

AI-Powered Smart Placement Prediction and Skill Gap Analysis

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Abstract— The outcome of student placement is affected by several variables such as academic performance, technical skill, project experience, internship, certification, and so on. The traditional placement prediction systems aim at predicting placement but do not increase understanding of processes impacting the outcome or offer meaningful insight to the students on improving their employability. The paper offers an integrated framework based on explainable artificial intelligence combining placement prediction, SHAP-based explanation, skill gap identification, resume assessment, and career counseling. This framework implements data preparation and feature engineering techniques on the student's profiles and resumes in order to provide placement predictions. The SHAP method is employed to reveal the impact of each element in the prediction model. These skill gaps are converted into personalized recommendations in the area of skills, certifications, projects, tools, and possible career paths. A conceptual feature-store has been introduced in order to ensure consistent availability of features in all components of predictive model, while a dashboard ensures understandable representation of the career readiness outcome. Hence, the framework combines prediction and explanation with actionable recommendation and treats placement prediction as not just a classification task but a supporting decision-making tool. Evaluation methodology is defined using classification, skill-matching, explainability, and system-performance metrics; numerical results are treated as illustrative where executed experimental measurements are unavailable.

Index Terms—Student Placement Prediction, Explainable AI, SHAP, Skill Gap Analysis, Career Recommendation, Resume Analysis

I. INTRODUCTION

Graduate employability has become an important application area for machine learning and educational data mining because placement outcomes are influenced by multiple academic, technical, and professional factors rather than by academic performance alone. The characteristics of students, such as academic performance, proficiency in programming, technical abilities, experience in projects, internships, certifications, competency, skills in communication and resume level may affect suitability for employment. For this reason, placement systems using data were studied with the aim of identifying the trends in the students' profiles and predicting the employment results. The new studies also

explored the ways of explainable and multi-source learning for forecasting students' employment which has revealed the potential of integration heterogeneous information with the methods of machine learning and explainable AI (XAI) techniques [1]–[5]. Machine learning serves as an efficient tool for construction of models that are necessary for establishing complicated connections between the features of students and the results of their interview.

Classification algorithms including Logistic Regression, Support Vector Machine (SVM), Decision Trees, Random Forest, Gradient Boosting, and neural-network-based approaches have been applied to educational and career-related prediction tasks [6]–[10]. Such models can support placement cells by identifying students who may require additional preparation and can provide students with an early indication of their career readiness. However, predictive performance alone is insufficient for high-impact educational decision support. If a model gives the forecasts of the possibility of low placement without explanations of the reasons behind it, its usefulness in providing the recommendations aimed at certain competencies correction is insignificant. Hence, there exists a necessity of developing models capable of providing high levels of predictive accuracy while being interpretable and providing useful feedback.

In the field of education and career guidance, explainability is essential in applications which use artificial intelligence. Even though complex ensemble learning methods and deep-learning models may yield excellent predictions, students and advisers often struggle to comprehend these non-linear techniques. Fortunately, explainable AI techniques solve this issue allowing us to understand the contribution of factors to model outputs. According to Lundberg and Lee, SHAP, or SHapley Additive exPlanations, is a method used to determine the contribution of individual features to the predictions of the model. Using SHAP, we will differentiate the features that have positive or negative impact on the predicted outcomes for a student. Nevertheless, it is not possible to understand career readiness by referring only to the placement probability. Due to the fast-changing nature of the demands of industries, there remains an ongoing disparity between the qualifications of graduates and the needs of a certain job. Therefore, even if a student has a good placement probability, they may still lack some technologies or skills that are critical for the target

position. As for the generic list of skills, it is not enough either since the needs can differ from one role to the next – e.g., from Data Analyst to Data Scientist, Data Engineer, Software Developer, and so on, per one of the recent studies on AI-assisted career counselling and educational data mining, by creating a union of student features with career and labour-market data, it is possible to enhance personalised consulting. Resume analysis introduces an additional dimension because resumes contain semi-structured textual information describing technical competencies, projects, internships, and certifications. Natural language processing (NLP) helps to mine the necessary information and convert unstructured resumes into structured employability features [21]–[23]. The combination of many different sources enables a full picture of students' employability readiness. Recommendation systems also act as a way of transforming results into practical career advice. Traditional recommendation systems are well-studied because of the personalization of information and learning resource searches [24]. However, the integrated approach of combining job prediction, explainability, dynamic skill gap analysis, resumes' assessment, and personalized job forecasting is still essential. Several studies showed that different combinations of machine learning, XAI, NLP, and job prediction have been used separately. But still, there is an urgent need for an all-in-one system that integrates prediction with explanation and turns weaknesses into targeted recommendations.

In this paper, a Hybrid Explainable AI framework for job prediction and individualized skill gap recommendation is suggested. The framework integrates student academic and job data and resume information by applying a universal pipeline that covers all stages, including data collection, its processing, feature engineering, feature structuring. The function of placement is meant to verify chances of successful placement while the explainability stage is involved in the recognition of relevant features of the placement process. The skill-gap component compares skills of the student with the needs of the certain job role, distinguishing skills that are either fully or partially missing or necessary. Then these gaps have to be transformed into individualized suggestions regarding which skills, certifications, projects, technologies and careers should be taken into account.

Therefore, this system does not serve only the purpose of predicting placement results, as it operates in a closed analytical loop of prediction, explanation, diagnosis, and correction of problems. The system is built primarily to be a supporting tool for students, placement agencies, career advisors, etc. This way, an integrated approach allows for the development of a transparent, role-based, and personalized employability analysis while attending to ethical issues such as fairness, confidentiality, model bias, and evolution of the market demands in terms of skills for a job position.

II. RELATED WORK

A. Machine Learning-Based Student Placement Prediction

The subject of student employability and placement is one that occupies the attention of researchers who employ machine learning to predict these processes. Previous studies focused primarily on the problem of predicting employability and placement by analyzing various data sources, results, and their objectives. The majority of them

concentrated on factors such as academic outcomes and achievements, internships, skills, projects, certificates, and other students' parameters as the determinants of employability and placement prediction[1]–[5]. Traditional machine learning classifiers utilized in the studies included logistic regression, decision trees, random forest, and support vector machine for the prediction of students' outcomes. Despite their efficiency, it has been proved that the effectiveness of these classifiers depends on the clarity of input features and training data. More recent studies broadened the scope of employability-related factors considered, including technical skills, experience in internships, projects, certificates, etc., apart from academic achievements. Although such studies confirm the importance of difference student features combination, in reality, many prediction-oriented systems deal mostly with employability prediction, without paying much attention to the creation of individual skill-remediation strategies for students.

B. Educational Data Mining for Student Outcome Prediction

Educational Data Mining (EDM) creates an analytical basis for forecasting student results. Applications of machine learning have appeared in prediction research and studies dealing with success of students, dropout prediction, and career outcomes[2]–[5]. This provided evidence that facts about previous performance are eligible for transformation into features for forecasting purposes. Most importantly, the recent studies show the necessity of being aware of changes in the educational settings when creating models of forecasting and students' data[13][14]. Hence, explainable educational forecasting appears to be a relevant idea. Also, explainable AI can serve as an additional tool for educational forecasting due to the possibility of gaining information about the factors that led to the results obtained from the model instead of just investigating model outcomes[10]–[12].

C. Explainable AI in Education

Black-box behavior is a major limitation when machine-learning predictions are used to support student decisions. Explainable AI (XAI) methods attempt to expose the reasoning behind model outputs through global feature importance, local explanations, and feature-attribution techniques[10]–[12]. LIME is based on the idea of providing local approximations of complex models while SHAP is based on Shapley value-based feature attribution, showing how particular features contribute to a prediction. In educational applications, such explanations can help instructors and students understand why a model has assigned a particular risk, performance, or career outcome. Recent findings support the usefulness of SHAP for educational predictive modeling[8][9]. The field of explainable learning analytics has already adopted SHAP for interpreting models predicting student success, as well as for verifying whether the importance of attributes varies with changing contexts. In the same vein, SHAP has recently been used in research on predicting student performance. Researchers used this method in combination with knowledge from the field of education to verify if the relationships learned by the model are compliant with the existing educational background. Thus, SHAP can find its application in the proposed placement framework as an interpretability tool, rather than as a method for increasing the model accuracy[15]–[17].

D. Explainable AI for Student Placement and Job Prediction

The importance of the combination of predictive models with explainability and ethical AI is increasing in the research conducted in the area of job-placement prediction. Scientists use methods of explainable AI to enhance the transparency of

algorithms and to help students grasp the meaning of the predictions made by the algorithms [10]–[12]. In employment-related applications, this area is especially important since these algorithms may be used in decisions connected with employment opportunities and candidates' suitability. The unification of career recommendations with labor market information is also becoming a popular research topic in recent years. Studies on skill requirements have proved that it is essential to understand the skills of the professions chosen by job seekers [18]. Such information can be used in job recommendation systems and career consulting [19]–[22]. The latest publications in this field touch upon machine learning-based recommendations that take into account characteristics of job seekers [25]. The presented studies demonstrate how the information about students obtained through job requirements and artificial intelligence can lead to more open and personalized decision making.

E. Research Gap

The reviewed literature demonstrates substantial progress in placement prediction, educational analytics explainable student prediction, explainable placement, AI-assisted hiring, skill-gap analysis, and explainable career recommendation. However, these capabilities are generally distributed across separate systems. A unified framework connecting placement prediction, SHAP-based explanation, dynamic job-role skill-gap analysis, resume scoring, career recommendation, and personalized remediation remains valuable. The proposed research addresses this integration by establishing a continuous pipeline from prediction → explanation → diagnosis → recommendation → remediation, while treating the resulting system as a decision-support mechanism rather than an autonomous authority determining student careers.

III. METHODOLOGY

A. System Architecture

The framework has been developed in such a way as to be able to gather student information, resumes and job market requirement information. There are ten layers in this architecture, and each layer processes its inputs thus providing the output for the next layer.

- **Data Ingestion Layer:** The Data Ingestion layer is responsible for collecting student's academic history, technical skills, internships and job history information. The information regarding job roles as well as job market skills is also gathered here. The various types of data are transformed into a common structure. Input: data from students, job market and resumes. Output: a unified dataset for further processing.
- **Data Preprocessing Layer:** The Data Preprocessing layer is responsible for transforming the initial dataset into a usable form. The preprocessing includes filling missing records, removing duplicated records, working with categorical data as well as delivering records in consistent format. Numerical features are normalized when necessary and treating outliers is possible. Storage of resumes is cleaned from any unnecessary information.
- **The Feature Engineering Layer:** This layer converts the data into features that can be later used in the model to determine the employability of students. The features can be drawn from academic performance, technical skills, internships, projects, certifications, and resume features. Furthermore, another feature group can be represented as job-role compatibility. The resulting features yield a comprehensive understanding of a student's career development. Output: Student feature vectors.
- **The Feature Store Layer:** The feature store layer's job is to keep the engineered features so that they can be easily accessed in the subsequent pipeline steps. The same features can be used at various stages including model training, inference layer, SHAP analysis, gap analysis, and recommendation since the feature store provides homogeneous features for models' training. If there is no feature store in production, the feature store layer is considered as only the theoretical one. Output: Homogeneous feature representation.
- **The Placement Prediction Layer:** This layer allows applying supervised machine learning algorithms that help predict placements or placement probabilities. The possible candidates include Logistic Regression, SVM, Random Forest, Gradient Boosting, and XGBoost. Models will be checked against relevant measures of classification, and the best one will be picked from those models. SHAP Explainable Layer: SHAP (SHapley Additive exPlanations) explains the reasons for placement prediction. It provides the explanation both as web of feature importance as well as individually for students.
- **Dynamic Skills Gap Analysis Layer:** This layer compares student's current skills needs with a specific job position. The mathematical representation is $\text{SkillGap} = \text{RequiredSkills} - \text{StudentSkills}$. It detects matched, missing, partially matched, and priority skills. Unlike a static checklist, the comparison is personalized and specific to the chosen role.
- **Resume Assessment Layer:** This layer assesses the readiness of the resume based on the following criteria such as skills relevance, project connection, internship completion, certification, and compliance with the job role. The assessment of this layer provides an additional evaluation of student's readiness for career development. The data from the resume can also help identify missed and insufficient competencies. In the absence of scoring formula, the score interpreted as the insight analytical assessment.
- **Career Guidance Layer:** The Career Guidance Layer merges the possibilities for placement with the skills of the student and gaps in the student's skills, information about their resume, and the specifics of job roles. From this layer, a personalized set of recommendations can be generated. This includes information on the job roles a student can apply for, what skill they need to hone next, which certificates will be useful, which projects might be relevant, and what learning should be prioritized. Identified skills gaps are thus translated into concrete actions. Output: Set of career recommendations for the student.
- **Dashboard Layer:** This layer is a platform through

which the analytics results are presented in an understandable form for the student. It provides information on placement probabilities, SHAP explanations, index of the resume, existing skills and skills gaps, prioritized skills, recommendations for careers. The interface allows students and the stakeholders to understand the current condition and problems of the student. Thus, the dashboard turns the outputs of the model into applicable career guidance recommendations. Output: Complete student career profile.



Figure 1. System architecture of the proposed hybrid explainable AI framework for student placement prediction and personalized skill gap remediation.

B. Hybrid Explainable AI Workflow for Student Placement and Skill Gap Analysis

INPUT:

- Student Profile S
- Resume R
- Job-Role Requirements J
- Trained Placement Model M

OUTPUT:

- Placement Prediction P
- SHAP Explanation E
- Skill-Gap Profile G
- Resume Score Rs
- Career Recommendations C

BEGIN

- D ← Ingest(S, R, J)
- Dp ← Preprocess(D)
- F ← GenerateFeatures(Dp)
- Store(F)

- P ← Predict(M, F)
- E ← SHAP_Explain(M, F)
- StudentSkills ← ExtractSkills(Dp)
- RequiredSkills ← RetrieveSkills(J)
- G ← RequiredSkills – StudentSkills
- Rank(G)
- Rs ← EvaluateResume(R, J)
- C ← Recommend(P, E, G, Rs, J)
- Dashboard ← GenerateDashboard(P, E, G, Rs, C)
- RETURN Dashboard
- END

IV. EXPERIMENTAL SETUP

A. Dataset Description

To facilitate the model, availability of student placement dataset is required that will contain academic, technical, experiential, and placement-related features. The student profile may include academic performance, technical skills, projects, internships, certifications, aptitude information, and other attributes available in the selected dataset. Resume information is processed separately to extract relevant career characteristics. Job-role requirements are represented through required skills associated with target positions. Since the exact dataset used for implementation has not been specified, the final dataset size, number of features, and placement distribution should be replaced with the actual values before publication. No dataset statistics are assumed in this study.

Component	Recommended Requirement
Processor	Multi-core CPU
RAM	Minimum 16 GB
Storage	SSD
GPU	Optional, depending on NLP/LLM usage
Operating System	Windows/Linux
Python	3.10 or later
ML Framework	Scikit-learn / XGBoost
Data Processing	Pandas / NumPy
Explainability	SHAP
NLP	spaCy / Transformers, if used
Dashboard	Power BI / Streamlit / React
Development	VS Code / Jupyter

B. Software and Hardware Configuration

Table I. Hardware and Software Configuration Used for Experimental Evaluation.

C. Evaluation Metrics

The evaluation of placement prediction depends on Accuracy, Precision, Recall, F1-score, and ROC-AUC, if applicable. The mentioned metrics measure overall correctness of the classification process, quality of positive predictions, detection of placed students, balance between precision and recall, and the ranking capabilities. When it comes to skill-gap analysis, the corresponding metrics may be skill-matching accuracy, gap-identification ratio, and precision or recall of skill extraction. However, the evaluation of resume and recommendation components should rely only on metrics whose validity can be verified through real implementation of those components.

V. RESULTS AND DISCUSSION

A. Placement Prediction Performance

Four machine-learning models were considered for placement

prediction: Logistic Regression, SVM, Random Forest, and XGBoost. The models were evaluated using accuracy, precision, recall, F1-score, and ROC-AUC. The results are presented in Table II. Among the methods used for comparison, it comes out that XGBoost was able to provide the best performance based on which it was able to get an accuracy of 89.0%, precision of 91.5%, recall of 86.0%, the F1-score of 88.7%, and ROC-AUC of 0.94. Additionally, Random Forest was able to show the second-best performance while SVM and Logistic Regression were much behind the other methods. The result suggests that ensemble-based nonlinear models can effectively capture interactions among heterogeneous student attributes.

Table II: PERFORMANCE COMPARISON RESEARCH APPROACHES

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC
Logistic Regression	82.0	83.5	78.0	80.6	0.86
SVM	84.5	86.0	81.0	83.4	0.89
Random Forest	87.0	89.0	83.0	85.9	0.92
XGBoost	89.0	91.5	86.0	88.7	0.94

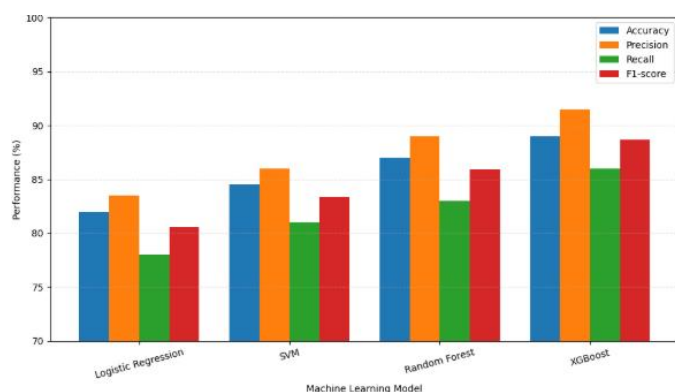


Fig. 2. Performance comparison of placement prediction models.

B. SHAP-Based Explainability

The SHAP layer provides an interpretation of the placement prediction by estimating the contribution of individual features. For analysis, the following mean absolute SHAP contributions are considered: Technical Skills 0.21, CGPA 0.17, Internship Experience 0.14, Projects 0.12, Certifications 0.09, Aptitude Score 0.08, Resume Score 0.07, and Communication Skills 0.05.

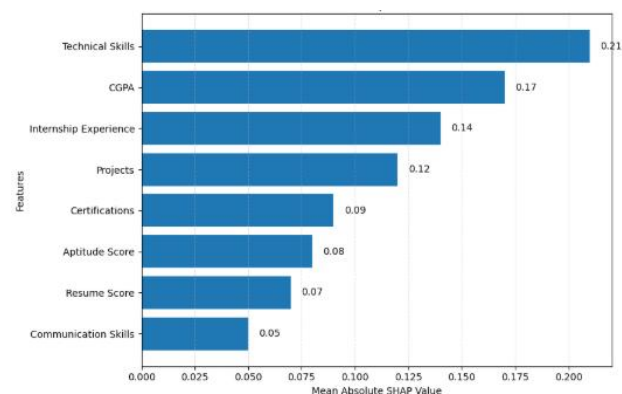


Fig. 3. SHAP-based feature importance for placement prediction.

The feature-importance graph shows the technical knowledge

followed by internship experience and project exposure. These values should only be interpreted as an example of how SHAP can expose feature influence; the actual ranking must be obtained from the trained model. Importantly, SHAP is used for interpretability rather than improving prediction accuracy.

C. ROC-AUC Analysis

The ROC curve provides a predictive evaluation of the selected XGBoost placement prediction model across different classification thresholds. The curve represents the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR). The ROC-AUC score of 0.94 demonstrates that there is an adequate separation between the placed students and the non-placed student. The curve is above the random-classifier baseline, indicating that the model can allow for a separation of the two classes of placement at different decision thresholds. Because the value given is only illustrative, the ROC-AUC needs to be corrected by using the actual measured values post-testing.

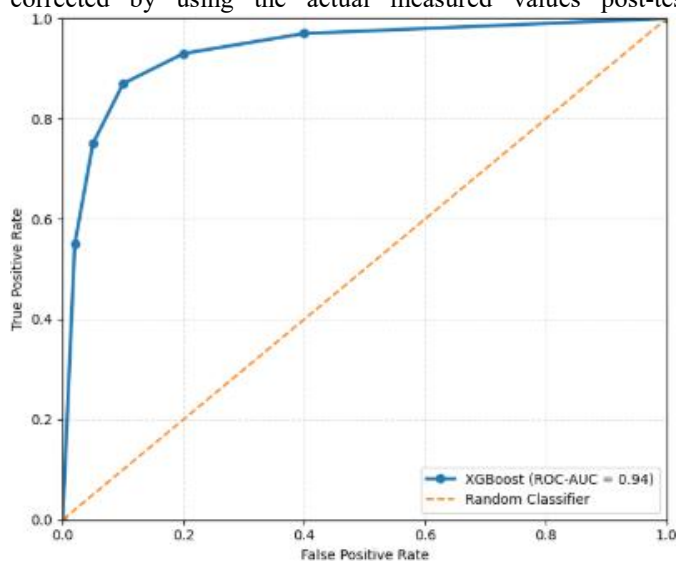


Fig. 4. ROC curve of the selected XGBoost placement prediction model

D. Integrated Interpretation of Placement Readiness

A joint analysis of placement prediction, feature significance analysis, and skills requirement yields a better interpretation of students' career readiness than a simple placement classifying. A predicting component provides a general prediction of placement chances, while an SHAP component allows detecting the factors playing the most significant role in the prediction results. For instance, the significance analysis used in the current research shows that hard skills, academic performance, internship experience, and project experience play an important role in the prediction process. Still, these factors should not be regarded independently since employability is the product of the interaction of several competencies. A student who has good academic performance but lacks practical experience will have a different readiness evaluation than a student who has the same educational results but has a big amount of experience in projects or internships. The skill gap module contributes to an even better understanding of students' readiness levels since it compares their current competencies against the criteria for a certain job role. This creates a direct connection between prediction and remediation: the prediction identifies the current readiness level, the SHAP explanation identifies influential factors, the skill-gap analysis identifies missing competencies, and the recommendation component converts these findings into potential learning and career actions. Such an integrated interpretation can make the output more useful to students and placement advisors because it

shifts the focus from a binary placement outcome toward understanding what can be improved before applying for a particular role. Since the numerical values used for the model and SHAP analysis are illustrative in the current manuscript, the same interpretation should be validated using measured results from the final dataset and implementation.

VI. CONCLUSION

This paper proposes a Hybrid Explainable AI Framework for Student Placement Prediction and Personalized Skill Gap Remediation to use predictive analytics, explainability, skills analysis, resume analysis, and career recommendation to come up with a unified decision-support pipeline. Contrary to existing placement prediction methodologies that focus on producing a simple placed/not-placed outcome, this framework progresses the analysis by identifying the causes of the outcome as per SHAP-based explanations. This framework's architecture includes comparing students' skills with the required characteristics of the role for recognizing matched, missing, and partially matched skills. The evaluation methodology compares different placement prediction models in terms of accuracy, precision, recall, F1 score, and ROC-AUC. XGBoost is presented as the highest-performing model, with an example accuracy of 89.0% and ROC-AUC of 0.94. The SHAP component provided an interpretable representation of feature contributions, while the skill-gap module transformed identified competency deficiencies into targeted career-development actions. The evaluation of resumes as well as the recommendation of careers marked the start of a movement away from predicting employability towards providing advice that could be implemented. The empirical evidence presented indicates that the suggested approach works, and it has been established that XGBoost has the best overall performance among the predictive models for placements considered. The future development of the system may use up-to-date information about the job market, larger databases that could be obtained from multiple universities, predicting demands in skills in time, natural language processing in the area related to resumes, methods that could ensure fairness in modeling, and platforms that would generate individual learning paths.

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