Using AI to Guide Course Selection: Enhancing Information Flow from Ugandan Graduates to Prospective University Entrants

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Abstract:

In Uganda, graduate unemployment persists due to a misalignment between university programmes and labour-market needs. This study introduces a Course Guidance System that predicts individual employment likelihood and informs academic choices. We assembled a graduate dataset of the university, Grade Point Average (GPA), course, A-level scores and real-time, community-sourced employment outcomes. After one-hot encoding and data cleaning, an XGBoost classifier was trained and evaluated via Leave-One-Out cross-validation. The model attained 98.9 % accuracy and a 99.1 % F1-score. Predicted probabilities were categorised as "Less Likely" ($p < 0.50$), "Likely" ($0.50 \leq p \leq 0.75$), and "Very Likely" ($p > 0.75$) to generate actionable guidance. Results highlight course of study, institution, and GPA as key employability factors. By leveraging up-to-date, community-collected data, the system overcomes static advisory limitations, offering dynamic insights for students, universities, and policymakers. Future work will integrate soft-skill metrics and employ explainable AI to enhance transparency.

Keywords: *Unemployment; Graduate employability; Machine learning; Course guidance; Labour market.*

Introduction

Unemployment remains one of the most pressing socio-economic challenges in Uganda (Pettersen, 2017), significantly affecting graduates' livelihoods and the country's overall economic development. The National Labour Force Survey carried by UBOS (2021) directly addresses the "mismatches between labour supply and demand", which it defines as the "unmet need for employment". The scale of this mismatch is quantified by the composite measure of labour underutilisation (LU4), which stands at a staggering 42% of the extended labour force. This represents 6.6 million people who are either unemployed, underemployed, or part of the potential labour force, highlighting a significant gap between job seekers and available, adequate employment opportunities. A study by Mpanga (2023) established the existence of a high graduate unemployment rate of 80% despite economic growth in Uganda. Ugandan youth unemployment increased from 12.7% in 2012/13 to

13.3%, despite a decline in the overall national unemployment rate from 11.1% to 9.2% in 2017 (Egessa et al., 2021). The National Labour Force Survey (2021) estimated the youth unemployment rate (ages 18–30) at 16.5%. The rate is particularly severe for young women, whose unemployment rate of 20.4% is significantly higher than that of young men at 13.5%. This stark contrast translates to an employment rate of only about 22.5% among graduates, leaving a vast majority struggling to find sustainable jobs. This phenomenon underscores a deeper structural issue within the education and labour sectors, particularly concerning the alignment of university courses with market demands.

A study by Muthima et al. (2023) found that a critical factor contributing to this unemployment crisis is the nature of the courses pursued by students at university. Science, Technology, Engineering, and Mathematics (STEM) have a high chance of attracting employment compared to non-STEM courses, due to their higher industry demands. Many students opt for academic programmes that have limited relevance to the current job market while neglecting courses that have higher employability prospects. This misalignment is often fuelled by a lack of access to comprehensive and up-to-date information about which courses lead to better job opportunities. As a result, many students complete their education only to face immense difficulty in securing employment, leading to frustration, economic distress, and underemployment in unrelated fields. One of the root causes of this issue is the prevalent ignorance regarding course selection and its impact on future employment prospects (Al-Samarrai & Bennell, 2007; Kakai et al., 2004; Mugabi, 2014).

In their study, Bongomin et al. (2022) revealed that multiple interconnected factors shape programme selection decisions, including personal motivations, market perceptions, and institutional influences. Similarly, Tayebwa (2021) reported that undergraduate programme choice motivations at Makerere University have demonstrated that students' decision-making processes are influenced by a complex interplay of personal aspirations, family expectations, and perceived career prospects. Existing research (Patacsil & Tablatin, 2017; Forret, 2014; Barnwell, 2016; Manacorda & Petrongolo, 1999) also highlights the multifaceted nature of employability, noting the influence of factors beyond academic performance, such as soft skills, professional networking, and practical experience. Studies (Wen & Zhou, 2025; Cha et al., 2024) utilising machine learning for career guidance, have incorporated diverse variables, including demographic data, prior employment, and student interests, to enhance predictive scope. However, there remains a critical gap in the development of data-driven tools that provide students with predictive insights into employment outcomes based on current market dynamics and their academic choices in Uganda.

Existing advisory methods in Uganda, such as the Uganda Bureau of Statistics (UBOS), Labour Market Information Systems, Career Guidance and Counseling Services in educational institutions, and the Ministry of Education career advisory frameworks, typically rely on static and outdated information that fails to incorporate real-time labour market trends (Datzberger, 2018). UBOS labour market data, while comprehensive, is often published with significant time lags and lacks the granular, programme-specific employment outcome predictions that students need for informed decision-making (UBOS, 2022). These conventional advisory approaches fall short of providing dynamic, data-driven insights that reflect rapidly changing labour market conditions and emerging industry requirements. Furthermore, while machine learning has been applied in various educational contexts, such as personalised course recommendation systems focusing on student interests and grades (e.g., Chang et al., 2023; Cha et al., 2024) or predicting course modality preferences (Mehrabi et al., 2024), there remains a gap in data-driven tools specifically designed to predict the employment outcomes for graduates based on their academic and institutional choices. Unlike these systems which prioritise aligning recommendations with individual preferences and curricular needs or predicting delivery format, a system that directly bridges academic choices to career success by forecasting employment likelihood is needed. This absence of an effective, real-time data-driven course guidance mechanism exacerbates the unemployment crisis, as students make uninformed decisions about their academic paths without fully understanding the current and projected employment implications of their choices.

To address this critical gap, this study presents the implementation of a Course Guidance System, an intelligent platform designed to bridge the information gap between students and the job market. The system is built on top-of-efficient machine learning algorithms that predict the likelihood of a student landing a job based on various features. Unlike conventional course advisory methods that rely on static and outdated information, this system integrates real-time, community-collected data from individuals who have completed these courses and are now in the job market. By gathering firsthand experiences and employment outcomes from graduates, the system ensures that students receive up-to-date and relevant guidance when choosing their academic paths. The primary contribution of this project included the curation of a comprehensive dataset combining student academic and demographic attributes with current job market trends, developing a predictive model that assesses each student's likelihood of securing employment, and implementing a robust evaluation system that leverages this dataset and model to determine individual employment potential.

The objectives of this study include ensuring clear information flow from graduates to undergraduates and the respective new university entrants on which course they should take based on the market demand. This study also aims to allow prospective university entrants to make better decisions based on this collectively gathered community data. Furthermore, this study aims to introduce an AI-based decision-making guide for all the new entrants on the best courses to opt for based on the market demands.

Methodology

This section outlines the systematic approach employed in this study, encompassing data collection, model architecture, and training methodologies utilised to develop and evaluate the machine learning model predicting graduate employment status.

Data collection

The data collection process was executed through an implemented system designed to differentiate between two user categories: graduates and current students. For this study, the dataset was exclusively derived from graduate records. The collected data comprised several key attributes: the graduate's university, GPA, course of study, Advanced Level

(A-level) score, and a Boolean variable indicating employment status, which served as the target variable for the predictive model. The data was collected through a questionnaire distributed within an online community comprising participants from both rural and urban backgrounds, with a greater representation from urban areas due to easier accessibility. The dataset was subsequently cleaned to ensure accuracy and validity, including verification of submitted GPA values. To maintain anonymity and minimise potential bias, all personally identifiable information (PII) was excluded. A sample of the dataset, showing the first 10 universities represented, is presented in Table 1.

Table 1: *Academic background and employment status of university graduates in Uganda. Source sampled data from a community of graduates*

University	GPA	Course	A-Level	Working?
Makerere University	4.67	Computer Science	18	Yes
Kampala International Uni.	3.67	Mechanical Engineering	16	Yes
Mbarara Uni. Sci. & Tech.	4.0	Electrical Engineering	14	Yes
Kyambogo Uni.	3.5	Civil Engineering	12	No
Uganda Christian Uni.	3.6	Business Administration	10	No
Uganda Martyrs University	3.8	Accounting	11	Yes
Gulu University	3.4	Information Technology	17	Yes
Busitema University	4.0	Software Engineering	15	Yes
Islamic Uni. Uganda	3.8	Mass Communication	9	No

In curating this dataset, we assumed that the primary determinants of a graduate's employability are the institution attended, cumulative GPA, chosen course of study, and A-level examination scores. Although these attributes form a useful foundation for predictive modelling, they are not exhaustive; additional relevant features, such as soft skills and professional experience, are discussed in the Future Work section.

Model architecture

The design of the predictive model aimed to classify graduates' employment status based on the collected features, with the Boolean variable *Working* as the target. To provide interpretable outputs, the model's predicted probabilities were categorised into three levels: "Less Likely" ,"Likely", and "Very Likely", as delineated by the thresholds in Equation 1. For x = 0 and x = 1, the model returns "Less Likely" and "Very Likely", respectively.

$$f(x) = \begin{cases} \text{"}\mathit{Less\ Likely}\text{"} & x < 0.5 \\ \text{"}\mathit{Likely}\text{"} & 0.5 \leq x \leq 0.75 \\ \text{"}\mathit{Very\ Likely}\text{"} & x > 0.75 \end{cases} \qquad (1)$$

The model is further analysed in subsection 2.2.1.

XGBoost implementation

The classification task was addressed using Extreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2016; Osman et al., 2021), chosen for its robustness with small to medium-sized datasets and its efficacy in handling classification problems. XGBoost operates as an ensemble method, iteratively building decision trees that minimise a loss function while correcting errors from previous trees (Natras et al., 2022). XGBoost works by creating a series of simple "yes/no" rules (decision trees) and then combining them into a single, stronger predictor. Each new tree focuses on the examples that were misclassified by the previous trees, so the model keeps learning from its mistakes until its overall performance improves. Its objective function is formalised as shown in Equation (2) below:

$$l(\theta) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{k} \omega\left(f_k\right) \qquad (2)$$

where $l\left(y_i, \hat{y}_i\right)$ denotes the loss incurred by predicting $\hat{y}_i$ when the true response is y_i. The term $\omega\left(f_k\right)$ is a regularisation penalty applied to each individual tree f_k so as to limit its complexity and thus mitigate overfitting. Finally, K represents the total number of trees in the ensemble, and the trees $f_1, f_2, f_3, \ldots, f_k$ are added sequentially during the boosting procedure.

Tree construction leverages a second-order Taylor expansion of the loss function, with leaf weights updated via the following equation (3):

$$\bar{\omega} = -\frac{\sum_{i \in I} g_i}{\sum_{i \in I} h_i + \lambda} \qquad (3)$$

where g_i and h_i are the first and second derivatives of the loss, λ is a regularisation parameter, and I is the set of samples in a leaf. To prepare the data, categorical variables (e.g., university and course of study) were transformed using one-hot encoding, enabling compatibility with XGBoost's numerical requirements.

Model analysis

To properly understand XGBoost classifier's use of input features to differentiate between employed and unemployed graduates, we used two methods: examining the model's built-in feature-importance scores, and analysing pairwise correlations between predictors and the target.

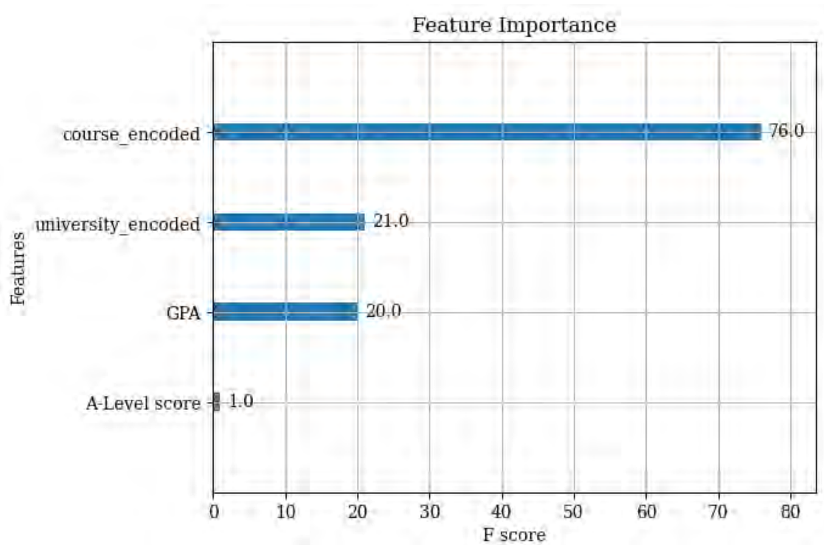

Figure 1: **Dataset features against the feature importance score (F-score) of the XGBoost model**

Figure 1 reveals that Course of Study (one-hot encoded) dominates the model's decision process, with an F-score of 76, more than three times that of any other variable. University (F = 21) and GPA (F = 20) provide secondary predictive strength, indicating that institutional affiliation and overall academic performance both inform employment likelihood. In stark contrast, A-level score contributes almost no unique information (F = 1), implying redundancy once downstream academic achievements are accounted for.

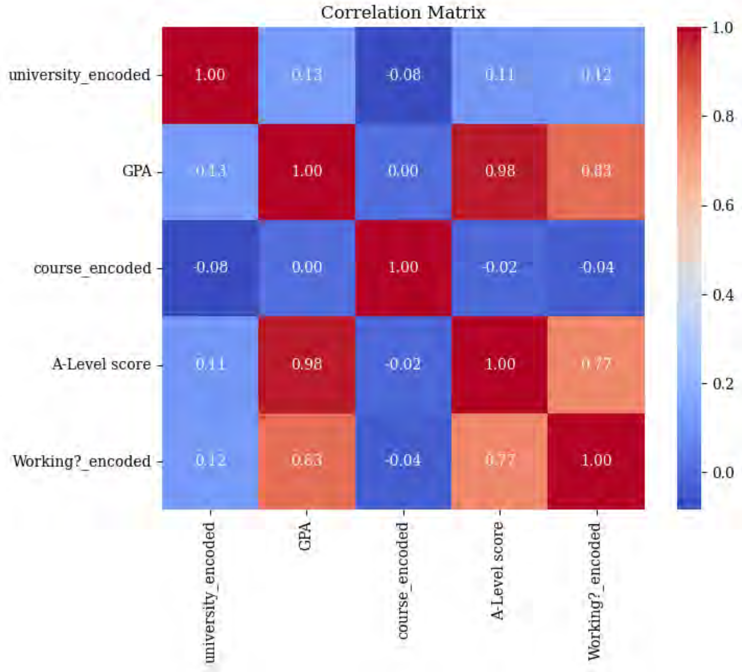

Figure 2: **Pearson correlation matrix for the encoded features alongside the binary employment outcome**

In Figure 2, the GPA and A-level scores exhibit an almost perfect positive correlation (r = 0.98), reflecting the continuity from secondary to tertiary academic performance. Both of these academic indicators also correlate strongly with employment status (r = 0.83 for GPA, r = 0.77 for A-level), underscoring their roles as general measures of candidate quality. By contrast, Course of Study, despite its outsized importance in the model, shows virtually no linear correlation with employment (r = –0.04). This discrepancy indicates that its predictive power arises from non-linear interactions and decision rules within the boosted trees rather than a simple monotonic trend. University maintains a modest positive correlation with employment (r = 0.12), consistent with its intermediate feature-importance ranking.

Taken together, these analyses highlight that the model leverages both domain-specific and broad academic indicators to make robust employment predictions. Disciplinary specialisation provides the most distinctive signal, while institutional reputation and cumulative GPA refine the predictions. More analysis of the model's performance is included in the results section.

Training and evaluation

Given the constrained sample size, the Leave-One-Out (LOO) cross-validation method was adopted for training and evaluation (Dong et al., 2017). In LOO, each of the *n* samples in the dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$ is used as a test instance once, with the remaining *(n-1)* samples forming the training set. This process repeats *n* times, and the overall performance metric M is averaged across iterations:

$$M = \frac{1}{n}\sum_{i=1}^{n} M_i \quad (4)$$

Equation 4 shows the formula for calculating the average performance metric M for LOO iterations.

where M_i represents the performance metric (e.g., accuracy) for the i^{th} iteration. The choice of LOO was driven by:

- **Maximised data use**: It ensures all samples contribute to both training and validation, critical for small datasets.
- **Unbiased estimation**: Testing each sample individually yields a nearly unbiased generalisation error estimate (Cawley, 2006).
- **Small dataset suitability**: LOO avoids artificial data splits, aligning with the study's reliance on user engagement.
- **Model robustness**: It supports high-variance models like XGBoost by retaining training data integrity.

While LOO is computationally demanding, the modest dataset size rendered it practical, ensuring rigorous model assessment.

Results

The performance of the XGBoost classification model was evaluated using standard machine learning metrics, including accuracy, precision, recall, and F1-score. The model achieved an accuracy of 98.9% and an F1-score of 99.1%, indicating strong predictive capability in assessing the likelihood of a graduate securing employment. Figure 1 shows the confusion matrix of the model. A confusion matrix is a tabular summary of prediction outcomes showing the model's true positives (graduates correctly predicted as employed), true negatives (graduates correctly predicted as unemployed), false positives (graduates predicted as employed who are actually unemployed), and false negatives (graduates predicted as unemployed who are actually employed), enabling assessment of model errors in each category. In this study, the confusion matrix is particularly helpful because it reveals whether the model tends to misclassify unemployed graduates as employed (or vice versa), thereby offering insight into the reliability of predictions for each class and guiding potential refinements.

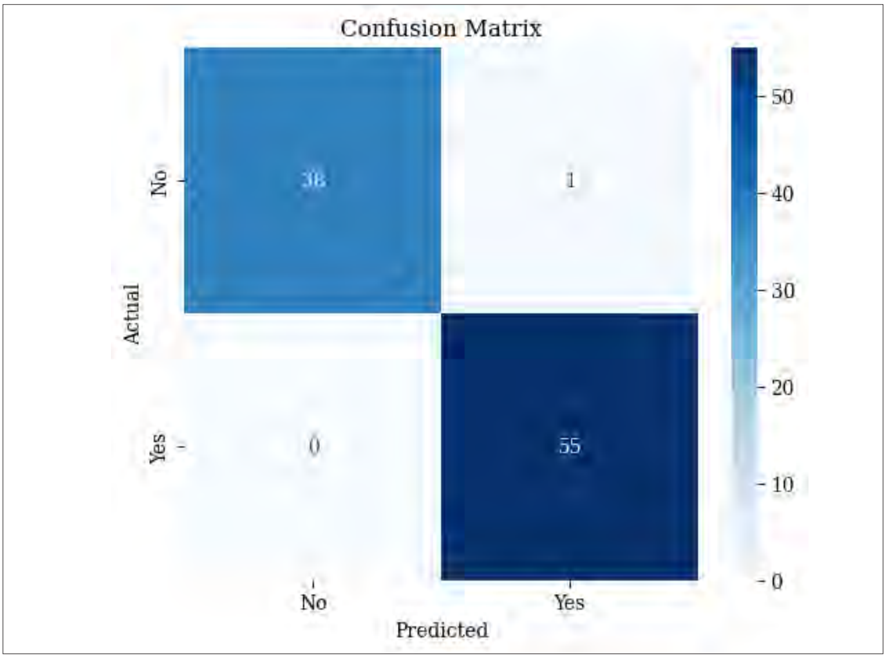

Figure 3: **The confusion matrix of the XGBoost model**

Furthermore, to provide a more intuitive interpretation of the model's predictions, the predicted probabilities were categorised into three likelihood groups: *Less Likely* ($p < 0.5$), *Likely* ($0.5 \leq p \leq 0.75$), and *Very Likely* ($p > 0.75$), as illustrated in Figure 2. This classification allows for a clearer understanding of how the model perceives different probability ranges in relation to employment outcomes.

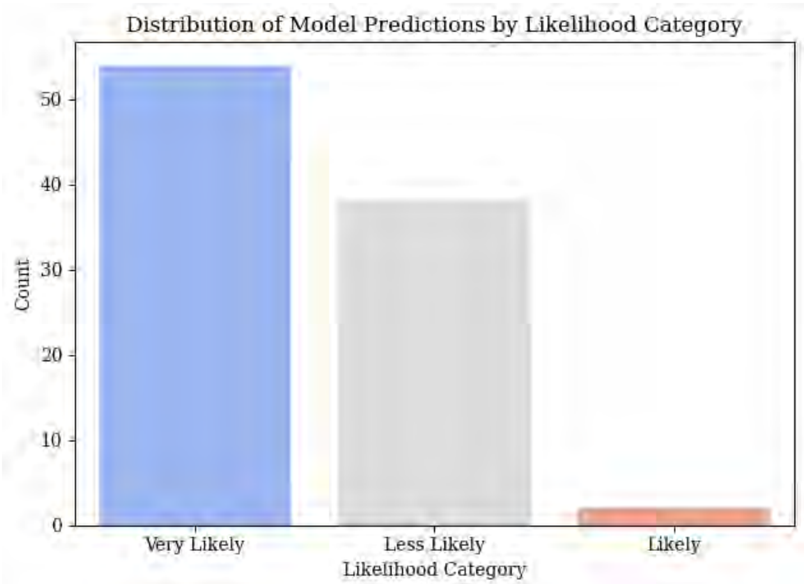

Figure 4: **Distribution of predicted probabilities across employment likelihood categories, with most graduates classified as "Very Likely".**

The results indicate that the trained model effectively predicts a student's likelihood of securing a job with high accuracy. Notably, the LOO cross-validation method was employed due to the current limited dataset size. However, as the dataset expands, we plan to transition to more memory-efficient validation techniques to enhance computational efficiency while maintaining robust model performance.

Discussion and Limitations

The findings from this study underscore the effectiveness of the Course Guidance System in predicting employment outcomes for graduates based on academic and institutional factors. Utilising the XGBoost model, this system achieved a predictive accuracy of 98.9%, demonstrating its robust capability to classify employment likelihood. The high accuracy and F1 score affirm that academic attributes, such as university attended, GPA, course of study, and A-level scores, play a significant role in determining employability. Existing research reveals both similarities and distinctions in the application of ML within educational contexts; the high predictive performance of our model aligns with findings from other studies. Abuzayeda et al. (2024) reported a 97.3% accuracy using a random forest model to identify students requiring intensive academic advising, while Wen and Zhou (2025) achieved 95% accuracy with a Wild Horse Optimised Resilient XGBoost (WHO-RXGBoost) model for career guidance predictions. WHO-RXGBoost represents a hybrid optimisation approach that combines meta-heuristic optimisation with the core XGBoost framework. The relationship between these models is characterised by shared algorithmic DNA in their boosting mechanisms, yet differ significantly in optimisation strategies and implementation complexity. The model results collectively demonstrate the effectiveness of ensemble and gradient boosting methods in handling complex educational datasets. Notably, our adoption of XGBoost mirrors trends observed in Wen and Zhou (2025), where a variant of this algorithm was employed for similar predictive purposes, reinforcing its suitability for classification tasks in educational data mining.

A key contribution of this study lies in its novel application within the African, specifically Ugandan, higher education system. To the best of our knowledge, this research represents one of the first efforts to leverage ML for predicting graduate employment outcomes in this region. It is tailored to Uganda's unique socio-economic and educational landscape. By harnessing a dataset derived from Ugandan universities and incorporating locally relevant indicators, such as A-level scores and institutional reputation, this model addresses challenges specific to Ugandan graduates, including limited resources, varying educational quality, and a dynamic job market influenced by both local and global factors. This localised approach distinguishes our study from broader, often more generalised, applications of ML in education.

Despite its strengths, the model's limitations include its reliance exclusively on academic and institutional factors and omission of other critical determinants of employment, such as soft skills (Patacsil & Tablatin, 2017), professional networking (Akkas, 2023), internship experience (Barnwell, 2016), labour market trends (Manacorda & Petrongolo, 1999), internship experience, number of certifications, and extracurriculars as they are increasingly pivotal in competitive job markets, as employers value practical competencies alongside academic credentials. The absence of such variables in our dataset may constrain the model's ability to fully capture the multifaceted nature of employability. Future research should aim to incorporate a broader spectrum of features to enhance predictive accuracy and provide a more holistic view of employability.

Conclusion

This study introduced an intelligent Course Guidance System designed to address Uganda's graduate unemployment challenge by offering data-driven insights into course selection. Utilising an XGBoost model to predict employment likelihood based on academic attributes, the system achieved strong predictive performance, underscoring the viability of AI-driven solutions in career guidance. By integrating real-time, community-sourced data, the platform delivers more current and relevant advice than traditional static methods, thereby helping students, universities and policymakers align academic programmes with evolving labour-market demands.

Future work should focus on incorporating additional determinants of employability, such as soft skills, internship experience, and dynamic labor-market indicators, to improve prediction accuracy and generalisability. Expanding the dataset to encompass these variables will better capture the multifaceted nature of employment outcomes. Additionally, integrating explainable AI techniques could enhance transparency in model decision-making, and the development of complementary recommendation modules for suggesting internships, certifications, or skill-enhancement programs could also increase the system's practical utility.

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