A Hybrid Recommender Model for Career Pathway Selection in Competency-based Education

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ABSTRACT

Learners in Competency-based education (CBE) follow a personalized, flexible learning path based on their prior knowledge and skills. Still, career pathway decisions are frequently influenced by parents, teachers, and career counsellors, missing the critical elements that help learners make informed choices. While recommender models are widely used in education for course selection and career advising, they have typically failed to integrate these diverse factors comprehensively. To address this gap, the study developed a hybrid recommender model that integrates deep neural networks and random forest using the stacking ensemble method to enhance CBE career pathway selection. A mixed-method research design was used, and data were collected through an online survey from teachers teaching junior secondary schools in Meru County, focusing on factors influencing career pathway decisions. SPSS was used for analysis and revealed that academic performance, personal interests, extracurricular activities, career goals, and job market trends are important in these decisions. Hence, a CBE senior school dataset was created, and a hybrid recommender model was developed using the hybrid filtering technique with deep neural networks and random forest algorithms, combined through the stacking ensemble method. K-fold cross-validation was used to validate the model, achieving an accuracy of 90.06% and a precision of 92.07% when used for STEM career pathway tracks compared to existing approaches. These results indicate that the hybrid model is suitable for assisting learners in identifying the right STEM career pathway tracks in CBE. Future work could include the examination of more sophisticated algorithms and the extension of the model to encompass other career pathways.

General Terms

Machine learning, Algorithms, Recommender Model.

Keywords

Career Pathway, Competency-based Education, Hybrid Model, Recommender, Stacking Ensemble.

1. INTRODUCTION

Due to the increasing scope of the internet, everyone can get information from a vast number of sources, whether it is school information, world news, or information that is required to support a certain standard of living. Recommender systems are intelligent programs that prescribe a user’s next option based on factors, such as preference or user’s history[1]. Researchers began paying attention to recommender models as far back as the early 1990s. Recommender models have evolved beyondjust information retrieval and filtering [2]. Today they’re used in a wide range of fields, including streaming platforms, social networks, tourism, e-commerce, healthcare, education, and academic information services [3].

Machine learning algorithms are used by recommender models to give recommendations. Without the need for explicit programming, these algorithms can learn from sample data, also referred to as training data, to make decisions or predictions[4]. They are extensively utilized in domains including education.

In education, recommender models help students save time by suggesting relevant publications based on their knowledge and areas of interest. By offering expert recommendations, these systems guide students toward materials that align with their potential and academic goals [5]. Competency-based education (CBE) offers flexible learning paths, allowing students to focus on the skills and knowledge that best align with their interests and career goals [6]. Most existing CBE recommender models focus on a narrow set of factors when suggesting career pathways [7], which limits their ability to provide well-rounded guidance tailored to learners' unique needs and potential. The hybrid model takes a more comprehensive approach by integrating machine learning algorithms and considering a wider range of factors, including personal interests, favorite subjects, extracurricular activities, career goals, and job market trends. By incorporating these elements, the model aims to deliver more personalized and effective career path recommendations, ensuring learners are guided toward STEM career pathways that align with their profiles and aspirations.

The study aimed to develop a hybrid recommender model for career pathway selection in competency-based education. The research is driven by the need to improve career pathway selection and provide more accurate data-driven recommendations.

2. RELATED LITERATURE

Competency-based education (CBE) offers flexible learning paths, allowing students to focus on the skills that best align with their interests and career goals[6]. To support this, career pathway recommender models developed by experts help students identify study areas by considering their background, skills, abilities and experiences. Choosing the right academic path is a crucial decision, as it can shape a student’s future. Factors such as personal interests, ease of learning, social status, long-term career goals, and the structure of available pathways all play a role in influencing a student’s choice of senior secondary education [5].Choosing a career path has become increasingly challenging for adolescents and youngadults in today’s complex job market. Many struggle with career indecision, and understanding its different aspects can help shape effective career guidance and support programs[8], [9]. The right career choice can open doors to future opportunities and long-term success, making it especially important for high school students[10]. Uncertainty about career goals is common, but it's crucial to find a path that aligns with one's interests- after all, job satisfaction plays a major role in overall success and well-being[11].

Recommender models can help by offering personalized suggestions based on individual preferences, making it easier to navigate the overwhelming amount of information available. These models rely on techniques like collaborative filtering, content-based filtering, knowledge-based filtering, and hybrid approaches to provide tailored recommendations.

A Personalized Career-Path Recommender System (PCRS) is proposed[12]to provide guidance and help high school students choose an engineering discipline. The design of PCRS was based on fuzzy intelligence using students' academic performance, personality type, and extracurricular skills. An experiment was conducted using a sample of 177 engineering college students, and a slight agreement between the recommendations of PCRS and the actual career choice was proved based on an evaluation sample. Cohen's kappa was used to determine the agreement between recommender output and students' current specializations. The results revealed that there is a slight agreement between them ($\kappa = 0.23$, 95 % CI, $p < 0.05$). The agreement level is affected by the small number of participants in the evaluation sample; thus, they proposed an increase in the evaluation sample to enhance the agreement results of the evaluation test in the future.

Using a knowledge-based recommender model[13], a Student career path recommendation was proposed in the engineering stream based on a three-dimensional model. The recommender can appropriately recommend career streams to students by generating a desired score based on the analysis hierarchical decision-making process. However, to provide effective recommendations, it relies heavily on extensive data from students' social interactions and academic records.

Similarly, [14] developed a collaborative filtering model for recommending university elective courses.This system suggests courses based on the similarity between students' course selection and utilizes two popular algorithms: collaborative filtering with the Pearson Correlation Coefficient and Alternating Least Squares (ALS). When tested on a dataset of university students' academic records, the results showed that ALS performed better, achieving an accuracy of 86%, outperforming the Pearson Correlation Coefficient-based approach.

To help guidance counsellors assist their students in choosing a suitable career track, a Deep Neural Network model-based career track recommender system[15]was proposed. . .1500 students from the first through third batches of the K-12 curriculum were used in the study. Their academic strand in senior high school was predicted by their grades in 11 subjects, sex, age, number of siblings, parent income, and academic strand. To assess the prediction model, the technique of 5-fold cross-validation and the percentage split method was executed. In the percentage split method, the dataset training set of 70%) was used to train the model, while the remaining 30% was for testing the model. A validation accuracy comparison between the Neural Network and Decision Tree classifiers was conducted in an attempt to maximizeprediction or classification achievement in this study. This case study demonstrates that the DNN algorithm reasonably predicts the academic strand of students at a prediction accuracy of 83.11%.

IT graduates can choose a career path based on their skills with the aid of a recommendation model[16]called CareerRec, which makes use of machine learning algorithms. A dataset of 2255 workers in Saudi Arabia's IT industry was used to train and test CareerRec. The accuracy of five machine learning algorithms in predicting the most appropriate career path among the three classes was evaluated through a performance comparison. The tests show that the XGBoost algorithm performs better than other models and provides the highest accuracy (70.47%).

Using a machine learning approach[17]proposed a recommendation system was proposed to suggest suitable courses to learners based on their past learning details and performance. The model employed a K-Means clustering algorithm to classify students according to their performance ratings. Collaborative filtering techniques were then applied to the clusters to identify appropriate courses for each student. Subsequently, the students were evaluated in the recommended courses. This study revealed the need to enhance the system by incorporating a knowledge base to uncover shared characteristics among students. This would enable the identification of more students with similar areas of interest and target needs.

A hybrid student's career path recommender was proposed[18]using the Ensemble technique. An experiment was carried out using a dataset of 700 entries from students and 12 attributes. The system considers individuals' interests and academic records to recommend the correct Computer Science career path that would be best suited for them. The model achieved an accuracy of 90% and a precision of 90.7%.

3. METHODOLOGY

3.1 Experimental Setup

The study employed a mixed-research design utilizing the descriptive technique of research, which is designed to gather data, ideas, facts, and information related to the study. An experimental design method was used to build, test, and validate a hybrid recommender model developed for career pathway. The model was built using the stacking ensemble method which improves accuracy by combining several machine learning algorithms. In Meru County, Kenya, data was obtained through an online questionnaire sent to teachers instructing 7th and 8th grade students in junior secondary schools.The model was built using supervised machine learning algorithms, such as Deep Neural Network (DNN), Random Forest (RF), Support Vector Machine (SVM) and Logistic Regression.The recommendations of the model were improved by using a stacking ensemble approach.Stacking is an ensemble learning technique that increases predictive accuracy by using a collection of models. It consists in two steps. The defined base model level step consists of training multiple algorithms independently on the same dataset from which each attempts to capture and learn different features of the data. In the second step, a meta model is trained using predictions from these base models as inputs. Then this meta model learns how to combine the outputs of the base models' predictions to provide a more accurate and precise final recommendation[4].By utilizing this approach, the career pathway recommender system aims to provide more precise and personalized guidance, helping students make informed decisions about their future careers. It is a heterogeneouslearning technique that combines diverse base learners by training a model, unlike the homogeneous bagging and boosting methods which directly aggregate the outputs of several learners to obtain the final prediction[19]. To enhance the results of single-base learners, a stacking ensemble technique was applied, combining DNN_RF, DNN_SVM, RF_SVM, DNN_RF_SVM and Logistic regression used as the meta-model.

Figure 1 below show the experimental set up stages and flow

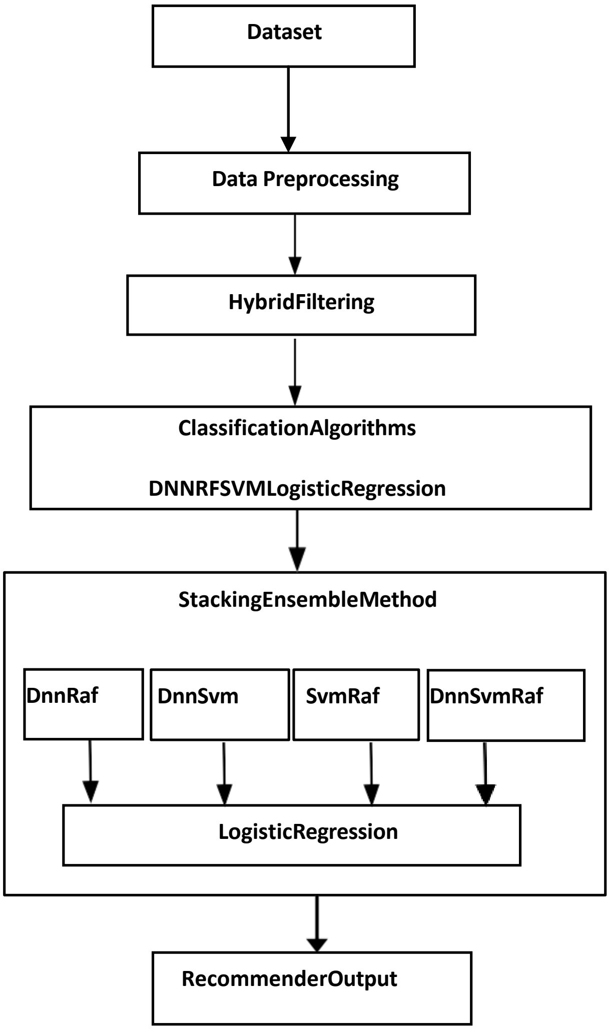

Fig 1: Experimental Setup

3.2 Dataset

The data utilized in this study was obtained from teachers teaching seventh and eighth graders at junior secondary schools in Meru County, Kenya, through an online questionnaire. A dataset for Competency-Based Education (CBE) Senior School was specially developed for this research. The dataset, stored in CSV format, had five features and 5000 records. It included four tracks in the STEM career pathway: Applied Sciences, Career and Technology, Pure Sciences, and Technical and Engineering, which could be recommended to learners'. The dataset contains both qualitative and quantitative data. Categorical features were transformed prior to training the classifiers. Data preparation entails cleaning, reformatting, and structuring the unprocessed data so that it can be analyzed and modeled

Table 1 below shows the description of the variables in the CBE Senior School dataset.

Table 1. Data Description

Attribute	Description	Values
Subject	Favorite subject	Subject
Performance	Best performing subject	Best Subject
Personal Interests	Interests	Interests
Extra-curricular activities	Extra-curricular activities	Activities
Career goals	Long-term career goals	Career goals

3.3 Modeling

This involved model selection, training and cross-validation. The hybrid filtering combining content-based filtering and collaborative filtering was used. Hybrid filtering merged content-based similarities, collaborative filtering predictions and original encoded features into one feature set. This enriched feature set was then used to train machine learning models. The dataset was split into an 80 percent training and 20 percent test set. Support vector machine and Random Forest are defined and trained on X_train. The deep neural network was defined and trained separately with early stopping for overfitting. As a meta model, logistic regression was used to combine the predictions of the base models. The meta-model (Logistic Regression) was trained using the predictions of the base models (X_train_base_pred). Cross-validation was performed to improve the accuracy of the model through several iterations. The model was validated using 5-fold cross- validation with a testing dataset to figure out how well the model performs with new data. Building the DNN_RF model from the preprocessed CBE senior school dataset was done with python. Various libraries in python were used such as pandas, seaborn, and scikit-learn. The visualizations to understand the results better were done with matplot and optuna.

4. RESULTS AND DISCUSSIONS

4.1 Model Performance Results

On the CBE Senior School dataset, experiments were carried out using Python to examine DnnRaf, SvmRaf, DnnSvm and DnnRafSvm Stacking ensemble classification methods. The experiments evaluated different classification models based on their accuracy in correctly categorized data. Each model used the same dataset and variables to ensure consistency. To measure performance, several key metrics were compared, including precision, recall, accuracy, the ROC curve, and the F1 score. Precision refers to how consistently a model provides the same result, while recall measures how well the model identifies true positives by calculating the ratio of true positives to the sum of false negatives and true positives.A hybrid filtering approach was implemented by combining collaborative filtering and content-based filtering to improve recommendations. For the base models, Deep Neural Networks (DNN), Random Forest (RF), (SVM) were selected due to their effectiveness in handling classification tasks. To further enhance performance, a stacking ensemble method was applied, testing various combinations such as SvmRaf, DnnRaf, DnnSvm, and DnnRafSvm. This strategy sought to improve forecast accuracy by utilising the advantages of several models. Training accounted for 80% of the dataset, whereas testing accounted for 20%. Training data with known output values was used to build the DNN-RAF stacking ensemble model. After that, each time a fresh data point with an unknown output value was employed, the data was sent through the Stacking ensemble DnnRaf model to produce the intended output.A Confusion Matrix is a table (or matrix) used to describe the performance of a classification model. The basic terms used in the confusion matrix are: True Positives (TP), which is an outcome where the model correctly predicts the positive class.The confusion matrix is used to calculate the value of the qualitative evaluation index of the recommendation model[3].Figure 2 below shows the model confusion matrix.

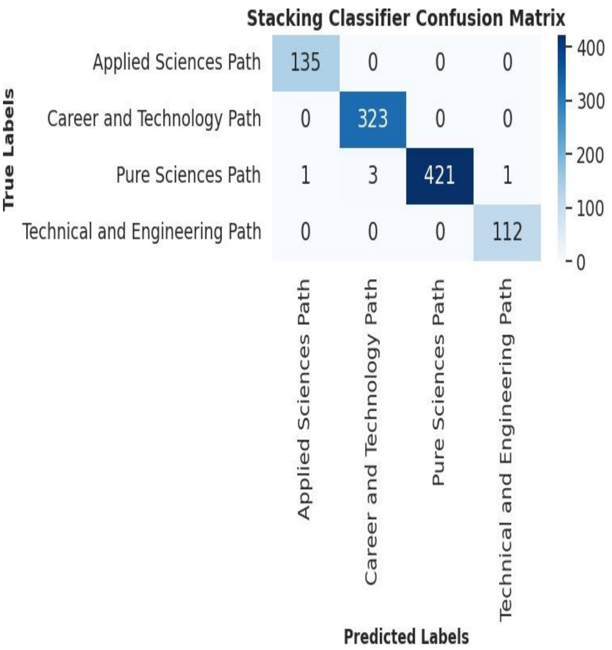

Fig 2:Stacking Ensemble Confusion Matrix.

The confusion matrix generated for the DnnRaf stacking ensemble model (Figure 2) exhibited an exceptionally high degree of classification accuracy across all predefined categories, namely the Applied Sciences, Career and Technology, Pure Sciences, and Technical and Engineering pathways. All instances were classified without error, yielding zero false negatives and zero false positives across all classes. This result suggests not only high class-specific precision but also perfect recall (sensitivity), underscoring the model's suitability for high-stakes decision-making tasks such as career path recommendation in a competency-based education (CBE) system.

The confusion matrix forms the foundational basis for deriving several critical performance metrics in classification tasks. Precision (Positive Predictive Value) measures the proportion of correctly predicted positive observations to the total predicted positives. High precision indicates a low false positive rate. Recall (Sensitivity or True Positive Rate) assesses the ability of the classifier to correctly identify all actual positive cases. High recall reflects a low false negative rate. Specificity (True Negative Rate) gauges the model's capacity to correctly exclude negative instances. F1 Score represents the harmonic mean of precision and recall, providing a single metric that balances both false positives and false negatives. Accuracy denotes the overall proportion of correctly classified instances across all categories.Area under the Curve (AUC) from the Receiver Operating Characteristic (ROC) analysis evaluates model discrimination capability, with values closer to 1.0 indicating stronger separability. To evaluate the relative efficacy of the DnnRaf model, its performance was benchmarked against other ensemble configurations as shown in Figure 3 and Table 1. The comparison involved three alternate stacking configurations: DnnSvm, SvmRaf, and DnnRafSvm. Figure 3 below shows the performance metric comparison of recall, precision, F1 score and accuracy.

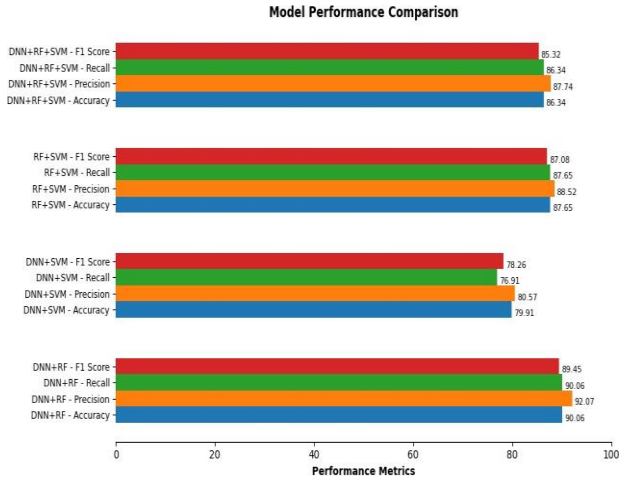

Fig 3: Stacking Ensemble Evaluation Metrics

Table 2 below shows the performance metric comparison of recall, precision, F1 score and accuracy

Table 2. Stacking Ensemble Evaluation Metrics

Model	Accuracy	Precision	Recall	F1 Score
DNN+RF	**90.06%**	**92.07%**	**90.06%**	89.45%
DNN+SVM	79.91%	80.57%	76.91%	78.26%
RF+SVM	87.65%	88.52%	87.65%	87.08%
DNN+RF+SVM	86.34%	87.74%	86.34%	85.32%

Among the models evaluated, the DNN+RF ensemble consistently outperformed all others across every metric, substantiating the hypothesis that the combined use of deep feature representation (via DNN) and decision-level generalization (via RF) can yield a classifier with both high discrimination capacity and low generalisation error. Notably, the inclusion of SVM in tri-modal configurations (e.g., DNN+RF+SVM) did not improve performance, possibly due to overfitting, redundant model bias, or the limited marginal utility of margin-based classifiers in this ensemble context.

4.2 Comparative analysis of the Hybrid Model with the existing models

To position the proposed hybrid model in the context of prior studies, a comparative analysis was conducted against benchmark hybrid recommendation models from recent literature.Table 3 below provides a synthesis of related studies, highlighting recommender model types, data characteristics, classifiers employed, and the reported performance metrics.

Table 3. Comparative analysis of the hybrid recommender model with existing models

Study	Recommender Model	Dataset	Classifier	Metric
[17]	Collaborative filtering model	300 students' records with 12 attributes	K-means clustering	-
[18]	Hybrid Filtering Model.	700 students 12 attributes	Ensemble	Accuracy 90% Precision 90.7%
[15]	Hybrid filtering model	1500 students' records 7 attributes	Decision Tree, Deep Neural Network	Accuracy 83.11%
[20]	Hybrid CBRM+CFRM) Model	612 students	Pearson correlation	Precision 53.5% Recall 6.5%
[21]	Collaborative filtering model	200 respondents	C4.5 algorithm	Accuracy 78.84%
Hybrid recommender model	**Hybrid filtering**	**5000 records 5 attributes**	**Stacking ensemble (DNN+RF)**	**Accuracy 90.06% Precision 92.07%**

Despite utilizing a relatively lower-dimensional feature space (only five attributes), the proposed DNN+RF model surpassed earlier approaches in both classification accuracy and precision. This illustrates the efficiency and scalability of the ensemble architecture, where performance gains are achieved not by increasing attribute dimensionality but by optimizing inter-model synergy and meta-level learning.The robustness and generalizability of the DNN+RF architecture are further reinforced by its near-perfect class-wise predictive balance, as reflected in the confusion matrix outcomes.These empirical results are consistent with ensemble learning theory, which emphasizes the importance of combining diverse base learners to capitalize on their complementary strengths and error diversity[22].The study integrates a deep neural architecture with stacking ensemble, enabling deeper representation learning and improved generalisation. These findings underscore the importance of model architecture sophistication over mere data volume in predictive modelling for educational recommendation systems.

5. CONCLUSION AND FUTURE WORK

This study developed and empirically validated a stacking ensemble recommender model that combines Deep Neural Networks (DNN) and Random Forests (RF) to recommend suitable career pathways within a competency-based education (CBE) framework, specifically focusing on STEM tracks in senior secondary education. Through rigorous experimentation on a dataset comprising 5,000 student records and five core attributes, the proposed DNN_RF stacking ensemble emerged as the best-performing model, achieving 90.06% accuracy and 92.07% precision, surpassing traditional hybrid filtering approaches and alternate ensemble configurations such as DNN_SVM, RF_SVM, and DNN_RF_SVM. The significance of these findings lies in the model's architecture-agnostic scalability, reduction in data dependency, and robust predictive capability in classifying educational trajectories. By leveraging the deep representational power of DNNs and the variance reduction of RFs, the model delivers high fidelity predictions even in low-dimensional settings. Such capability is critical in educational environments where access to high-quality, multidimensional data may be limited.Future studies could investigate the transferability of the DNN_RF stacking architecture to tertiary and vocational education systems, enabling intelligent career advisement beyond secondary education and addressing the diverse needs of adult learners and non-traditional students.The integration of real-time student performance data, learning behaviors, and preference patterns could evolve the static model into a dynamic, personalized recommendation engine, adaptable to students' learning progress and evolving interests. The adoption of advanced meta-learners (e.g., XGBoost, LightGBM, Transformer-based classifiers) may further enhance the ensemble's decision-making capabilities, especially in highly non-linear, sparse, or noisy educational datasets. Although this study focused on STEM, expanding the recommender model to include tracks in humanities, social sciences, arts, and interdisciplinary domains could foster equitable access to career counseling and support holistic student development. Future versions of the model could embed Explainable AI (XAI) components to provide transparency behind recommendations and ensure ethical compliance, especially in high-stakes educational decisions involving marginalized or underrepresented student populations.Collaborating with educational institutions and policymakers to deploy and validate this model in operational settings could accelerate its adoption as a decision-support tool in national competency-based education reforms.

In summary, the DNN_RF stacking model not only addresses current gaps in educational recommendation accuracy but also opens a wide array of research possibilities across AI, pedagogy, and policy. Its adaptability and high performance make it a promising candidate for future intelligent educational systems.

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