RADemics

Machine Learning and Hybrid Models for Placement Prediction and Career Path Forecasting

Rohini Chittakula, C. Senthilkumar
VNR VIGNANA JYOTHI INSTITUTE OF ENGINEERING AND TECHNOLOGY, ERODE SENGUNTHAR ENGINEERING COLLEGE

Machine Learning and Hybrid Models for Placement Prediction and Career Path Forecasting

[1]Rohini Chittakula, Assistant Professor, Department of Information Technology, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana, India. rohini_ch@vnrvjiet.in

[2]C. Senthilkumar, Assistant Professor, Department of Artificial Intelligence and Data Science, Erode Sengunthar Engineering College, Perundurai, Erode, Tamilnadu, India. scsenthilkumar23@gmail.com

Abstract

Predicting student placement and forecasting career trajectories have become critical challenges in higher education due to the increasing complexity of skill requirements and dynamic labor market demands. Traditional statistical approaches often fail to capture the multifactorial determinants of employability, including academic performance, behavioral traits, and industry-aligned competencies. Machine learning (ML) and hybrid modeling frameworks provide advanced solutions by integrating multiple algorithms to handle nonlinear relationships, heterogeneous datasets, and temporal variations in student development. This chapter presents a comprehensive analysis of ML and hybrid models for placement prediction, emphasizing ensemble learning, deep neural networks, and graph-based architectures. Techniques for feature selection, importance evaluation, and model interpretability are explored to ensure actionable insights for academic administrators and career counselors. Comparative evaluation highlights the advantages of hybrid frameworks in achieving higher accuracy, robustness, and generalizability across diverse institutional contexts. The chapter also examines the integration of explainable AI for transparent decision-making and dynamic adaptation to evolving skill requirements, supporting evidence-based interventions for personalized career guidance. The proposed framework establishes a foundation for AI-driven educational analytics, offering scalable and interpretable solutions that align student potential with professional opportunities.

Keywords: Machine Learning, Hybrid Models, Placement Prediction, Career Forecasting, Educational Data Mining, Explainable AI

Introduction

The rapid evolution of global labor markets has elevated the importance of accurate student placement prediction and career path forecasting [1]. Educational institutions face increasing pressure to align student competencies with industry requirements, ensuring employability and long-term professional success [2]. Traditional evaluation methods, which rely primarily on academic performance metrics such as grade point averages and standardized test scores, fail to capture the holistic attributes influencing employability [3]. Factors such as communication skills, leadership qualities, problem-solving abilities, and adaptability play a critical role in determining career readiness [4]. The complexity of these multidimensional factors, combined with dynamic organizational requirements, necessitates advanced analytical approaches capable of integrating diverse datasets [5].

Machine learning and hybrid modeling frameworks have emerged as powerful tools to address these challenges by enabling predictive analysis that extends beyond conventional metrics [6]. The ability to process heterogeneous data sources—including academic records, psychometric assessments, co-curricular activities, and internship experiences—allows institutions to construct comprehensive student profiles for accurate placement prediction [7]. These frameworks also facilitate the identification of skill gaps, enabling personalized interventions that enhance both short-term employability and long-term career growth [8].

The limitations of conventional predictive approaches become evident when analyzing complex educational datasets. Linear statistical models, while interpretable, often struggle to capture nonlinear interactions and dependencies among multiple variables [9]. Single-algorithm machine learning models improve predictive performance but remain vulnerable to overfitting, noise, and data imbalance, reducing their generalizability across diverse institutional contexts [10]. Ensemble and hybrid models address these challenges by combining the strengths of multiple algorithms, including decision trees, support vector machines, and deep neural networks [11]. Ensemble methods—such as bagging, boosting, and stacking—enhance robustness, reduce variance, and improve overall predictive accuracy [12]. Hybrid frameworks further integrate complementary paradigms to handle heterogeneous data structures, model temporal dependencies, and account for feature interrelationships [13]. These advanced systems offer a dual advantage: high predictive performance and adaptability to varying institutional and demographic contexts [14]. By leveraging multiple algorithmic perspectives, hybrid frameworks also enable a more nuanced understanding of employability determinants, supporting evidence-based interventions for student skill development and career planning [15].