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Utilizing Machine Learning for Predictive Analytics in Career Path Forecasting

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Abstract— Despite the presence of excellent educational institutions in India, the country still faces a high student dropout rate. This can be attributed to various factors, primarily being the selection of an inappropriate career path. To tackle this concern, it is crucial to offer students appropriate guidance, so that they can make informed decisions about their future careers which are aligned with their preferences and interests. This will help in avoiding future complications like discontentment, poor performance, fear and stress, social neglect etc. Machine Learning (ML) paves the path for students by making predictions regarding the future career path selection, with the help of application of various algorithms like Decision Tree (DT)[1], Random Forest (RF)[2], Support Vector Machine (SVM)[3], k Nearest Neighbor (kNN)[4], Naïve Bayes (NB) [5], Adaboost [6] and Logistic Regression (LR).

Therefore, the objective of this paper is four folds. Initially, to carry out an in-depth literature review emphasizing the application of ML techniques in predictive analysis. Top of Form

Secondly, the paper compares and contrasts the ML techniques most suitable and apt for students' choosing their career option. Thirdly, the paper applies these ML techniques on a dataset and evaluates them against different parameters like accuracy, precision and recall. Finally, the paper concludes while analyzing the results.

Keywords- Career Prediction; Supervised ML; ML Classifiers, SVM, Adaboost, RF, DT

I. INTRODUCTION

In the contemporary landscape of workforce dynamics and career development, the utilization of predictive analytics and machine learning for career path prediction has emerged as a transformative area of research and practice. The ability to forecast and anticipate future career trajectories is of paramount importance for individuals navigating the complexities of the job market and for organizations seeking to strategically manage their talent pool. By harnessing advanced data analytics techniques and machine learning algorithms, researchers and practitioners aim to enhance the accuracy and reliability of career path predictions, thereby empowering individuals to make informed decisions about their professional growth and assisting organizations in talent acquisition, retention, and succession planning. This research topic delves into the intersection of predictive analytics, machine learning, and career development, exploring the potential of data-driven approaches to revolutionize how career paths are envisioned, planned, and navigated in the era of digital transformation and rapid technological advancements. Through a comprehensive review of existing literature, methodologies, and case studies, this review paper aims to provide insights into the current state-of-the-art in predictive analytics for career path prediction, identify key challenges and opportunities in this domain, and outline future directions for research and application in leveraging machine learning for enhancing career planning and progression strategies.

This paper centers on the application of various supervised machine learning algorithms on a students' dataset using the methodology shown in Fig.1 below, aiming to ascertain the most efficient algorithm with the highest accuracy and precision for predicting the career path. The subsequent sections are structured as follows: Section 2 provides an overview of the existing literature; Section 3 offers a comparison of diverse machine learning algorithms used for the prediction tasks; Section 4 delves into the application of these algorithms to the dataset and their evaluation against predefined criteria.

Ultimately, the paper concludes with results and findings in the subsequent sections.

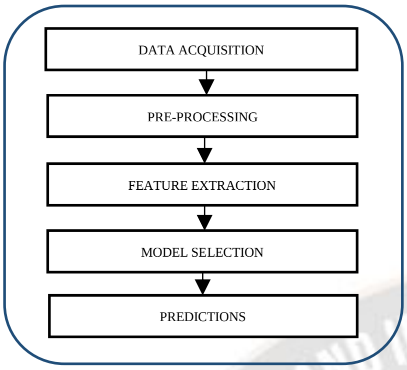

Fig. I: Stages of Career Path Prediction Model

1.1 Role of role of machine learning in career path prediction

Machine learning plays a pivotal role in revolutionizing career path prediction by leveraging data-driven insights to forecast future trajectories with enhanced accuracy and precision. Through the analysis of vast amounts of historical data, including individual profiles, skills, experiences, and market trends, machine learning algorithms can identify patterns, trends, and correlations that enable the prediction of potential career paths.

1.2 Challenges faced by machine learning while predicting career path options

- Dynamic Job Market: The rapid evolution of job roles, skill requirements, and industry trends poses a challenge for machine learning models to accurately capture and predict future career paths in a constantly changing landscape.
- Data Quality and Bias: Ensuring the quality, relevance, and diversity of data sources used for training machine learning algorithms is crucial to avoid biases and inaccuracies that can skew predictions and hinder the effectiveness of career path recommendations.
- Interpretability of Models: Complex machine learning algorithms often operate as black-box models, lacking transparency in explaining the reasoning behind specific career path predictions, which can lead to challenges in user trust, acceptance, and understanding.
- Scalability and Generalizability: Ensuring the scalability and generalizability of predictive models across different industries, job sectors, and demographic groups is essential to make predictions applicable and relevant in diverse contexts and for a wide range of individuals.
- Skill and Experience Dynamics: Incorporating the dynamic nature of individual skills, experiences, and personal preferences into predictive models presents a challenge in accurately forecasting career paths that align with an individual's evolving aspirations and goals.

1.3 Motivation

The motivation behind conducting this review study on predictive analytics using machine learning for career path prediction stems from the increasing importance of leveraging advanced technologies to enhance career planning and decision-making processes. With the rapid evolution of the job market and the emergence of new industries and roles, individuals are faced with the challenge of navigating complex career trajectories and making informed choices about their career development. By exploring the application of machine learning techniques in predicting career paths, this study aims to address the need for more accurate, data-driven insights that can empower individuals to make strategic decisions about their careers.

1.3.1 Limited review work

Considering the review work on this topic is limited, more focus has been given on the experimental aspects of machine learning in career path prediction.

1.3.2 Advancement of deep learning technologies

The current technical era has witnessed a humongous advent in various technologies like Machine Learning, Deep Learning and other hybrid approaches in the development of career path prediction model. Thus, we were hyped to research on this topic.

II. Literature Study

Traditionally, career path selection was determined through questionnaires by professionals, but predicting individual career paths was challenging due to the unique aspirations and goals of each student. However, with advancements in Science and Technology, Machine Learning has emerged as a solution for predicting students' career paths, which significantly impacts their lives. There are various supervised machine learning algorithms which primarily focus on classification problems, including Linear Classifiers, Logistic Regression, Naïve Bayes Classifier, Perceptron, Support Vector Machine, Quadratic Classifiers, K-Means Clustering, Boosting, Decision Tree, Random Forest, Neural networks, Bayesian Networks, and more.

Sharma et al. developed the Placement Predictor System (PPS) using a logistic regression model with an accuracy of approximately 83.33%. Nagaria et al. utilized the Random Forest model, achieving an accuracy of 85% by considering various parameters. S. Venkatachalam et al. employed a fuzzy inference system with the Naive Bayes algorithm, achieving an accuracy of 86.15%. Other researchers have also proposed models like ACCBOX and utilized machine learning algorithms such as SVM, decision tree, and XGBoost for career predictions.

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Additionally, applications like career guide applications and Automated Career Guidance Expert Systems have been developed using machine learning techniques.

There are various supervised machine learning algorithms which deal more with the problem of classification: Linear Classifiers, Logistic Regression[7], Naïve Bayes Classifier, Perceptron[8], Support Vector Machine; Quadratic Classifiers[9], K-Means Clustering[10], Boosting, Decision Tree, Random Forest (RF); Neural networks[11], Bayesian Networksand so on.

Traditionally, questionnaires were used by the specialized profession people to identify the important factors affecting selection of career paths. Still, it was very difficult to predict the career path due to difference in every student's aim and dreams. Then with advancements in the field of Science and Technology, Machine Learning paved the way to make predictions for students regarding their career path selection as selecting the most suitable career path plays a major role in the student's life.

Sharma et al.[12]created the Placement Predictor System (PPS) utilizing a logistic regression model. The model achieved an accuracy of approximately 83.33%.Nagaria et al.[13] employed the Random Forest model, incorporating multiple parameters such as degree type, work experience, e-test percentage, specialization, and MBA percentage. The model achieved the highest accuracy, reaching 85%.S. Venkatachalam et al.[14] developed a fuzzy inference system for campus placement prediction using the Naive Bayes algorithm. The model achieved the highest accuracy, reaching 86.15%.Min Nie et al.[15] proposed ACCBOX (Approach Cluster Centers Based On XGBOOST) model, to forecast student's choices in their career. K.Sripath Roy et al.[16] used machine learning algorithms such as the SVM, decision tree and X.G. boost to create a model of student career predictions. Vivek Kumar Mourya et al.[17] developed a career guide application that employs machine learning. The predictive aspect of the application utilizes a clustering algorithm called K-means algorithm.Ezenkwu.C.Pet al.[18] introduced an Automated Career Guidance Expert System (ACGES) employing the case-based reasoning (CBR) technique.

After conducting the literature study, it becomes evident that Machine Learning classification techniques, such as Decision Trees, Random Forests, SVM, Naïve Bayes, Logistic Regression, kNN, etc., have been extensively employed in the domain of Career Prediction. Hence, in the next section, a comparative analysis of these classifiers has been made.

III. Comparative Analysis Of Machine Learning Classifiers

This section offers the comparison drawn among various machine learning classification models. The following table I consists of the comparative analysis:

TABLE I: COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES

Classifier/Model	Pros	Cons	Applicability	Suitable for Career Prediction (YES/NO)
Decision Trees	- Easy to interpret and visualize - Handle both numerical and categorical data	- Prone to overfitting - Sensitive to small changes in data	- Simple problems with categorical features - Transparent decision-making	YES
Random Forests	- Reduces overfitting by ensemble method - Handles both numerical and categorical data	- More computationally expensive than individual Decision Trees	- Medium to large datasets - Complex problems with high-dimensional data	YES
Support Vector Machines (SVM)	- Effective in high-dimensional spaces - Handle both linear and non-linear tasks	- Computationally intensive on large datasets - May not handle complex datasets well	- Binary and multiclass classification tasks - Problems with clear margin between classes	YES
Logistic Regression	- Simple and interpretable - Efficient with large datasets	Limited to linear decision boundaries	- Binary classification problems - Problems with linear decision boundaries	YES
Neural Networks	- Highly flexible and learn complex patterns	- Require large amounts of data and	- Large datasets - Complex and non-linear problems	YES

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	- Handle both linear and non-linear tasks	computational power for training - Lack of interpretability ("black-box" models)	- Applications where predictive performance outweighs interpretability	
kNN	-Intuitive -No training phase required	-Sensitive to noise -Computationally expensive	-when the dataset is not too large and -the feature space is not too high-dimensional.	YES

The "Suitability for Career Prediction" column indicates whether the technique is suitable for predicting career-related outcomes or not. After conducting a comparative study on various Machine Learning classifiers, it can be inferred that all are suitable for Career Path Prediction but have their respective pros and cons. The actual performance may depend on various factors like the size and quality of the dataset, feature engineering, and hyper parameter tuning. Hence, in order to select the most suitable technique for Career Path Prediction problem, it becomes essential to implement them on the same dataset for performing thorough experimentation and validation. Further, all these are assessed by calculating various parameters like accuracy, Recall, Precision and F1-score.

In order to achieve this, a pilot study has been conducted and presented in different stages in order to evaluate the behavior of different Machine Learning classifiers. The findings from this pilot study will guide the design and execution of the full-scale research project on career path prediction using machine learning and deep learning.

IV. Stages Of Model

The career path prediction model utilizing machine learning encompasses several key stages to effectively forecast and guide individuals in their professional trajectories as shown in figure II. The initial stage involves Data Collection and Preprocessing, where relevant data points such as educational background, skills, work experience, and career preferences are gathered and cleaned to ensure data quality. Subsequently, Feature Engineering is conducted to extract meaningful features from the dataset, enabling the model to capture essential patterns and relationships. The next stage, Model Selection and Training, involves choosing appropriate machine learning algorithms such as decision trees, random forests, or neural networks, and training them on the prepared dataset to learn the underlying patterns. Following this, Model Evaluation and Validation are crucial steps to assess the model's performance, accuracy, and generalization capabilities using metrics like accuracy, precision, recall, and F1 score. Finally, the model is deployed in the Prediction and Recommendation stage, where it provides personalized career path predictions based on individual profiles, offering valuable insights and guidance for career development and decision-making.

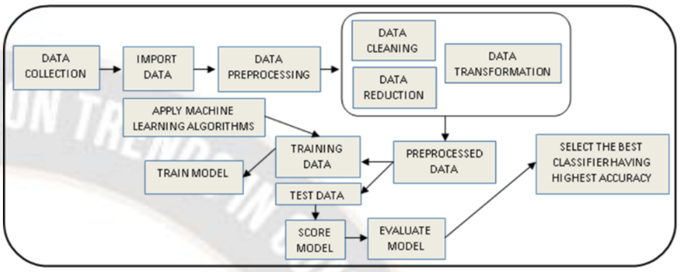

Fig. II: Detailed processes under different stages

A. *Data Collection and Description*

In the dataset/data acquisition phase of this study on career path prediction using machine learning, the collection of diverse and comprehensive data sources is paramount to ensure the model's accuracy and effectiveness in forecasting career trajectories. Data acquisition involves gathering information on various aspects such as educational qualifications, professional experience, skills, certifications, career preferences, and industry trends. Ensuring the quality, relevance, and diversity of the acquired data is essential to develop a robust and reliable career path prediction model that can cater to the dynamic and evolving needs of individuals in navigating their professional journeys. The standard dataset has been taken for this pilot study [19]. Screenshot of the selected dataset is shown in figure III.

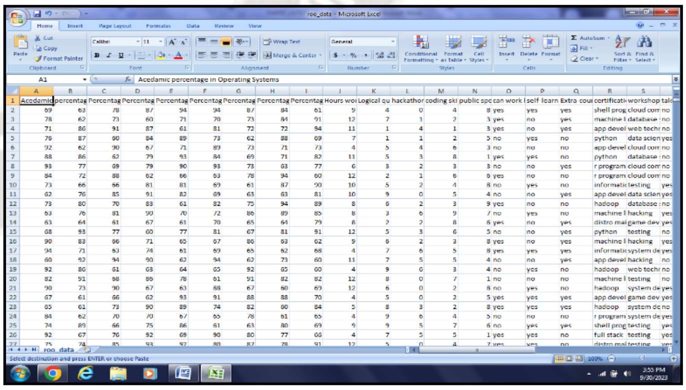

Fig.III: Screenshot of Dataset used for study

B. *Tools Used:*

In order to implement the Machine Learning classifiers, Jupyter Notebook is used. It is an open-source tool used for developing and managing data analytics. It allows to create and share documents like live code, equations, visualizations, and

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text. The term Jupyter is derived from the available programming languages (Julia, Python, R). The IPython kernel that comes with the Jupyter, allows to develop Python programs.

C. *Data Preprocessing:*

In the data preprocessing phase of the career path prediction model using machine learning, several crucial steps are undertaken to ensure the quality, consistency, and readiness of the dataset for training the predictive model. The initial step involves Data Cleaning, where missing values, outliers, and inconsistencies in the dataset are identified and addressed through techniques such as imputation, outlier detection, and data normalization, followed by Feature Scaling and Transformation to standardize the numerical features and bring them to a common scale, preventing certain features from dominating the model training process. Feature Encoding is then performed to convert categorical variables into numerical representations, enabling the machine learning algorithms to process and interpret the data effectively. Dimensionality Reduction techniques like Principal Component Analysis (PCA) may be employed to reduce the complexity of the dataset and enhance computational efficiency. Moreover, Data Splitting into training and testing sets is essential to evaluate the model's performance on unseen data and prevent overfitting. By meticulously preprocessing the dataset, the model can effectively learn from the data and make accurate predictions regarding individuals' career paths based on their unique profiles and preferences. Next, the data has been checked that whether it is balanced or not as shown in figure IV below.

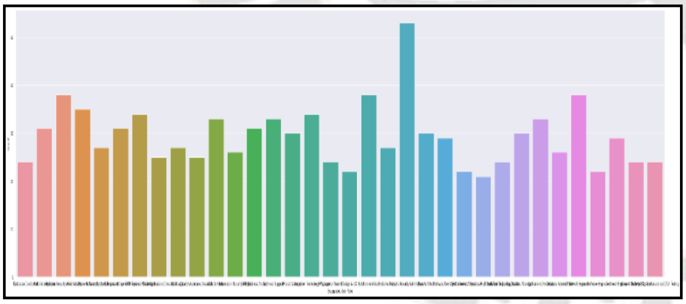

Fig. IV: Checking the Data Balance

Finally, after the data has been processed, it is divided into two parts i.e. training data and testing data. We have used 80% of the massive data set collected for training, while 20% is used for testing. Training is the process of teaching a new skill to the machine and enabling it to generate new predictions based on the previous training, on the testing data. Testing data means that we already have predefined datasets along with the output that is previously labeled. It is used to check if our model works correctly, and generate correct predictions. More the number of correct predictions, the higher will be the accuracy of the model. Else we can modify the model with a better one. It also expands the dataset with additional model inputs and predictions, making it more powerful and accurate.

D. *Implementation of Machine Learning Classifiers on a Standard Dataset*

❖ Classifier I: Decision Tree

A decision tree algorithm is a supervised machine learning method that recursively splits a dataset into subsets based on the most significant attributes, creating a tree-like structure. It uses these splits to make predictions for classification tasks by traversing the tree from the root to a leaf node.

Methodology:

Step 1: Start by establishing the root node, denoted as S, which encompasses the entire dataset.

Step 2: Identify the optimal attribute within the dataset by employing an Attribute Selection Measure (ASM).

Step 3: Partition S into subsets, each containing potential values for the chosen best attribute.

Step 4: Construct a decision tree node, incorporating the selected best attribute.

Step 5: Iteratively produce new decision trees using the subsets generated in step 3. This process continues until a point is reached where further classification is no longer possible, at which stage it is referred to as the final node, or a leaf node.

The confusion matrix of the above algorithm using Python is displayed below in figure V:

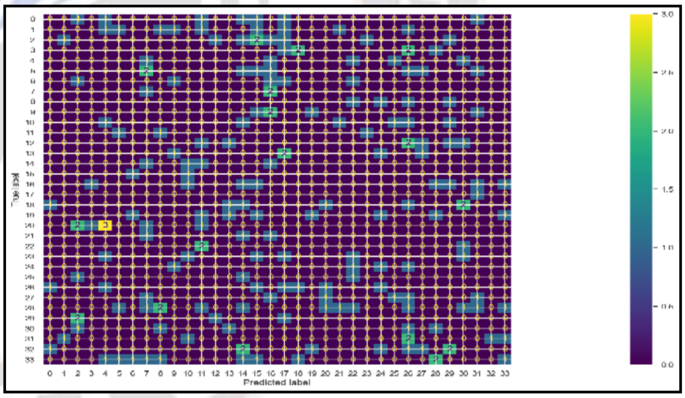

Fig. V: Decision Tree Confusion Matrix

❖ Classifier II: Random Forest

Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve predictive accuracy and reduce overfitting. It works by training each tree on a random subset of the data and features, and then averaging or voting on their individual predictions to produce a more robust and accurate final prediction.

Methodology:

Step 1: Randomly pick K data points from the training set.

Step 2: Construct decision trees based on the chosen data points (forming subsets).

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Step 3: Determine the desired number N of decision trees to create.
Step 4: Iterate through Steps 1 and 2.
Step 5: When dealing with new data points, predict their categories using each decision tree, and then allocate the new data points to the category that receives the highest number of votes from the decision trees.

The confusion matrix of the above algorithm using Python is displayed below in figure VI:

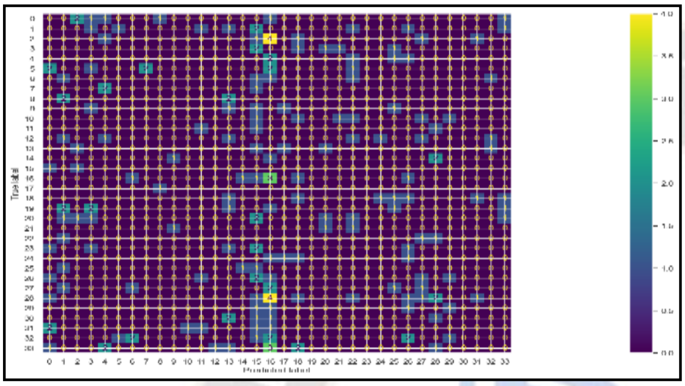

Fig. VI: Random Forest Confusion Matrix

❖ Classifier III: Support Vector Machine

Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification tasks. It finds a hyperplane that best separates data points of different classes while maximizing the margin between them. SVM can handle both linear and non-linear problems by mapping data into higher-dimensional space and is effective for tasks where clear class boundaries exist.

Methodology:

Step 1: Begin by selecting pertinent features from your dataset and, if necessary, perform preprocessing tasks such as feature scaling or normalization.
Step 2: Choose a kernel function tailored to the data's characteristics and the research problem at hand, as it will transform the data into a higher-dimensional space.
Step 3: Locate the hyperplane that optimally separates data points belonging to distinct classes by identifying the support vectors.
Step 4: Strive to maximize the margin, which represents the distance between the hyperplane and the closest support vectors. SVM introduces a regularization parameter denoted as 'C' to manage the trade-off between maximizing the margin and minimizing classification errors.
Step 5: Experiment with various kernel functions and hyperparameter values (such as C, gamma, degree, etc.) to discover the most effective combination for the specific problem under investigation.

The confusion matrix of the above algorithm using Python is displayed below in figure VII:

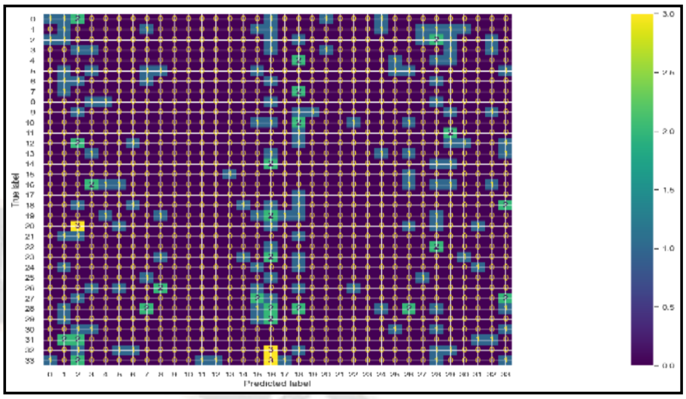

Fig. VII: SVM Confusion Matrix

❖ Classifier IV: Logistic Regression

Logistic Regression is a statistical model and a classification algorithm used in machine learning. It predicts the probability of a binary outcome (e.g., 0 or 1) based on one or more predictor variables. It employs the logistic function to model the relationship between the predictors and the probability of the outcome, making it suitable for binary classification tasks.

Methodology:

Step 1: Ensure feature consistency by normalizing or standardizing them to a common scale.
Step 2: Logistic Regression models the connection between input features and output through the logistic (sigmoid) function. This function transforms a linear combination of input features into a value ranging from 0 to 1, indicating the probability of the positive class. The model equation is expressed as:

$$P(Y=1)=1/(1+e-(b_0+b_1x_1+b_2x_2+\dots+b_nx_n))$$

Where:

- $P(Y=1)$ is the probability of the positive class.
- b_0 is the intercept term.
- $b_1, b_2,\dots,b_n$ are the coefficients for the input features $x_1, x_2,\dots, x_n$.

Step 3: Utilize the training data to estimate the coefficients b0, b1, …, bn that minimize the logistic regression cost function. Following training, employ the testing dataset to assess the model's performance.
Step 4: Employ the trained logistic regression model for predictions on new, unseen data.

The confusion matrix of the above algorithm using Python is displayed below in figure VIII:

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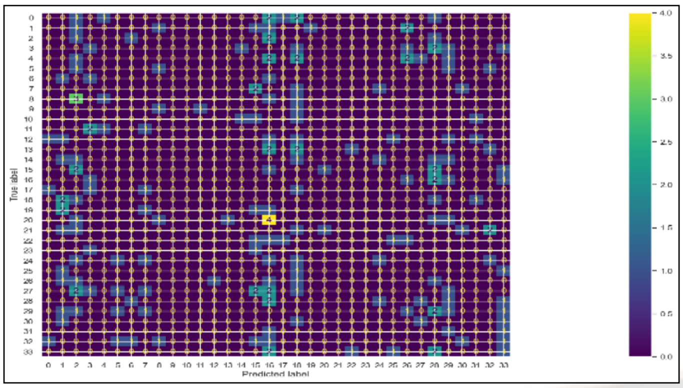

Fig. VIII: Logistic Regression Confusion Matrix

❖ Classifier V: kNN

The k-Nearest Neighbors (KNN) algorithm is a supervised machine learning method used for classification and regression. It works by finding the k nearest data points in the training dataset to a given test data point and assigns the most common class label (for classification) or the average of the k-nearest neighbors' values (for regression) as the prediction for the test point, based on their proximity in feature space. KNN's performance and behavior depend on the choice of the parameter k and the distance metric used.

Methodology:

Step 1: Determine the desired quantity of neighbors, denoted as K.

Step 2: Compute the Euclidean distance for K neighbors.

Step 3: Select the K nearest neighbors based on the calculated Euclidean distances.

Step 4: Within these K neighbors, tally the occurrences of data points in each category.

Step 5: Allocate the new data points to the category with the highest neighbor count.

Step 6: Model is now prepared for use.

The confusion matrix of the above algorithm using Python is displayed below in figure IX:

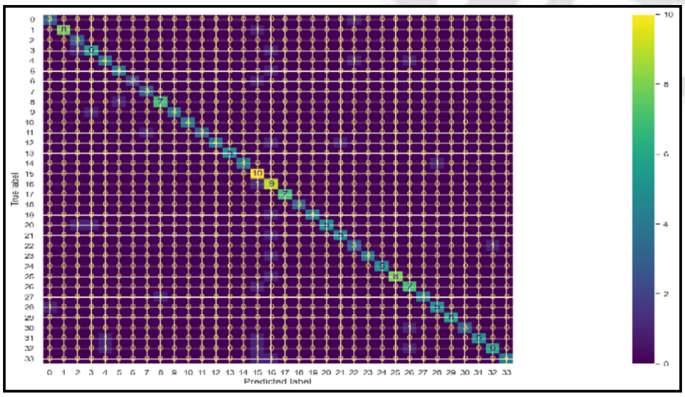

Fig. IX: kNN Confusion Matrix

❖ Classifier VI: Naïve Bayes

Naive Bayes is a probabilistic machine learning algorithm used primarily for classification tasks. It's based on Bayes' theorem and makes the "naive" assumption that features are conditionally independent, simplifying the calculation of probabilities. It calculates the probability of a data point belonging to a particular class by multiplying the probabilities of its individual features, then selects the class with the highest probability as the prediction. Naive Bayes is efficient, especially for text classification tasks like spam detection and sentiment analysis.

Methodology:

Step 1: Express the data as a collection of attributes or features.

Step 2: Compute the prior probability for each class within the training dataset.

Step 3: Determine the likelihood of each feature occurring within each class.

Step 4: Employ Bayes' theorem to calculate the posterior probability for each class concerning a given instance.

For each instance, evaluate the posterior probability for each class and select the class with the highest probability as the predicted class.

The confusion matrix of the above algorithm using Python is displayed below in figure X:

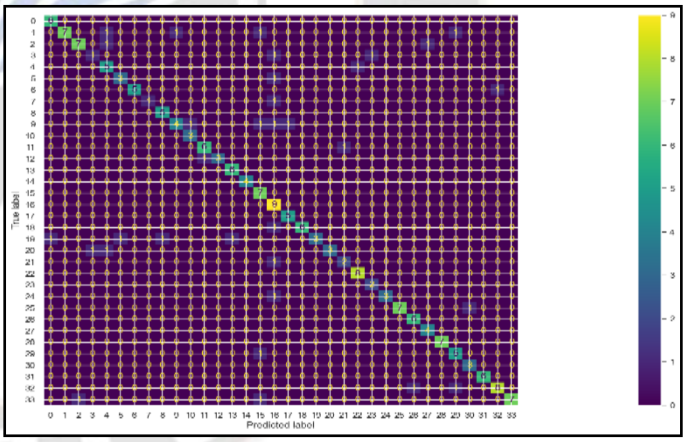

Fig. X: Naïve Bayes Confusion Matrix

By executing the below mentioned code, the output of different classifiers can be computed by supplying the user defined data for all the features. Then the predicted output and the actual output can be compared to find the accuracy for that data.

E. Results and Analysis

After implementing various Machine Learning classifiers on students' dataset, all these have been evaluated using various metrics like accuracy, recall, precision, F1-score etc as shown in table II and figure XI. Evaluation metrics refer to numerical measures utilized for evaluating the performance and efficacy of statistical or machine learning models. By offering valuable insights into the model's performance, these metrics facilitate the comparison of various models or algorithms.

Accuracy is the fraction of predictions our model got right out of all the predictions. Accuracy ranges between 0 and 1. Precision tells what proportion of positive predictions was actually correct. Recall aims at measuring what proportion of actual positives was identified correctly.

TABLE II: PERFORMANCE EVALUATION METRICS

	Accuracy	Recall (0-1)	Precision (0-1)	F1-score (0-1)
Decision Trees	0.728	0.643	0.662	0.642
Random Forest	0.615	0.436	0.434	0.431
SVM	0.684	0.543	0.559	0.542
Logistic Regression	0.582	0.239	0.219	0.218
kNN	0.855	0.853	0.856	0.836
Naïve Bayes	0.835	0.871	0.843	0.832

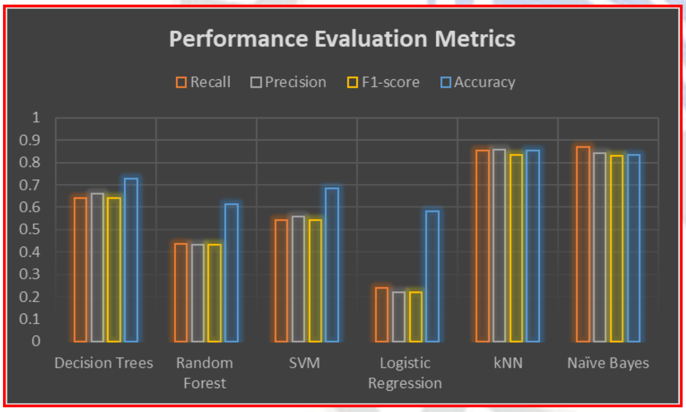

Figure XI: Performance Evaluation Metrics

Accuracy: Decision Trees, kNN, and Naïve Bayes exhibit relatively high accuracy, indicating that they make accurate overall predictions. Logistic Regression and Random Forest, on the other hand, have lower accuracy scores.

Recall: Naïve Bayes has the highest recall, suggesting that it effectively identifies true positive cases. kNN also performs well in this regard. Logistic Regression has the lowest recall, indicating a potential weakness in identifying positive instances.

Precision: kNN has the highest precision, indicating that it makes fewer false positive predictions. Naïve Bayes also demonstrates strong precision. Decision Trees and SVM show moderate precision, while Logistic Regression and Random Forest have lower precision.

F1-score: Naïve Bayes achieves the highest F1-score, balancing precision and recall effectively. kNN also performs well in terms of F1-score. Decision Trees and SVM exhibit moderate F1-scores, while Logistic Regression and Random Forest have lower F1-scores, suggesting room for improvement in their model balance.

Overall, the choice of the best algorithm depends on the specific requirements of the career path prediction system, with Naïve Bayes and kNN showing strong performance across multiple metrics.

V. FUTURE SCOPE

The future scope of career path prediction models using machine learning holds immense potential for advancement and innovation, particularly with the integration of deep learning techniques. Deep learning, a subset of machine learning that mimics the human brain's neural networks, offers unparalleled capabilities in processing complex and unstructured data, thereby enhancing the accuracy and predictive power of career path models. By leveraging deep learning algorithms such as deep neural networks, convolutional neural networks (CNNs), and recurrent neural networks (RNNs), researchers can extract intricate patterns and relationships from vast amounts of data, enabling more precise and personalized career predictions. The ability of deep learning models to automatically learn hierarchical representations of data features without the need for manual feature engineering makes them well-suited for capturing nuanced insights from diverse sources such as job postings, resumes, and professional profiles. Furthermore, the continuous advancements in deep learning architectures, optimization algorithms, and computational resources pave the way for developing more sophisticated and efficient career path prediction models that can adapt to evolving job market trends and individual aspirations. Embracing deep learning in this field not only enhances the predictive accuracy and scalability of career path models but also opens up new avenues for personalized career guidance, talent development, and workforce planning in the ever-changing landscape of the professional world.

VI. CONCLUSIONS

In conclusion, the development and implementation of a career path prediction model using machine learning techniques present a promising approach to guiding individuals in making informed decisions about their professional trajectories. Through the stages of data acquisition, preprocessing, model training, and prediction, this study has demonstrated the potential of leveraging diverse datasets and advanced algorithms to forecast career paths accurately. The utilization of deep learning technologies, such as neural networks and convolutional neural networks, has shown significant improvements in capturing complex patterns and enhancing the predictive capabilities of the model. By harnessing the power of machine learning and deep learning, individuals can benefit from personalized career recommendations based on their unique profiles, skills, and aspirations. The future of career path prediction models lies in further advancements in deep learning architectures, data integration, and model optimization, paving the way for more accurate, scalable, and adaptive solutions to meet the evolving needs of individuals in navigating their professional journeys. This study contributes to the growing field of AI-driven career guidance and underscores the importance of leveraging technology to empower individuals in achieving their career goals and aspirations.

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Conflict of interests: *The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper*

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