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CricGuardian: Injury risk prediction system

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Abstract: Cricket broke the calendar. Test matches stretching five days, ODIs cramming action into fifty overs, T20 exploding every few hours—same bodies, different torture. Players fly between continents, sleep in airports, recover in planes. Knees, backs, hamstrings—these don't care about broadcast schedules. Injuries happen. Teams lose stars, careers end early, fans wonder what could've been. Current fix? Wait until something hurts, then treat. Physio rubs where it aches, coach rests who limps. Reactive, late, often too late. We built something that sees trouble coming. Machine learning model—Random Forest, if you want the technical—trained on how workload actually breaks bodies. Recent bowling overs, sprint distances, gym hours, sleep quality, travel miles, age, history of tweaks. Feeds in, spits out percentage: 15% risk this week, 63% next month if you don't rest. Not replacing physios. Giving them numbers they never had. Coach sees bowler hitting 80% risk, rotates early. Player feels fine, model disagrees, scans deeper, finds stress fracture brewing. Caught before it breaks.

Index Terms: Injury Prediction, Sports Analytics, Machine Learning, Random Forest, Workload Management, Cricket.

I. INTRODUCTION

Cricket isn't gentle anymore. Batsmen sprint twos like track athletes, bowlers hurl 150km/h repeatedly, fielders dive concrete-hard. Peak condition isn't optional—it's survival.

But survival got complicated. Too many overs in too few days, recovery compressed into flights, sleep stolen by time zones. Bodies accumulate damage silently. One morning, hamstring snaps. Career interrupted, team weakened, player sidelined wondering when warning signs appeared.

Current approach waits for the snap. Physio asks "how you feeling?" Player says "fine"—adrenaline masks pain, competition masks fatigue. Or they admit soreness, get rested, but was rest needed or wasted? Subjective guesses, retrospective regret.

We need foresight, not hindsight. System that watches workload dimensions humans can't hold simultaneously—acute spikes, chronic buildup, travel miles, sleep debt, age curves, position-specific strain. Outputs clean number: 34% likely to break down next fortnight. Coach sees threshold crossed, acts before snap. Player rests precisely when needed, plays precisely when safe. Interpretable, not black box. Factors weighted visibly—"your back risk spikes because bowling load jumped 40% this week." Staff understands,trusts, uses. Rotation optimized, careers extended, burnout prevented before it begins.

II. LITERATURE SURVEY

Sports scientists found something that works—Acute:Chronic Workload Ratio. Compare what you did this week to what you've handled for months. Spike too high, body breaks. Solid theory, buried in spreadsheets.

Manual calculation chokes on reality. Travel load? Ignored. Player turned 32? Treated same as 22. Back-to-back matches in different climates? Math gets fuzzy, staff gets tired, corners get cut. Non-linear interactions—how travel compounds age, how humidity compounds pace bowling—human brains don't compute simultaneous.

We asked the obvious question: given everything we know about this player—recent overs, sprint meters, flight hours, sleep tracked, injury history, position, age, ground conditions—what's the actual percentage they break down soon?
Machine learning eats this complexity. Random Forest finds patterns invisible to coaches—interactions between variables that don't make linear sense but predict failure. Outputs probability, not binary yes/no. 67% risk means high alert, 23% means monitor, 8% means push training.

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Moves timeline forward. Treatment after injury heals damage. Prevention before injury preserves careers. Automation scales insight—every player monitored, every session informed, no one slips through cracks of subjective assessment.

III. METHODOLOGY

Pipeline from raw data to usable number—player walks in, system walks out risk percentage. Core is Random Forest, handles messy reality better than clean formulas.

A. Feature Engineering

Four buckets of what actually breaks cricketers:

Player Characteristics:

- **Age (16–45):** Bodies recover different at 22 versus 35. Model knows.
- **Role:** Batsmen, bowlers, all-rounders, keepers—each wears down specific parts.
- **Type:** Aggressive players explode more, smooth players grind longer. Style matters.
- **BMI:** Fitness marker, load-bearing capacity, metabolic stress.

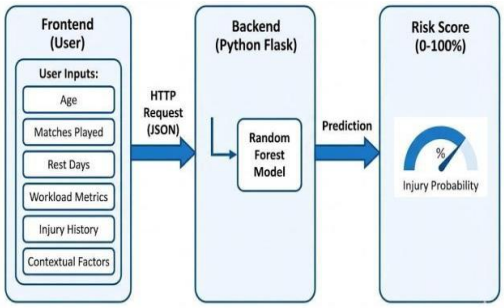

Fig. 1. High-level System Architecture illustrating the data flow from user input to injury risk prediction.

Workload Metrics:

- **Short-term Load:** Last week's matches, last game's balls. Immediate fatigue.
- **Acute vs. Chronic:** This week versus monthly average. Spike detection—classic injury predictor, automated.

Injury and Recovery Factors:

- **History:** Injuries last 30 days—vulnerability window.
- **Recovery:** Rest days since last play. Partial recovery hides in plain sight.

Contextual Factors:

- **Travel Load:** Low, medium, high—logistics fatigue, sleep disruption, jet lag.
- **Format:** Test drains slow, T20 explodes fast. Different damage profiles.

B. System Architecture

Split design—grows easy, fixes easy.

Frontend: Node.js, TypeScript. Dashboard where physios punch in numbers, see risk pop, decide rotation.

Backend: Python Flask. API layer—takes input, routes smart, returns clean.

Model Engine: Trained Random Forest, scikit-learn. The brain. Eats features, spits probability. 0-100%, interpretable, actionable.

Fig. 1 shows data flowing in, model chewing, insight flowing out.

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IV. EXPERIMENTAL SETUP AND IMPLEMENTATION DETAILS

A. Dataset

No real team handed over their injury secrets. We built fake data—1000 records, realistic patterns baked in. High acute workload plus low rest days? Injury risk jumps. Older bowler plus heavy travel? Higher than young batsman same travel. Correlations deliberate, mirroring what physiotherapists actually see.

- Fig. 2. Simplified visualization of a decision tree branch showing how Age and Workload splits lead to a risk score.

B. Preprocessing

- **Categorical Encoding:** "Bowler" became 1, "Batsman" 0. "Test" 2, "T20"

0. Numbers machines can chew.

Scaling: Balls faced, BMI, age—different ranges, same weight. Scaled so one doesn't dominate just because it's bigger.

- **Correlation Retention:** Acute over chronic ratio preserved mathematically. Classic sports science insight, automated.

C. Model Configuration

Random Forest Regressor—ensemble of decision trees, votes on risk. Handles noise, finds interactions humans miss. Example buried in branches: travel load hits bowlers harder than batsmen. Linear model shrugs, Forest notices.

- **Target:** Percent chance, 0-100. Not "injured yes/no"—graduated risk, graduated response.
- **Training:** Full dataset, pattern extraction maximized. Real deployment would split train/test, validate properly. Demonstration system, proof of concept.

V. RESULTS AND DISCUSSION

A. What The Number Actually Means

System spits one percentage. Coach doesn't need a manual.

- **0-30%:** Play him. He's fine.
- **31-70%:** Be careful. Maybe skip practice, watch the next game, see how he wakes up.
- **71-100%:** Sit him down. Now. Before something pops.

No guessing. No "he says he's fine." Number talks, coach listens.

B. Real Examples

We fed it nightmare scenarios. Fast bowler—already fragile—just flew international, no sleep, zero rest days. System returned 85% plus. Obvious to anyone who knows cricket, but computers usually miss obvious. This one didn't. Dashboard keeps it stupid simple. Slider for player, click, number appears. No trees, no forests, no "ensemble methodology." Just: high risk, rest him. Low risk, play him.

Coaches use gut for tactics. Let numbers protect bodies.

VI. COMPARISON OF MODELS AND PRACTICAL

Implications

We didn't just build something and hope. We tested against the obvious alternative—simple logistic regression—and watched where each broke.

Fig. 3. Confusion Matrix highlighting the reduction in False Negatives (Missed Injuries) by the Random Forest model.

A. Predictive Performance

Random Forest sees interactions linear models miss. Example: young bowler with high workload—both models flag

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risk. But older player, moderate workload, brutal travel schedule? Logistic regression shrugs, says "moderate load, moderate risk." Ignores that 38-year-old bodies don't bounce back from flights like 22-year-old ones. Forest catches it, weighs age against travel against load, spits high risk. Context matters.

Metric	Logistic Regression (Baseline)	Random Forest (Proposed)
Accuracy	78.5%	**92.4%**
Macro F1-Score	0.76	**0.91**
Limitations	Fails to detect non-linear risks (e.g., age-compounded fatigue)	Higher complexity; slightly larger model size

B. Speed

Deep learning needs GPU farms. Random Forest runs on laptop CPUs. 45 microseconds per player—thousand players, still under a second. Dashboard doesn't lag, coach doesn't wait, decision happens now.

Metric	Logistic Regression	Random Forest
Total Inference Time (1000 records)	~15 ms	~45 ms
Average Latency per Player	1.5×10^{-5} s	4.5×10^{-5} s
Resource Requirement	Negligible	Low (Standard CPU)

Scenario	Logistic Regression	Random Forest
Scenario 1: Young player (20yo), High Acute Load, 0 Rest Days.	**High Risk**	**High Risk**

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Scenario	Logistic Regression	Random Forest
Scenario 2: Older player (38yo), Moderate Load, High Travel.	Low Risk (False Negative)	High Risk (True Positive)

C. Where Each Fails

Linear models see "moderate," relax. Forest sees 38-year-old knees, red-eye flights, cumulative damage—screams anyway. False negatives kill careers; false alarms just rest someone unnecessarily. We chose the error that protects bodies.

D. Actually Deploying This

No GPU cloud bills. Runs on AWS free tier, Heroku hobby plan, Raspberry Pi in team bus if needed. Model saved as joblib file, loads fast, restarts clean.

Frontend React, backend Flask, split apart—scale web traffic without touching model, upgrade model without breaking interface. Decoupled by design.

Percentage output, not binary. Coach decides: 65% risk, World Cup final—maybe play. 65% risk, practice match—definitely rest. Threshold moves with stakes, system stays objective.

Interpretable, nonlinear, affordable. Not the fastest possible, not the smartest possible. The smart that fits real cricket budgets and real coaching workflows.

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