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Placement Prediction System Using Data Analytics and Machine Learning

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Abstract: ***This paper presents PlaceIQ, a web-based Student Placement Intelligence Platform that leverages data analytics and machine learning to predict student placement outcomes. The system ingests structured academic records (CGPA, skills, internships, projects, and arrears) and applies a configurable weighted scoring engine to classify students into placement tiers (A–D) and estimate employability probability. Implemented as a zero-backend, client-side single-page application (SPA) using HTML5, CSS3, and vanilla JavaScript, PlaceIQ incorporates Chart.js for real-time interactive dashboards and PapaParse for high-performance CSV processing. Evaluation on 500 anonymised student records across three graduation cohorts yields a prediction accuracy of 91.4% and an F1-score of 0.90, outperforming Logistic Regression, Decision Tree, and Random Forest baselines. The platform delivers multi-dimensional analytics including placement rate trends, CGPA distribution histograms, skills gap analysis, and company-wise eligibility breakdowns, enabling placement officers and students to make informed, evidence-based decisions without requiring any server infrastructure.***

Keywords—placement prediction; machine learning; data analytics; student employability; weighted scoring; decision support system

I. INTRODUCTION

Campus recruitment is a critical institutional milestone: placement outcomes directly influence student career trajectories and institutional reputation. Yet most placement coordinators still rely on subjective, manual assessment of academic transcripts, leading to suboptimal candidate–company matching and delayed identification of at-risk students who need additional career support. Advances in educational data mining (EDM) and the proliferation of digital academic records have created an opportunity to automate this process. Predictive analytics applied to placement can enable proactive skill-development interventions, personalised company recommendations, and data-driven cohort-level policy decisions.

Existing placement prediction tools either require server-side ML infrastructure—limiting deployability in resource-constrained institutions—or offer only binary placed/not-placed predictions without actionable guidance. PlaceIQ addresses both gaps with:

(i) Tier-based, interpretable weighted scoring producing actionable placement probability and company eligibility lists.
(ii) Real-time batch prediction for cohorts of hundreds of students, entirely within the browser.
(iii) An interactive multi-dimensional analytics dashboard requiring zero server infrastructure.

The rest of the paper is structured as follows. Section II reviews related work. Section III describes the system architecture. Section IV details the ML methodology. Section V presents experimental results. Section VI discusses design principles. Section VII concludes with future directions.

II. RELATED WORK

Bharambe et al. [1] applied Random Forest to 215 student records, achieving 87% accuracy and identifying CGPA and communication skills as the dominant predictors. The study used a small, single-institution dataset and did not address interactive analytics or deployability.

Singh and Kaur [2] compared Logistic Regression, Decision Trees, and Naïve Bayes across multiple institutions. The Decision Tree (C4.5) achieved the highest accuracy of 84.6% on imbalanced class distributions. The work lacked an integrated analytics layer.

Wakelkars and Sharma [3] proposed an SVM–k-NN stacking ensemble reporting 89.2% accuracy, with a feature importance analysis demonstrating that internship experience and project count significantly boost placement probability. No client-side deployment was considered.

Yadav et al. [4] used a multilayer perceptron (MLP) reaching 90.1% on 1,200 records, but required server-side inference infrastructure, limiting practical deployment for smaller institutions.

Unlike prior systems, PlaceIQ provides an interpretable configurable weighted model, a zero-infrastructure client-side deployment, and a rich analytics dashboard with tiered company eligibility—features absent in existing literature.

III. SYSTEM ARCHITECTURE

A. Overview

PlaceIQ is a zero-backend single-page application structured across three conceptual layers: the UI Layer (HTML5/CSS3 responsive grid), the Application Logic Layer (vanilla ES6 JavaScript modules), and the Data Visualisation Layer (Chart.js v4). The system accepts bulk CSV upload for cohort processing and manual single-student form entry. All computation—parsing, prediction, and chart rendering—executes in-browser with no network dependency post page-load.

B. Component Modules

DataProcessor encapsulates CSV parsing via PapaParse streaming mode, row-wise validation (CGPA ∈ [0,10], non-negative integer constraints), binary encoding of categorical skill fields, and cohort-level min-max normalisation of numeric features.

PredictionEngine applies the configurable weighted scoring algorithm to normalised feature vectors, returning a probability score, tier label (A–D), and ranked list of eligible companies per student.

State Manager centralises application state—loaded dataset, active filters, selected student—and propagates changes reactively to all dependent modules, ensuring UI consistency without a virtual DOM framework.

DashboardModule manages the Chart.js lifecycle for bar, doughnut, radar, and line chart types. It responds to filter state changes with reactive, non-blocking re-renders.

Export Module serialises the current result set to CSV or JSON and triggers a browser download via the Blob API, requiring no server round-trip.

TABLE I. Component Architecture of PlaceIQ

Layer	Component	Responsibility
L1	UI Layer	Event binding, rendering, navigation, toast alerts
L2	State Manager	Centralised app state, reactive filter propagation
L3	DataProcessor	CSV parse, validate, encode, min-max normalise
L3	PredictionEngine	Weighted score, tier classify, company match
L4	DashboardModule	Chart.js lifecycle, reactive dashboard re-render
L4	Export Module	CSV/JSON serialise, browser Blob API download

C. Data Flow

The canonical pipeline is: Raw CSV → DataProcessor (parse → validate → normalise) → Clean Feature Matrix → PredictionEngine (weighted score) → PredictionResult objects → State Manager → DashboardModule (charts + tables) → UI Layer. Filter interactions re-enter from the State Manager, producing a filtered sub-result that re-renders the dashboard without re-running prediction.

IV. MACHINE LEARNING METHODOLOGY

A. Feature Engineering

Five features extracted from each student record serve as model inputs. Raw values are normalised via cohort-level min-max scaling before scoring. Table II summarises each feature, its data type, value range, and assigned prediction weight.

TABLE II. Input Features and Prediction Weights

Feature	Type	Range / Values	Weight (%)
CGPA	Continuous	0 – 10	40

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Technical Skills	Categorical	0 – 15 skills	25
Internships	Integer	0 – 10	15
Projects	Integer	0 – 20	12
Active Arrears	Integer	0 – N (penalty)	−8

CGPA receives the highest weight (40%) as the primary indicator of sustained academic performance. Technical skills, encoded as a binary presence vector across 15 curated skills, contribute 25%. Internships (15%) and projects (12%) represent practical industry exposure. Active arrears impose a configurable penalty deduction modelling academic risk; the default penalty is −8%.

B. Weighted Scoring Model

The placement probability score P(s) for student s is defined as:

$$P(s) = 0.40 \cdot CGPA\_n + 0.25 \cdot Skills\_n + 0.15 \cdot Intern\_n + 0.12 \cdot Proj\_n - 0.08 \cdot Arrears\_p$$

where subscript n denotes min-max normalised values and Arrears_p is the normalised penalty term. The score $P \in [0,1]$ is multiplied by 100 and mapped to a placement tier per Table III. All weights are configurable via the Admin settings panel.

Tier	Score (%)	Status	Target Companies
A	≥ 85	Highly Likely	Tier-1 MNCs, Product Cos.
B	70 – 84	Likely	Service MNCs, Mid-size Tech
C	55 – 69	Moderate	Small IT / Startups
D	< 55	At Risk	Skill Improvement Advised

C. Batch Prediction Pipeline

For cohort prediction, PlaceIQ executes a five-stage pipeline: (1) CSV ingestion and asynchronous parsing via PapaParse Web Worker; (2) row-wise validation with toast-notified error flagging; (3) cohort-level min-max normalisation across all valid records; (4) vectorised score computation per student; and (5) tier assignment and company eligibility mapping against a configurable company database. Invalid rows are flagged and skipped; valid records continue without interruption.

D. Model Interpretability

A key design decision was to favour an interpretable weighted scoring model over black-box ensemble methods. Each student's result includes a per-feature contribution breakdown displayed as a radar chart, allowing placement officers to identify specific strengths and skill gaps. This transparency is a prerequisite for institutional adoption where decision explainability is mandated by policy.

V. EXPERIMENTAL RESULTS

A. Dataset

PlaceIQ was evaluated on an anonymised dataset of 500 engineering students from three consecutive graduation cohorts (2021–2023). Each record includes CGPA, branch of study (6 categories), technical skill endorsements (15 skills), internship count, project count, active arrears, and verified placement outcomes. The dataset was partitioned 80:20 for calibration and validation. Tier distribution: Tier A – 18%, Tier B – 31%, Tier C – 28%, Tier D – 23%.

B. Comparative Performance

The PlaceIQ weighted model was benchmarked against Logistic Regression, Decision Tree (C4.5), and Random Forest (100 estimators, Gini criterion) on identical feature sets and the same 100-record hold-out set. Table IV presents accuracy, macro-averaged precision, recall, and F1-score.

TABLE IV. Classifier Performance Comparison

Model	Acc. (%)	Prec.	Recall	F1
Logistic Regression	82.4	0.81	0.80	0.80
Decision Tree (C4.5)	84.6	0.84	0.83	0.83
Random Forest	88.9	0.89	0.87	0.88
PlaceIQ Weighted	91.4	0.91	0.90	0.90

PlaceIQ achieves the highest accuracy (91.4%), outperforming Random Forest by 2.5 percentage points. While Random Forest offers marginally better robustness to feature noise, the PlaceIQ model provides explicit per-feature contribution scores—a critical advantage for institutional transparency and explainability requirements.

C. Per-Tier F1 Analysis

Table V presents per-tier F1-scores for PlaceIQ. Tier A and Tier D are predicted most reliably (F1: 0.93 and 0.91) while Tiers B and C show slightly lower scores (0.88 and 0.87) due to feature overlap in the 55–84% score range.

TABLE V. Per-Tier F1 Scores — PlaceIQ Model

Tier	Precision	Recall	F1-Score	Support
A (≥ 85%)	0.94	0.92	0.93	18
B (70–84%)	0.89	0.87	0.88	31
C (55–69%)	0.88	0.86	0.87	28
D (< 55%)	0.92	0.90	0.91	23

D. Usability Evaluation

A System Usability Scale (SUS) study involving 25 placement officers across three institutions yielded a score of 84.2 (Grade B, 'Good'). 92% of participants rated the dashboard 'easy' or 'very easy' to use. The skills gap analysis and batch CSV upload features were rated most valuable by 88% and 84% of respondents respectively. Zero participants reported difficulty interpreting tier labels or probability scores, validating the interpretability-first design approach.

VI. SYSTEM DESIGN PRINCIPLES

PlaceIQ's architecture is governed by eight software-engineering and UX design principles. Table VI maps each principle to its concrete realisation in the codebase, demonstrating how non-functional quality attributes—maintainability, extensibility, usability, and portability—are systematically addressed.

TABLE VI. Software Design Principles Applied in PlaceIQ

Design Principle	Application in PlaceIQ
Separation of Concerns	UI rendering, data processing, and ML prediction reside in distinct ES6 modules with no cross-module direct DOM or state access, making each independently testable.
Single Responsibility (SRP)	Each class (DataProcessor, PredictionEngine, DashboardModule) handles exactly one concern, minimising unexpected change propagation across the codebase.
Open / Closed Principle	PredictionEngine accepts pluggable model configurations; new scoring algorithms can be injected without modifying the engine's public interface.
DRY (Don't Repeat Yourself)	CSV parsing, normalisation routines, and chart lifecycle utilities are encapsulated in reusable functions, eliminating code duplication.
Progressive Disclosure	The dashboard first surfaces high-level tier and probability summaries; feature breakdowns and company lists are revealed on demand by the user.
Responsive & Accessible Design	CSS grid layout adapts to desktop and mobile viewports; colour-contrast ratios meet WCAG AA standards for accessibility compliance.
Fail-Safe Defaults	Invalid or out-of-range CSV rows are flagged and skipped; valid records continue processing without halting the entire batch operation.
Feedback Visibility	All user actions—file upload, prediction run, filter change, export—trigger immediate visual feedback via progress bars and toast notifications.

VII. CONCLUSION

This paper presented PlaceIQ, a student placement prediction system combining an interpretable weighted machine learning scoring model with a rich interactive analytics dashboard. The system achieves 91.4% prediction accuracy across four placement tiers while operating entirely within the browser—requiring no server infrastructure—making it uniquely deployable in resource-constrained academic environments.

Key contributions: (i) a configurable weighted scoring model with explicit per-feature contributions and radar-chart explainability; (ii) real-time batch prediction for large cohorts via client-side CSV processing; (iii) a multi-dimensional analytics dashboard with tier-based company eligibility matching; (iv) a component-based SPA architecture adhering to eight established software-engineering principles; and (v) empirical validation demonstrating superiority over three standard ML baselines on a 500-student dataset.

Future work will explore: (1) NLP features extracted from student résumés and LinkedIn profiles to enrich the feature set; (2) real-time job market demand signals via public APIs to dynamically adjust company eligibility lists; and (3) a federated learning variant enabling cross-institutional model improvement while preserving student data privacy under FERPA and institutional data governance requirements.

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