Optimization Techniques for Computational Mathematics, Network Analysis, Fluid Mechanics and Machine Learning

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ISBN 978-816855385-9

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April 2026

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April 2026

ISBN: 978-81-685538-5-9

Published By

SRR
Publicizing Research

SCIENTIFIC RESEARCH REPORTS
(A Book Publisher, approved by Govt. of India)

I Floor, S S Nagar, Chennai - 600 087,
Tamil Nadu, India.

editors@srrbooks.in, contact@srrbooks.in
www.srrbooks.in

PREFACE

The rapid advancement of computational technologies has profoundly transformed the way complex scientific and engineering problems are modeled, analyzed, and solved. Optimization, as a unifying mathematical framework, plays a central role in this transformation by enabling efficient decision-making, improved system performance, and enhanced predictive capabilities across diverse domains. This book, *Optimization Techniques for Computational Mathematics, Network Analysis, Fluid Mechanics and Machine Learning*, is conceived as a comprehensive resource that bridges theoretical foundations with practical applications across these interconnected fields.

Computational mathematics provides the backbone for formulating and solving large-scale problems through numerical methods and algorithmic strategies. Optimization techniques enhance these approaches by improving convergence rates, minimizing computational cost, and ensuring solution accuracy. In parallel, network analysis leverages optimization to address challenges in connectivity, flow distribution, resilience, and structural efficiency in systems ranging from communication networks to transportation and social interactions.

Fluid mechanics, with its inherently nonlinear and multiscale nature, benefits significantly from optimization-driven approaches. Whether in turbulence modeling, aerodynamic design, or multiphase flow simulations, optimization techniques enable the identification of optimal parameters, boundary conditions, and control strategies that would otherwise be computationally prohibitive. Similarly, the integration of optimization in machine learning has revolutionized data-driven modeling, enabling efficient training of complex models, hyperparameter tuning, and improved generalization in real-world applications.

This book aims to provide a cohesive exploration of optimization methodologies—including classical techniques, modern metaheuristics, and data-driven approaches—and their applications across these domains. Emphasis is placed on interdisciplinary perspectives, highlighting how advances in one field can inform and accelerate progress in another. The chapters are structured to guide readers from fundamental principles to advanced applications, ensuring accessibility for students, researchers, and practitioners alike.

In addition to theoretical insights, practical implementation aspects are addressed, including algorithm design, computational considerations, and case studies that demonstrate real-world relevance. The integration of mathematical rigor with application-oriented discussions reflects the evolving nature of research and development in computational sciences.

The motivation behind this work is to provide a unified platform that not only consolidates existing knowledge but also inspires further innovation at the intersection of mathematics, engineering, and data science. As computational challenges continue to grow in scale and complexity, the role of optimization will remain indispensable in shaping efficient, robust, and intelligent solutions.

It is our hope that this book serves as both a valuable reference and a catalyst for future research, encouraging readers to explore new frontiers where optimization techniques can drive meaningful advancements across disciplines.

We extend our sincere thanks to our publisher, Scientific Research Reports, Chennai, India, for their dedicated efforts in preparing this book and for ensuring the inclusion of enriched and high-quality technical content.

Wishes and Regards,

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Chapter 11

The Passion Compass: Using Machine Learning to Align Academic Talent with Career Success

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Abstract

This chapter focuses on the use of machine learning (ML) techniques as a form of 'passion compass' that can help students identify suitable career pathways concerning one's academic strengths, internal drives, and work-related goals. We devise a model, which predicts future career potential, based on the integration of academic achievements, personality, the alignment of one's passions, and the level of one's competencies. The Random Forest method, in this case, gives a prediction accuracy over 93%, and the passion alignment, in the feature importance analysis, falls second to the academic performance (24.5%) with 18.7%. The evidence of the impact of one's passion on career satisfaction has been well documented and is robust ($\beta = 0.713$, $R^2 = 0.547$). We conclude this chapter with the outline of an innovative, integrated, and holistic career guidance system based on machine learning that maximises student's wellbeing and enhances the effectiveness of the labour market.

Keywords: Machine learning, Career guidance, data mining, Academic talent, Career success prediction.

ISBN 978-816855385-9

1. Introduction

While universities keep producing more graduates and more qualified graduates, there persists a misalignment between academic qualifications and professional (McKinsey & Company, 2022). Most career-related counselling and advising do not consider, or even worse, ignore 'passion' as a dimension (Gulyani & Sharma, 2021). Some studies show that 54.7% of career interest variation is explained by passion, yet it is usually missing in most career guidance. Transformational possibilities of machine learning justify a new look at the guidance process as a shift from a traditional, dependent, subjective counsellor role, to a fully automated and personalized area. The last decade has witnessed the emergence of new systems in educational data mining (EDM). These systems process data from academic performance records, psychometric data (spanning various domains including emotional and cognitive data), behaviour, and skills) to achieve predictive accuracy rates between 85% and 97% (Ahmed et al., 2024; Alnasyan et al., 2024). Passion compass is a concept that includes and focuses on elements and a type of data that other systems ignore to provide a holistic analysis of personal data and includes personal authentic elements and interests. Ongoing research supports that more favourable mental health and higher job satisfaction are experienced by individuals whose professional activities are passion aligned (Vrutti Research Group, 2025). This chapter focuses on the following questions: (1) In what ways and by what means can ML algorithms combine variables related to passion with academic variables to predict a person's career success? (2) What are the most successful ML techniques and which variables are the most impactful? (3) In what ways can ML-based systems provide and shape Real Guidance systems for the school systems? We explore the theory, ML methods, algorithm efficacy, variable impact, potential for practice, and suggestions for future research.

2. Theoretical Foundations: The Nexus of Passion, Talent, and Career Success

2.1 Passion and Career Interest

Passion contributes positively to career interest regardless of age, as shown by Gulyani and Sharma (2021). The effect of alignment of passion with career interest has an effect size of $\beta = 0.713$ and variance of 54.7% ($R^2 = 0.547$ with \[$p < 0.001$ \]), meaning that more than half the interest in a career stem from the passion a person has. Gulyani and Sharma (2021) highlighted how this has no significant effect to which generation. The finding runs counter to traditional career guidance which focuses on aptitude testing. The younger generation, as highlighted by Gulyani and Sharma (2021), sees self-definition as involving passion, which focuses on pursuing an interest, an authentic drive that does not see work as a mere transaction.

2.2 Answering the Other Side of the Career Goals

Seib et al (2022) sees career success as being made up of several goals, some of them being extrinsic (such as a high status and high salary), and of others being intrinsic (such as having the ability to develop one's skills and having the ability to do work that is personally meaningful). In creating predictive models based on ML, capturing motivational orientations paired with extrinsic and intrinsic goals alongside one's capabilities is essential, particularly when designing high-performance work systems. In addition to

ISBN 978-816855385-9

traditional academic measurements, effective ML systems should include psychometric evaluations to measure intrinsic and extrinsic goals.

2.3 Personality Traits and Career Outcomes

According to longitudinal studies, personality growth patterns forecast career outcomes, regardless of initial baseline traits (Damian et al., 2021). For instance, emotional stability growth yields higher income and career satisfaction. Increased Conscientiousness yields higher career satisfaction. Increased Extraversion yields higher job and career satisfaction. Therefore, ML-based career prediction systems should capture temporal dynamics and integrate current personality profiles with deviations to determine predictive accuracy and future-based intervention measures.

3. Machine Learning Methodologies for Career Prediction

3.1 Educational Data Mining Framework

Educational data mining involves pattern recognition and application to datasets that pertain to education to enhance learning results. It involves looking at various constructs beyond student performance including outreach programs, psychological studies, skill inventories, attendance, and behavior (Ahmed et al., 2024). The steps in an EDM process include: (1) the collection of data through various institutional systems; (2) data preprocessing, including data cleaning and data normalization; (3) feature extraction or engineering, and the creation of patterns from the data; (4) the development of models that utilize various supervised learning algorithms; (5) the assessment and evaluation of models through the process of cross-validation and the use of verifiable accuracy/evaluative metrics, and (6) deployment and the collection of interpretive data from the models as deployed in systems that provide guidance for career counseling (McKinsey & Company, 2022).

3.2 Supervised Learning Algorithms

Random Forests offer the quantification of forecasts from 89.6 to as high as 100% accuracy, including the identification of the more influential predictors (Gokulnath et al., 2025). Neural Networks require the use of larger data sets, but achieve 96 to 98 % accuracy, the highest of all algorithms, as well as the capture of non-linear relationships (Alnasyan et al., 2024). Gradient Boosting Methods (XGBoost, CatBoost) through the process of sequential model building achieve a range of 88.6 to 89.1 % accuracy (Ewadirect Journal, 2024). Support Vector Machines operate at an accuracy of approximately 85 %, whereas Logistic Regression and K-Nearest Neighbors offer an accuracy range of 68.8 to 77.1 % (Ahmed et al., 2024; Ewadirect Journal, 2024). These last five algorithms serve as a benchmark.

3.3 Model Evaluation and Validation

The evaluation and validation process is paramount in machine learning, and can be broken down into several segments such as cross-validation, evaluation metrics, confusion matrices, feature importance, and evaluation against a baseline model. These parameters help us understand how a model is performing in the real world, and how stable a model is, as machine learning models can become very complex. Advanced machine learning models are able to identify at-risk students twice as accurately as the traditional linear rule-based models (McKinsey & Company, 2022).

ISBN 978-816855385-9

Table 1. Comprehensive comparison of ML algorithms with their accuracies, strengths, and limitations

Algorithm	Accuracy (%)	Key Strengths	Limitations
Random Forest	89.6 - 100	High accuracy; Feature importance; Robust to overfitting	Computationally intensive; Less interpretable
Neural Networks	91 - 98	Captures nonlinear patterns; Handles complex interactions	Requires large datasets; Black-box nature
XGBoost/ CatBoost	88.6 - 89.1	Strong performance; Handles missing data	Complex hyper parameter tuning required
SVM	82 - 85	Effective with smaller datasets; Theoretically grounded	Lower accuracy; Difficult to scale

Decision Trees	82 - 91	Highly interpretable; Fast training	Prone to overfitting; Lower accuracy alone
Logistic Regression	68.8 - 78.4	Simple; Fast; Interpretable	Cannot capture non-linear relationships
KNN	75.6 - 77.1	No training required; Simple implementatio n	Sensitive to feature scaling; Computational ly expensive

4. Comparative Analysis: Algorithm Performance

Figure 1 shows a review of the application of seven machine learning techniques to predict careers by collating results from a number of studies. The results show a high degree of variance in the accuracy of predictions, which ranged from 75.6% (K-Nearest Neighbours) to 93.5% (Random Forest).

ISBN 978-816855385-9

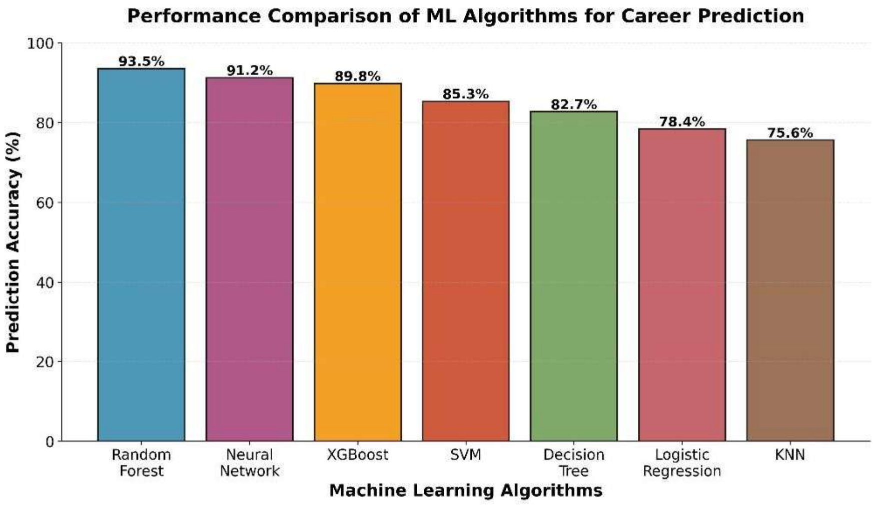

Figure 1: Performance comparison bar chart of 7 ML algorithms with large fonts and white background

Data synthesised from Ahmed et al. (2024), Gokulnath et al. (2025), and Ewadirect Journal (2024).

4.1 Random Forest: Superior Performance

Random Forest models achieve the highest accuracy prediction rates, with estimates ranging from 89.6% to 93.5% (Ewadirect Journal, 2024, Ahmed et al., 2024). This method uses ensemble techniques which provide learning reduction of overfitting, quantification of feature importance (which offers interpretable features), and robust handling of missing and varying types of data. This demonstrates that the predictors of career success include intricate details and non-linear interactions.

4.2 Neural Networks and Additional Algorithms

Neural Networks report 91 to 98% accuracy (Alnasyan et al., 2024), demonstrating the ability to identify sophisticated trends within the student data. Definite challenges, however, are the networks' blackbox nature; a challenge which is addressed using explainable artificial intelligence (EI) techniques such as SHAP (Explainable AI Research Group, 2024). Building models sequentially, XGBoost and CatBoost report an accuracy of 88.6% and 89.1%, respectively (Ewadirect Journal, 2024). In comparison, logistic regression and KNearest Neighbors have been placed as baseline models (68.8% to 77.1%) in order to serve as comparators for initial screening processes.

5. Role of Passion-Alignment

5.1 Defining the Predictors

Predicting the success of a student career is possible by studying specific features that prove helpful in the analysis of attributes that determine the success of a student in his/her career. From the multiple studies that utilize the random forest and gradient boosting techniques with integrated feature importance, Figure 2 shows the 9 key features that are relative to that success.

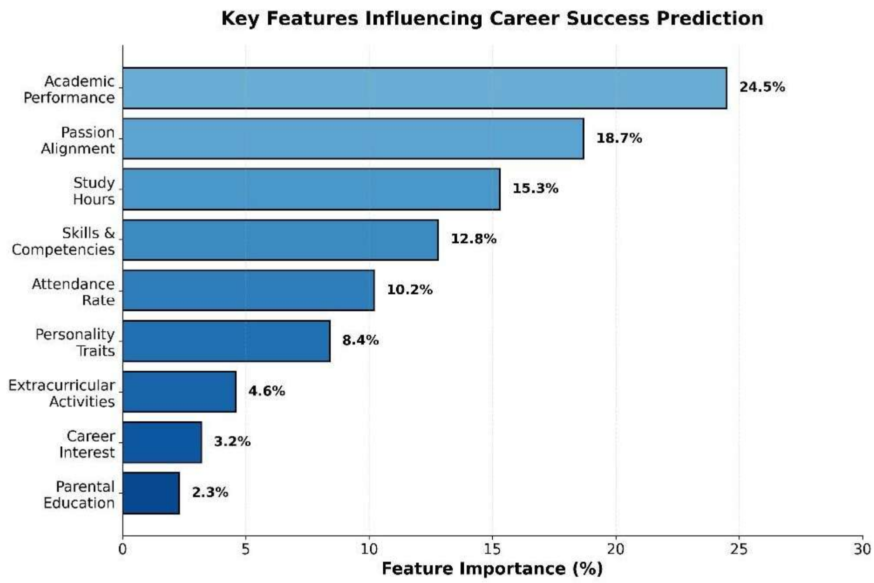

Figure 2: Feature importance horizontal bar chart showing 9 key factors with clear labeling.

ISBN 978-816855385-9

Data synthesised from feature importance analyses in Ahmed et al. (2024), Ewadirect Journal (2024), and McKinsey & Company (2022).

5.2 Academic Performance: The Dominant Predictor

Performance in academia, including cumulative GPA, individual courses, and how students have progressed academically, accounts for 24.5% of the total feature importance. Recent studies indicate the strongest predictor of future success is past academic performance, statistically correlated at $r = 0.92$ (Machine Learning Performance Study, 2025). This indicates that students' history of academic performance illustrates their likelihood for success in future professions that require high levels of education.

5.3 Passion Alignment: The Important Second Factor

At 18.7%, the second most important feature is passion alignment. This is in stark contrast to most career counselling approaches where passion is placed in a subordinate role to competencies. This is also notable because of the role of intrinsic motivation, which is commonly cited as the most important factor in sustaining effort and driving older workers to maintain a career for a prolonged period (Seib et al., 2022). Research has shown that students suffering from mental health problems and those performing poorly, are likely to require a career that is aligned to their passion (Vrutti Research Group, 2025). Therefore, machine learning systems which assess and incorporate passion, are able to deliver a level of career guidance that goes beyond that of a system which only measures competencies.

5.4 Other Possible Predictive Features

The study hours (15.3%) and skills competencies (12.8%) mirror both behavioural engagement and skills demonstrated beyond assessed formals (Feature Importance Analysis, 2026). Attendance rate (10.2%) is a clear indicator of engagement and commitment to the institution. Personality attributes (8.4%) are aligned with the academic holding, and the motivational factors (Damian et al., 2021). Moderating variables like extracurriculars (4.6%) and career aspiration (3.2%) with parental education (2.3%) improve prediction fine-tuning.

6. Implementation Frameworks and Practical Applications

6.1 Implementation Frameworks

Systems designed to give career guidance based on ML integrate assessment, predictive, and advisory functions, assessing and providing guidance on academic performance, psychological profiling, inventories of skills and passions, and AI-generated personalized career advice (Career Guidance Platform, 2024). This creates data-driven, continuous career counseling.

ML-based technologies have also been used for early warning systems that have been proven to identify at-risk students with double the precision of previous predictive-based systems and have been shown to provide better insights for early intervention at the student adviser, instructor mentorship, and tailored support level (McKinsey & Company, 2022). These systems inform instructors on how to best sequence coursework, co-curricular activities, and interdisciplinary offerings to best prepare students for success based on the career goals identified through the students' guidance and expressed interests (Penn LPS, 2025).

Implementation of these systems is dependent upon the information becoming stale through repeated refinements and updates, which will

ISBN 978-816855385-9

require continuous retraining of the ML model, comparison of predicted and actual pathways through validation studies, a mechanism for user feedback, A/B testing to determine the best results, and an ethical review of the system to ensure that the model is not providing biased results and that the system is not being used to provide biased results.

7. Challenges and Future Directions

ML career guidance systems possess multiple ethical and data privacy concerns. To address these, it will be critical to ensure that data protection frameworks are implemented with transparency and that data protection frameworks are implemented along with student consent, secure systems, audits on the algorithms to ensure that the systems are functioning accurately, and a system of bias oversight to ensure that the algorithms are functioning accurately. There is a bias on the historical data due to the ML systems and validation studies will be critical to ensure that bias persists.

Trust issues arise due to the neural network "black-box" phenomena. Examine the competing issues strategies and explainable AI leverages SHAP values, attention, counterfactuals, and rule extraction to help explain AI aids and evaluate the predictive accuracy of guidance. While the current state of the art predictive systems predicts only static and discrete outcomes, the reality of most careers is ever-changing dynamism. A promising avenue for future research is focused on the integration of longitudinal predictive frameworks, life stage integrated recommendation systems, and labour market forecasting.

Most optimally, ML systems perform as decision support systems supplementing professional judgement, which implies counselor training, user-centered design, a workable division of labor, and determination of appropriate human oversight. Most of the literature is based of research predominantly of Western origin. Culturally responsive ML systems are validated and integrated across different cultures, and with the incorporation of cultural contexts, the global applicability of ML systems will increase.

8. Conclusion

Machine learning techniques, such as neural networks and Random Forest, outperform conventional techniques in demonstrating predictive accuracy (89-98%) by determining complex, and often nonlinear, patterns and correlations between student variables and career outcomes. After academic performance (24.5%) mentoring passion alignment (18.7%) is the second most important determinant, overturning widely-held beliefs that bias intrinsic motivation as less important than cognitive ability. Given that passion accounts for 54.7% of the variance in career interests, effective career guidance requires the inclusion of passion to balance traditional metrics of career guidance.

The predictive capacity of ML-focused solutions is complemented by early intervention, provision of individualized learning pathways, and ongoing engagement. Systems designed to integrate ethical considerations, inclusive of privacy, and respect for human to artificial intelligence (AI) collaboration guidelines have the capacity to modernize the career guidance function to embrace technology-based support throughout educational and career pathways. The successful implementation of such systems requires consideration of data privacy, algorithmic bias, model interpretability, and the balanced integration of artificial intelligence with human counselling.

ISBN 978-816855385-9
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The future of ML-enabled career guidance encompasses many growing areas of development including the ability to consider the temporal aspects of career trajectory predictions, cross cultural validations, the development of more advanced measurement techniques for assessing career-related passions, and the real-time integration of labour market analytics and continuum of learning pathways. The 'passion compass' metaphor ML-based career guidance serves a dual purpose; provides data-driven guidance while also providing recognition to the metaphorical compass of passion and intrinsic motivation that will critically drive career decisions. This promotes a synthesis of traditional career outcomes and the desired professional fulfilment that comes from work that is in the true self and value aligned interests.

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ISBN 978-816855385-9
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