Career Recommendation Based on Feature Selection for Undergraduate Students Using Machine Learning Techniques

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***Abstract*—Undergraduate students worldwide face difficulties choosing the career paths that should stay with them for at least several years. It is widespread for graduates to work in jobs or join a career path they are not interested in. Also, sometimes these jobs do not suit the skills and preferences of undergraduates. On the other hand, some jobs require certain criteria and various skills that may not be available to some undergraduates. Although an undergraduate can study a major that he/she is interested in, this does not guarantee that he/she will be successful in his/her future career path. Undergraduates in various majors need advice on career paths that suit their skills and interests. When a graduate feels dissatisfied with his/her job, this dissatisfaction can impact his/her productivity and performance in his/her assigned tasks and job responsibilities. Moreover, the overall performance of the organization where these workers work can be negatively affected by having less talented and less motivated workers. As a result, in this paper, a recommendation system is designed and proposed to guide undergraduates in choosing the optimal career path. Various machine-learning techniques were used in the recommendation system. The proposed system was applied to two datasets related to Information Technology jobs; "Dataset A" consisted of 20,000 records and "Dataset B" consisted of 500 records. Feature selection techniques were applied on "Dataset A" to determine the most important features that enhance the accuracy of the proposed recommendation system. It has been shown that the random forests technique performed the best among the other machine learning techniques.**

***Keywords*—Career path; feature selection; machine learning techniques; recommendation systems**

I. Introduction

Recommendation systems have become a popular tool during the past years to provide a personalized experience for users. Recommendation systems suggest items that are expected to be interesting to users and will likely be selected by them for usage or purchase. The suggested item can be a movie, a song, a book, an educational course, etc. In general, recommendation systems track the users' behaviors to generate patterns about the users' interests and preferences. Various techniques can be applied to these patterns to recommend items to users. The main objective of recommendation systems is to improve the user experience by presenting options to users that match their interests. Usually, recommendation systems recommend items to users based on their search history and queries. Recommendation systems play a crucial role in several industries and have many applications in various disciplines. One of these disciplines is the educational domain and the learning environment of undergraduate students who enrolled in universities.

In the learning environment, recommendation systems can recommend a course, a major, a specialization, or even a job career to students. Monitoring the students' learning behaviors and interests can greatly assist the recommendation systems in suggesting suitable learning components or modules to students. Moreover, the recommendation systems can have a larger scope than just selecting a course or a major, these systems can recommend a career path based on the student's learning behavior, interests, and skills.

II. Motivation

Jobs related to information technology (IT) continue to expand in various disciplines. Companies need to recruit well-qualified candidates to support their business needs and enhance overall business performance. Although there are a lot of Computer Science graduates worldwide, some graduates feel that they are not satisfied with their occupations, although they are interested in the Computer Science field. This is because their skills and interests do not directly match their jobs. For example, sometimes IT graduates work in cyber security, however, they can be more skilled and talented in another area, such as Requirements Analysis. Although both areas are related to Computer Science, a person can be more productive in one area than another. This is because each person has his/her own academic and personal characteristics that may let him/her be more successful in one certain job instead of another. Job descriptions and responsibilities vary across careers, so each job requires suitable candidates that best suit the job's roles. On the other hand, each person has certain traits, either educational or personality-based, that make him/her successful in a certain career.

All graduates, including IT graduates, seek to find a job that best suits their skills. These skills can be either academic-based or personality-based. Undergraduate students who enroll in faculties need assistance in choosing the career paths that they should stay with them for the rest of their lives. Failing to work in a job that satisfies the person's needs can affect the person's daily life as he/she feels less motivated to do his/her assigned job responsibilities and daily life activities. Moreover, a less motivated person can face psychological and social difficulties that impact his/her daily routine. Sometimes, dissatisfaction with a certain job can make a person leave a job without even having another alternative. In addition, having a less motivated employee will affect the company's performance where this employee works.

Selecting a major that will most probably affect the choice of a future job is a challenging task because undergraduate students do not have enough knowledge or experience that help them select the optimal job that matches their skills. Students do not have information about the available careers in their relevant industries.

Usually, students know about the available careers from their parents, relatives, or friends. Even students sometimes try to search for jobs and employment fairs to learn more about the available jobs in the industry. Also, they do not know how their skills could match the available current jobs. Choosing a career path can affect the student's whole life [1]. As a result, in this paper, a framework for career path recommendations for undergraduate students is proposed. The main contributions of this paper are as follows:

- Proposing a framework for career path recommendation for undergraduate students.
- Applying various machine learning techniques to recommend the most suitable career path for undergraduate students.
- Applying different feature selection techniques to get the optimal features to be used in the career path recommendation.

The remainder of this paper is as follows. Section III presents the literature work. Section IV explains the proposed approach. Section V presents the results and Section VI presents the Evaluation and Discussion. Finally, Section VII presents the conclusion and future work.

III. Related Work

In study [2], the authors presented a model of a recommender system for the e-learning platform that recommended the most appropriate learning resources to the students according to their requirements and allowed them to reach the learning goals of the courses. This system was based on cloud computing infrastructure and made use of Google cloud services.

In study [3], a recommendation system for determining learning strategies for students was proposed. Collaborative filtering techniques based on the Naive Bayes algorithm were utilized to determine the learning strategies that are the most suitable for students.

In study [4], this research proposed a model of an e-learning recommendation system that recommended courses to students according to their needs. The proposed model used big data tools namely Hadoop and Spark to enhance data collection, storage, analysis, and visualization.

In study [5], the authors proposed an architecture that constructed semantic recommendations with the help of virtual agents based on user requirements and interests, helping academia in seeking suitable courses in a real-world setting. It has been shown that the virtualized agent-based recommendation system enhanced the user learning skills and made the selection of courses easier.

In study [6], a WebApp was proposed that recommended a course to students based on information about their academic performance, extracurricular activities, and personal preferences. Also, the WebApp acted as the role of a career counselor to interact with the students through a chatbot. The WebApp recommended to students the suitable branches of engineering that suited their interests by making use of machine learning techniques.

In study [7], this research presented existing career recommendation systems and mentioned the defects of these systems, such as cold start and scalability. Moreover, possibilities for enhancements in these systems have been presented to develop a career recommendation system using the content-based filtering approach.

In study [8], this research presented a job recommendation system that used machine learning techniques and historical data to predict the best candidate for a job. The input of the system was the requirement of a job and the profile of the applicants while the output was a score indicating how suitable each applicant is for a certain job.

In study [9], a career recommendation for college students was presented. The proposed system was based on deep learning and machine learning. A hybrid convolutional neural network was proposed, which utilized a convolution operation to learn high-level features to reach a personalized employment recommendation.

In study [10], a recommendation system was proposed, which made use of machine learning algorithms to assist IT graduates in choosing a career path based on their skills. A performance comparison between five machine learning algorithms was presented to measure their accuracy in predicting the best-suited career path. The experiments showed that the XGBoost algorithm had the highest accuracy.

IV. Proposed Approach

In this section, the proposed approach is presented along with the features used, the techniques applied, and the datasets used. The main idea of our proposed approach is to recommend careers to students using predictive analysis and machine learning. The recommender system uses some integrated features such as the average academic score, Intelligence Quotient (IQ), coding skills, some personality features, workshops attended by students, certificates gained by students, etc. The details of the features will be described in detail in the following section. The proposed approach was implemented in Python.

A. Proposed Architecture

The following Fig. 1 presents the architecture of our proposed approach, which shows the steps, and the methodology applied in the proposed approach. The first step focused on data cleaning and preprocessing, then the most appropriate features were selected using feature selection techniques, after that, the data was divided into training data and testing data. Then the next step is to build the machine learning model based on the selected features using six different machine learning prediction techniques that will be described in detail in the following paragraphs. Finally, the last step is to build the recommendation system and recommend the job careers to students based on the selected features.

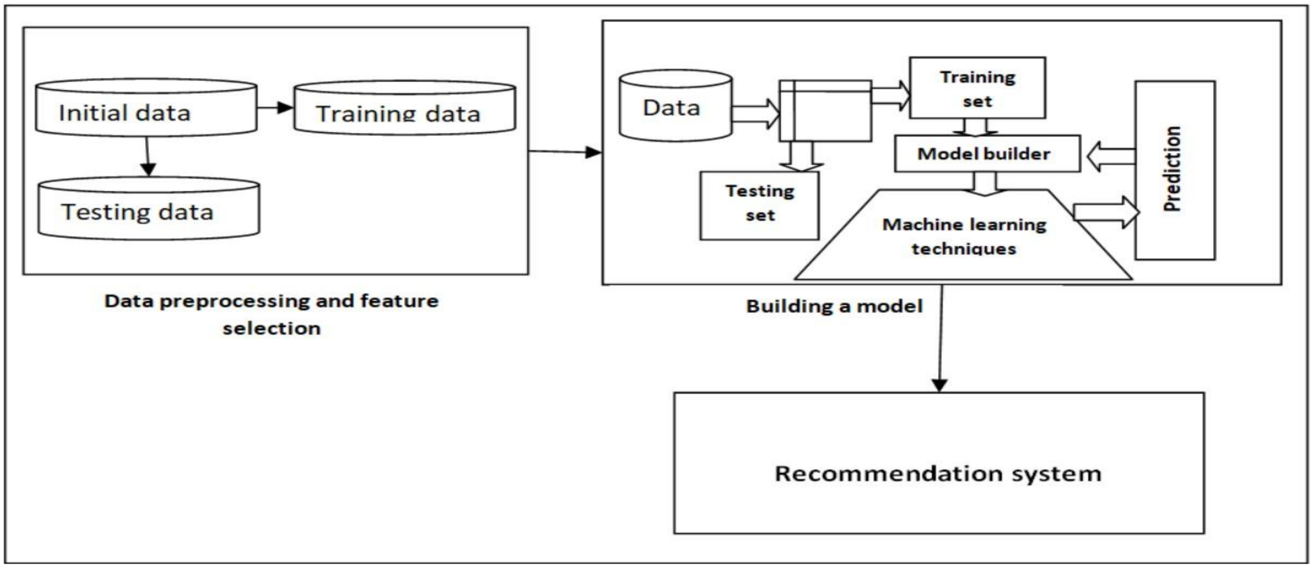

Fig. 1. Proposed architecture.

1) Dataset a preprocessing: The first step in "Dataset A" preprocessing is to encode and normalize the categorical data to numerical data using "Python pandas" and "Standard Scaler Python" libraries. "Dataset A" contains 35 features which may lead to inaccurate prediction results, so feature selection techniques were applied to clean the data and to select the most important and appropriate features.

2) Dataset b preprocessing: The questionnaire has been designed to collect the most important features extracted from "Dataset A". So, "Dataset B" consists of the same features used in "Dataset A" but from different students. As the data was collected from a questionnaire, some data preprocessing steps were performed such as moving redundancy, minimizing noise, and normalizing the categorical features into numeric features.

B. Data Set and Data Preprocessing

Two datasets were used to train the models. The first dataset "Dataset A" consists of 20,000 records with 35 features and it is available in study [11]. The second dataset "Dataset B" consists of 500 records collected from level four students in the Faculty of Computers and Artificial Intelligence, Cairo University via a Google form questionnaire.

C. Feature Selection

Feature selection techniques were used for the following reasons [12]:

- Increasing the speed of training of the machine learning models.
- Decreasing the complexity of the model.
- Decreasing the overfitting of the model.
- Making the model more accurate and precise by selecting the best-fitted features.
- Avoiding underfitting of the machine learning models.

There are three types of feature selection techniques, filter methods, wrapper methods, and embedded methods. The embedded methods combine the advantages of wrapper methods and filter methods. The advantages of embedded methods are:

- Providing high accuracy.
- Having an easy interpretation.
- Avoiding overfitting.

Random forest feature selection technique is one of the most popular methods of embedded feature selection methods [13].

Random forests are made up of four to twelve hundred decision trees, each built over a random extraction of the observations from the dataset and a random extraction of the features. Since no tree checks every feature or every observation, random forests ensure that the trees are de-correlated and are less likely to overfit.

Either the information gain/entropy or the Gini impurity [14] is used as the measure of impurity for classification models. As a result, when training a tree, it is easy to calculate the amount that each feature reduces impurity. A feature's importance increases with its ability to reduce impurities. Attributes chosen at the top of the trees are typically more significant than attributes chosen at the end nodes of the trees.

Our proposed recommendation model is considered a multi-class classification model as the recommended job falls between 33 class labels. Some of these labels are Application Developer, Business Intelligence Analyst, CRM, Business Analyst, Database Developer, Software Developer, System Analyst, Project Manager, etc. Random forest feature selection techniques were used for classification models.

The random forest feature selection method has been implemented using "Python Pandas" and "Sklearn" (RandomForestClassifier, FeatureSelection, and SelectFromModel) libraries and feature importance Python function [15].

Best practice in all feature selection methods to rely solely on the training set, without considering the testing set, to prevent overfitting.

After applying the feature selection method to our dataset, "22 features" were removed because they have less importance on the model's performance. The most important features were 13 features that are as follows:

1) Average Academic Score (AVG)
2) Intelligence Quotient (IQ)
3) Coding Skills Rating (CSR)
4) Self-learner (SL)
5) Certificates (CERT)
6) Workshops
7) Memory (MEM)
8) Interested Career Area (ICA)
9) Books
10) Behavior
11) Hard Worker / Smart Worker (HorS)
12) Work in a Team (WinT)
13) Introvert (I)

Our model utilized the aforementioned features as inputs and generated outputs based on various combinations of these inputs. For instance, the model took into consideration the student's high average score in database-related subjects, with an IQ score of 6, a coding skills rate of 3, and the student being a self-learner with certifications and courses in data management and workshops in the same field, having average memory, and an interested career area related to data. Additionally, the model considered the student's reading habits, gentle behavior, the ability to be a hard worker, and could work well in a team. The student was also outgoing and non-introverted. When all these features and their combinations were inputted into the model, it yielded the output that the most suitable career for this student is a Database Manager. This is what the model learned and trained on in the training data, and this example applies to all available jobs found in the dataset.

D. Building the Model

After the data preprocessing stops, the dataset is divided into a training set and a testing set with a ratio of 70%-30% respectively. Six different machine-learning classification models were applied to train and test the model:

1) K-Nearest Neighbor (KNN): KNN is used for regression and classification, which are two applications of the nonparametric supervised machine learning classifier method [16].

2) Naive Bayes (NB): NB is a probabilistic model used for classification that is based on the Bayes theorem [17].

3) Random Forest (RF): RF is a regression and classification model that contains multiple decision trees [18].

4) Decision Tree (DT): DT is a regression and classification model. It is a non-parametric supervised machine learning classifier technique. It is organized as a hierarchical tree [19].

5) Support Vector Machine (SVM): SVM is a model that is employed for both classification and regression, which is a supervised learning model [20].

6) Gradient Boosting (GB): GB is a classifier that combines several learning models to produce a single, powerful prediction model. Typically, decision trees are employed in gradient boosting. Gradient boosting models are gaining attraction due to their efficiency in categorizing intricate datasets [21].

E. Correlation Matrix

The correlation matrix was created to determine the correlation and dependencies between the features [22] as presented in Fig. 2.

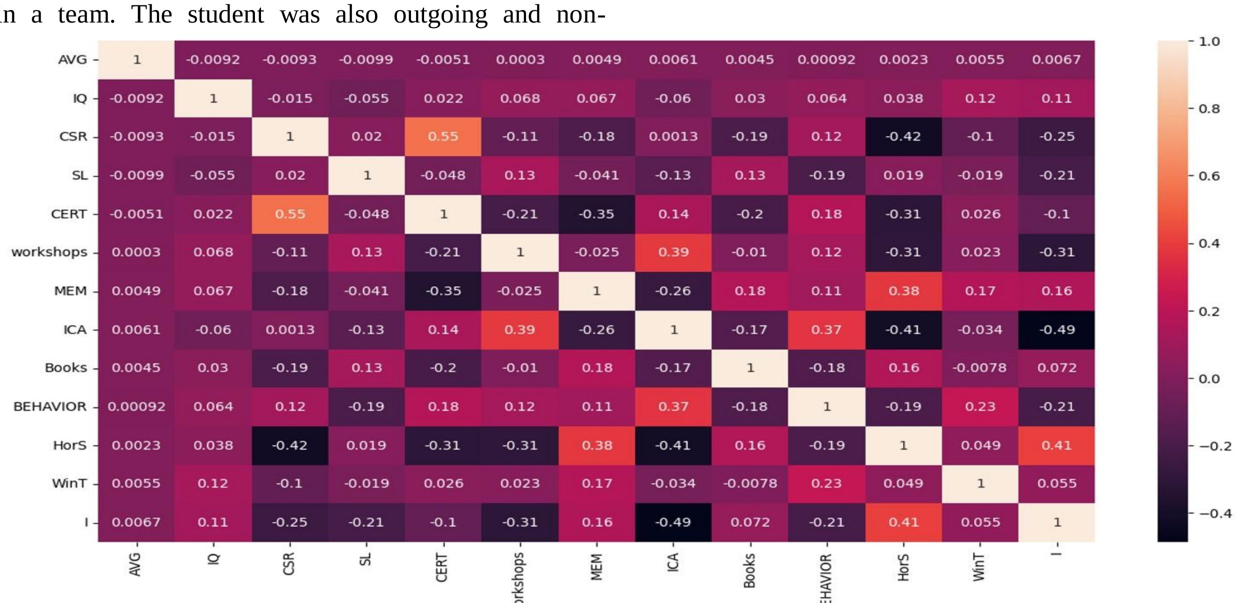

Fig. 2. Correlation matrix.

The degree to which one feature influences another is reflected in their correlation. A stronger correlation exists between two features when the correlation coefficient is higher, indicating a more significant positive or negative relationship.

Conversely, values near 0 were obtained from the less associated attributes. A score that approaches zero indicates less correlation between the features.

A positive correlation is indicated when the value of one associated feature rises along with the value of the other feature, or when the value of one associated feature decreases along with the value of the other feature.

Conversely, a negative correlation is shown when one correlated feature's value rises while the other feature's value falls, and vice versa.

V. RESULTS

After applying the techniques to "Dataset A", the performance of the model was measured by computing the accuracy, precision, recall, and F1-measures [23]. The results of all six techniques are compared and presented in the following Table I.

TABLE I. RECOMMENDATION RESULTS OF THE SIX TECHNIQUES IN "DATASET A"

Technique	Accuracy	Precision	Recall	F1-measure
KNN	0.82	0.82	0.82	0.81
NB	0.88	0.87	0.88	0.88
SVM	0.88	0.93	0.88	0.90
DT	0.84	0.89	0.85	0.87
RF	0.90	0.95	0.91	0.93
GB	0.85	0.84	0.85	0.84

As shown in Table I, the random forest technique had the best performance compared with the other techniques with accuracy = 0.90, precision = 0.95, recall = 0.91, and F1 measure = 0.93. Precision, recall, accuracy, and F1-measure are calculated respectively by the following equations:

Precision =

$$\sum_{C=1...N} TPs / \sum_{C=1..N} (TPs + FPs) \tag{1}$$

Recall=

$$\sum_{C=1...N} TPs / \sum_{C=1..N} (TPs + FNs) \tag{2}$$

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \tag{3}$$

$$\text{F1} = 2*(\text{Precision}*\text{Recall})/(\text{Precision}+\text{Recall}) \tag{4}$$

Where the True Positive, True Negative, False Positive, and False Negative values are defined as follows:

- True Positive (TP): When the expected and actual values are the same, this is known as the true positive value, or TP [24], [25].
- True Negative (TN): The total of all columns and rows, excluding those for the class for which we are calculating the values, is the True Negative value (TN) for that class [24], [25].
- False Positive (FP): The total of all the values in the applicable column, except the TP value, is the False positive value for a class [24], [25].
- False Negative (FN): The total of the values in the corresponding rows, excluding the TP value, represents the False-negative value for a class [24], [25].

After applying the techniques to "Dataset A", we further validated the model's generalizability by applying it to "Dataset B". This ensured that the model didn't overfit the training data in "Dataset A". The model's performance trained on "Dataset B" was evaluated by computing the accuracy, precision, recall, and F1-measure. The results of the six techniques are compared and presented in Table II.

TABLE II. RECOMMENDATION RESULTS OF THE SIX TECHNIQUES IN "DATASET B"

Technique	Accuracy	Precision	Recall	F1-measure
KNN	0.80	0.81	0.81	0.80
NB	0.86	0.85	0.87	0.87
SVM	0.87	0.99	0.86	0.89
DT	0.82	0.87	0.86	0.86
RF	0.88	0.90	0.90	0.91
GB	0.85	0.82	0.84	0.83

As shown in Table II, the random forest technique had the best performance compared with the other techniques; the results are very close to the results shown in Table I, that was related to "Dataset A". This leads to ensuring that all models do not overfit on specific data and introduces more generalization to the model.

VI. EVALUATION AND DISCUSSION

To test the efficiency of our proposed approach, we trained the model on the data in "Dataset A" without using any feature selection techniques and measured all performance measures. After that, we compared the results in Table III with those in Table I. This resulted in proving that the feature selection techniques enhanced and improved the performance of the model.

TABLE III. PERFORMANCE MEASURES BEFORE USING FEATURE SELECTION TECHNIQUES

Technique	Accuracy	Precision	Recall	F1-measure
KNN	0.52	0.53	0.52	0.51
NB	0.55	0.55	0.57	0.57
RF	0.60	0.62	0.62	0.63
DT	0.56	0.58	0.58	0.57
SVM	0.58	0.57	0.58	0.60
GB	0.56	0.54	0.55	0.54

By comparing the findings in Table III with those in Table I, it is obvious that using the feature selection techniques (Table I) significantly improved model performance as reflected in all evaluation measures.

Before using feature selection techniques (Table III), the results showed low performance due to the misclassified instances and the unclarity of some features that will lead the model to under-fit and this will be presented in the chart in Fig. 3 that presented the comparison of all performance measures before and after using feature selection techniques. This emphasizes that applying feature selection techniques in our recommendation system has a very significant role in predicting the most suitable job for the undergraduates.

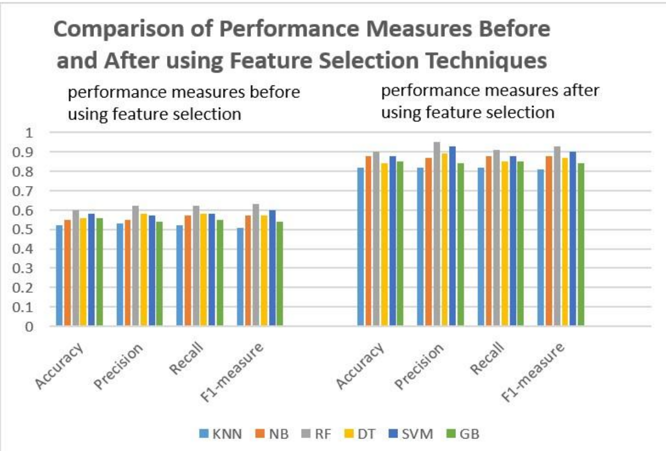

Fig. 3. Comparison of performance measures before and after using feature selection techniques.

VII. Conclusion and Future Work

Recommending a student's career (job) is very important for students and graduates to improve and speed up the processes of seeking a job after graduation. In this paper, the main idea is to identify the most important features that have the most significant impact on the career recommendation system and predict the job that fits the model based on the features that are released from the feature selection method. A career recommendation system was built by applying different machine learning techniques to different features extracted from feature selection methods.

The recommended jobs are addressed to Information Technology (IT) students. These jobs fall within 33 class labels, some of them are Application Developer, Business Intelligence Analyst, CRM Business Analyst, Database Developer, Software Developer, System Analyst, Project Manager, etc.

Education makes extensive use of machine learning multiclass label classification models. The student's career (job) was recommended using K-nearest Neighbor, Naive Bayes, Random forests, Decision Trees, Support Vector Machines, and Gradient Boosting techniques. The Random Forest technique performed the best in recommending the student's career (job).

To improve the effectiveness of the proposed approach, feature selection methods were applied using the random forest feature selection technique to extract the most important features to use. Then the performance measures were computed. The random forest technique gave the best performance measures compared with the other five machine learning models.

One limitation of this study is that the scope is confined to the information technology field, which narrows the scope of the model. However, our model has the potential to be extended to be more generic and inclusive, covering multiple diverse domains such as the medical field, the engineering field, and others.

Some challenges were encountered during the research, including the difficulty of data collection from students, data redundancy, data noise, and irrelevant data.

Finally, a lot of research can be done in recommending student careers (jobs) so further research can be conducted for future work. Furthermore, deep learning techniques may help in enhancing the performance of the recommendation systems by using neural networks and other deep learning techniques [26], [27]. Our model has the potential to be extended to be more generic and inclusive, covering multiple diverse domains such as the medical field, the engineering field, and others as mentioned in the limitations.

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