Interpretable Decision Tree Model for Classification of Acute Appendicitis Using Clinical, Laboratory, and Imaging Data: A Retrospective Single-Center Study

Ali Bekraki[1], *Ahmad Shahin*[2]

[1] Department of General Surgery, University of Health Sciences, Hamidiye Medical Faculty, Istanbul, Türkiye
[2] Faculty of Economics and Business Administration, Laboratory of Informatics and Their Applications, Lebanese University, Tripoli, Lebanon

Correspondence: Ali Bekraki, MD; abekraki@hotmail.com

Abstract

Background: Acute appendicitis remains a common surgical emergency, and diagnostic uncertainty persists despite the use of clinical scores and imaging. We examined whether an interpretable decision tree could support classification of appendicitis using routinely available clinical, laboratory, and imaging variables. **Methods:** This retrospective single-center study included 281 patients who presented to El-Youssef Hospital with suspected appendicitis between June 2015 and May 2020. A J48 decision tree was developed in WEKA using age, fever, white blood cell count, neutrophil percentage, C-reactive protein, ultrasound findings, and computed tomography findings. Model performance was estimated with 10-fold cross-validation and reported using the confusion matrix. **Results:** The decision tree achieved an overall accuracy of 84.3%, with a sensitivity of 89.8%, a specificity of 76.3%, a positive predictive value of 84.8%, and a negative predictive value of 83.7%. Ultrasound, computed tomography, white blood cell count, and neutrophil percentage were the most informative predictors. Misclassifications were most common in patients with atypical presentations or borderline laboratory values. **Conclusion:** In this single-center retrospective cohort, a decision tree classifier showed good internal performance for distinguishing appendicitis from non-appendicitis. The findings support the feasibility of an interpretable decision-support model, but they do not establish clinical effectiveness. External multicenter validation and comparison with alternative algorithms and existing scoring systems are needed before clinical implementation.

Keywords: Acute appendicitis; data mining; decision tree; machine learning; diagnostic classification; clinical decision support

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1. Introduction

Improving diagnostic accuracy while avoiding unnecessary intervention remains an important challenge in emergency surgical care[1]. Acute appendicitis accounts for a substantial proportion of emergency surgical admissions, and delays in diagnosis may increase the risk of perforation, peritonitis, and prolonged hospitalization[2,3]. Appendectomy remains the definitive treatment and one of the most frequently performed emergency abdominal surgeries. At the same time, unnecessary appendectomy remains clinically relevant because avoidable surgery contributes to healthcare costs and procedure-related morbidity[4].

Multiple clinical scoring systems, including the Alvarado, RIPASA, and Tzanakis scores, have been introduced to assist diagnostic stratification in suspected appendicitis[2,3,5-7]. Even so, diagnostic performance remains variable across settings and patient groups. Because diagnostic performance varies across patient populations and clinical settings, interest has grown in machine-learning approaches capable of integrating multiple diagnostic variables simultaneously.

Advances in computational analysis have expanded the use of data-driven models in clinical decision support research. These approaches aim to identify relationships within complex datasets that may not be readily apparent using conventional analytical methods[8]. Initially applied in healthcare in the early 1990s, data mining has gained traction in recent years due to advancements in information technology and the widespread availability of electronic medical records[9]. In surgical practice, such models may help organize heterogeneous diagnostic information into reproducible classification frameworks.

The present study investigated whether a transparent decision tree classifier could distinguish appendicitis from non-appendicitis using routinely collected emergency department data. A decision tree algorithm was selected because its rule-based structure permits direct visualization of how individual predictors contribute to classification outcomes.

Table 1. Attributes and their descriptions that are significant to diagnose acute appendicitis

Attribute	Description
Nausea and Vomiting	The patient went to the emergency department (ER) with this symptom.
Abdominal pain	The patient went to the ER with this symptom.
Tenderness	The doctor localizes the presence or absence of right lower quadrant tenderness.
Age	A numeric value between 0 and 100
Sex	Male or Female
Fever	Numerical values ranging from less than 37°C to more than 40°C
White Blood Cell (WBC)	Numerical values ranging from less than 10,000 Cells/mm^3 to more than 20,000 Cells/mm^3
Neutrophilia	Numerical values ranging from less than 70% to more than 70%
C Reactive Protein (CRP)	Numerical values ranging from less than 5 to more than 5
Urine	The presence of significant quantity of Red Blood Cell (RBC) or WBC in the urine
Lymphocyte	Numerical values ranging from less than 50% to more than 50%
Monocyte	Numerical values ranging from less than 10% to more than 10%
Eosinophil	Numerical values ranging from less than 5% to more than 5%
Ultrasound (US)	Is a string attribute
Computerized Tomography (CT)	Is a string attribute
Appendectomy	Yes or No

2. Materials and Methods

2.1.Study Design and Data Collection

This retrospective single-center study included patients who presented to the emergency department of El-Youssef Hospital in Akkar, Lebanon, with suspected acute appendicitis between June 2015 and May 2020. The study aimed to evaluate the performance of an interpretable decision tree classifier for distinguishing appendicitis from non-appendicitis using routinely available clinical, laboratory, and imaging variables.

Patients were eligible if they had a provisional diagnosis of acute appendicitis and a complete medical record, including a final histopathological report for the resected appendix. Patients with incomplete records were excluded. A total of 281 patients were included in the final analysis. Reporting of the study was guided by TRIPOD principles for prediction model research.

The extracted variables were age, sex, fever, white blood cell count, neutrophil percentage, C-reactive protein, urinalysis results, ultrasound findings, computed tomography findings, and appendectomy status. The reference standard outcome was final histopathology, classified as appendicitis or non-appendicitis. The complete list of attributes is presented in Table 1.

2.2.Ethical Approval

This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval for the study was obtained from the Scientific Committee of the Lebanese University, Faculty of Economics and Business Administration, 3rd Branch (approval date: April 2015; approval number: 12022015). Due to the retrospective design of the study and the use of fully anonymized patient data, the requirement for individual informed consent was waived by the ethics committee. Hospital administrative permission was obtained prior to data collection, and strict measures were implemented to ensure patient confidentiality throughout the study.

2.3.Data Pre-Processing and Feature Selection

Data cleaning, integration, and transformation were performed before model development. Variables containing substantial missing or inconsistent data were excluded before model construction. Symptoms such as nausea and vomiting, and urinalysis results, were also removed because they demonstrated little discriminatory value in this dataset. Continuous variables were categorized to facilitate decision tree construction; however, this transformation was used for model building rather than as a claim of clinically validated thresholds.

2.4.Attribute Definition and Data Transformation

Continuous variables were categorized primarily to improve interpretability of the resulting classification rules and facilitate bedside applicability. Age was categorized into four groups: 18–30, 31–50, 51–70, and ≥71 years[10]. Fever was classified into five categories: normal (<37°C), mild (37–38°C), moderate (38–39°C), high (39–40°C), and malignant (>40°C). WBC counts were categorized as normal (<10,000 cells/mm^3), slightly elevated (10,000–15,000), moderately elevated (15,000–20,000), and high (>20,000). Neutrophil percentage was categorized as normal (<70%), slightly elevated (70–80%), and high (>80%), while CRP values were classified as normal (<5 mg/L) or elevated (>5 mg/L).

2.5.Imaging Findings

Ultrasound findings were classified as appendicitis, other pathology, or normal. Appendicitis on ultrasound was defined by at least one of the following: appendiceal diameter greater than 6–7 mm, wall thickening greater than 3 mm, non-compressibility, appendicolith, a blind-ended tubular structure, or peri-appendiceal fluid/abscess.

Computed tomography findings were classified in the same way, with appendicitis defined by appendiceal enlargement greater than 6 mm, mesenteric fat stranding, appendicolith, cecal thickening, adenopathy, or abscess formation.

2.6.Outcome Variables

Appendectomy status was recorded as a binary variable (yes/no). The final diagnosis (appendicitis vs. non-appendicitis) was determined according to the histopathological examination of the resected appendix. The final dataset structure is shown in Table 2.

Table 2. Data transformation and optimization

Attribute	Type	Value
Age	Nominal	18–30, 31–50, 51–70, and ≥71 years
Sex	Nominal	M, F
Fever	Nominal	Normal, Mild, Moderate, High, Malignant
WBC	Nominal	Normal, Slightly_elevated, Moderately_elevated, High
Neutrophil	Nominal	Normal, Slightly_elevated, High
CRP	Nominal	Normal, High
US	Nominal	Diagnose_appendicitis, Diagnose_other_pathology, Normal
CT	Nominal	Diagnose_appendicitis, Diagnose_other_pathology, Normal
Appendectomy	Boolean	Yes, No
Diagnosis	Nominal	Appendicitis, Not_Appendicitis

2.7.Machine Learning Model Development and Validation

Data mining analysis was performed using WEKA version 3.8 (University of Waikato, New Zealand)[11]. A J48 decision tree classifier, corresponding to the C4.5 algorithm, was selected because its rule-based structure allows transparent visualization of predictor interactions. Model performance was assessed using 10-fold cross-validation, with metrics averaged across all internal folds to reduce overfitting and provide robust validation.

Classification performance was comprehensively evaluated via a standard confusion matrix, calculating overall diagnostic accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). Furthermore, the J48 algorithm identified the most informative clinical attributes based on mathematical information gain, allowing for an objective estimation of the relative contribution of individual laboratory and imaging variables in predicting acute appendicitis.

2.8.Statistical Analysis

All predictive modeling and performance calculations were performed within the WEKA environment. Model validation and calculation of diagnostic performance metrics—including accuracy, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV)—were performed within the WEKA analytical environment based on the confusion matrix obtained from the classification results. No external validation cohort was available, and no comparison with alternative machine-learning algorithms or conventional diagnostic scores was performed in the present study.

3. Results

This study evaluated the classification performance of a decision tree–based data mining model for acute appendicitis using a dataset of 281 patient records with six attributes: neutrophil percentage, WBC count, CRP, ultrasound (US), computed tomography (CT), and final diagnosis. Analysis was performed in WEKA Explorer, which provided both numerical performance metrics and a visual representation of the decision tree (Figure 1). Internal validation with 10-fold cross-validation was performed to obtain a more stable estimate of model performance across dataset subsets.

The model correctly identified 150 cases of appendicitis (true positives) and 87 cases of non-appendicitis (true negatives), while 17 appendicitis cases were misclassified as non-appendicitis (false negatives) and 27 non-appendicitis cases as appendicitis (false positives).

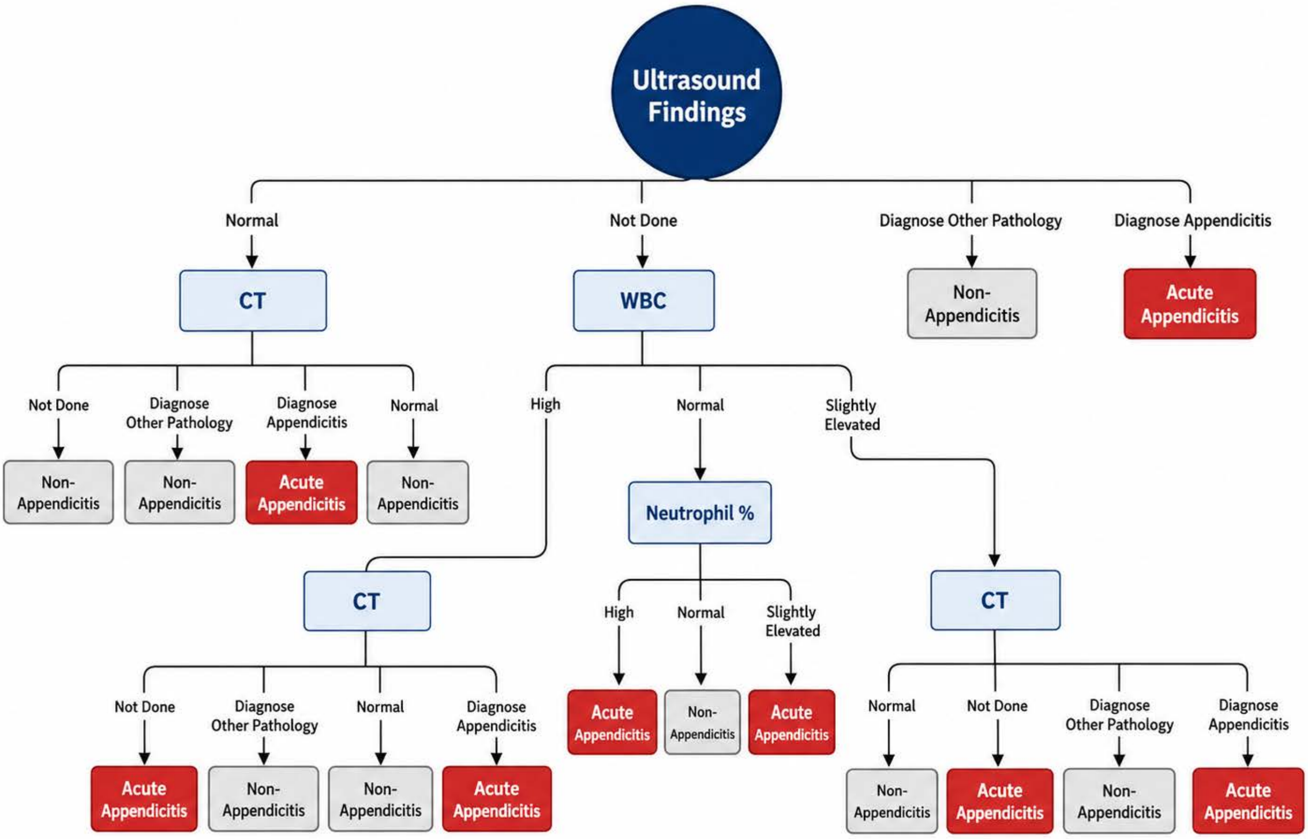

Figure 1. Flowchart of data mining model as produced by WEKA.

This corresponded to an overall accuracy of 84.3%, with a sensitivity of 89.8%, specificity of 76.3%, positive predictive value (PPV) of 84.8%, and negative predictive value (NPV) of 83.7% (Table 3). Most misclassifications occurred in patients with atypical presentations or borderline laboratory values.

In contrast to prior reports describing male predominance, appendicitis cases in the current cohort were distributed similarly between male and female patients (male-to-female ratios ranging from 2.6:1 to 1:0.03)[12]. The lifetime risk of developing acute appendicitis is 8.6% in males and 6.7% in females[13]. Most patients presented with low-grade fever, and elevated CRP levels were common among appendicitis cases, consistent with classical clinical presentations[14].

Table 3. Performance metrics of the decision tree model for predicting acute appendicitis

Metric	Value (%)
Accuracy	84.3
Sensitivity / Recall	89.8
Specificity	76.3
Positive Predictive Value (PPV)	84.8
Negative Predictive Value (NPV)	83.7

The decision tree model highlighted the diagnostic significance of imaging findings, particularly US and CT, as well as laboratory parameters such as WBC and neutrophil percentage. Integration of these clinical, laboratory, and imaging variables contributed substantially to model discrimination and reflected practical considerations of surgical decision-making.

4. Discussion

4.1.Epidemiology and Clinical Significance

Acute appendicitis continues to represent a major component of emergency general surgical practice across all age groups, affecting approximately 7% of individuals over their lifetime[15,16]. The highest incidence occurs between 10 and 30 years of age, while only 5–10% of cases are observed in elderly patients[15]. Although overall mortality is low (<1%), delayed or missed diagnoses can lead to severe complications, including peritonitis and sepsis, particularly in children, elderly patients, and pregnant women, where mortality may reach 50%[17]. Notably, approximately 15% of appendectomies are performed unnecessarily, reflecting the persistent challenges in achieving timely and accurate diagnosis[18]. Diagnostic errors are frequent, with 7.1–10% of adults and 4.8–15% of children initially misdiagnosed[19,20], underscoring the clinical and medico-legal implications of diagnostic failure[21,22].

Specific populations are particularly vulnerable to misdiagnosis. Children often present with symptoms mimicking gastroenteritis or respiratory infections (25–30%), while women of childbearing age may be misdiagnosed with gynecological or urinary conditions (33%)[23]. Pregnant women, although exhibiting a similar incidence, often present atypically, increasing the risk of appendicular perforation and fetal loss (up to 20%) compared with uncomplicated cases (3–5%)[22]. In elderly patients (>60 years), misdiagnosis is common due to comorbidities and alternative abdominal pathologies such as diverticulitis and colonic ischemia, resulting in higher complication rates (18–70%) compared to younger adults (3–29%)[24,25,26]. Collectively, these findings illustrate the ongoing diagnostic challenges associated with appendicitis, particularly in clinically atypical populations.

4.2.Current Diagnostic Tools and Scoring Systems

The diagnosis of acute appendicitis relies on a combination of clinical evaluation, laboratory markers, and radiological investigations. Imaging modalities, including ultrasonography (US) and computed tomography (CT), improve diagnostic precision, reduce negative appendectomy rates, and facilitate early surgical intervention[27]. Scoring systems such as the Alvarado, RIPASA, and AIR scores (for adults), as well as PAS, Lintula, and Tzanakis scores (for pediatric populations), assist in risk stratification but demonstrate variable sensitivity and specificity[28]. For example, a 2022 meta-analysis reported the Alvarado score with 72% sensitivity and 77% specificity, whereas RIPASA exhibited higher sensitivity but lower specificity. The variability observed among currently available scoring systems suggests that no single diagnostic strategy performs consistently across all clinical settings.

4.3.Data Mining in Healthcare and Rationale for This Study

In acute appendicitis, diagnosis depends on integrating clinical, laboratory, and imaging findings, yet accurate diagnostic classification at the individual-patient level remains challenging. Machine-learning approaches, including decision tree classifiers, have therefore been explored for appendicitis diagnosis and for other clinical prediction tasks[29]. More broadly, data mining in healthcare information systems has been used to extract clinically meaningful patterns from complex datasets and support decision-making[30,31]. Recent reviews also note that artificial intelligence and data science may improve healthcare delivery, although their application remains constrained by issues such as implementation complexity, privacy concerns, and variable clinical readiness[32,33].

Among available analytical tools, WEKA was selected because it provides an accessible framework for exploratory classification modeling and visualization[34]. Comparative reviews of data mining tools for healthcare likewise identify WEKA as a flexible and accessible platform for this purpose[35]. In the present study, this approach was used to examine whether an interpretable decision tree could capture diagnostic patterns associated with acute appendicitis.

4.4.Study Findings and Implications

In this study, the decision tree model showed moderate internal classification performance, correctly identifying 150 cases of appendicitis and 87 non-appendicitis cases, yielding an overall accuracy of 84.3%. Laboratory parameters (WBC count, neutrophil percentage) and imaging findings (US, CT) emerged as the most informative predictors, aligning closely with established surgical decision-making. The lifetime risk of developing acute appendicitis is significant, being 8.6% in males and 6.7% in females[13], and the model provides a systematic approach to support diagnostic evaluation in this population.

These findings suggest that combining clinical, laboratory, and imaging variables within a predictive model may be useful for supporting diagnostic evaluation. However, the present results should be interpreted as preliminary and exploratory. The present findings should be interpreted as preliminary evidence from an exploratory classification framework requiring further validation.

4.5.Limitations and Future Directions

This study has several limitations. First, it was conducted at a single center and included a relatively small sample, which limits generalizability. Second, the model was evaluated only with internal 10-fold cross-validation; no external validation cohort was available. Third, only one machine-learning algorithm was tested, so the present results do not show whether J48 is superior to other classifiers or to established clinical scores. Fourth, the use of ultrasound and computed tomography as predictors means that the model reflects a later stage of diagnostic workup rather than an early bedside tool. Fifth, although categorization improved interpretability, it may also have reduced the granularity of predictive information contained within continuous variables. Sixth, because the outcome was final histopathology in operated patients, the model was assessed in a selected surgical population rather than in all patients presenting with abdominal pain.

Accordingly, the findings should be interpreted as preliminary internal validation results rather than evidence of clinical effectiveness or implementation readiness.

5. Conclusion

In this retrospective single-center cohort, a J48 decision tree classifier demonstrated moderate internal classification performance for distinguishing appendicitis from non-appendicitis using routinely available clinical, laboratory, and imaging variables. Ultrasound findings, computed tomography findings, white blood cell count, and neutrophil percentage contributed most substantially to model classification performance. Although these findings suggest potential utility for structured diagnostic classification, external validation and comparison with established clinical scoring systems and alternative machine-learning methods remain necessary before clinical implementation.

genAI: No artificial intelligence-based tools or generative AI technologies were used in this study. The entire content of the manuscript was originally prepared, reviewed, and approved by all authors.

Statement of Ethics: This study was conducted in accordance with the principles of the Declaration of Helsinki. Ethical approval was obtained from the Scientific Committee of the Lebanese University, Faculty of Economics and Business Administration, 3rd Branch (approval date: April 2015; approval number: 12022015). Due to the retrospective design and use of fully anonymized patient data, individual informed consent was waived by the ethics committee.

Data Availability: The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Author Contributions: Ahmad Shahin was responsible for conceptualization, software application, and data analysis, and revised the manuscript after it was written and approved its validity. Ali Bekraki collected data, supervised the software, analyzed results, approved the flowchart, and wrote the manuscript.

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