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Decision Tree-Based Model Prediction of Lower Extremity CTA Angiography Using Laboratory Biomarkers in Young Takayasu Arteritis Patients

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Abstract

Takayasu arteritis (TAK) is a rare, chronic large vessel vasculitis that primarily affects young patients, leading to arterial wall thickening, stenosis, or occlusion with potentially severe complications. Computed tomography angiography (CTA) is a key diagnostic tool but involves risks due to contrast media and radiation, particularly in young populations. This study aimed to develop and evaluate a decision tree model using routine laboratory biomarkers to predict lower extremity arterial abnormalities detected by CTA in young patients suspected of TAK. We retrospectively analyzed 194 patients under 40 years old with lower limb CTA and comprehensive laboratory data, excluding confounding comorbidities. Ten laboratory parameters including hs-CRP, LDH, HDL, creatine kinase, coagulation factors, IL-6, ESR, and albumin were incorporated into a decision tree classifier. The model achieved 80% accuracy, sensitivity, and specificity in internal cross-validation. External validation on 20 patients showed 80% accuracy, outperforming an expert radiologist's 55% accuracy based on laboratory data alone ($p < 0.05$). Albumin was the only individual biomarker significantly different between groups, highlighting the utility of integrating multiple biomarkers rather than relying on single parameters. The decision tree model offers a transparent, noninvasive, and safer adjunct or alternative to CTA for early detection of arterial involvement in young TAK patients, potentially reducing unnecessary imaging and associated risks. Further prospective multicenter validation is warranted to confirm its clinical applicability and integration into diagnostic workflows.

Keywords: Decision Tree, Lower Extremity CTA, Takayasu Arteritis, Machine Learning, Laboratory Findings

Background

Takayasu arteritis (TAK) is a rare, chronic, progressive, large vessel vasculitis characterized by granulomatous inflammation targeting the aorta and its major branches. The disease leads to fibrosis and thickening of the arterial wall, resulting in stenosis, occlusion, or aneurysmal dilatation of affected vessels. These vascular changes compromise blood flow and oxygen delivery to critical organs such as the brain, heart, and kidneys, potentially causing life-threatening complications [1-4].

According to the Global estimates, TAK incidence is around 0.5–2 per million, but regional differences are substantial with higher burden consistently been reported in East and Southeast Asia and among individuals of Asian descent and African populations, while European and American cohorts show lower yet non-negligible rates [5-7]. The disease most often manifests

in women, with female-to-male ratios frequently in the 3:1 to 4:1 range, and onset commonly occurs before age 40 [6, 7]. This epidemiological pattern underscores the global relevance of TAK in young adults and supports the need for external validation of predictive tools across diverse cohorts.

The American College of Rheumatology (ACR) criteria for TAK, established in 1990, emphasize onset at or before 40 years of age, symptoms such as limb claudication, and imaging evidence of vascular abnormalities including stenosis or occlusion of major arteries [8]. Imaging modalities remain central to diagnosis and disease monitoring. Among these, computed tomography angiography (CTA) has become a widely accepted method for evaluating large vessel pathology owing to its ability to visualize vessel lumen, wall thickening, and vascular calcifications with high spatial resolution [9, 10]. Although primarily used for diagnosing peripheral artery disease (PAD) in elderly patients, such as those with atherosclerosis or diabetes mellitus, lower limb CTA is optionally employed to screen for arteritis in selected young patients [11-15].

However, despite its diagnostic utility, CTA has several important limitations that restrict its use in certain patient populations. The requirement for iodinated contrast media can exacerbate renal impairment, making CTA contraindicated in patients with renal insufficiency [16, 17]. Additionally, ionizing radiation exposure during CTA has cumulative risks, particularly in young and potentially fertile patients, which necessitates caution and limits its repeated use [15, 18, 19]. These concerns underscore the importance of identifying alternative or adjunctive diagnostic approaches that are noninvasive, safe, and cost-effective, especially in young patients suspected of TAK or other forms of large vessel vasculitis.

Laboratory tests in TAK often reveal nonspecific inflammatory and hematological abnormalities, such as elevated erythrocyte sedimentation rate, C-reactive protein, and alterations in coagulation and lipid profiles [20, 21]. While these markers provide useful clues about disease activity, their sensitivity and specificity for arterial involvement remain limited when used individually [9, 22-27]. To date, limited studies have systematically explored the relationship between routine laboratory parameters and imaging findings on lower extremity CTA in young patients suspected of TAK. Given recent advances in machine learning, there is an emerging opportunity to integrate multiple laboratory findings into predictive models that can noninvasively estimate vascular status [28, 29]. Decision tree algorithms, in particular, offer transparent and interpretable classification tools suitable for clinical decision support, even in relatively small datasets [30]. By combining various laboratory parameters, such models hold promise for accurately predicting CTA outcomes, potentially reducing the need for invasive or radiation-exposing imaging examinations.

In this study, we investigated the feasibility of using a decision tree model based on multiple laboratory findings to predict the presence of arterial abnormalities detected by lower extremity CTA in young patients. Our approach aims to provide a novel, safer, and more accessible diagnostic tool to assist clinicians in managing TAK and related vascular diseases, ultimately helping to minimize reliance on contrast-enhanced imaging and its associated risks.

Methods

Study Design and Population

This retrospective study enrolled a total of 194 patients who underwent lower limb CTA at Tongji Hospital between January 2020 and December 2023. This included patients less than 40 years, with lower limb CTA images and complete laboratory results, including blood routine, blood biochemistry, coagulation profile, and interleukin-6 (IL-6), within one week of imaging. Patients with comorbidities such as diabetes mellitus, renal insufficiency, tuberculosis, or malignancy were excluded from the study to reduce confounding conditions affecting vascular status or laboratory parameters.

Imaging and Diagnostic Classification

Lower limb CTA examinations were performed using a standardized protocol with iodinated contrast agents. An experienced radiologist with over 20 years in PAD diagnosis independently reviewed all CTA images, including source and reconstructed data. The radiologist was blinded to the clinical and laboratory information. Based on arterial findings, patients were classified into two groups: normal lower limb arteries and diseased arteries characterized by arterial wall thickening or luminal occlusion.

Laboratory Data Collection

Laboratory data collected included hyper-sensitive C-reactive protein (hs-CRP), lactic dehydrogenase (LDH), high-density lipoprotein (HDL), creatine kinase, prothrombin activity (PTA), fibrinogen (FIB), activated partial thromboplastin time (APTT), IL-6, ESR, and albumin (ALB). All blood tests were performed using standard automated analyzers in the hospital clinical laboratory. Values closest to the time of the CTA study were used.

Decision Tree Model Development

A decision tree classifier was developed to predict the presence of lower limb arterial disease based on the ten selected laboratory biomarkers. All features were included simultaneously to account for potential interactions. Model training and validation were conducted using Python with the scikit-learn library. The decision tree was configured with a maximum depth of 7, a minimum of 10 samples required to split an internal node, a minimum of 5 samples per leaf node, and a maximum of 10 leaf nodes to avoid over fitting while maintaining interpretability. A fixed random seed ensured reproducibility.

Model Evaluation and External Validation

Model performance was primarily assessed by accuracy computed from confusion matrices on internal validation sets obtained via cross-validation. Sensitivity and specificity metrics were also calculated to evaluate diagnostic performance. To validate generalizability, the trained model was applied to an external cohort of 20 patients (10 normal and 10 diseased), independently evaluated by the radiologist using laboratory findings alone. Comparative accuracy, sensitivity, and specificity between the decision tree model and radiologist predictions were statistically compared using Chi-square tests.

Statistical Analysis

Continuous variables were first assessed for normality using the Shapiro-Wilk test. Normally distributed data were reported as mean ± standard deviation, while non-normally distributed data were expressed as median with interquartile ranges (IQR). Comparisons between groups were conducted using the two-sample t-test for normally distributed variables and the Mann-Whitney U test for non-normal distributions. A p-value less than 0.05 was considered statistically significant.

Results

Patient Demographics

A total of 194 patients were enrolled, with 100 patients classified in the normal lower limb artery group (Group A) and 94 patients in the diseased group exhibiting arterial wall thickening or occlusion (Group B). The two groups showed no statistically significant differences in age or gender distribution ($p > 0.05$), ensuring comparability of baseline demographic characteristics.

Table 1: Baseline Demographic characteristics of patients by arterial group

Characteristics	Group A (Normal Artery)	Group B (Diseased Artery)	p-value
Number of patients	100	94	-
Age	Comparable between groups	Comparable between groups	>0.05
Gender distribution	Comparable between groups	Comparable between groups	>0.05

Laboratory Findings

Comparison of laboratory parameters between the two groups revealed a significant difference in ALB levels, with Group A showing 40.5 ± 7.1 g/L and Group B showing 42.6 ± 6.7 g/L ($p = 0.012$). Other laboratory tests, including hs-CRP, LDH, HDL, CK, PTA, FIB, APTT, IL-6, and ESR, did not differ significantly between groups ($p > 0.05$). Nonetheless, these features had relatively lower p-values compared to other laboratory indicators, suggesting some discriminatory potential.

Table 2: Comparison of Laboratory Findings Between Groups

Laboratory Parameter	Normal Group (mean ± SD)	Diseased Group (mean ± SD)	P-value
Albumin (ALB)	40.5 ± 7.1 g/L	42.6 ± 6.7 g/L	0.012
hyper-sensitive CRP (hs-CRP)	No significant difference		>0.05
Lactic dehydrogenase (LDH)	No significant difference		>0.05
High density lipoprotein(HDL)	No significant difference		>0.05
Creatine kinase (CK)	No significant difference		>0.05
Prothrombin activity (PTA)	No significant difference		>0.05
Fibrinogen (FIB)	No significant difference		>0.05
Activated partial thromboplastin time (APTT)	No significant difference		>0.05
Interleukin-6 (IL-6)	No significant difference		>0.05
Erythrocyte sedimentation rate (ESR)	No significant difference		>0.05

Decision Tree Model Performance

A decision tree model incorporating ten laboratory biomarkers (hs-CRP, LDH, HDL, CK, PTA, FIB, APTT, IL-6, ESR, and ALB) was developed. Internal validation demonstrated an overall accuracy of 80%, with both sensitivity and specificity reaching 80%, indicating balanced predictive capability for detecting arterial disease versus normal findings based on laboratory data.

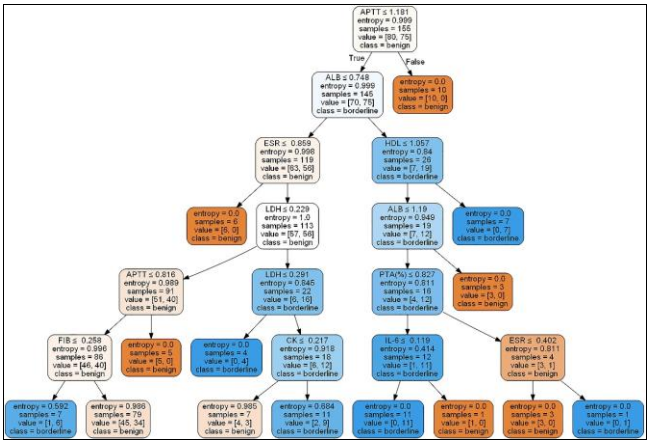

Fig 1: The decision tree based on laboratory findings for predicting lower extremity CTA result

Table 3: Decision Tree Model Performance in Internal Validation

Metric	Value (%)
Accuracy	80
Sensitivity	80
Specificity	80

External Validation and Radiologist Comparison

Applying the model to an external dataset of 20 cases (10 normal and 10 diseased), the decision tree correctly predicted 16 cases, achieving 80% accuracy. In comparison, a radiologist's predictions based solely on laboratory findings reached 55% accuracy, which was significantly lower than the model's performance ($p < 0.05$). The radiologist's sensitivity and specificity were 60% and 50%, respectively, both substantially lower than the decision tree model's corresponding metrics.

Table 4: Model vs. Radiologist Performance on External Dataset (n=20)

Metric	Decision Tree (%)	Radiologist (%)	P-value
Accuracy	80	55	<0.05
Sensitivity	80	60	-
Specificity	80	50	-

Discussion

This study investigated the feasibility of using a decision tree model based on multiple laboratory biomarkers to predict the results of lower extremity CTA in young patients suspected of TAK. The model achieved encouraging accuracy of 80% in internal validation and demonstrated superior predictive performance on an external dataset compared to an experienced radiologist relying solely on laboratory findings. These findings suggest that the integration of routine laboratory tests into an interpretable

machine learning framework holds promise as a non-invasive diagnostic adjunct or alternate to CTA in selected clinical situations, particularly in young patients where imaging carries higher risks due to radiation exposure and contrast-related nephrotoxicity [15-19].

Among the laboratory parameters studied, ALB was the only biomarker that significantly differed between patients with normal and diseased lower limb arteries. This aligns with the recognized role of hypoalbuminemia as an indicator of systemic inflammation and chronic disease severity, which are key features in TAK pathogenesis [31, 32]. Although other markers such as hs-CRP, IL-6, ESR, and coagulation indices did not reach individual statistical significance, their inclusion in the multivariate decision tree model improved overall predictive accuracy. This highlights the complex interplay of inflammatory and hematological factors in TAK and underscores the value of integrating multiple biomarkers over reliance on any individual parameter.

The decision tree approach highlighted notable advantages as it easily interpretable results that clinicians can understand and apply, addressing a common critique of more complex machine learning models lacking transparency [33]. Furthermore, it performed well on relatively small datasets typical in rare diseases [33-35], making it feasible for clinical adoption without extensive data collection. The model's balanced sensitivity and specificity indicate reliable discrimination between patients with and without lower limb arterial disease on CTA. In comparison, the radiologist's accuracy based solely on laboratory data was substantially lower, emphasizing the added value of algorithmic integration of multi-parametric laboratory data.

Clinically, this approach may reduce the need for CTA examinations in young patients who are vulnerable to radiation and contrast-related risks, offering a safer, cost-effective preliminary screening tool. This is especially relevant for patients with renal insufficiency or young women concerned about fertility risks related to ionizing radiation [36-38]. Moreover, it could be valuable in resource-limited settings lacking ready access to advanced vascular imaging, expanding diagnostic accessibility.

However, several limitations warrant consideration. The moderate sample size and retrospective design may limit generalizability, and larger, prospective multicenter studies are needed. CTA was used as the reference standard instead of vessel wall biopsy due to invasiveness, potentially introducing diagnostic uncertainty. Additionally, continuous laboratory values can be challenging to model effectively using decision trees, suggesting exploration of other machine learning methodologies or data transformations in future research. Integration of clinical features, imaging data, and longitudinal biomarker trends could further enhance predictive performance.

Future directions should focus on validating the model in larger, diverse cohorts and incorporating additional clinical variables and imaging findings. Comparative studies with other machine learning techniques and cost-effectiveness analyses will help delineate the model's role in clinical practice. Development of user-friendly clinical decision support tools embedding this model could facilitate real-time risk stratification and personalized patient management.

Conclusion

The decision tree model based on multiple laboratory findings demonstrated feasibility and promising accuracy in predicting lower extremity CTA results in young patients with suspected Takayasu arteritis. By effectively integrating routine blood biomarkers, this approach offers a non-invasive, interpretable, and potentially safer alternative to CTA imaging for early detection and monitoring of lower limb arterial involvement. Further prospective validation and integration with clinical workflows are needed to fully establish its clinical utility and potential impact on patient care.

List of Abbreviations

Abbreviation	Full Term
CTA	CT angiography
ALB	Albumin
hs-CRP	hyper-sensitive C Reactive Protein
LDH	Lactic Dehydrogenase
HDL	High Density Lipoprotein
CK	Creatine Kinase
PTA	Prothrombin Activity
FIB	Fibrinogen
APTT	Activated Partial Thromboplastin Time
IL-6	Interleukin-6
ESR	Erythrocyte Sedimentation Rate
TAK	Takayasu Arteritis
PAD	Peripheral Artery Disease
IQR	Interquartile Range

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