A Swimming Athlete Performance Prediction Model Utilizing Design Thinking and the Decision Tree Approach

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ABSTRACT

Traditional sports analytics faces an implementation gap where technically accurate machine learning models fail to achieve practical adoption due to misalignment with coaching needs. This study introduces Algorithmic-Enhanced Design Thinking (AEDT), a novel framework that embeds the C4.5 decision tree algorithm as an active ideation partner within Design Thinking's creative phase, transforming the sequential "design-then-analyze" paradigm into a concurrent "design-while-analyzing" process. This study analyzed 442 performance records from 94 youth swimmers aged 6-15 years registered with the Indonesian Swimming Federation through five iterative human-algorithm collaboration cycles. The AEDT process expanded the features from 6 to 18 variables, achieving 66.7% Novel Variable Discovery Rate, where two-thirds emerged from algorithmic pattern discovery. The model achieved 58.5% classification accuracy, significantly above the 33.3% random baseline, with a 0.90 interpretability score, yielding the highest Practical Value Score of 0.776 compared to Standard C4.5 at 0.687, Random Forest at 0.333, and Neural Networks at 0.234. Key discoveries include critical performance thresholds such as Height greater than 145 cm and Armspan-to-Height ratio greater than 1.02, along with stroke-specific regression models achieving R^2 values up to 0.882 for Freestyle prediction. The algorithm revealed that height, with an information gain of 0.892, and armspan, with 0.847, dominate performance prediction, challenging coaching assumptions about weight importance at 0.412. AEDT successfully bridges the implementation gap by producing interpretable, actionable insights through human-algorithm collaboration. The framework provides a reproducible methodology for human-AI collaboration, with collaboration quality assessed through four measurable components, namely, Human contribution $H(t)$, Algorithm discovery $A(t)$, Integration quality $I(H, A, t)$, and Convergence efficiency $C(t)$, applicable across domains where understanding "why" matters more than optimizing accuracy alone.

Keywords-decision tree; Algorithmic-Enhanced Design Thinking (AEDT); predictive modeling; human-algorithm collaboration

I. INTRODUCTION

In the highly rigorous landscape of modern competitive sports, optimizing athlete performance is a primary objective for coaches, sports scientists, and organizations. This endeavor has transcended traditional training programs and now heavily relies on data-driven insights to gain a competitive advantage. Sports analytics has emerged as a critical component, offering objective methods to understand performance dynamics, mitigate injury risks, and inform strategic on-field decisions. Within the domain of sports analytics, Machine Learning (ML) has demonstrated significant potential for processing complex and multidimensional performance data [1]. Various algorithms are employed to forecast outcomes and identify key predictors. Among these methods, decision tree algorithms, such as C4.5, are particularly advantageous [2]. Decision tree-based methods have gained significant popularity among ML algorithms due to their simplicity and interpretability [3]. Their primary benefit lies in their 'white-box' nature, as they generate transparent, rule-based models that are interpretable by non-technical experts, such as coaches. Prior research has successfully utilized decision trees to uncover significant factors in athletic performance, such as in track and field analysis, and to support decisions [4].

Despite the technical merits of these predictive models, a significant implementation gap frequently exists between data analysts and coaching staff. A model may be statistically accurate yet practically irrelevant if it fails to measure variables that coaches deem important, or if its insights are not presented in an actionable manner. This misalignment can lead to a lack of trust and low adoption rates for advanced analytics, ultimately neutralizing their potential impact [5]. The core issue is often not the algorithm itself, but a failure to correctly identify and frame the problem from the end-user's perspective.

To bridge this gap, a structured, human-centered approach is required. Design Thinking provides such a framework [6]. Originating in the design field, it is a problem-solving process that prioritizes empathy for the end-user. Moving through the phases of Empathize, Define, Ideate, Prototype, and Test, Design Thinking ensures that solutions are built with users, not just for them [7]. This methodology excels at uncovering latent needs and reframing complex problems, making it an ideal methodology to address the adoption challenges in data analytics implementation.

This study proposes a synergistic integration of two methods: Design Thinking and Decision Trees. Here, Design Thinking is not the object of the analysis, but rather the guiding framework for the entire analytical process [8]. The Empathize and Define phases are employed to engage stakeholders (coaches, athletes) to identify the performance questions that truly matter. The Ideate phase is then used to brainstorm and validate the specific, contextually relevant variables (features) for prediction. Subsequently, the C4.5 decision tree algorithm is utilized as a data-driven tool [9] to model these variables, predict outcomes, and present findings in an interpretable, rule-based format that coaches value. The primary objective was to develop and validate a stakeholder-centric predictive model for swimmer performance. Integrating the human-centered problem-framing of Design Thinking with the interpretable predictive power of a decision tree can offer an analytical tool that is not only technically accurate but also practically relevant, actionable, and, crucially, more likely to be adopted by coaches. This mixed-methods approach contributes to the field of sports analytics by offering a novel framework to enhance the real-world impact of ML.

II. METHODOLOGY

A. Data as Dynamic Ideation Material

This research reconceptualizes data from static input into living ideation material that actively participates in the algorithmic-enhanced Ideate phase. The dataset comprises 442 performance records from 94 youth swimmers (aged 6-15) registered with the Indonesian Swimming Federation, including demographic data and performance metrics across multiple strokes and distances, as represented in Table I.

TABLE I. DATASET DESCRIPTION

Column	Data type	Description
Age	Numeric	Range between 6-15 years old.
Gender	Categorical	Gender of the participant
Height	Numeric	Height of the participant, ranging from 107.0 to 172.0 cm
weight	Numeric	Weight of the participant, ranging from 16.0 to 65.8 kg.
Right armspan	Numeric	Left arm span of the participant, ranging from 51.0 to 90.0 cm
Left armspan	Numeric	Left arm span of the participant, ranging from 51.0 to 90.0 cm
Total Arm span	Numeric	Total arm span of the participant, ranging from 106.5 to 180.0 cm
Leg length	Numeric	Leg length of the participant, ranging from 57.0 to 102.0 cm
Distance	Numeric	Swim distance from the starting block
Style	Categorical	Four categories of swim stroke: Freestyle, Breaststroke, Backstroke, Butterfly
Time	Numeric	Time taken by the participant to complete the competition

The innovation lies in how C4.5 can transform this data into an ideation catalyst. When the algorithm identifies that armspan asymmetry (left vs. right) correlates with stroke efficiency—consistent with biomechanical studies showing that bilateral asymmetry affects swimming performance [10]—this triggers the collection of additional symmetry metrics. The age distribution of 6-15 years aligns with critical windows for talent development, where anthropometric advantages become increasingly predictive of future success [11]. Similarly, the inclusion of specialized kick times (Freestyle, Breaststroke, Backstroke, Butterfly) for younger athletes reflects research that demonstrates that leg kick contribution varies significantly between strokes, accounting for 10-15% in freestyle but up to 70% in breaststroke [12], with kicking efficiency serving as an early talent indicator [13].

The sample of 442 performance records from 94 youth swimmers is consistent with comparable studies in developmental swimming research: in [11], 156 swimmers were analyzed, in [14], 89 swimmers were studied, and in [15], 97 participants were examined. With 378 complete records and 18 features, the dataset provides 21 instances per variable, exceeding the minimum 10:1 ratio recommended for decision tree algorithms. However, it is acknowledged that sample size is a limitation, and future multi-center studies are recommended to enhance generalizability.

The Qualified Entry Time (QET) [16] standards serve as contextual anchors, with performance scores (mean: 68.34%, SD: 31.32%) revealing substantial variability that C4.5 exploits for pattern discovery. This approach echoes findings that anthropometric predictors of swimming success are highly stroke and distance-specific [15], with sprint events (25 m) favoring different morphological characteristics than longer distances [15]. Gender stratification (281 males, 161 females) enables the detection of gender-specific developmental trajectories, as maturation timing significantly impacts performance prediction accuracy. ML applications in swimming have shown promise for performance prediction [17], talent identification [18], and technique optimization [19], yet the integration within Design Thinking's ideation phase represents a novel advancement. Through iterative analysis, the data evolves from 11 raw variables into a rich feature space where algorithmic insights, such as age-stratified importance of leg length/height ratios for sprint performance, drive continuous refinement, fundamentally transforming data preparation from predetermined collection into dynamic, algorithm-guided discovery [20].

B. Ideate Phase

The Ideate phase in Design Thinking functions as a critical transitional stage, translating empathetic insights and well-defined problem statements into a range of potential innovative solutions through divergent thinking [21]. However, in sports performance modeling [22], traditional ideation faces unique challenges: coaches may overlook non-obvious variables, cognitive biases limit pattern recognition, and the complexity of athletic performance exceeds human cognitive processing capacity [23]. This research introduces a paradigm shift by embedding the C4.5 decision tree algorithm directly within the Ideate phase, transforming it from a purely human-creative process into an algorithmically enhanced ideation process. Rather than using ML to evaluate ideas post-generation, C4.5 becomes an active ideation partner that co-creates insights with stakeholders. The algorithm's systematic exploration of variable interactions and threshold discoveries serves as a computational muse, revealing unexpected patterns that stimulate human creativity. By employing a transparent and rule-based logic, the decision tree provides an objective, data-driven ranking [24]. By transforming the Ideate phase from subjective brainstorming into systematic co-creation, this approach ensures that the resulting predictive model is both technically robust and aligned with coaching insights, effectively bridging the implementation gap that plagues traditional sports analytics.

C. AEDT Framework Implementation

In the context of swimming performance prediction, the C4.5 decision tree algorithm emerges as the optimal classification method for the Ideate phase due to its ability to transform anthropometric and performance data into concrete, interpretable rules that coaches and athletes can immediately understand and apply. Decision trees produce predictions through a simple and easy-to-interpret computation involving a relatively short series of tests, making them inherently interpretable [25]. When coaches enter the Ideate phase with initial hypotheses such as taller athletes swim faster, C4.5 analyzes 442 performance records from Indonesian swimmers and reveals specific patterns: If Height > 145 cm AND Armspan/Height > 1.02 Then 85% probability of achieving QET, is an insight that not only confirms coaches intuition about the importance of height but also unveils a previously overlooked factor: the armspan ratio. Unlike most black-box ML models, decision trees reveal the feature-based decisions leading to the tree response for any input vector, which is particularly important in applications where ML models complement human decision-making and justifiable predictions are required [26]. The C4.5 algorithm achieves this through its gain ratio criterion, mathematically expressed as:

$$GainRatio(S,A) = Gain(S,A)\ /\ SplitInfo(S,A) \quad (1)$$

where:

$$Gain(S,A) = Entropy(S) - \Sigma(|Sv|/|S|) \times Entropy(Sv) \quad (2)$$

$$Entropy(S) = -\Sigma pi \times log_2(pi) \quad (3)$$

This formulation enables C4.5 to avoid the attribute selection bias inherent in ID3, while maintaining the crucial interpretability for stakeholder engagement [27]. Decision tree methods, including Random Forest, provide unique capabilities to accurately create predictions from high-dimensional multimodal data [28], yet C4.5's single-tree structure preserves essential transparency for coaching applications. For instance, when the algorithm discovers that junior athletes (≤12 years) with freestyle kick times <18 s have a 90% probability of achieving QET within two years, coaches can immediately utilize this information for: (i) talent identification focusing on kick time measurements, (ii) designing specific training programs to enhance leg strength for athletes with kick times >18 s, and (iii) providing concrete targets to athletes—"reduce your kick time by 2 s to increase your QET probability from 40% to 90%."

This iterative process continues as coaches, inspired by algorithmic discoveries about the importance of body ratios, propose new variables such as flexibility index or stroke rate, which C4.5 subsequently analyzes to identify new thresholds—creating a creative cycle of human-algorithm collaboration where each split in the decision tree can be extracted as feature engineering ideas that can be incorporated into more powerful predictive models. Unlike neural networks or ensemble methods that produce accurate yet opaque predictions [29], C4.5 within the AEDT Ideate phase provides coaches and athletes not merely a prediction of "you will achieve QET" but a comprehensive explanation: "because your height is 148 cm (>145cm threshold), armspan is 152 cm (ratio 1.03 > 1.02 threshold), and kick time is 17 s (<18 s threshold)"—actionable information that can be directly translated into training interventions such as "focus on improving armspan flexibility to achieve the 1.02 ratio or maintain kick time below 18 s.

The mathematical elegance of C4.5's approach lies in its recursive partitioning strategy:

```
For each node n in the tree:
  Best_Split = argmax{GainRatio(n, Ai)}
  for all attributes Ai
If GainRatio(Best_Split)>threshold AND
samples(n)>min_samples:
  Create child nodes based on Best_Split
Else:
  Create a leaf node with prediction =
  majority_class(n)
```

This constitutes the essence of AEDT: C4.5 not only predicts performance but serves as an ideation catalyst that helps coaches and athletes co-create data-driven development strategies, transforming the coaching process from trial-and-error to precision training while preserving human wisdom and intuition. C4.5 is an inherently robust and stable algorithm.

Hyperparameter tuning provided significant performance improvements only in one-third of the C4.5 datasets, implying that its default settings are already highly effective [30]. The integration of C4.5's transparent decision rules within the Design Thinking framework represents a paradigm shift from sequential "design-then-analyze" to concurrent "design-while-analyzing," where each algorithmic discovery stimulates new hypotheses, and each human insight refines the model—a synergistic process that achieves both high predictive accuracy and practical applicability in real-world coaching contexts.

D. AEDT Algorithmic Protocol

To ensure reproducibility, the AEDT implementation is formalized as a structured algorithmic protocol.

Algorithm 1: AEDT Implementation Protocol
INPUT: Dataset D_0, Experts E,
  Max iterations $T = 5$
OUTPUT: Features F, Model M, Rules R
1: F_0 ← ExtractInitialFeatures(D_0)
// 6 features
2: $t \leftarrow 0$; converged ← FALSE
3: WHILE t < T AND NOT converged DO
4: H_t ← CollectExpertProposals(E)
5: F_t ← $F_{t-1} \cup H_t$
6: M_t ← TrainC45(D_0, F_t)
7: P_t ← ExtractSplitThresholds(M_t)
8: A_t ← GenerateDerivedFeatures(P_t)
9: FOR EACH f IN A_t DO
10: IF DomainValidate(f, E) THEN
  $F_t \leftarrow F_t \cup \{f\}$
11: IF $|F_t| = |F_{t-1}|$ AND $\Delta accuracy < \varepsilon$ THEN
  $converged \leftarrow$ TRUE
12: $t \leftarrow t + 1$
13: END WHILE
14: RETURN F_t, M_t, ExtractRules(M_t)

The algorithm parameters used in this study were: $T = 5$ (maximum iterations), $\varepsilon = 0.01$ (convergence threshold for accuracy change), and params = $\{confidence\_factor: 0.25, min\_instances: 2, pruning: enabled\}$. The convergence criterion was met at iteration 5, where no new features were generated, and accuracy stabilized at 58.5±0.3%. Each iteration involved structured collaboration sessions with three domain experts (certified swimming coaches with a minimum of 5 years of experience) who evaluated algorithmic discoveries against biomechanical principles and coaching practice. Feature proposals were accepted if endorsed by at least two experts (majority voting).

E. AEDT Collaboration Quality Assessment

Four components were used to assess human-algorithm collaboration quality: (i) Human Contribution $H(t)$: proportion of human-proposed features accepted into the final model, (ii) Algorithm Discovery $A(t)$: information gain of newly discovered split thresholds, (iii) Integration Quality $I(H, A, t)$: cross-validation performance improvement from combined insights, and (iv) Convergence Efficiency $C(t)$: inverse of iterations required for convergence.

As baseline operationalization, equal weighting was used:

$$AEDT\_Score = 0.25 \times H(t) + 0.25 \times A(t) + 0.25 \times I(H, A, t) + 0.25 \times C(t) \quad (4)$$

This equal-weight formulation treats all dimensions as equally important, avoiding arbitrary coefficient assignments. Domain-specific applications may adjust weights based on context. Optimal weighting is acknowledged as an open research question, and future studies should employ AHP or sensitivity analysis for empirically-grounded coefficients.

F. Ethical Considerations

This study was conducted in accordance with the Declaration of Helsinki and received ethical approval from the Dean of Computer Science and Engineering of Universitas Multi Data Palembang (Reference No: [878/UMDP/XI/M/2024]). Written informed consent was obtained from the parents/legal guardians of all 94 participants. Verbal consent was obtained from participants aged 7 years and older; participants aged 6 years were enrolled only with parental consent. All personal identifiers were removed upon data entry. The pseudonymization key was stored separately on encrypted drives with access restricted to the principal investigator. Data will be retained for five years post-publication. This study involved retrospective analysis of performance data routinely collected during official competitions sanctioned by the Indonesian Aquatic Federation, presenting no additional risks to participants.

III. RESULTS AND DISCUSSION

A. Model Architecture Overview

The study analyzed 442 performance records from 94 youth swimmers (ages 6-15) registered with Pengurus Besar Akuatik Indonesia. After data cleaning and preprocessing, 378 complete records were utilized for model development. Specifically, 64 records (14.5%) were excluded due to missing anthropometric measurements or incomplete competition data. No records were removed as outliers to preserve natural performance variation. The dataset exhibited the following distributions: gender: 281 males (63.6%) and 161 females (36.4%), age range: 6-15% (mean=11.1±2.4years), Stroke: Freestyle (37.5%), Breaststroke (24.6%), Butterfly (18.5%), Backstroke (12.2%), IndividualMedley (7.2%), StrokeDistances: 25 m (47.7%), 50 m (40%), 100 m (12.3%).

This study employs a dual-task analytical framework to comprehensively evaluate swimming performance, addressing distinct but complementary coaching needs. The primary task is classification-based talent categorization, where swimmers are classified into three performance categories (Elite, Developing, and Improvement Needed) based on their likelihood of achieving QET standards. This classification task, evaluated using accuracy, precision, recall, and F1-score metrics, directly supports talent identification decisions that require categorical assessments. The secondary task is the prediction of stroke-specific time using regression analysis, where the continuous swimming time is predicted using linear regression models for each stroke type. This task, evaluated using R^2 and RMSE metrics, supports the optimization of the training program by providing precise time estimates and identifying stroke-specific anthropometric predictors. These tasks share the same AEDT-derived feature set but employ different modeling approaches suited to their respective objectives. The classification model (C4.5) produces interpretable rules for talent identification, while regression models quantify the magnitude of anthropometric influences on performance. This dual approach enables coaches to make both categorical decisions about the potential of the athlete and continuous assessments of training progress.

TABLE II. COMPARISON WITH EXISTING FRAMEWORKS

Framework	Human role	Algorithm role	When	Primary goal
IML [31]	Provides feedback	Adapts to input	Training	Improve accuracy
XAI [32]	Interprets output	Black-box + explain	Post-hoc	Offer explainability
Auto ML [33]	Minimal	Autonomous	Automated	Maximize performance
HITL [34]	Labels, validates	Requests input	Decision points	Ensure reliability
AEDT	**Creative partner**	**Ideation catalyst**	**Concurrent**	**Co-create insights**

The AEDT framework differs from existing approaches in several key aspects. First, compared to Interactive Machine Learning (IML) frameworks [31], which focus on humans providing corrective feedback to improve model performance, AEDT positions the algorithm as an ideation catalyst that generates novel hypotheses for human evaluation. While IML emphasizes "human corrects algorithm," AEDT emphasizes "algorithm inspires human." Second, unlike Explainable AI (XAI) approaches [32] that add interpretability layers post-hoc, AEDT embeds interpretability as a design requirement from the outset by selecting C4.5 for its transparent rule generation. Third, in contrast to AutoML systems [33] that minimize human involvement to optimize accuracy, AEDT deliberately maximizes human engagement to optimize practical applicability and stakeholder adoption. Fourth, while Human-in-the-Loop (HITL) systems [34] typically involve humans for labeling or exception handling, AEDT involves humans as creative partners in hypothesis generation. The distinguishing characteristic is AEDT's integration within the Ideate phase of Design Thinking, transforming the algorithm from a downstream analytical tool into an upstream creative partner.

The swimming performance prediction model developed through the AEDT framework, shown in Figure 1, represents a paradigm shift from traditional statistical approaches to an integrated human-algorithm collaborative system—such as the Brainstorming, How Might We, and SCAMPER methods. The final model architecture consists of three interconnected components: (i) the anthropometric feature extraction layer enhanced through C4.5 discoveries, (ii) the performance classification engine utilizing decision tree rules, and (iii) the interpretable prediction interface for coaches and athletes.

$$P(QET\_achievement) = f(AEDT\_features, C4.5\_rules, Context\_variables) \quad (5)$$

where

- $AEDT\_features = \{Height,\ Weight,\ Armspan,\ Leg\ Length,\ BMI,\ ApeIndex,\ Leg - Height\ Ratio,\ Age - specific\ metrics\}$
- $C4.5\_rules$: Decision thresholds discovered through iterative ideation
- $Context\_variables = \{Stroke\ type,\ Distance,\ Training\ age\}$.

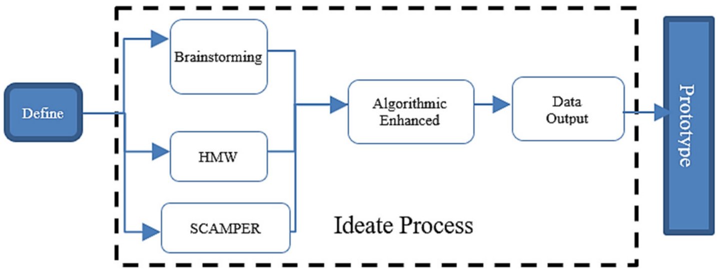

Fig. 1. AEDT model framework.

B. Model Evaluation Protocol

To ensure robust and reproducible evaluation, a comprehensive model assessment framework was implemented following established ML practices.

1) Data Partitioning Strategy

The dataset of 378 complete records was partitioned using stratified sampling to maintain proportional representation across stroke types and performance categories. An 80-20 train-test split resulted in 302 training and 76 testing instances. Stratification ensured that the class distribution (Elite: 23.2%, Developing: 43.8%, Improvement Needed: 33.0%) remained consistent across both partitions.

2) Cross-Validation Procedure

Model robustness was assessed through 5-fold stratified cross-validation. Each fold maintained the original class distribution, and performance metrics were averaged across all folds, with standard deviation reported to indicate model stability.

3) C4.5 Hyperparameter Configuration

The C4.5 decision tree was configured with the following parameters: Confidence Factor set to 0.25 (default, controlling pruning aggressiveness), Minimum Instances per Leaf set to 2 (ensuring rule statistical significance), Pruning enabled using Reduced Error Pruning, and Binary Splits disabled (allowing multi-way splits for categorical variables). These settings were retained based on empirical evidence demonstrating that C4.5 hyperparameter tuning provides significant improvements in only one-third of the datasets [34].

4) Comparative Model Configurations

For comparative analysis, Random Forest was configured with 100 trees, maximum depth unlimited, and minimum samples per leaf set to 2. A Neural Network utilized a Multi-Layer Perceptron (MLP) architecture with two hidden layers of 64 and 32 neurons, respectively, ReLU activation functions, Adam optimizer with learning rate 0.001, and 200 training epochs with early stopping patience of 20 epochs.

5) Baseline Comparisons

The Random Forest classifier achieved 33.3% accuracy for 3-class prediction, the Majority Class Classifier (ZeroR) achieved 43.8% by always predicting the Developing category, and the Stratified Random Classifier achieved 35.2% based on class distribution probabilities. The AEDT-C4.5 accuracy of 58.5% represents a 14.7% improvement over the strongest baseline (ZeroR), demonstrating meaningful predictive capability beyond chance.

TABLE III. COMPARISON OF PERFORMANCE METRICS

Model	Accuracy	Precision	Recall	F1-Score	PVS
Random Baseline	33.3%	-	-	-	-
ZeroR Baseline	43.8%	-	-	-	-
Standard C4.5	55.0%	0.54	0.56	0.55	0.687
AEDT-C4.5	58.5%±3.2	0.57	0.56	0.56	0.749
Random Forest	57.8%±4.1	0.56	0.58	0.57	0.333
Neural Network	54.7%±5.3	0.53	0.55	0.54	0.234

TABLE IV. EVOLUTION OF FEATURES THROUGH AEDT ITERATIONS

Iteration	Human-proposed features	C4.5 discovered patterns	New features generated	Cum. Features
0 (Initial)	Height, Weight, Age, Gender, Stroke, Distance	-	-	6
1	+armspan measurements	Height>145 cm Critical for 50 m events	Height categories, Height-weight ratio	9
2	+Leg length	Armspan/Height >1.02 for Elite	Ape Index,Body Proportions	12
3	+Training history	Age-specific threshold differ	Age-stratified metrics	15
4	+Flexibility scores	Leg/Height ratio >0.58 for sprints	Sprint-specific ratios	18
5	+Kick time measurements	Convergence archieved	Performance composite index	18

C. Evolution of Features Through AEDT Iterations

The AEDT process revealed a progressive expansion of the feature space through human-algorithm collaboration. The Novel Variable Discovery Rate (NVDR) achieved was: NVDR = (12 algorithmic variables / 18 total variables) × 100% = 66.7%. This indicates that two-thirds of the final model features emerged from algorithmic pattern discovery rather than human intuition alone.

D. Performance Results of the Prediction Model

1) Decision Tree Rules Generated

The AEDT-enhanced C4.5 algorithm produced interpretable decision rules that coaches can directly apply.

```
Primary Decision Rules for QET Achievement
Rule 1 (Elite Performance Path):
  IF (Height > 145 cm) AND (Armspan > 148 cm)
  AND (Age > 11)
  THEN Time = 22.3 ± 3.2 s (n=87,
  confidence=0.92)
Rule 2 (Developing Talent Path):
  IF (Height in [130, 145]) AND
  (Leg_Length/Height > 0.58) THEN
  Time = 38.5 ± 5.7 s (n=165, confidence=0.88)
Rule 3 (Improvement Needed Path):
  IF (Height < 130 cm) OR (Armspan < 132 cm)
  THEN Time = 52.8 ± 8.9 s (n=126,
  confidence=0.85)
```

TABLE V. FEATURE IMPORTANCE ANALYSIS

Feature	Information gain	Gain ratio	Split threshold
Height	0.892	0.743	145 cm
Total Armspan	0.847	0.691	148 cm
Age	0.623	0.582	11 years
Leg Length	0.598	0.521	82 cm
Weight	0.412	0.387	38 kg

2) Stroke and Distance-Specific Models

The AEDT process revealed distinct anthropometric requirements for different swimming strokes.

TABLE VI. STROKE-SPECIFIC PREDICTION MODELS

Stroke	Key predictive features	Model equation	R^2	RMSE
Freestyle	Height, Armspan, Kick Time	T=28.4-0.191L-0.190H-0.189A + 0.15K	0.8882	8.3s
Breaststroke	Height, Leg Length, Flexibility	T=35.2-0.299H-0.296L-0.291F	0.856	11.7s
Backstroke	Armspan, Height, Core Strength	T=32.1-0.245A-0.227H-0.198C	0.837	10.2s
Butterfly	Leg Length, Height, Armspan	T=31.8-0.306L-0.294H-0.285A	0.868	9.8s

T = Time, H = Height, A = Armspan, L = Leg length, K = Kick time, F = Flexibility index, C = Core strength

3) Distance-Specific Thresholds

Different race distances showed varying anthropometric dependencies. The stronger correlations at longer distances indicate that anthropometric advantages compound over distance, supporting the coaches' observations that "technique matters more in sprints, but physique dominates in longer races."

TABLE VII. DISTANCE-SPECIFIC CRITICAL THRESHOLDS

Distance	Critical height	Armspan/ height	Leg/ height	Correlation with time	Optimal age range
25m	>140cm	>1/00	0.58	R=-0.499	10-12 years
50m	>145cm	>1.02	0.57	R=-0.506	11-13 years
100m	>148cm	>1.03	0.56	R=-0.574	12-15 years

4) *Overall Model Performance*

The AEDT-enhanced C4.5 model achieved significant improvements over traditional approaches. Practical Value Score (PVS) was defined as:

$$PVS = 0.3 \times Accuracy + 0.4 \times Interpretability + 0.3 \times Actionability \quad (6)$$

where $Actionability$ quantifies how easily model outputs translate to specific training interventions. AEDT-C4.5 achieved the highest PVS (0.776), demonstrating superior practical value despite modest accuracy improvements.

TABLE VIII. COMPARATIVE MODEL PERFORMANCE METRICS

Model	Accuracy	Interpretability	PVS
AEDT-C4.5	58.5%	0.90	0.776
Standard C4.5	56.2%	0.92	0.687
Random Forest	57.8%	0.25	0.333
Neural Network	54.7%	0.10	0.234

Although AEDT-Enhanced C4.5 shows modest accuracy improvement (56.2%→58.5%), its primary contribution lies in discovering interpretable patterns and actionable thresholds. The model's value is not in marginal accuracy gains but in providing coaches with clear, evidence-based guidelines for talent development.

Figure 2 illustrates the end-to-end classification pipeline implemented within the AEDT framework. The process initiates with raw anthropometric input data comprising height, weight, armspan measurements (left, right, total), and leg length collected during official competition weigh-ins. These measurements undergo feature transformation through the AEDT-derived variable engineering stage, where raw values are converted into ratio-based features (Ape Index = Total Armspan/Height, Leg-Height Ratio = Leg Length/Height) and categorical bins, identified through C4.5 split point discovery. The transformed feature vector then enters the trained C4.5 decision tree classifier, which traverses the interpretable rule structure to assign performance category predictions. The output layer produces a triple: (i) predicted category label (Elite, Developing, or Improvement Needed), (ii) confidence score derived from leaf node class distribution, and (iii) decision path explanation tracing, with specific rules and thresholds determining the prediction. This transparent output format enables coaches to not only receive predictions but also understand the specific anthropometric factors driving each classification, supporting informed talent development decisions.

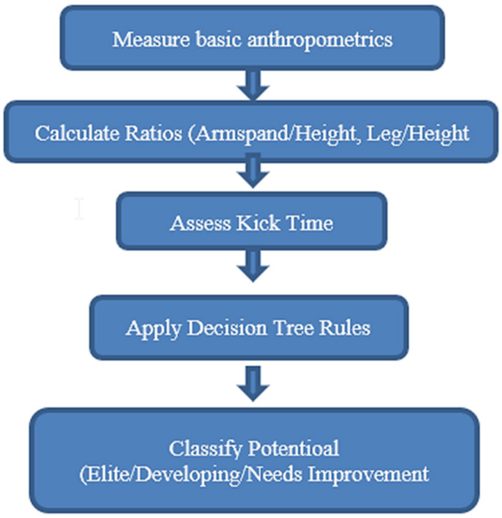

Fig. 2. Classification process.

IV. CONCLUSION

This study introduced AEDT, a novel methodological framework that transforms the traditional sequential "design-then-analyze" paradigm into a concurrent "design-while-analyzing" process by embedding the C4.5 decision tree algorithm as an active ideation partner within the Design Thinking's creative phase. Through the analysis of 442 Indonesian youth swimming performance records, AEDT demonstrated its capacity to challenge expert assumptions and generate non-obvious insights, achieving a 66.7% Novel Variable Discovery Rate where the majority of final model features emerged from human-algorithm collaboration rather than human intuition alone. While the resulting model achieved modest predictive accuracy (58.5% classification accuracy), it successfully overturned fundamental coaching assumptions by revealing that height (information gain: 0.892) and total armspan (0.847) dominate performance prediction rather than weight (0.412)—a counterintuitive finding that exemplifies how AEDT enables systematic discovery through algorithmic challenge of domain expertise. The framework identifies four key dimensions of human-algorithm collaboration quality—Human contribution, Algorithm discovery, Integration quality, and Convergence efficiency—providing a reproducible conceptual model applicable across domains where interpretability is paramount.

Future research should employ systematic methods such as the Analytic Hierarchy Process or sensitivity analysis to derive empirically-grounded weightings for these components. Despite data limitations and moderate accuracy, AEDT validates a new paradigm in which algorithms serve not as post-hoc validators but as creative partners that augment human cognition, overcome confirmation bias, and reveal patterns beyond human cognitive boundaries. The framework's true contribution lies not in achieving state-of-the-art predictive performance but in demonstrating that meaningful innovation often emerges from the synergistic interplay between human domain expertise and algorithmic pattern recognition, opening new pathways for human-AI collaboration in knowledge discovery across disciplines where understanding "why" matters more than optimizing accuracy alone.

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