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Recommendation of Vocational Major Recommendation Using Artificial Neural Networks with ADAM Optimization

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Abstract−This study proposes an Artificial Neural Network (ANN)-based recommendation framework for vocational major selection using student academic-feature profiles and ADAM optimization. The dataset consisted of 9,984 student records from West Java, derived from the school proposal recapitulation linked to DAPODIK. The predictive task was formulated as a six-class classification problem covering major categories in vocational education. Data preprocessing included data checking, target encoding, feature standardization, and train-test splitting. The ANN model used two hidden layers with ReLU activation and a softmax output layer, and was trained for 50 epochs using the ADAM optimizer. To enhance practical usability, predicted class probabilities were combined with major-specific qualification thresholds to enable the system to produce both primary and alternative recommendations. Experimental results showed that the model achieved 82% accuracy, an average precision of 0.88, a recall of 0.82, and an AUC of 0.8748, indicating useful discriminative performance for vocational major recommendation. The study provides a clearer distinction among the recommendation basis, predictive model, and operational qualification screening in educational decision support. However, the system still relies mainly on academic features and has not yet been benchmarked against alternative classifiers. Future work should incorporate interest and aptitude variables, class-wise error analysis, and comparative baseline evaluation.

Keywords: Major Recommendation; Artificial Neural Network; ADAM Algorithm; Content-Based Filtering; Decision Support System; Model Evaluation; Vocational School

1. INTRODUCTION

Vocational education plays a strategic role in preparing students for employment, industrial adaptation, and skills-based economic development. In Indonesia, vocational high schools (Sekolah Menengah Kejuruan, SMK) are expected to produce graduates whose competencies align with labor-market needs [1], [2], [3]. However, this expectation depends heavily on students entering majors that match their academic preparedness and potential [4], [5]. When major selection is poorly aligned with students' capabilities, the consequences may include low learning motivation, weak academic performance, poor competency development, and an eventual mismatch between educational background and occupational outcomes [6], [7], [8].

In practice, major selection is still often supported by manual counseling, teacher judgment, or general administrative screening. Although such approaches remain important, they are limited by subjectivity, time constraints, and the difficulty of consistently processing large student cohorts. As school systems increasingly collect structured academic data, there is a strong rationale for developing data-driven decision-support tools that can assist students and schools in identifying more suitable vocational pathways [9], [10], [11].

Recommendation systems provide one possible solution. In educational settings, recommender systems have been used to support course selection, learning resource discovery, and academic planning. Content-based recommendation logic is particularly relevant when recommendations are derived from user-specific attributes rather than from peer similarity [12], [13], [14]. In the present context, student academic records can be treated as a feature profile that is matched against the competency demands of different vocational majors. In recommender-system scholarship, content-based recommendation is typically understood as a mechanism for linking user profiles and item attributes rather than as a stand-alone predictive model [15], [16], [17], [18].

To model complex relationships between student profiles and major suitability, this study uses an Artificial Neural Network (ANN). ANN is appropriate when the relationship between academic inputs and recommendation outputs is potentially non-linear and multi-dimensional [19], [20]. However, ANN performance depends not only on architecture, but also on training stability. The ADAM optimizer is especially relevant here because it adapts the learning rate using first- and second-moment gradient estimates and is widely used for efficient neural network training [21], [22].

Despite the broader growth of machine learning in educational prediction, the specific problem of vocational major recommendation remains underdeveloped. While ANN have been widely applied to educational prediction tasks, relatively few studies have examined vocational major recommendations using real student academic records and an explicit multiclass recommendation framework [23], [24]. Prior work in education has more often focused on academic performance prediction, course recommendation, or generalized student analytics than on practical major recommendation for vocational placement [25], [26], [27], [28]. In addition, existing studies in educational recommendation often emphasize descriptive rule matching or general recommender logic, with limited attention to convergence behavior, optimizer choice, and post-prediction qualification screening for operational deployment [29], [30], [31]. As a result, the distinction between the basis for recommendations, predictive modeling, and actionable

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decision outputs often remains unclear. These limitations indicate the need for a more explicitly structured recommendation framework that combines predictive accuracy, training stability, and operational interpretability.

This study addresses these gaps by developing a vocational major recommendation model using academic-feature profiles derived from student records, ANN-based multiclass classification, and ADAM optimization. The proposed framework does not treat content-based logic and ANN as two separate methods. Instead, content-derived academic features and major qualification criteria provide the recommendation basis, while ANN serves as the primary predictive model and ADAM as the optimization mechanism. To make the system operationally useful, predicted class probabilities are further combined with qualification thresholds to generate both primary and alternative recommendations. Accordingly, this study addresses the following research questions:

RQ1. How can student academic-feature profiles be used to predict vocational major suitability through an ANN-based multiclass classification model?
RQ2. How does the proposed recommendation framework translate predicted probabilities into primary and alternative major recommendations?
RQ3. How well does the ANN model optimized with ADAM perform in terms of accuracy, precision, recall, AUC, and convergence behavior?

This study makes three contributions. First, it offers a clearer conceptual separation between the recommendation basis, the predictive model, and the optimization strategy in vocational major recommendations. Second, it proposes a practical two-stage framework that combines ANN-based prediction with qualification-based alternative recommendation. Third, it provides empirical evidence from 9,984 student records and evaluates the model not only through classification metrics, but also through training dynamics relevant to optimization stability.

2. RESEARCH METHODOLOGY

2.1 Research Workflow

This study was conducted through five main stages: dataset acquisition, data preprocessing, ANN-based model development, recommendation generation, and model evaluation [32], [33], [34]. The overall research workflow is presented in Figure 1**.** The workflow was designed to ensure that the recommendation framework addressed not only predictive classification, but also the practical translation of model output into operational vocational-major recommendations.

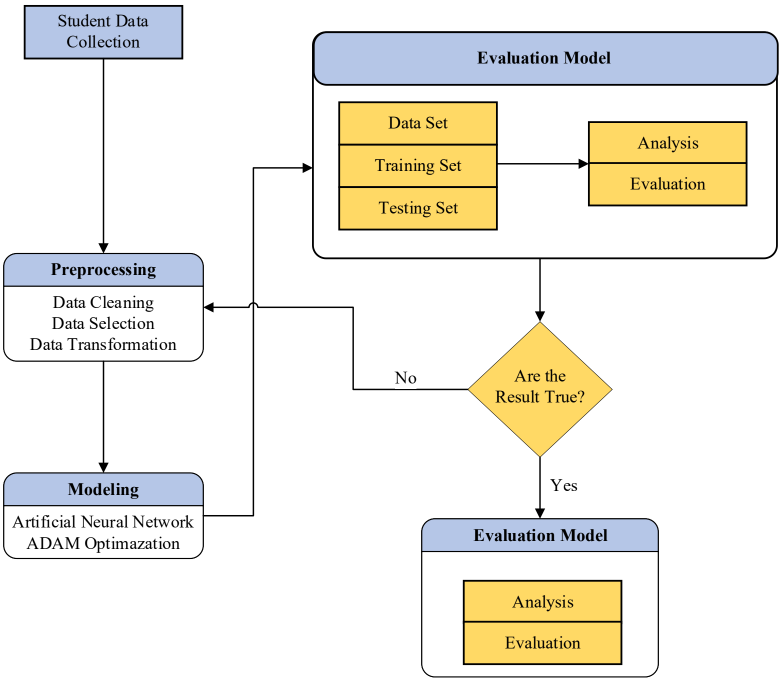

Figure 1. Research Stages

2.2 Dataset and Study Variables

The dataset used in this study consisted of 9,984 student records from the school proposal recapitulation in West Java, linked to the DAPODIK system. Each record represented one student and contained two main components: (1) academic-feature inputs and (2) vocational-major labels. The academic features used in the predictive model were Indonesian Language (N_BIND), English Language (N_BING), Mathematics (N_MTK), and Natural Science (N_IPA) scores. The target output consisted of six vocational-major categories: Light Vehicle Engineering (M_TKR),

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Motorcycle Engineering and Business (M_TSM), Computer and Network Engineering (M_TKJ), Accounting (M_AK), Visual Communication Design (M_DKV), and Office Administration (M_ADM).

In addition to the predictive labels, the study also defined major-specific qualification thresholds. These thresholds were not used as training targets, but as operational screening criteria after prediction. In this way, the recommendation framework distinguished between the predictive model and the qualification-based decision layer, enabling model probabilities to be translated into both primary and alternative recommendations.

2.3 Data Preprocessing

Data preprocessing was conducted to prepare the student records for multiclass classification. First, the dataset was checked for missing values, duplicate entries, and invalid score records. The final dataset used for modeling did not contain blank values or duplicated rows. Second, the vocational-major labels were converted into integer-encoded class targets. Third, the academic-score features were standardized using StandardScaler so that all input variables had comparable numerical scales. This step was important to support stable ANN training, especially under gradient-based optimization. Finally, the dataset was divided into 80% training data and 20% testing data using train_test_split. The preprocessing stage did not create new decision rules; rather, it transformed the raw student records into a format suitable for multiclass ANN training. The preprocessing workflow is illustrated in Figure 2.

```
# Encode Major
le = LabelEncoder()
data['major_encoded'] = le.fit_transform(data['major'])

# Features and labels
X = data.drop(['major', 'major_encoded'], axis=1)
y = to_categorical(data['major_encoded'])

# Normalization
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Figure 2. Data Preprocessing

2.4 ANN Model and ADAM Optimization

The predictive component of the framework was implemented using an Artificial Neural Network (ANN) [35], [36]. The model architecture consisted of an input layer, two hidden layers with 64 and 32 neurons, respectively, both using ReLU activation, and a six-unit softmax output layer for multiclass classification. The basic neuron computation is expressed as:

$$a = \sigma \left(\sum_{i=1}^{n} w_i x_i + b\right) \quad (1)$$

In this computation, a represents the neuron output generated after processing all input values. The variable w_i denotes the weight assigned to the i-th input, reflecting its contribution to the final output. Meanwhile, x_i refers to the value of the i-th input received by the neuron. The variable b represents the bias term, which helps adjust the activation threshold. Furthermore, n indicates the total number of inputs, while σ denotes the activation function used to transform the weighted sum into the final neuron output.

The model was trained for 50 epochs with a batch size of 16. Optimization was performed using the ADAM optimizer [37], [38] with a learning rate of 0.001, while the loss function used was sparse_categorical_crossentropy, which was appropriate because the target classes were stored in integer-encoded form. The ADAM update rule is expressed as:

$$\theta_t = \theta_{t-1} - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (2)$$

In the optimization process, θ_t represents the model parameters at iteration t, which are continuously updated during training to minimize the loss function. The parameter α denotes the learning rate, controlling the step size of each update. Meanwhile, $\hat{m}_t$ refers to the bias-corrected first moment, which estimates the mean of the gradients, while $\hat{v}_t$ represents the bias-corrected second moment, estimating the variance of the gradients. Additionally, ϵ is a small constant added to prevent division by zero and ensure numerical stability during computation.

To assess convergence behavior during training, 20% of the training portion was used as validation data. Training loss and validation loss were recorded at each epoch.

2.5 Recommendation Generation

The proposed recommendation system used a two-stage framework. In the first stage, the ANN generated class probabilities for the six vocational majors, and the class with the highest probability was selected as the primary recommendation. In the second stage, the predicted major was checked against the predefined major qualification thresholds. If the student did not satisfy the qualification criteria of the top-ranked major, the system generated alternative recommendations based on the next-highest predicted probabilities. This design made the framework operationally more useful than a classifier-only approach, because it allowed the recommendation output to remain interpretable and actionable in school decision-support settings.

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2.6 Evaluation Metrics

Model performance was evaluated on the held-out test set using accuracy, precision, recall, F1-score, and multiclass AUC. These metrics were selected because they reflect overall correctness, class-level relevance, class-level completeness, balanced classification performance, and probability-based discriminative ability. The formulas used are as follows:

a. Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

b. Precision

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

c. Recall

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

d. F1-Score

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

In addition to these metrics, the study also evaluated training dynamics through a training-loss versus validation-loss curve across 50 epochs. This was included to assess convergence stability and to identify potential signs of overfitting.

3. RESULT AND DISCUSSION

3.1 Dataset Characteristics and Qualification Basis

The student dataset used in this study is presented in Table 1. The dataset consisted of 9,984 student records, where each row represented a student, and each major was represented as a one-hot vector in the original data structure. The first six columns indicated the selected major category, while the remaining academic-score columns served as predictive input variables.

Table 1. Student Dataset

No	M_TKR	M_TSM	M_TKJ	M_AK	M_DKV	M_ADM	N_BIND	N_BING	N_MTK	N_IPA
1	0	0	0	1	0	0	74	80	69	97
2	0	0	0	0	1	0	62	60	86	92
3	0	0	1	0	0	0	90	65	78	65
…	…..	…..	…..	…..	…..	…..	…..	…..	…..	…..
…	…..	…..	…..	…..	…..	…..	…..	…..	…..	…..
9982	0	0	0	1	0	0	78	68	78	78
9983	0	1	0	0	0	0	74	71	72	90
9984	0	0	0	0	0	1	91	88	86	95

The qualification criteria for each vocational major are presented in Table 2. These criteria served as operational thresholds for the second-stage screening of recommendations. For example, Computer and Network Engineering required relatively higher Mathematics, English, and Science scores, whereas majors such as Accounting and Office Administration placed stronger emphasis on language and numeracy-related thresholds.

Table 2. Major Qualification Score Data

Major	Indonesian Language Score	English Grade	MTK score	Science Score
Light Vehicle Engineering	-	-	75	70
Motorcycle Engineering	-	-	70	65
Computer Network Engineering	-	70	80	75
Accounting	75	-	70	-
Visual Communication Design	80	80	-	-
Office Administration	75	-	-	70

Taken together, Table 1 and Table 2 show that the recommendation problem in this study was built on two linked but distinct components: a multiclass student-major dataset for prediction and a qualification-based rule set for operational recommendation filtering.

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3.2 Preprocessing Outcomes and Recommendation Pipeline

The preprocessing stage confirmed that the dataset was already usable, with no retained blank values, duplicate entries, or major formatting inconsistencies. The major labels were converted into encoded class targets, while the academic features were standardized before training. The preprocessing flow is shown in Figure 2, and the output structure of the recommendation system is illustrated in Table 3.

Table 3. Sample Recommendation Output from the ANN–ADAM Framework

Student_Id	Major_Selected	Probability	Qualification	Recommendation
1	Accounting	100	No	There is no alternative
2	Visual Communication Design	100	No	Light Vehicle Engineering, Motorcycle Engineering
3	Computer Network Engineering	100	No	Motorcycle Engineering, Accounting
…	…..	…..	…..	…..
…	…..	…..	…..	…..
9982	Accounting	100	Yes	No alternative
9983	Motorcycle Engineering	100	Yes	There is no alternative
9984	Office Administration	100	No	Visual Communication Design, Accounting, Light Vehicle Engineering, Computer Network Engineering, Motorcycle Engineering

As shown in Table 3, the system output did not stop at the most probable class. It also reported whether the predicted major satisfied the qualification rules and, when necessary, generated alternative recommendations. This confirms that the framework functioned as a two-stage recommendation mechanism rather than as a single-step classifier only.

3.3 ANN Modeling Results

The ANN modeling process is illustrated in Figure 3. The model used two hidden layers and a softmax output layer to classify students into six vocational majors. The ADAM optimizer was used to support efficient weight updating during training.

```
# Split the data into 80% train and 20% test
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y_encoded, test_size=0.2, random_state=42
)

# Build the ANN model
model = Sequential([
    Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(32, activation='relu'),
    Dense(len(np.unique(y_encoded)), activation='softmax')
])

# Model compilation
model.compile(optimizer=Adam(learning_rate=0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Figure 3. Modeling Process of ANN Method and ADAM Optimization

An example of the recommendation output for one student case is shown in Figure 4. In this example, the model assigned the highest probability to Computer Network Engineering, followed by Light Vehicle Engineering. Other majors received considerably lower probabilities.

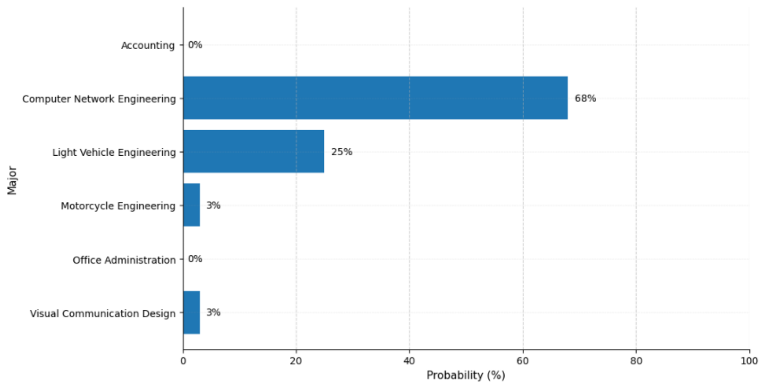

Figure 4. Modeling Results of ANN and ADAM Optimization Methods

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This output format is important because it shows that the model generated a ranked probability distribution rather than a single class label. That ranked output then became the basis for the qualification-screening step and the generation of alternative recommendations.

3.4 Convergence Behavior

To evaluate the stability of the ANN training process, the study examined the relationship between training and validation losses over 50 epochs. The resulting loss trajectory is presented in Figure 5.

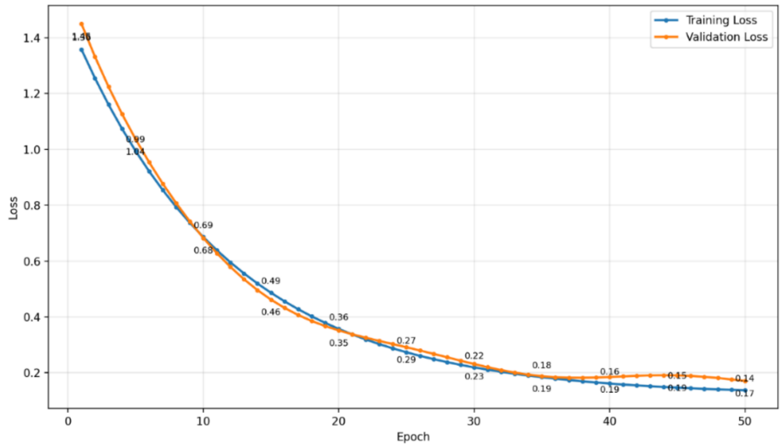

Figure 5. Training Loss and Validation Loss Across 50 Epochs

Figure 5 shows that both training loss and validation loss decreased consistently across the 50 training epochs and stabilized in the later stages. The relatively similar trajectories of the two curves indicate that the model converged stably, with no strong signs of overfitting during training. This finding supports the use of ADAM as an effective optimizer for the present multiclass recommendation task. At the same time, the loss curve is interpreted as evidence of stable convergence behavior within this study, rather than as proof of superiority over all alternative optimization methods.

3.5 Artificial Neural Network Model Evaluation with ADAM Optimization

This study evaluates the performance of the major recommendation system, developed using an Artificial Neural Network (ANN) optimized with the ADAM optimizer. The model is assessed using accuracy, precision, and recall. Accuracy measures the proportion of correct predictions, precision indicates the proportion of correctly predicted positive cases, and recall reflects the model's ability to identify all relevant cases. These metrics are computed on test data separate from the training data to ensure a more reliable evaluation of model performance. The evaluation workflow is illustrated in Figure 6, while the final results are presented in Figure 7.

```
# Model evaluation
loss, accuracy = model.evaluate(X_test, y_test, verbose=0)
y_probs = model.predict(X_test)
y_pred = np.argmax(y_probs, axis=1)

# ROC AUC
if len(np.unique(y_encoded)) == 2:
  roc_auc = roc_auc_score(y_test, y_probs[:, 1])
else:
  roc_auc = roc_auc_score(y_test, y_probs, multi_class='ovr')
```

Figure 6. Artificial Neural Network Model Evaluation Process with ADAM Optimization

```
Classification Report: ANN & Optimizer ADAM
              precision    recall  f1-score   support

       Tidak       1.00      0.72      0.83      1289
          Ya       0.66      1.00      0.79       708

    accuracy                           0.82      1997
   macro avg       0.83      0.86      0.81      1997
weighted avg       0.88      0.82      0.82      1997

accuracy      : 0.82
precision     : 0.88
recall        : 0.82
ROC AUC       : 0.8748
```

Figure 7. Artificial Neural Network Model Evaluation Results with ADAM Optimization

The evaluation results indicate that the ANN model achieved 82% accuracy, 0.88 average precision, 0.82 recall, and 0.8748 AUC. These values show that the model had useful discriminative performance in classifying student profiles into the six vocational-major categories.

Importantly, the evaluation in this study should be interpreted as multiclass prediction performance, not as a binary "yes/no" recommendation task. The "qualification" outcome reported in the recommendation table belongs to the second-stage operational screening layer rather than to the ANN classification target itself. This distinction is necessary to maintain methodological consistency across the model design, evaluation metrics, and recommendation logic. Overall, the results suggest that academic-feature profiles contain meaningful signals for vocational-major prediction and that the proposed ANN–ADAM framework can translate those signals into practically usable recommendation outputs.

3.6 Discussion

The findings of this study show that student academic-feature profiles can be used to support vocational-major recommendation through an ANN-based multiclass classification framework. The model achieved useful predictive performance, with 82% accuracy and an AUC of 0.8748, indicating that the academic variables in the dataset contained sufficient signal to differentiate among the six vocational-major categories. This result supports the view that vocational-major placement can be approached not only through manual guidance, but also through data-driven prediction using structured school records.

A second important contribution of this study lies in its conceptual and procedural clarity. In many studies on educational recommendation, recommendation logic, predictive modeling, and post-processing rules are often blended without clear separation [39], [40], [41]. In contrast, this study explicitly distinguishes three layers: the recommendation basis (student academic-feature profiles and major qualification criteria), the predictive model (ANN), and the optimization mechanism (ADAM). This distinction is methodologically important because it clarifies exactly what drives the recommendation and prevents the recommendation system from being described as if content-based logic and ANN were two unrelated, parallel methods [42], [43].

The study also contributes an operational two-stage framework. The ANN produces a ranked probability output, while the qualification-screening stage evaluates whether the top-predicted major satisfies predefined academic thresholds. If not, the system provides alternative recommendations from the next-most probable classes. This makes the recommendation output more practically useful than either a pure rule-based system or a classifier-only system. In other words, the framework improves interpretability for real educational decision support, where schools often need not only the most likely major, but also feasible alternatives [44], [45], [46].

The addition of the training-versus-validation loss curve strengthens the methodological robustness of the study. The loss trajectory indicates that the model converged efficiently and remained stable throughout training, supporting the use of ADAM for this task. This is important because earlier versions of the manuscript relied mainly on final classification metrics, whereas the revised version now also reports training dynamics. For neural-network-based recommendation studies, such reporting is necessary to substantiate claims about optimization stability rather than merely asserting them [47].

At the same time, the results should be interpreted with appropriate caution. First and foremost, the framework relies primarily on academic features, meaning that non-academic determinants of major suitability, such as interests, aptitudes, and psychological readiness, are not yet represented. Additionally, although the ANN model performed well, the study did not directly compare it with other classifiers such as decision trees, support vector machines, random forests, or gradient boosting models. For that reason, the findings support the practical utility of the proposed framework, but they do not justify a blanket claim that an ANN with ADAM is universally superior. Finally, potential imbalance in class distribution across majors may affect class-level performance and should be examined more explicitly in future studies.

Taken together, the results indicate that the proposed framework is a strong proof of concept for data-driven vocational-major recommendation. Its main value lies not only in predictive accuracy but also in combining probability-based multiclass classification with qualification-based alternative recommendations. This gives the framework both analytical relevance and operational usefulness in school-level decision-support settings. Future research should therefore extend the model by incorporating non-academic variables, conducting class-wise error analysis, and benchmarking ANN against alternative machine-learning models further to strengthen the validity and applicability of vocational-major recommendation systems.

4. CONCLUSION

This study developed a vocational major recommendation framework that combines academic-feature-based multiclass prediction using an Artificial Neural Network with ADAM optimization and a qualification-based post-prediction screening stage. Based on 9,984 student records from West Java, the model achieved 82% accuracy, 0.88 average precision, 0.82 recall, and 0.8748 AUC, indicating useful predictive performance for vocational-major recommendation. These results show that structured academic records can support a data-driven recommendation process for vocational placement. The main contribution of this study is not limited to predictive performance. It also

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provides a clearer methodological distinction between the recommendation basis, the predictive model, and the operational recommendation rule. In this framework, academic-feature profiles and qualification thresholds provide the content basis, ANN performs the multiclass prediction, and qualification screening generates primary and alternative recommendations. This makes the framework more interpretable and operationally usable than simple rule-only matching and more scalable than purely manual recommendation practices in large student cohorts. However, the study does not establish superiority over alternative classifiers because no direct benchmarking was conducted. In addition, the framework still relies primarily on academic features and has not yet incorporated interest, aptitude, or psychological variables. Future work should therefore compare ANN with alternative machine-learning models, include non-academic student indicators, and report class-wise error patterns to strengthen the robustness and practical value of vocational-major recommendation.

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