# Prediction of Career Suitability for Graduates of Teacher Education Programs as Support for Higher Education Decision-Making using Random Forest and XGBoost Algorithms

**Bayu Eka Susanto, Muhammad Syahputra Novelan**

## ABSTRACT

The alignment between graduates' educational backgrounds and their employment fields is an important indicator for evaluating the relevance of higher education programs to labor market needs. This study aims to classify the career suitability of graduates from teacher education programs using Random Forest and XGBoost algorithms to support higher education decision-making. The dataset consists of 730 graduates from 2025 in the Stabat area. The predictor variables include gender, study program, Grade Point Average (GPA), and employment status, while career suitability serves as the target variable. The research process involves data preprocessing, categorical variable encoding, stratified data splitting using an 80:20 ratio, model development, and performance evaluation based on accuracy, precision, recall, and F1-score. The results show that 454 graduates (62.19%) were classified as having careers suitable for their fields of study, while 276 graduates (37.81%) were classified as having unsuitable careers. According to the model performance comparison table, Random Forest achieved an accuracy of 66.44%, precision of 81.82%, recall of 59.34%, and F1-score of 68.79%. Meanwhile, XGBoost achieved an accuracy of 65.75%, precision of 75.95%, recall of 65.93%, and F1-score of 70.59%. Random Forest achieved higher accuracy and precision, whereas XGBoost obtained higher recall and F1-score. These findings suggest that both algorithms have the potential to provide preliminary information for evaluating graduate career suitability, reviewing curriculum relevance, and improving graduate competencies and career guidance services. However, the predictive performance of both models remains limited, and further testing and validation are required before practical implementation in decision-making.

***Keywords**:*
Career Suitability; Graduate Prediction; Random Forest; XGBoost; Higher Education Decision Support.

Bayu Eka Susanto
Magister of Information Technology, Universitas Pembangunan Panca Budi, Indonesia
e-mail: bayususanto2311@gmail.com

Muhammad Syahputra Novelan
e-mail: putranovelan@dosen.pancabudi.ac.id
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## Introduction

The dynamic development of job market needs presents a challenge for higher education institutions in ensuring that the graduates produced have competencies that align with the requirements of the job market[1]. Higher education institutions are not only required to conduct the educational process but also need to pay attention to the career sustainability of graduates after completing their education[2], [3]. Information regarding the alignment between the field of education and employment becomes one of the indicators that can be used to see the connection between educational outcomes and the needs of the job market[4], [5]. This condition becomes increasingly important in teacher education programs because graduates in this field are generally prepared to have competencies related to education and teaching[6], [7]. However, in practice, not all graduates work in fields that are directly related to their educational background.

The career alignment of graduates can provide an overview of the extent to which the competencies acquired during their education can be applied in the workforce[8]. Graduates who work in their field of study have the potential to demonstrate a connection between the learning process, academic competencies, and job requirements. Conversely, graduates who work outside their field of study or have not yet found suitable employment can provide important information for universities to evaluate the education process, curriculum, competency training, and student career development services. Therefore, the management of alumni data should not only be used as administrative documentation but can be developed into a source of information to support the evaluation and decision-making processes.

Teacher education programs have different characteristics compared to other study programs because their competency orientation is closely related to the field of education[9]. The competencies of graduates are not only formed through theoretical learning but also through teaching experience, training, certification, and various activities that support readiness to enter the workforce[10]. Nevertheless, changing labor market needs allow graduates to have diverse career paths. Some graduates can work as teachers, while others can work in administration, companies, entrepreneurship, or other fields. This diversity necessitates that higher education institutions adopt a data-driven approach to gain insights into the career alignment patterns of their graduates.

In the Stabat District, there is data on graduates of teacher education programs that can be utilized for career suitability analysis. This research data includes 730 graduates of teacher education programs in 2025. The data includes several characteristics of the graduates, such as gender, study program, cumulative grade point average (GPA), employment status, job field, and field suitability information. The relatively large amount of data provides an opportunity to apply data processing techniques and machine learning to identify career suitability patterns among graduates. By utilizing this data, universities can obtain more structured information regarding the characteristics of graduates whose career paths align with their fields of study.

One of the approaches that can be used for prediction is data mining with classification methods. Data mining allows patterns within data sets to be identified and utilized to generate information that can support decision-making. In the context of this research, classification is used to predict the career suitability of graduates into predetermined categories based on the characteristics of the graduates' data. This approach is expected to help identify patterns of relationships between academic characteristics and graduates' status with career field suitability.

The Random Forest algorithm is one of the ensemble learning methods that can be used for classification by building a number of decision trees and combining the prediction results from those trees[11], [12],[13]. This approach can be used to handle data with diverse variable characteristics and has the ability to identify the relative contribution of variables to the prediction process. In addition to Random Forest, XGBoost is a gradient boosting-based ensemble algorithm that builds models incrementally by correcting the prediction errors of previous models. The use of both algorithms allows for comparative analysis to observe the differences in the models' abilities to predict career suitability for graduates.

Research related to predicting graduates' careers generally utilizes academic data and student characteristics to identify job readiness or employment opportunities. However, studies that specifically compare Random Forest and XGBoost to predict the career suitability of graduates from teacher education programs can still be developed, especially by utilizing graduate data at certain regional levels[14]. In addition, the prediction results are not only aimed at measuring the performance of the algorithm but can also be utilized as supporting information for universities in evaluating and planning graduate development. This gap in research became the basis for conducting this study.

This research aims to predict the career suitability of graduates from teacher education programs using the Random Forest and XGBoost algorithms based on data from 730 graduates in 2025 in Stabat District. Both algorithms are compared based on classification evaluation metrics, such as accuracy, precision, recall, and F1-score, to determine the performance of each model in making predictions[15], [16]. In addition to producing a predictive model, this research is expected to provide data-based information on the career suitability patterns of graduates, which can be utilized by universities as one of the supporting materials in evaluating study programs, developing student competencies, and planning strategies to enhance the relevance of graduates to the needs of the job market.

## Literature Review

Graduate employability is widely treated as an indicator of how well higher education prepares graduates for the labour market. A systematic review by Vlachopoulos and Pachni Tsitiridou emphasises employability skills development and university–industry collaboration as ways of preparing graduates for labour market demands [1]. Healy et al. mapped research on graduate employability and career development in higher education through a citation network analysis [3], while Andrade et al. examined how learning affects student persistence in higher education [2]. Other studies relate graduate outcomes directly to labour market needs, as in the case of Jouf University graduates [4], and highlight transversal competencies as a link between higher education and employment [5]. Aljohani et al. further used a data-driven analysis of the scientific literature to examine the skill gap between university curricula and job market requirements [8]. Together, these studies show that the relationship between education and employment is a recurring concern for universities, and that information on graduate outcomes is relevant for evaluating curriculum and competency development.

In the context of teacher education, graduates are prepared for competencies related to education and teaching. Bardelli et al. studied how teacher preparation programs relate to graduates' growth in instructional effectiveness [6], and Fitriati et al. discussed the challenges of preparing

prospective teachers for teaching 4C skills in the mathematics classroom from the perspective of school–university partnerships [7]. Jegstad et al. described teacher educators' understanding of professional knowledge in research-based teacher education as both dichotomous and multifaceted [9]. In the Indonesian setting, Nugroho et al. reviewed the work readiness of students and graduates of higher education systematically [10]. These studies indicate that the competencies of teacher education graduates are shaped by several components of preparation, so the extent to which graduates actually work in education-related fields is a relevant subject for evaluation.

From the methodological side, classification is a commonly used data mining approach for predicting categories from recorded characteristics. Random Forest is an ensemble method that combines the predictions of many decision trees, and it has been described and applied in several studies [11], [12], [13]. Helmud et al. compared the classification performance of Random Forest and Decision Tree algorithms using a confusion matrix [11], Salman et al. provided an overview of the Random Forest algorithm [12], and Ibrahim compared Support Vector Machine and Random Forest on student behaviour and achievement at a vocational school in Stabat [13]. In evaluating classification models, accuracy, precision, recall, and F1-score are commonly used metrics. Sujon et al. examined these measures, together with MCC, for evaluating predictive models [15], and Widyawati and Faradibah compared the performance of several classification models using such metrics in a prediction case [16]. Using several metrics rather than accuracy alone allows the strengths and weaknesses of each model to be seen more clearly.

Research on predicting graduate outcomes has also been developed with machine learning. Shannaq, for example, developed an intelligent tool for recent graduate employability and analysed its key determinants using explainable AI [14]. However, the studies reviewed above mostly address employability, skills, and work readiness in general, or discuss algorithm performance in other domains. Studies that specifically compare Random Forest and XGBoost for predicting the career suitability of teacher education graduates, using graduate data at a regional level, remain limited [14]. This gap motivates the present study, which compares the two algorithms on graduate data from the Stabat area to provide supporting information for higher education decision-making.

## Methods

### 2.1 Types and Stages of Research

This research uses a quantitative approach with data mining methods and classification techniques. This approach is used to build a career suitability prediction model for graduates of teacher education programs based on the characteristics of the graduates' data. The research was conducted through several stages, namely data collection, data preprocessing, determination of research variables, formation of career suitability classes, data splitting, model building using the Random Forest and XGBoost algorithms, model evaluation, and interpretation of prediction results.

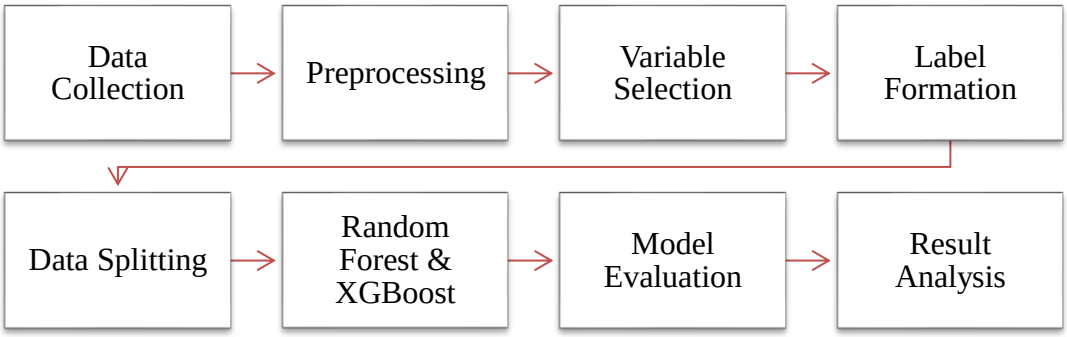



**Figure 1.** Research Stages

## 2.2 Research Data

The data used consists of graduates from the teacher education program at one of the universities in the Stabat Regency area. The data comprises 730 graduates from the year 2025. This data is used as a research dataset to identify patterns of alignment between the graduates' educational backgrounds and their career fields after completing their education. The data used includes several characteristics of graduates, namely graduate ID, gender, age, study program, GPA, study duration, teaching experience, certification, educational training, employment status, job field, job waiting time, and field suitability.

**Table 1.** Research Dataset Variables

| No | Variable | Description | Role |
|---|---|---|---|
| 1 | Graduate ID | Anonymous identity of each graduate | Identification |
| 2 | Gender | Graduate gender | Predictor |
| 3 | Program_Studi | Program of study undertaken | Predictor |
| 4 | IPK | Cumulative Grade Point Average of graduates | Predictor |
| 5 | Job_Status | Graduate employment conditions | Predictor |
| 6 | Field of Work | Field of work after graduation | Information/label |
| 7 | Field Suitability | Career Suitability Category | Target |

Variables that do not have value variation or do not have data are used as part of the preprocessing process and are not used as model predictors. ID_Lulusan is also not used as a prediction feature because it only serves as data identity.

## 2.3 Data Preprocessing

The preprocessing stage is carried out to ensure that the data can be used by machine learning algorithms[17], [18]. It included checking data completeness, identifying missing and duplicate data, removing identity variables and variables that provide no predictive information, and converting categorical variables into numerical form with encoding techniques (details in Section 3.2). The process can be formulated as $D' = \text{Preprocess}(D)$, where D is the initial dataset of 730 records and $D'$ is the dataset after cleaning and transformation.

## 2.4 Determination of Prediction Targets

The research target is Field Suitability (Kesesuaian_Bidang), which classifies graduates by the alignment of their careers with their field of education. The target has two classes: Appropriate, meaning the graduate's career field is relevant to the field of education or teaching competencies, and

Inappropriate, meaning the career field is not relevant or has not yet shown suitability. Class assignment is based on information about the graduate's field of work.

### 2.5 Data Splitting

The 730 records were divided 80:20 into training data (584 records) and testing data (146 records) using stratified sampling, so that the proportion of each target class is maintained in both sets. The training data was used to build the models, while the testing data was used to measure their ability to predict data not used during training.

### 2.6 Random Forest Algorithm

Random Forest is an ensemble algorithm that builds a number of decision trees and combines their predictions; in classification, the class receiving the most votes is the final prediction. In general, $\hat{y} = \text{mode}\{T1(x), T2(x), \ldots, Tn(x)\}$, where $\hat{y}$ is the final prediction, $Ti(x)$ is the prediction of the i-th decision tree, and n is the number of trees. It is used here to identify patterns of relationships between graduate characteristics and career suitability classes.

### 2.7 XGBoost Algorithm

XGBoost (Extreme Gradient Boosting) is a gradient boosting-based ensemble algorithm that builds models incrementally, each new tree correcting the prediction errors of the previous model. Its prediction can be expressed as $\hat{y}i = f1(xi) + f2(xi) + \ldots + fK(xi)$, where K is the number of trees, fk is the k-th decision tree function, and xi is the i-th data record. It is used as a comparison model against Random Forest.

Evaluation uses a confusion matrix consisting of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Accuracy is the proportion of correct predictions over all test data; precision is the correctness of predictions for a class; recall is the ability to find data that actually belong to a class; and F1-score balances precision and recall:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$\text{Precision} = TP / (TP + FP)$$

$$\text{Recall} = TP / (TP + FN)$$

$$\text{F1-score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

The results of both algorithms were compared descriptively based on these metrics.

### 2.8 Implementation Environment

The model implementation was carried out using the Python programming language with the help of processing and machine learning libraries[17]. The data processing stages included the use of libraries for dataset manipulation, preprocessing, building Random Forest and XGBoost models, and evaluating the classification results. The final result of the research is a classification model and information on the career alignment patterns of graduates, which can be used as one of the supporting information sources in the evaluation and decision-making process of higher education institutions.

```python
results = []
output_dir = Path("hasil_python")
output_dir.mkdir(exist_ok=True)

for model_name, estimator in models.items():
    pipeline = Pipeline([
        ("preprocessing", preprocessor),
        ("model", estimator),
    ])
    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    acc = accuracy_score(y_test, y_pred)
    prec = precision_score(y_test, y_pred, pos_label=1, zero_division=0)
    rec = recall_score(y_test, y_pred, pos_label=1, zero_division=0)
    f1 = f1_score(y_test, y_pred, pos_label=1, zero_division=0)
    cm = confusion_matrix(y_test, y_pred, labels=[0, 1])

    results.append({
        "Algoritma": model_name,
        "Accuracy": acc,
        "Precision": prec,
        "Recall": rec,
        "F1-Score": f1,
    })

    print("\n" + "-" * 72)
    print(f"HASIL EVALUASI: {model_name}")
    print("-" * 72)
    print(f"Accuracy : {acc:.4f} ({acc * 100:.2f}%)")
    print(f"Precision: {prec:.4f} ({prec * 100:.2f}%)")
    print(f"Recall   : {rec:.4f} ({rec * 100:.2f}%)")
    print(f"F1-Score : {f1:.4f} ({f1 * 100:.2f}%)")
    print("\nConfusion Matrix (baris=aktual, kolom=prediksi)")
    print("Urutan kelas: [Tidak Sesuai, Sesuai]")
    print(cm)
    print("\nClassification Report:")
    print(classification_report(
        y_test, y_pred,
        labels=[0, 1],
        target_names=["Not Suitable", "Suitable"],
        zero_division=0,
        digits=4
```

**Figure 2.** Python Code for Model Training and Evaluation

The model implementation was carried out using the Python programming language with the scikit-learn library. Preprocessing and model training were combined in a Pipeline, where each model (Random Forest and XGBoost) was fitted on the training data and evaluated on the testing data using accuracy, precision, recall, F1-score, confusion matrix, and classification report. The evaluation code is shown in Figure 2.

## Results and Discussion

### 3.1 Dataset Description

The dataset consists of 730 teacher education graduates from 2025 in the Stabat area: 433 male and 297 female graduates from six study programs (Indonesian Language Education, Mathematics Education, English Education, Primary School Teacher Education/PGSD, Biology Education, and Physics Education). A total of 648 graduates were employed and 82 were not yet employed. The predictors are gender, study program, GPA, and employment status; field suitability is the classification target.

As shown in Table 2, 454 graduates (62.19%) were classified as having careers suitable for their field of study and 276 (37.81%) as not suitable. Because the two classes have different proportions, stratified splitting was applied to maintain class proportions in the training and testing data.

**Table 2.** Distribution of Career Suitability Categories

| Category | Number | Percentage |
|---|---|---|
| Suitable | 454 | 62.19% |
| Not Suitable | 276 | 37.81% |
| Total | 730 | 100% |

### 3.2 Data Preprocessing

Before modeling, the dataset was examined for completeness, value variation, and the relevance of each variable. The Unnamed: 0 column (all values empty), ID_Lulusan (identifier only), and Usia (no values) were excluded. Lama_Studi, Pengalaman_Mengajar, Sertifikasi, Pelatihan_Pendidikan, and Waktu_Tunggu_Kerja were also excluded because all observations shared the same value and therefore could not help distinguish the classes. Bidang_Pekerjaan was excluded because it is directly related to the determination of career field suitability, and including it could cause data leakage and overstate the predictive capability of graduate characteristics.

Gender, study program, and employment status were converted into numerical form using one-hot encoding, while GPA was retained as a numerical variable.

### 3.3 Training and Testing Data Split

The dataset containing 730 observations was divided using an 80:20 ratio. A total of 584 observations were used as training data, while 146 observations were used as testing data. The data splitting process was performed using stratification based on the target class so that the proportions of suitable and unsuitable categories remained consistent.

The testing dataset consisted of 55 observations classified as not suitable and 91 observations classified as suitable. These observations were used to evaluate the models' ability to make predictions on data that were not used during the training process.

### 3.4 Random Forest Prediction Results

The Random Forest model was trained on the preprocessed training data and evaluated on 146 testing observations, producing an accuracy of 66.44% (Table 3). Its confusion matrix is shown in Figure 3.

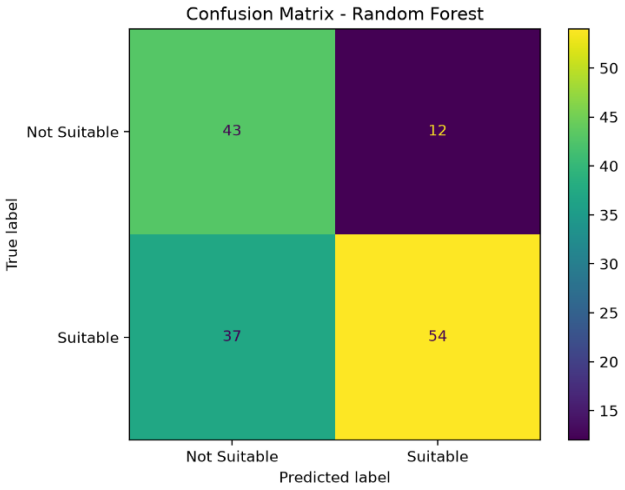



**Figure 3.** Random Forest Confusion Matrix

Random Forest correctly classified 43 not suitable and 54 suitable observations, while 12 not suitable observations were predicted as suitable and 37 suitable observations were predicted as not suitable. The precision of 81.82% indicates that most observations predicted as suitable were indeed suitable, whereas the recall of 59.34% shows that some suitable graduates were not identified. The F1-score of 68.79% reflects the balance between the two.

### 3.5 XGBoost Prediction Results

XGBoost was trained on the same training data as Random Forest, so both algorithms were compared under identical testing conditions. It achieved an accuracy of 65.75% (Table 3); its confusion matrix is shown in Figure 4.

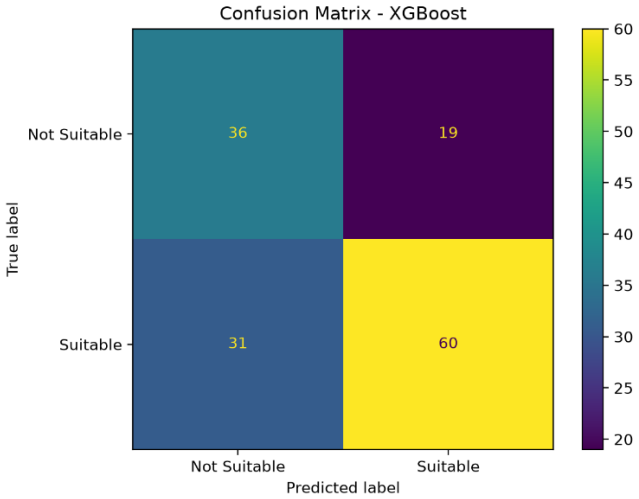



**Figure 4.** XGBoost Confusion Matrix

XGBoost correctly classified 36 not suitable and 60 suitable observations, while 19 not suitable observations were predicted as suitable and 31 suitable observations were predicted as not suitable. Its precision of 75.95% indicates relatively accurate predictions for the suitable class, and its recall of 65.93% shows that it identified a larger proportion of suitable graduates than Random Forest. The F1-score of 70.59% indicates a balance between precision and recall.

### 3.6 Comparison of Random Forest and XGBoost

The two algorithms were compared on accuracy, precision, recall, and F1-score, as shown in Table 3 and Figure 5.

**Table 3.** Model Performance Comparison

| Metric | Random Forest | XGBoost |
|---|---|---|
| Accuracy | 66.44% | 65.75% |
| Precision | 81.82% | 75.95% |
| Recall | 59.34% | 65.93% |
| F1-Score | 68.79% | 70.59% |

Random Forest achieved slightly higher accuracy (66.44% vs. 65.75%, a difference of about 0.69 percentage points) and higher precision (81.82% vs. 75.95%). XGBoost achieved higher recall (65.93% vs. 59.34%), meaning it identified a larger proportion of suitable graduates, and a higher F1-score (70.59% vs. 68.79%). The two algorithms therefore show different performance characteristics on this dataset.

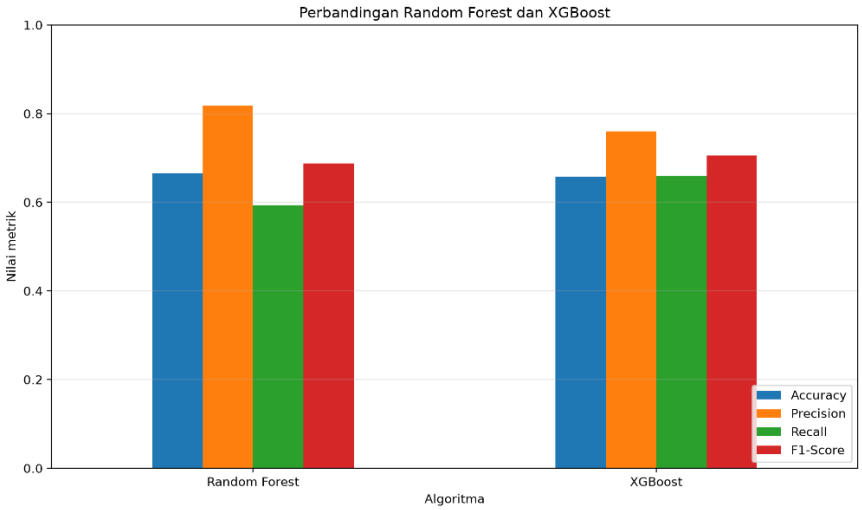



**Figure 5.** Model Comparison Graph

The comparison graph can be used to visually illustrate the performance differences between the two models. The graph shows that the performance of both models is within a relatively close range, with XGBoost producing higher accuracy, recall, and F1-Score values in the testing process.

### 3.7 Analysis of Graduate Career Suitability

Of the 730 graduates, 454 (62.19%) had careers suitable for their field of study and 276 (37.81%) did not. Although most graduates work in aligned fields, a substantial proportion experience mismatch, which highlights the need to evaluate the relationship between teacher education programs and graduate outcomes. Using gender, study program, GPA, and employment status, Random Forest and XGBoost reached accuracies of 66.44% and 65.75%, respectively. Both models therefore capture some patterns associated with career suitability, but these characteristics alone are not sufficient for highly accurate classification. Future research could add variables such as professional competencies, teaching experience, certification, and training, provided they contain reliable and sufficiently varied information.

Neither model outperformed the other on all metrics. Random Forest had higher precision, so its positive predictions were more reliable, while XGBoost had higher recall and F1-score, indicating a better balance between precision and recall. The choice of model should therefore depend on whether identifying suitable graduates or minimizing incorrect positive predictions matters more. For higher education institutions, the proportion of unsuitable careers can encourage a review of curriculum relevance, professional competency development, practical teaching opportunities, and career guidance services. These results do not show that any characteristic causes career suitability or mismatch; establishing this would require more comprehensive data.

The models also have limitations. The evaluation used a single dataset of 730 graduates from one area and one graduation year, which limits generalizability, and the moderate accuracy means predictions must be interpreted cautiously. Further studies should use broader datasets, additional relevant predictors, hyperparameter optimization, and validation across graduate cohorts.

### 3.8 Implications for Higher Education Decision-Making

The findings can serve as one source of data-driven information for evaluating graduate career suitability and supporting the evaluation of learning processes, competency development, career support activities, and the relationship between study programs and labor market requirements. The models could also be developed into a tracer study information system or graduate analytics

dashboard, so that graduate data are not only archived but also processed into predictive information. Nevertheless, predictions should serve only as supporting information and be combined with academic evaluation, graduate feedback, labor market requirements, and other relevant indicators.

## Conlusion

This study shows that Random Forest and XGBoost can serve as preliminary classification approaches for analyzing the career suitability of teacher education graduates. Of 730 graduates from 2025 in the Stabat area, 454 (62.19%) had careers suitable for their field of study and 276 (37.81%) did not. Random Forest achieved higher accuracy (66.44% vs. 65.75%) and precision (81.82% vs. 75.95%), whereas XGBoost achieved higher recall (65.93% vs. 59.34%) and F1-score (70.59% vs. 68.79%), so the choice of algorithm should consider which prediction errors need to be minimized. The findings can support the evaluation of curriculum relevance, the development of professional competencies, and career guidance services, but they do not establish causal relationships, and the moderate performance and single-area, single-year data limit generalizability. Future research should use more diverse data, additional predictors with sufficient variation, hyperparameter optimization, and validation across graduate cohorts. Predictions should be combined with academic evaluations, graduate feedback, and labor market information rather than used as the sole basis for decision-making.

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