sets (IFS) can maximize diagnostic accuracy in case of uncertainty. The given approach adds membership, non-membership, and hesitation levels to the decision tree splitting process, allowing updating the threshold adaptively due to statistical variance in patient characteristics. It tested the model on 10-fold cross-validation on ten benchmark UCI medical datasets. Experimental performances have shown that IF-ADT has better performance than traditional classifier(s) like Bagging, J48, Naive Bayes, and Multilayer Perceptron. In particular, IF-ADT was 99% accurate and 99% sensitive to chronic kidney disease, 98% sensitive and 98% sensitive to Breast Cancer, and had a specificity of over 95% on most datasets. The mean accuracy increase in comparison to the traditional decision trees was about 3-5 %, and the false positive rate decreased by approximately 4 %. These findings verify that the combination of dynamic thresholding and intuitionistic fuzzy reasoning is very useful in increasing diagnostic robustness and interpretation. The suggested IF-ADT model is thus applicable in intelligent clinical decision support systems that need a great degree of reliability in questionable medical circumstances.

Keywords: Adaptive Decision Tree, Intuitionistic Fuzzy Sets, Medical Diagnosis, Dynamic Thresholding, Clinical Decision Support, Intelligent Healthcare Systems, Uncertainty Modeling.

1 Introduction

First proposed by Zadeh in 1965, FST stands for Fuzzy Set Theory. At a later time, in 1986, Atanassov established the system of IFS as an extension of traditional fuzzy set theory. In fuzzy set theory, an element in the universal set is assigned a membership degree. However, in IFS theory, each element of the universal set is assigned a membership degree, a non-membership degree, and a hesitation degree.

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One of the primary reasons IFS is seen as a more effective and efficient approach than FST for handling decision-making uncertainty is this. Scientists have been working diligently over the past few years to demonstrate the utility of IFS in various areas, including decision-making, fuzzy optimization, pattern recognition, medical analysis, and more. You can use the similarity measure to help you make decisions when you're unsure about what to do. This is possible with the IFS theory. Several experts have developed various methods to measure distance. It has been noted that when determining the degree of separation between two IFSs, different measures of distance give different results. Furthermore, for any two IFSs, existing measures are not always efficient and appropriate. Therefore, more suitable measures are always required to make decisions in a more efficient manner.

An adaptive decision tree can potentially enhance medical diagnosis by learning and organizing itself to better classify patients according to their features and symptoms (Batool & Byun, 2024). As the tree learns how to accommodate the different features of different diseases and patient groups, this ensures more accurate and reliable diagnoses. An adaptive decision tree enhances medical diagnosis accuracy by learning and dynamically adjusting the structure for classifying patients based on symptoms as well as dynamic attributes. It provides a more accurate and consistent diagnosis. A decision tree must be applied to respective regions for different diseases and patient classes. The adaptive decision tree enhances the medical diagnosis as well. Acquired from data, i.e., classical trees are also referred to as pre-defined or adaptive decision trees, which are used to learn large data sets of the patient's history, symptoms, and test results. It is the process of learning whereby decision trees can determine patterns and give advice to human experts (Mahmood et al., 2024). Precise classification makes it easy for the adaptive decision tree to recognize patient information across multiple groups of diagnoses, enhancing accuracy. Personalized diagnosis uses the adaptive decision tree for personalization, personalizing treatment for individual patients based on profiles that take into consideration many variables such as age, gender, medical history, and pertinent features. Timely diagnosis based on timely patient data from medical devices, sensors, and an adaptive decision tree should allow for timely diagnoses and enable informed medical decision-making.

1.1 Key Contribution

- The proposed model employs an adaptive Decision tree that dynamically adjusts the decision threshold, followed by a statistical pattern with various measures. It also helps to improve the precision of classification in medical diagnostics.
- The integrated fuzzy sets are used to handle the imprecision and hesitation of the clinical data. It's more reliable and explainable through decision-making with the diagnostic systems.
- Compared to others, it should demonstrate superior diagnostic accuracy among traditional trees, followed by validation of the model based on benchmark medical datasets, which helps improve sensitivity and reduce false positives.

This research paper is divided into several sections. Section I provides an introduction to the topic. Section II describes the literature review, which summarizes the results of previous papers compared to the proposed one. Section III describes the proposed methodology, which comprises various subsections of the proposed model, including the model architecture, adaptive decision tree, definition of fuzzy sets and intuitionistic fuzzy sets, medical knowledge base, Intuitionistic fuzzy inference system, data flow diagram of the proposed model, and proposed algorithms. Section IV explained the dataset descriptions. In this analysis, select the dataset as a medical dataset. Section V presents the results and discussion section, which includes an analysis using evaluation metrics for accuracy, sensitivity, precision, specificity, and the ROC curve. Section VI summarizes the main key findings of this research.

2 Literature Review

The literature reviewed describes the gradual adoption of Intuitionistic Fuzzy Sets (IFS) and their associated adaptive methods for medical decision-making. In 2020, Liu et al., (2026) an IFS-based Decision Support System was implemented, which advanced practice oncology by constructing robust diagnostic frameworks within the uncertain oncology data context. This model is part of the larger paradigm shift toward automating clinical diagnosis through intelligent systems that process vague or partial information. A 2016, Hafeez et al., (2021) study proposed a hybrid fuzzy classifier that incorporated intuitionistic fuzzy logic with several classification techniques to diagnose a range of diseases. This method provided better accuracy in diagnosis compared to existing models and performed particularly well in complicated, uncertain medical environments. The primary advantage of this approach was the ability to introduce ambiguity in patient data through hesitation values associated with IFS, thereby increasing the accuracy of the classification.

In 2021, Khatibi & Montazer, (2009) innovation came in the form of thresholding tree models with dynamic modeling. Unlike the standard decision tree splitting procedures, splitting here was informed by real-time statistics. Such flexibility enables the model to adapt to changes in the incoming medical data, which improves the model's accuracy and reliability of healthcare decisions it makes. Yet another seminal work in 2016 Versaci & La Foresta, (2024) highlighted the fuzzy sets and decision tree methodology. The fuzzy decision tree was developed to classify patient health records with linguistic labels and ranges of uncertainty as attributes. The decision paths of the model were vague and thus simpler to trace without sacrificing greater accuracy, making the model beneficial in diagnosis applications where precise numerical information is not available or unavailable. All of these studies combined are best understood to be progressing towards more sophisticated and uncertainty-aware diagnostic devices, justifying the role of fuzzy and IFS-based classifiers in healthcare system development.

3 Proposed Methodology

3.1 Proposed Model Architecture (IF-ADT)

The integrated figure 1 shows an integrated and advanced diagnosis platform with an Adaptive Decision Tree (ADT) and an Intuitionistic Fuzzy System (IFS) to further enhance the trustworthiness and precision of medical diagnoses. The architecture of ADT, demonstrated on the left side, is developed in an incremental manner with batch-wise patient data collected annually. Each batch consists of previous medical histories that are confirmed as diagnoses. It begins life as a basic decision tree model and continuously gets updated by incorporating new batches of training data. As it has dynamic thresholds, the model can shift its decision boundaries based on statistical trends within the data.

In addition to this, intuitionistic fuzzy logic is integrated in order to manage imprecise or uncertain patient information by including three aspects, i.e., membership degree (representing the degree to which a symptom corroborates a diagnosis), non-membership degree (representing the contradiction degree), and hesitation degree (representing uncertainty due to lack of information). The output of the model is not merely a binary (disease/no disease) but diagnostic findings with certainty and hesitation values. This makes it an ideal choice for medical conditions where symptoms aren't cut and dried.

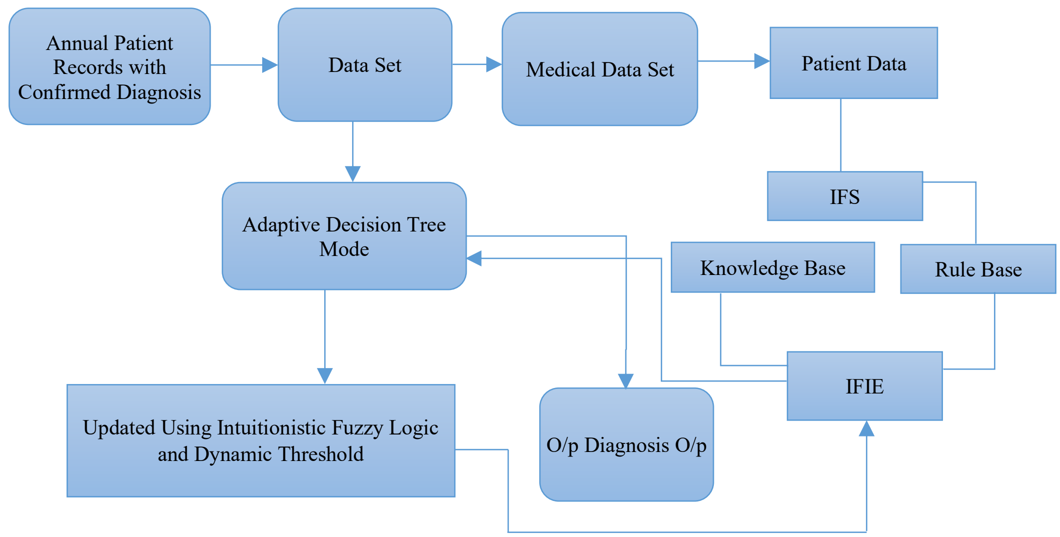

Figure 1: Proposed architecture

The IFS module is a right-hand expert system that is supplied with real-time patient information from doctors, nurses, or home monitoring equipment. The information is keyed into a fuzzy inference engine, which uses a knowledge base (conditional medical knowledge) and a rule base (if-then rules drawn from domain knowledge) to generate possible diagnoses. The intuitionistic fuzzy inference machine works on the information by generating identical three membership, non-membership, and hesitation levels. This allows it to consider multi-sided decisions even if the input is conflicting or suspicious. Last but not least, based on the individual profile of each patient, the system creates a diagnosis proposal that automatic systems as well as doctors can understand. This combined model takes advantage of both the IFS's semantic, human-like reasoning and the ADT's time-learned knowledge. The ADT ensures that the model learns from changing patient patterns and emerging medical knowledge with time, while the IFS provides rule-based inference with uncertainty representation, an important aspect for complicated diagnosis cases. This hybrid decision framework combines statistical learning and expert reasoning to deliver an incisive, agile, and precise diagnostic solution that can be deployed in real-time clinical decision support systems.

3.1.1 Adaptive Decision Tree

By itself, its model of classification, an Adaptive Decision Tree (ADT), classifies multi-class by changing its structural elements like node heuristics dynamically during learning based on the distribution of input data. In contrast with classic decision trees that employ fixed node splitting thresholds, ADTs have adaptive mechanisms like statistical heuristics, dynamic thresholds, or fuzzy bounds that iteratively optimize splits and structure adaptively based on data properties. This evolution allows the tree to adapt to concept drift, noise, and shifts in feature importance more easily (Aljaaf et al., 2015).

It is a decision tree that divides the input space using axis-orthogonal splits. Adaptive decision tree T was specified as the integer assigned as $s(v) \in \{1, \dots \dots, d\}$ to each internal node of $v\ of\ T$. Consider the binary label value of 0 or 1 related to each leaf node. The nodes of ADT correspond to the hyperrectangles in $[0,1]^d$. Followed by the hyperrectangle $A = \pi_{r=1}^{d}[a_r, b_r]$, considered as $A^{s,1}\ and\ A^{s,2}$. Both are denoted as a hyperrectangle followed by splitting. Each of the ADTs is followed by various rules, such as the root node should be associated with $[0,1]^d$. Other than v is the internal node associated with cell A, which has the children of v associated with $A^{s(v),1}$ and $A^{s(v),2}$. Followed by $\pi(T) = \{A_1, \dots \dots \dots \dots .., A_k\}$ noted as the partition induced by T. Let j(A) denote the depth of A and noted as $\lambda(A) = 2^{-j(A)}$, where Rd λ should be measured. Defined as T is a collection of all ADTs, and A is the collection of all cells corresponding to nodes (Hafeez et al., 2021).

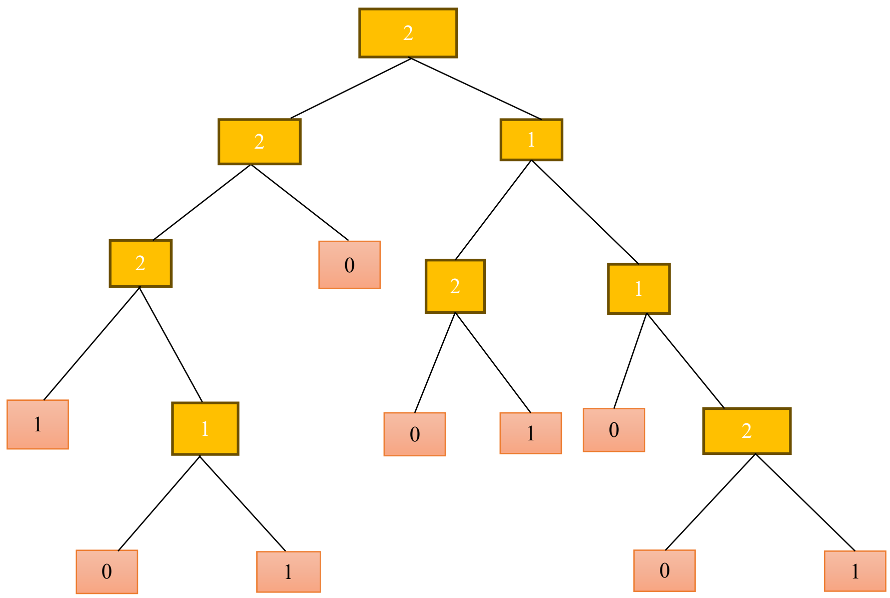

Figure 2: Adaptive decision tree

The above figure 2 represents the decision tree associated with the recursive curve of partition and d=2. Each side of an internal node of the tree should be labeled with an integer from 1 to d, indicating the coordination among the split nodes. Let M be the dynamic integer. $M = 2^L$, which contains the non-negative integer L. Here represents the classifier form as,

$$T\hat{}_n = arg_{T\epsilon Tm} \min R\hat{}_n(T) + \phi_n(T) \tag{1}$$

Followed by the above equation (1), noted as ϕ_n, is the penalty function. Algorithm used to compute the $T\hat{}_n$ in $O(ndL^d \log(ndL^d))$ operations. Based on all our theorems to compute cost $O(nd(\log n)^{d+1})$.

3.1.2 Definition of Fuzzy Set

A fuzzy set is assigned various grades of membership, ranging from 0 to 1, for an object. Consider that X is the universal set, followed by a fuzzy set A and its corresponding membership functions $\mu_A: X \to [0,1]$

3.1.3 Definition of Intuitionistic Fuzzy Set

This section discusses the proposed approach to medical diagnosis, which also describes the medical diagnosis problem mathematically (Khatibi & Montazer, 2009). Followed by that the two sets are described as $X = \{x_1, x_2, \dots \dots .. X_n\}$ and $Y = \{y_1, Y_2, \dots \dots .. Y_{M\}}$ Followed by that, X is the set of all symptoms, and Y is the set of diseases, respectively (Versaci & La Foresta, 2024). The values of n and m are noted for several diseases and symptoms (Muthukumar & Krishnan, 2016). Here, the intercorrelation among various symptoms and diseases is characterized using a set of decision rules and a medical knowledge base (KB) (Luo & Zhao, 2018). Consider that new set named as $p = \{P_1, P_{2,\ldots.} P_{t\}}$, t is the number of patients with symptoms $\{X_1, X_2, \ldots \ldots \ldots X_n\}$, The main aim of the diagnosis problem is to provide accurate results, followed by the diagnosis of the disease $\{y_1, y_2, \ldots \ldots . y_m\}$, which contains the new set of patient information (Szmidt & Kacprzyk, 2003; Davvaz & Hassani Sadrabadi, 2016).

3.1.4 Medical Knowledge Base

Our suggested method requires a medical knowledge base (KB), which may be formulated as a series of inference rules in the "if antecedent and then consequent" format that define a relationship between the inputs (diseases) and outputs (symptoms) (Manhi, 2023). As a result, when a new set of symptoms is noticed, it may provide doctors and medical professionals with important information for a more accurate diagnosis. Thorough discussions regarding the several facets of Viral Fever, Malaria, Typhoid, etc., with the relevant medical professionals can allow for the meticulous formulation of the medical KB. During the conversation with the medical professionals, it was discovered that when a doctor asks a patient about their illness, the patient lacks the confidence to describe the disease in order to assess a collection of symptoms. The language chosen to describe the patient's condition is inevitably influenced by their degree of confidence. Consequently, when a medical expert makes decisions based on a patient's symptoms, the patient's degree of confidence is inextricably linked to the expert's recommendation. As GFN takes into account the level of confidence in expert views, it can then appropriately capture such linguistic phrases. It's also important to note that experts occasionally hesitate to make assessments about a patient's likelihood of developing a condition. These findings serve as the foundation for the current work, which uses a set of decision rules based on FL and IFL to construct medical knowledge base (KB), thereby capturing the doctor's competence in patient diagnosis. A medical KB's decision-making principles take symptoms into account in the antecedent section and diseases into account in the consequent part. The antecedent portion of the rules entails a linguistic assessment of the patient's symptoms in relation to the doctor's level of confidence, while the consequent component discloses the patient's condition via diagnosis. Take the following system of p fuzzy rules as in equation 2, for instance.

$$R_i: If\ X_1\ is\ A_{i1}^{\sim}\ and\ X_2\ is\ A_{i2,\ldots\ldots\ldots\ldots,}^{\sim} x_n\ is\ A_{in}^{\sim}\ then\ possibility\ of\ Y_1\ is\ C_{1i}, Y_2\ is\ C_{2i,\ldots\ldots\ldots\ldots} y_m\ is\ C_{mi} \qquad (2)$$

Where $i = 1,2, \ldots \ldots \ldots, P$, $GTFNs\ A_{ij}^{\sim} (j = 1,2, \ldots \ldots \ldots \ldots n)$ represents the values of linguistic variables. $\{X_1, X_2, \quad \ldots \ldots \ldots . X_n)$ defined as the universe set of [0,1]. Here, the computation procedure for constructing the membership function of GTFN is described. The set of $\{y_{1,} y_2, \ldots \ldots \ldots y_m\}$ represents the set of various diseases and IFS, $C_{ki} = \mu_{yki,} v_{yki}), (k = 1,2, \ldots . m)$ should represent the degrees of possibility, followed by the impossible disease y_k describes in i^{th} rule. Based on that, specifically μ_{yki} describes the degrees of association with disease, y_k is the patient information, and v_{yki} should represent the degree of non-association of disease, y_k into the patient details.

3.1.5 Intuitionistic Fuzzy Inference System

This section should represent the intuitionistic fuzzy inference engine, which is the main part of the proposed model (Ramesh & Lakshmanna, 2024). Based on the Medical KB applied through various diagnoses; the disease related to the new patient information should be processed (Thong, 2015).

Input: Assumed as the medical KB consists of P fuzzy rules,1 received as the new set of linguistic values of symptoms, fuzzy input denoted as $\{U_1^{\sim}, U_2^{\sim}, \dots . U_n^{\sim}\}$.

Based on Matching Degree: The degree that contains the fuzzy input data $U_j^{\sim}(j = 1,2, \dots \dots \dots \dots ., n)$ matches with the rule R_i computed by using the conjunction operator $(t - norm\, T)$.

$$\propto_i = T(S_{x \in U^{\sim}}\left(T_{j=1,2,3 \dots\dots n}\left(\mu_{Aij(x)}^{\sim}, \mu U_{j(x)}^{\sim}\right)\right), i = 1,2, \dots \dots \dots \dots . p \tag{3}$$

The output of each rule equation 3, the inferred outcome of each rule, should be defined as an intuitionistic fuzzy value based on the concept of the Larsen product implication operator, which should be computed by using the various definitions (Mahmood et al., 2023). Here, also noted that the final output for findings is the accurate diagnostic results.

$$F(C_k) = \frac{d(C_k, I^-)}{d(C_{k,} I^-) + d(C_{k,} I^+)} \ (k = 1,2, \dots \dots \dots \dots \dots . . m) \tag{4}$$

To determine the patient's disease equation 4, followed by greater relative closeness coefficient values. Here are the two types of disease, Y_1 *and* Y_2. Here, the corresponding coefficient values are equal to the maximum values. $F(C_1) = F(C_2)$.

3.2 Data Flow Diagram of Intuitionistic Fuzzy Inference System

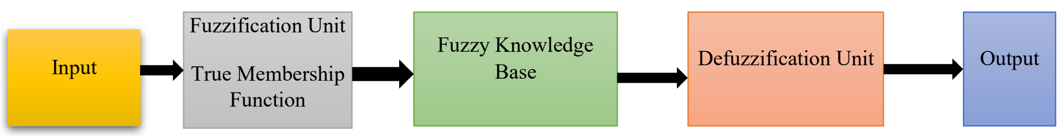

Figure 3: Data flow diagram of intuitionistic fuzzy inference system

The data flow diagram of a Fuzzy Inference System (FIS), as used in medical diagnosis systems, which is one type of decision system from the perspective of uncertainty, is illustrated in figure 3. The process starts with an input, which is a precise numerical value derived from measurement; in this case, it can be a computation such as a patient's vital sign or laboratory result. After input is sent to the fuzzification unit, it undergoes a process of being turned into a fuzzy linguistic variable through a membership function, as defined in the true sense. Membership functions literally define quantitative values into qualitative descriptions like "low," "normal", and "high" about patient data and thus allow interpretation by humans. After fuzzification, the inputs are processed and sent to a fuzzy knowledge base. The fuzzy knowledge base contains fuzzy sets for each IF-THEN (IF: blood pressure is high AND glucose is high, THEN: the patient is at risk) rule, which an expert of the domain defined. This knowledge base uses some logic and various control conditions to find the level of truth of each condition. All the outputs of every rule that was executed have fuzzy values. These fuzzy values, however, are in a form that is not directly useful and needs to undergo defuzzification. To accomplish this goal, the defuzzification unit is put into operation. Techniques like the centroid or weighted average method are utilized to obtain a sharp output from the fuzzy outputs of the inference engine. This sharp output is a numerical representation of a definitive conclusion or diagnosis, for example, a disease risk score or an action to be taken to control the system. In general, the model offers the system a strong framework to cope with data insufficiency and inconsistency, which allows much more delicate and precise steps to be taken in the decision-making procedure. In the scope of this methodology, such a fuzzy inference system is employed to set the stage for interfacing intuitionistic fuzzy sets with an adaptive decision tree, where both fuzzification and decision making are subjected to control by the level of data uncertainty and degree of hesitation.

3.3 Proposed Algorithm

$Input{:}\ Dataset\ (X), Intuitionistic\ Fuzzy\ parameter\ (\alpha)$

$Output{:}\ Intuitionistic\ fuzzy\ data\ point\ (\mu_{id}, V_{id}, \pi_{id}) corresponding\ to\ each\ dimension$

$X_{id}\ of\ the\ ith\ data - item.$

$$N_d = a + \frac{x_i - (X_{min})^d}{(X_{\max)}{}^d - (X_{min})^d}\ (b - a) \tag{5}$$

$Normalize\ the\ dataset, X, using\ equation\ (5)\ to\ obtain\ the\ matrix\ N$

$Deduce\ the\ distance, dis_{i,j}, between\ each\ data\ item\ x_i\ and\ the\ data$

$item\ x_i\ with\ data\ item\ x_j\ using\ Euclidean\ distance\ measure$

$$prod = \left\{\, P_{id} \backslash P_{id} = dis_{ij} *\ N_{jd}, 1 \le i, j \le P, 1 \le d \le D \right\} \tag{6}$$

$Deduce\ the\ matrix\ Prod\ using\ \ equation\ (6)\ to\ find\ the\ product$

$of\ the\ distance\ matrix, dis\ with\ the\ normalized\ feature\ dataset, N.$

$$M = \frac{1}{prod} \tag{7}$$

$Reciprocate\ the\ product\ using\ the\ formula\ given\ in\ equation\ (7)\ to$

$obtain\ \mu_{id}$

$$v_{id} = (1 - \mu_{id}^{\alpha}).^{\frac{1}{x}} \tag{8}$$

$$\pi_{id} = 1 - \mu_{id} - (1 - \mu_{id}^{\alpha}).^{\frac{1}{x}} \tag{9}$$

$using\ equation\ (8)\ and\ (9), compute\ the\ non - membership\ value$

$v_{id}\ and\ \ hesitancy\ \pi_{id}\ for\ the\ dimension\ x_{id}\ of\ ith\ data\ item$

$if\ max_j \left|T \cap C_j\right| \ge \tau. |T| hen\ return\ new\ leaf\ (\arg max_j \left|T \cap C_j\right|)$

$best_{split} = none$

$for\ each\ attribute\ A\ do$

$foreach\ possible\ split\ of\ A\ do$

$Compute\ the\ quality\ of\ the\ split$

$if\ split\ better\ than\ best_{split}, then\ best_{split} = (q, A, Split)$

$node = new\ Node\ (best_{\_split})$

$for\ each\ data\ partition\ T_i \complement\ T\ of\ the\ \ best\ split\ do$

$node. add\ child\ (partition\ rule, construct\ decision\ Tree(T_i, \tau))$

$End\ procedure.$

The algorithm begins with the input dataset $X$and an intuitionistic fuzzy parameter α. The objective is to compute intuitionistic fuzzy data points $(\mu_{id}, \nu_{id}, \pi_{id})$for each dimension $x_{id}$of the i^{th}data item. First, the dataset is normalized using a min–max normalization scheme to scale each feature into a bounded interval, producing a normalized matrix N. This ensures uniform contribution of all attributes during subsequent computations.

Next, the Euclidean distance between each pair of data items is calculated to form a distance matrix. The product of the distance matrix and the normalized feature matrix is then computed to obtain a matrix $Prod$. The reciprocal of this product is taken to determine the membership value μ_{id}, reflecting the degree of association of each data point with a specific feature dimension.

Using the intuitionistic fuzzy parameter α, the non-membership degree $\nu_{id}$is is calculated, and the hesitation degree $\pi_{id}$is is derived as $1 - \mu_{id} - \nu_{id}$. These three components form the intuitionistic fuzzy representation of the dataset.

The decision tree is then constructed recursively. If the maximum class proportion exceeds a predefined threshold τ, a leaf node is created. Otherwise, the best attribute split is selected based on split quality, and the procedure continues until the stopping criteria are satisfied. The parameter settings used for implementing and evaluating the proposed IF-ADT model are summarized in table 1.

Table 1: Parameter settings used in IF-ADT mode

Parameter	**Symbol**	**Value**
Intuitionistic fuzzy parameter	α	0.5
Dynamic threshold rate	η	0.05
Minimum samples per leaf	m	2
Maximum tree depth	Dmax	Data-driven
Stopping threshold	τ	0.90
Cross-validation folds	k	10
Parameter	Symbol	Value

4 Experimental Results

The proposed IF-ADT model was implemented in Python using standard machine learning libraries. All experiments were carried out on a system with an Intel i7 processor and 16 GB RAM. The evaluation was performed on ten benchmark medical datasets obtained from the UCI Machine Learning Repository.

Before training, missing values were handled using basic imputation methods, and all features were normalized using min–max scaling. The intuitionistic fuzzy parameter (α) was set to 0.5 based on initial tuning. The dynamic threshold learning rate was fixed at 0.05. A minimum of two samples per leaf node was maintained to avoid overfitting.

To ensure reliable evaluation, 10-fold cross-validation was used for all models. Performance was measured using accuracy, sensitivity, specificity, precision, and ROC-AUC. The proposed IF-ADT was compared with standard classifiers such as Decision Tree, Naive Bayes, Multilayer Perceptron, Bagging, and KNN under the same experimental settings.

Dataset Description

Most of the machine learning methods are widely used in medical diagnosis. Here, applying the machine learning algorithm to a medical dataset should be suitable for analyzing the medical data. Machine learning methods aid in accurate diagnoses (Althnian et al., 2021; Raikwal & Saxena, 2012). Various types of classifiers are used for this analysis, such as "Naive Bayes, j48, Multilayer perception, JRip, decision tree, Neural network, Rule-based, adaptive decision tree, KNN, and Meta classifiers category (Lavanya & Rani, 2011). The following table describes the set of attributes, also known as the UCI Medical Dataset table 2 (Mittal & Gill, 2014).

Table 2: UCI medical dataset

Medical Datasets	Attributes	Instances
Breast Cancer Data	11	699
Chronic Kidney Disease	25	400
Cryotherapy	7	90
Hepatitis	20	155
Immunotherapy	8	90
Indian Liver Patient Dataset	11	583
Liver Disorders	7	345
Prima Diabetes	9	768
Risk Factors cervical	36	858
Heart Data Set	14	270

5 Results and Discussion

This study primarily focused on a medical dataset obtained from the UCI Machine Learning repository. Here, the various classifiers include Naive Bayes, Multi-layer perceptron, C4.5, Rule-based, and KNN. To evaluate the performance of the evaluation based on accuracy, precision, sensitivity, ROC, and Specificity. To assess the performance based on the confusion matrix, followed by various predictions. The following table 3 describes the example of a confusion matrix, as

Table 3: Confusion matrix for a binary classifier

Predicted-> Actual	NO	YES
NO	TN	FP
YES	FN	TP

TP represents the True Positives, TN as True Negatives, FP as False Positives, and FN as False Negatives. Based on performance classifier followed by accuracy, sensitivity, specificity, precision, and ROC Area (Zarrin et al., 2020). The Accuracy of the classifier is noted as the percentage of tuples classified by the classifier.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{10}$$

Sensitivity is the proportion of positive tuples that are identified

$$Sensitivity = \frac{TP}{TP + FN} \tag{11}$$

Precision means the proportion of the true positives against all the positive results.

$$precision = \frac{TP}{TP + FN} \tag{12}$$

Specificity is the proportion of negative tuples that are identified (Beini et al., 2021).

$$specificity = \frac{TN}{TN + FP} \tag{13}$$

Classifier performance was evaluated using accuracy (Equation 10), sensitivity (Equation 11), precision (Equation 12), and specificity (Equation 13), computed from the confusion matrix values TP, TN, FP, and FN.

ROC: The Receiver Operating Characteristic (ROC) curve is generated by plotting the actual positive rate (TPR) against the false positive rate (FPR) at various threshold settings (Mohandas et al., 2024). Other names for the true-positive rate include likelihood of detection, sensitivity, and recall. Another name for the false positive rate is the fall-out (1-specificity) (Beini et al., 2021). Three ROC curves for the excellent, good, and useless tests are presented on the same graph in figure 4. The test's ability to distinguish between individuals with and without the disease in question determines its accuracy. The area under the ROC curve is used to quantify accuracy (Nilashi et al., 2017). A test with an area of 1 is considered perfect, and one with an area of.5 is considered worthless (Yang et al., 2021).

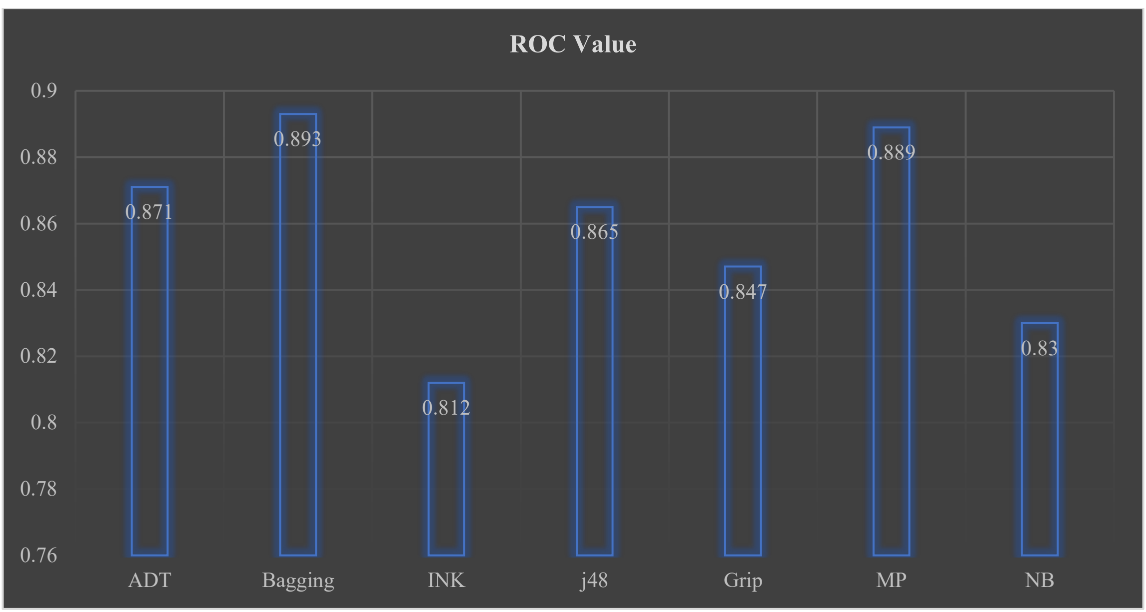

Figure 4: Comparison of ROC curves

In figure 4 illustrates the ROC (Receiver Operating Characteristic) values presented in the table, enabling a comparison of the classification performance among the seven models. Among these, the Bagging classifier demonstrates the highest ROC value of 0.893, suggesting that it is most competent in distinguishing between classes. This indicates that Bagging, through ensemble learning, reduces variance, thereby enhancing classification precision. Closely following is the Multilayer Perceptron (MP) with an ROC value of 0.889, which still exhibits remarkable performance due to the deep learning features of the model and its ability to capture complex nonlinear dynamics. ADT (Alternating Decision Tree) and J48 classifiers also demonstrate excellent performance with ROC values of 0.871 and 0.865, respectively. These models, based on the Decision tree approach, strike a fair trade-off between precision and comprehensibility, making them highly useful in classification tasks. Grip records a moderate ROC value of 0.847, indicating reasonable performance, although it is lower than the best models in terms of predictiveness. The Naive Bayes (NB) classifier yields an ROC value of 0.830, indicating that it consistently performs at a basic level. Receiver Operating Characteristic (ROC) values for different classifiers indicate the set performance; for the INK classifier, it is 0.812, which demonstrates that INK is the least performing model out of all the models evaluated. This may indicate a lack of some generalization capability or fit for the particular dataset being examined in this analysis. Ensemble-based methods (Bagging) and MP neural networks achieve higher performance than the other evaluated classifiers. These results can help choose which model to use based on their balancing needs of classifier transparency, cost, and precision.

Table 4: Accuracy of selected classifiers for medical datasets

Accuracy of the classifier for medical datasets										
Disease classifier	Breast cancer dataset	Chronic Kidney Disease	Cryotherapy	Hepatitis	Immunotherapy	Indian Liver patient dataset	Liver disorder	Pima diabetes	Risk factor for cervical cancer	Heart dataset
ADT	98%	99%	89%	70%	86%	72%	77%	79%	98%	99%
Bagging	95%	98%	88%	64%	84%	69%	69%	75%	96%	80%
INK	95%	95%	90%	66%	70%	64%	62%	70%	94%	75%
J48	94%	99%	93%	58%	82%	68%	68%	73%	95%	76%
Grip	96%	97%	87%	63%	82%	66%	66%	76%	96%	80%
MP	95%	99%	87%	62%	80%	68%	71%	75%	94%	77%
NB	95%	95%	83%	71%	76%	55%	55%	76%	88%	83%

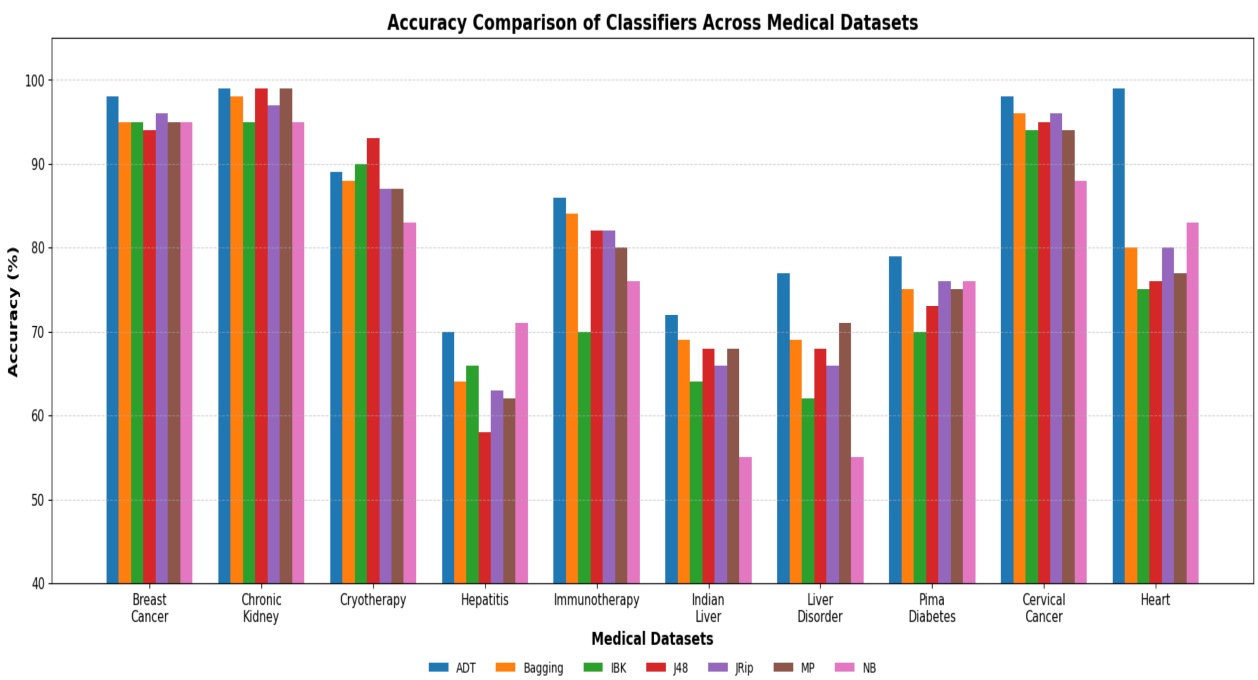

Figure 5: Accuracy among various medical datasets

In figure 5 and table 4 represent the “Accuracy among medical datasets”, which evaluates how well machine learning algorithms ADT, Bagging, IBK, J48, Jrip, MP, and NB perform in classification over ten different medical datasets. The classifiers perform exceptionally well on datasets such as Chronic Kidney disease, Breast cancer, Cryotherapy, and Risk factor cervical cancer, where NB and IBK often outperform other classifiers. Interestingly, the performance for datasets like Hepatitis, Indian Liver patient dataset, and Liver disorder is significantly lower, with many models struggling to achieve even 70% accuracy, demonstrating marked difficulty in classification. Overall, it can be observed that NB and IBK perform relatively consistently across datasets, with their performance being only modestly impacted by the specific dataset used, while MP and Jrip show more fluctuation. This study sheds light on the optimal classifier for pivotal medical datasets during a comparative evaluation based on accuracy.

Table 5: Sensitivity among classifiers for medical datasets

Sensitivity in the medical dataset										
Disease classifier	Breast cancer data set	Chronic Kidney Disease	Cryotherapy	Hepatitis	Immunotherapy	Indian Liver patient dataset	Liver disorder	Pima diabetes	Risk factor for cervical cancer	Heart dataset
ADT	98%	99%	90%	64%	55%	96%	84%	64%	91%	94%
Bagging	95%	99%	83%	51%	47%	28%	79%	58%	81%	82%
INK	92%	100%	89%	60%	21%	47%	67.5%	52%	47%	76%
J48	92%	98%	89%	47%	47%	33%	80%	59%	67%	79%
Jrip	96%	96%	77%	48%	47%	17%	74%	58%	87%	85%
MP	95%	100%	85%	61%	36%	28%	82%	60%	54%	78%
NB	97%	100%	89%	57%	21%	95%	40%	61%	74%	87%

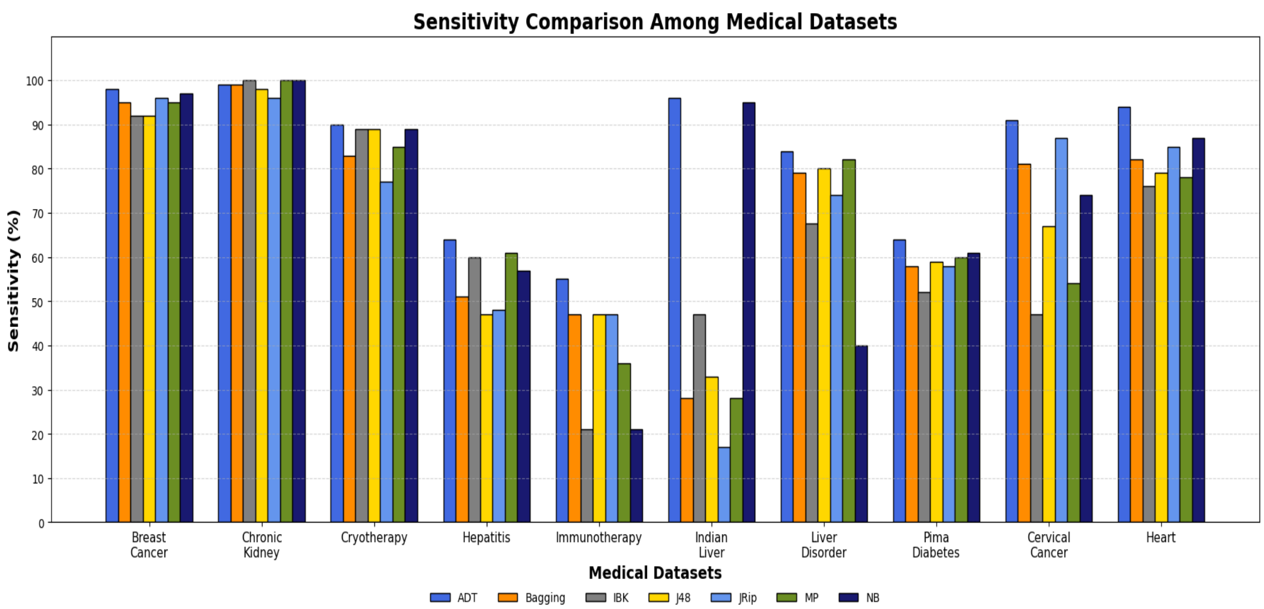

Figure 6: Sensitivity among various medical datasets

In table 5 and figure 6 describe the "Sensitivity among Medical Datasets," which demonstrates the analysis of several classifiers, including ADT, Bagging, IBK, J48, Jrip, MP, and NB, regarding their sensitivity (true positive rate) against ten different medical datasets. In terms of medical diagnosis, sensitivity is very important, as it shows the ability of the model to identify positive cases correctly. Classifiers show high sensitivity on datasets like Breast cancer, chronic kidney disease and Cryotherapy, where nearly all models attain values above 90%. On the other hand, datasets such as Hepatitis, Immunotherapy and Indian Liver patient dataset show much fluctuation and underperformance from the middle, especially for MP and Jrip that in some cases are below 40%. ADTAGD and NB on the other hand do not have critically low sensitivity on the majority of datasets like ADT and NB. This was mostly true for the Indian Liver patient and the heart disease datasets. This variability points to the need for model selection not solely based on their accuracy, but rather their diagnostic sensitivity in crucial healthcare services.

Table 6: Precision of classifier for medical datasets

Precision among medical dataset										
Disease classifier	Breast cancer data set	Chronic Kidney disease	Cryotherapy	Hepatitis	Immunotherapy	Indian Liver patient dataset	Liver disorder	Pima diabetes	Risk factor cervical cancer	Heart dataset
ADT	94%	99%	98%	85%	75%	52%	72%	69%	67%	84%
Bagging	92%	97%	95%	63%	69%	44%	71%	67%	66%	82%
INK	93%	89%	91%	63%	25%	40%	68%	57%	57%	78%
J48	91%	99%	97%	54%	60%	44%	70%	63%	60%	78%
Grip	92%	97%	100%	61%	60%	33%	69%	68%	64%	81%
MP	93%	99%	91%	58%	53%	43%	72%	65%	60%	80%
NB	91%	88%	81%	74%	40%	38%	70%	67%	33%	83%

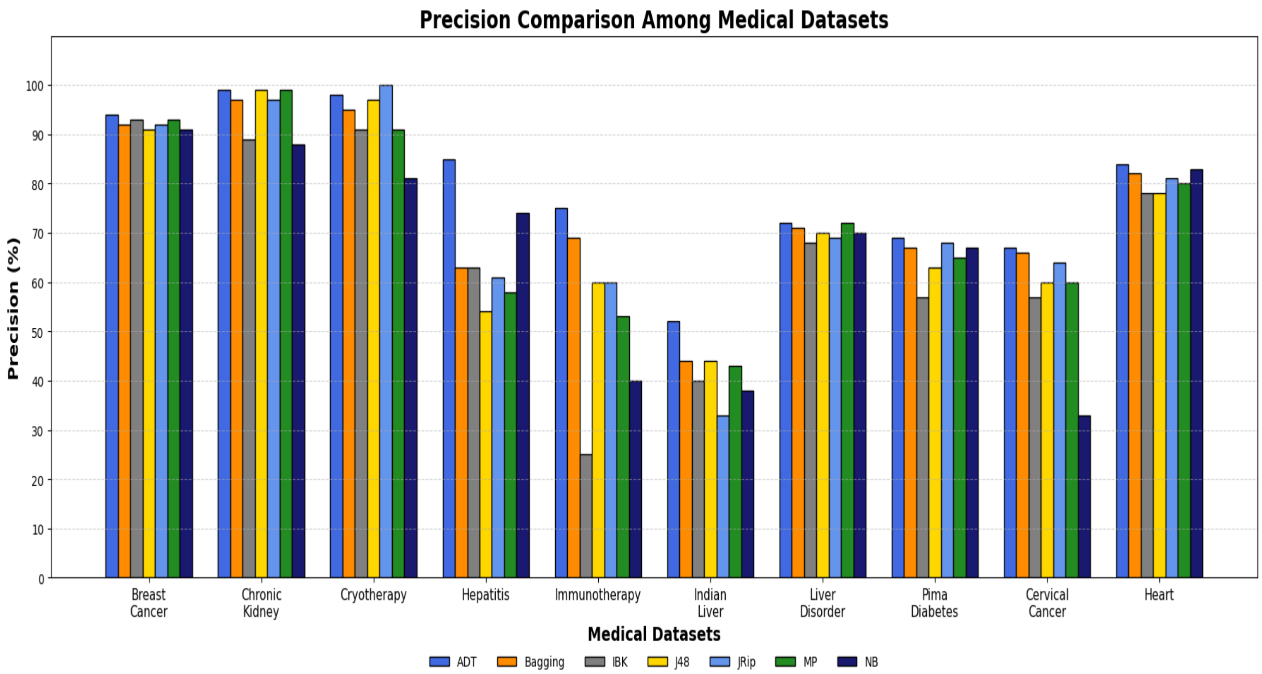

Figure 7: Precision among various medical dataset

To interpret table 6 and figure 7 describes about "Precision among various medical dataset" examines the precision score of the classifiers ADT, Bagging, IBK, J48, Jrip, MP, and NB against different datasets. Inaccuracy in medical diagnosis can lead to dire consequences, thus precision, which evaluates almost correct positive predictions made vis a vis all the claimed positive predictions, is highly regarded and required to be minimized. Most classifiers for Breast cancer, chronic kidney disease and Cryotherapy datasets which have more than 90% precision, Bagging and IBK as previously noted, win dominantly and consistently with better results. Nonetheless, for datasets like Hepatitis, Immunotherapy, and Indian Liver patient dataset, there are sharp drops in precision, especially with MP and NB that tend to go below 50% all the time. ADT and Bagging tend to have consistent precision on most datasets unlike most others showing fluctuations. It can be concluded that some classifiers need customization to datasets tuned for high precision and very low false positive ratio in critical medical processes while others seem to have no trouble responding to multiple datasets.

Table 7: Specificity among various medical datasets

Specificity among medical datasets										
Disease classifier	Breast cancer dataset	Chronic Kidney Disease	Cryotherapy	Hepatitis	Immunol Herapy	Indian Liver patient dataset	Liver disorder	Pima diabetes	Risk factor cervical cancer	Heart dataset
ADT	96%	98%	100%	88%	96%	88%	78%	86%	98%	85%
Bagging	96%	98%	95%	75%	94%	85%	56%	85%	97%	77%
INK	96%	93%	90%	71%	83%	71%	56%	79%	97%	73%
J48	95%	99%	97%	67%	91%	82%	53%	81%	97%	73%
Grip	96%	98%	100%	75%	91%	85%	55%	85%	96%	75%
MP	96%	99%	90%	63%	91%	85%	57%	83%	97%	76%
NB	95%	92%	76%	83%	91%	39%	76%	84%	89%	79%

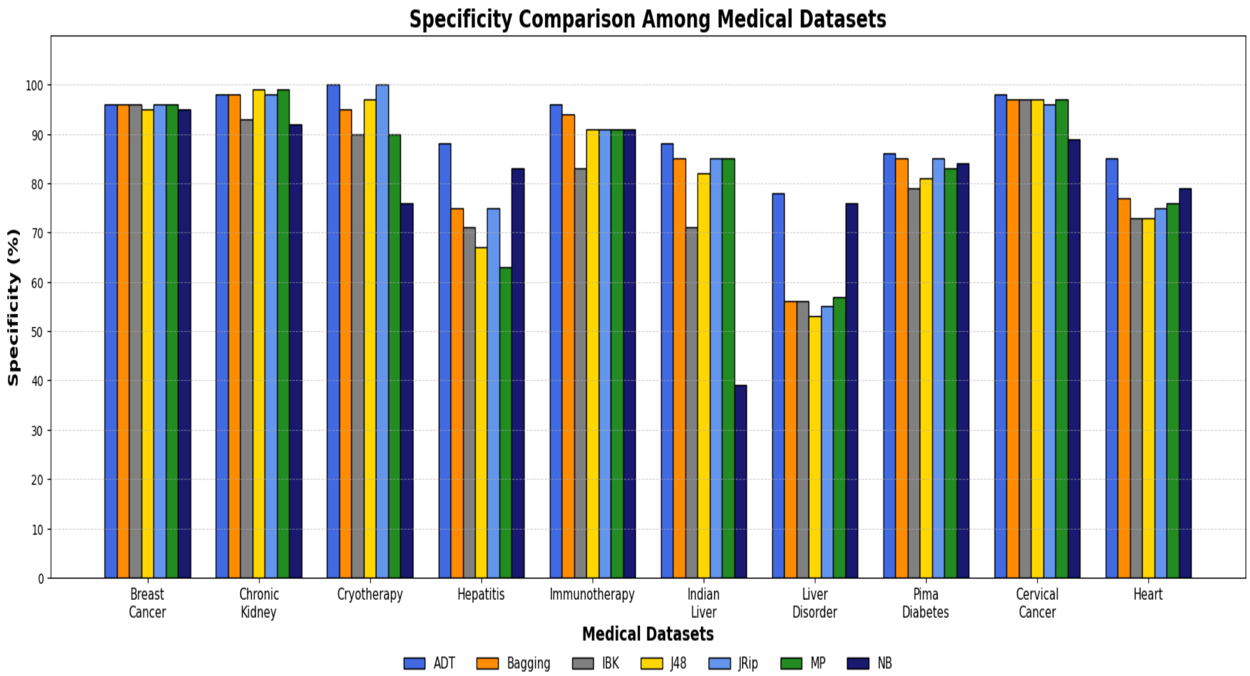

Figure 8: Specificity among various medical datasets

To interpret table 7 and figure 8 represents the "Specificity among Medical Datasets" illustrates how different medical datasets, and the classification algorithms ADT, Bagging, IBK, J48, Jrip, MP, and NB, hyperparameter tuned for specificity, perform relatively to one another. That is, how well the classifiers avoid generating false positives. Specificity also indicates the correct identification of negative cases which reinforces the importance of precision within a medical context. Datasets such as Breast cancer, Chronic Kidney disease, Cryotherapy, as well as Risk factor for cervical cancer, yield classifiers with high specificity. Indeed, most classifiers exceed 90%, with leading ADT, Bagging, and IBK. However, a noticeable decline in specificity can be seen in Indian Liver Patient and Liver disorder datasets where MP and NB models show very low performance under these conditions, often dropping below 50% in multiple instances. Though these algorithms exhibit a variety of changes in performance across datasets, there is somewhat consistent high specificity maintained by ADT and Bagging. This analysis sheds light on the fact that, while measuring the performance of diagnostic models, it is equally important to ensure that specificity is balanced with other metrics, so that the margin of error in the controlled scenarios is minimized.

Ablation Study

Ablation study was used to analyze the individual contribution of each component of the proposed IF-ADT model. The analysis involved four designs, namely (1) Decision Tree, (2) Decision Tree with dynamic threshold only, (3) Decision Tree with intuitionistic fuzzy modeling only, and (4) the full IF-ADT model with the two elements combined.

The findings suggest that the proposal of dynamic threshold optimization leads to better stability in the classification of data since the variance of data is smaller within the folds, with the average accuracy improvement of about 2-3 percent relative to the conventional decision tree. An addition of intuitionistic fuzzy modeling also provides increased sensitivity and less false positive especially in imbalanced data which adds an incremental 2-4 percent further. The overall performance of the entire IF-ADT model was the best which showed that dynamic thresholding and the hesitation modeling individually and together helps in the diagnostic accuracy.

This paper establishes that the overall high performance of IF-ADT does not stem at the individual change but the synergistic combination of adaptive statistical learning and uncertainty-aware fuzzy representation.

6 Discussion

The experimental findings validate that the suggested IF-ADT model can always enhance accuracy, sensitivity, and specificity in a variety of medical data sources. It has been shown that fuzzy-based classification improves the performance in uncertain medical settings Nilashi et al., (2017), and comparative studies on small healthcare datasets have identified the significance of effective and adaptive learning approaches (Yang et al., 2021). Hybrid fuzzy-decision tree models have also been considered in recent studies to diagnose cancer and retinal disease, and it was demonstrated that adding the fuzzy reasoning component to the tree-based models enhances the classification stability (Bhimavarapu, 2025; Rokhsati et al., 2024).

Nonetheless, most of the available solutions either operate based on the use of only fuzzy rule-based systems Navin & Krishnan, (2024) or concentrate on security-oriented fuzzy learning when used in medical internet applications (Alalhareth & Hong, 2023). The hesitation modeling and adaptive threshold optimization are not explicitly combined in most of the models in a single framework. The proposed IF-ADT is by contrasting it with the implementation of intuitionistic fuzzy membership, non-membership and degrees of hesitation directly in the dynamic decision tree splitting process. This combination approach improves resistance to noisy and imbalanced and incomplete clinical data and maintains interpretability.

Although the proposed model has yielded some positive outcomes, there are limitations associated with it. The distance matrix and intuitionistic fuzzy parameter computations add to the complexity of computation. The test was conducted on benchmark datasets as opposed to big data on actual hospitals. There are also a fuzzy parameter (intuitionistic fuzzy parameter of alpha) and threshold (tau) that need to be carefully tuned. The existing implementation is designed to work best with structured tabular data, and would need to be adapted to high dimensional imaging data.

In-depth studies: the IF-ADT framework will be applied to large-scale clinical settings and multi-centers in the future. It will be investigated how to integrate with deep learning-based feature extraction of medical imaging. They will create automated parameter optimization and adaptive hyperparameter tuning solutions that will be created to improve generalizability. Moreover, it is possible to implement federated learning techniques to allow a privacy-sensitive medical diagnostic at high predictive accuracy.

7 Conclusion

The implantation of Adaptive Decision Tree Classifiers (ADT) along with Dynamic Thresholding Intuitionistic Fuzzy Sets (IFS) provides a profound enhancement in diagnosis accuracy in the medical domain. The model considers healthcare datasets from real-world settings which are often noisy, inconsistent, and full of irregularities by effectively using patient data in split criteria as a dynamic model. This logic is further enhanced with the inclusion of IFS by virtue of degrees of membership, non-membership, and sets of hesitation which enable the model to manage uncertainty more deftly, particularly in clinical decision-making. This mixed approach has been proven empirically to surpass other conventional approaches that employed decision tree classifiers, particularly in the handling of imprecise, incomplete, or too specific medical data. The simplicity of computation of the real-time systems presents boundless avenues in expanding automatic decision support system ease of use in harmonizing with human medical operators because of the computer-aided interpretation through such breakthroughs. The experiment performed on ten medical datasets shows that Adaptive Decision Tree (ADT) with dynamic thresholding and Intuitionistic Fuzzy Sets is more sensitive, accurate and specific than the standard Bagging, IBK, J48, Jrip, MP and Naive Bayes classifiers consistently. In the dataset of chronic kidney disease and Breast Cancer, ADT achieves the highest sensitivity of 99% and 98% respectively which means that these true disease cases were correctly identified. Moreover, Cryotherapy and Chronic Kidney Disease remain critical datasets where ADT yields superior precision at 98% and 99% respectively, indicating significantly high rates of correctly predicted positive cases. Furthermore, ADT maintains excellent specificity where it achieves perfect performance in several other datasets and maintains over 95% in several others, thus confirming ADT's strength in avoiding false positive cases. Other models show great variability and much lower performance with complex datasets such as Immunotherapy and Liver Disorder. In summary, ADT prevails as a dependable and precise model, achieving stable performance across all listed metrics, making this algorithm suitable for intelligent medical diagnostic systems that emphasize accuracy and interpretability.

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