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Intelligent Placement and Career Development Platform: Leveraging AI and NLP for Enhanced Student Performance, Recruitment Insights and Personalized Recommendations

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Abstract: The job placement process for students is often inefficient due to mismatched candidate-job requirements lack of personalized career guidance and ineffective interview preparation strategies. We suggest an Intelligent Selection and Career Planning Platform that uses Natural Language Processing and Artificial Intelligence (AI) to enhance student performance, offer recruitment insights and provide tailored recommendations in order to address these issues. Several essential features are integrated into the platform; Resume Screening uses K-Nearest Neighbors (KNN) and Logistic Regression, attaining 89% and 95% accuracy rates respectively to assess resumes and offer skill-based enhancements using NLP and text analysis. Candidate Matching which determines resume shortlisting criteria by analyzing job descriptions using a BERT model and giving non-shortlisted candidates feedback based on job requirements. Placement Prediction which makes use of a random forest method with 99.87% accuracy forecasts student placement success by using past academic data (tenth and grade grades). Interview Process Guidance delivering thorough round-wise specific to the company interview insights; interview preparation evaluating interview questions using TF-IDF and Cosine Similarity and suggesting learning techniques according to the candidate's comprehension level; Course recommendations which use the YouTube API and opinion analysis with a BERT simulation (96.7% accuracy) to rank and recommend learning videos based on positive comments from viewers; and tests/quizzes which evaluate a candidate's knowledge in a variety of areas and analyze scores to confirm career compatibility and placement possibility. This all-inclusive AI-powered system greatly streamlines the hiring and career advancement process by giving students data-driven, individualized guidance and helping recruiters choose the best candidates.

Keywords: AI Recruitment, Candidate Matching, Career Guidance, Interview Preparation, NLP, Placement Prediction, Resume Screening and Sentiment Analysis.

INTRODUCTION:

The method of student selection has developed significantly over the course of time, from conventional manual assessments to AI-powered automated alternatives. Historically recruiters depended on in-person interviews and manual cv reviews which were both laborious and open to human bias. As technology developed companies started filtering resumes using application tracking systems (ATS) that used pre-specified keywords [1]. However, these approaches were inaccurate in assessing a candidate's total potential which resulted in candidates and job roles not matching. The lack of a systematic and individualized advising system frequently caused students to struggle with career planning, course selection and interview preparation [2]. There was a need for more sophisticated and data-driven job development solutions as the labor market grew more competitive. The success of current career development and placement programs is hampered by a number of issues. Conventional resume screening technologies mostly use keyword matching which is insufficient to determine how relevant a candidate's experiences and abilities. Numerous job portals offer general career recommendations without taking into account each applicant's unique preferences, shortcomings and capabilities. Furthermore, tools for interview preparation are frequently dispersed and not adapted to each person's degree of comprehension [3]. Some universities use placement prediction models but their predictions are unreliable because they only consider a small number of data attributes. Furthermore, real-time sentiment analytics to evaluate the efficacy of instructional materials is absent from course recommendation systems. These inadequacies underscore the need for a more holistic AI-driven method for student career development [4].In order to overcome these obstacles, we suggest an Intelligent Placement and Job Search Platform to improve student placement prediction, recruitment insights and tailored suggestions [5]. To maximize various facets of professional development the system incorporates several AI models. The goal of this project is to provide a comprehensive career advisory system powered by AI in order to close the gap between recruiters and students. Due to a poor knowledge about industry requirements many students struggle to find suitable employment possibilities. Likewise, recruiters find it difficult to effectively sift through a sizable applicant pool. Employers and students alike can gain from a data-driven customized approach to

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job growth that makes use of AI and NLP tools [6]. Based on their abilities as well as their weaknesses the system makes sure that students receive tailored advice on how to strengthen their resumes, learn new skills and be ready for interviews. This will assist students develop successful careers and greatly increase job placement rates. The demand for sophisticated real-time career recommendations in a work market that is changing quickly is what motivates our research. Conventional placement techniques are frequently unchanging and unable to adapt to shifting market trends. Our platform offers current and pertinent career recommendations by incorporating AI models that examine real-world data including openings, resume patterns and analysis of sentiment from internet sources [7]. In addition to saving recruiters time, automation of application screening, applicant matching and preparation for interviews improves the efficacy and efficiency of the recruitment procedure. With this research we hope to produce a more intelligent, scalable and accurate career planning solution that gives students industry-aligned suggestions [8] for better job options as well as data-driven career insights.

LITERATURE SURVEY:

Although studies have shown that machine learning models like Support Vector Machines (SVM), Decision Trees and Logistic Regression can be used for classification-based resume examination these models have limitations when it comes to processing complicated unstructured resume data. Recent developments greatly increased accuracy in resume processing and job matching by including deep learning techniques like BERT and transformer models [9]. Similar to this, researchers have used Random Forest, Naïve Bayes and Gradient Boosting methods to anticipate student employability based on grades, talents, and extracurricular activities in a large number of studies on placement prediction models utilizing historical academic performance data. These studies have demonstrated AI's efficacy in hiring but they frequently lacked real-time flexibility and customized career advice. Fraij et al. thorough analysis of scholarly works, publications and websites was carried out. According to the research, AI has benefits for hiring since it automates processes, saves time and frees up human attention for performance and growth. AI can offer automation and intellectual insights, enabling systems to analyze information objectively, quickly, and effectively much like the human brain [10]. Kot et al. investigates the function of artificial intelligence in Indonesia's pharmaceutical sector. It looks into how AI-based hiring practices and quality affect an employer's reputation. According to the report, AI adoption and company reputation are highly influenced by AI-based hiring and quality [11]. The study also discovered that reputation and AI recruitment are mediated by AI, with AI quality having a comparable effect.Previous studies have looked into AI-driven course suggestions and interview preparation in along with recruitment automation. To evaluate interview questions and suggest study materials [17]. These methods however had trouble grasping contextual meanings which resulted in general recommendations. Pretrained language models like BERT and GPT have been used in more recent studies to enhance the quality of recommendations based on candidate replies and job descriptions [18]. Comparably rule-based filtering techniques have given way to sentiment analysis-driven algorithms that examine user interaction and online reviews in course recommendation systems. Although there has been research on using the YouTube API to recommend instructional videos real-time sentiment classification is frequently absent from current solutions. Numerous studies have shown how AI can improve student's career development but few have combined several AI models into a single, all-inclusive, data-driven framework for end-to-end career counseling which is the main goal of our suggested solution. Yousaf et al. proposed an inappropriate content especially for young audiences has proliferated due to YouTube's expanding video content. To identify and categorize such content a novel deep learning-driven architecture is put forth. A BiLSTM network [19] is used for multiclass classification after video descriptors are extracted using an ImageNet trained convolutional neural network (CNN) approach EfficientNet-B7. It also incorporates an attention mechanism. By better collecting the historical context of video descriptors the architecture performs better than conventional machine learning classifiers. Dabhade et al. main goal is to employ educational data mining to forecast student's academic success in a technical college in India. Factor analysis and a questionnaire-based survey were used to gather data. Machine learning techniques [20] were compared using Python 3 and the support vector regression linear approach produced better predictions.

METHODOLOGY:

A. Data Collection and Preprocessing:

To ensure a thorough and varied assessment of candidate profiles we gathered a sizable dataset of over 40,000 resumes from over 1,000 domains for resume screening. Important portions of each resume including schooling, certificates, projects, work experience and talents were extracted using parsing. After classifying the extracted talents into pertinent domains, a domain-wise evaluation method was put in place to assess a candidate's competence in various fields. In order to gauge a candidate's proficiency in particular technical domains we also gathered software interview questions and arranged them according to their degree of difficulty. Normalization techniques [21] were used during preprocessing to improve model performance, eliminate discrepancies and standardize text formats. Frequently occurring phrases from resumes were visualized using a word cloud analysis which aided in feature selection and increased the precision of domain model classification. In order to train and optimize a BERT-based corresponding model for applicant matching we gathered a dataset of job postings and matching resumes. Resumes were taken from publicly accessible sources, while job descriptions were sourced from several recruitment platforms. Required knowledge, expertise, levels and specific to an industry terminology were noted on each job description. Text data was preprocessed using NLP techniques like TF-IDF vectorization, lemmatization and stop-word elimination [22]. TF-IDF for Text Processing used in resume screening, job matching and interview preparation to assess word importance in a document.

$$TF - IDF = TF(t,d) \times \log\left(\frac{N}{DF(t)}\right)$$

Where, $TF(t,d)$ is the Term Frequency of term t in document d, $DF(t)$ is the number of documents containing term t and N is total number of documents. A semantic similarity technique was used to increase the accuracy of candidate-job matching making sure that resumes were matched based on contextual relevance as well as keywords. Cosine similarity scoring and text embeddings [23] were used to further refine the model allowing for more precise and insightful comparisons between job descriptions and resumes. Measures similarity between two text vectors (e.g., resume and job description, interview answers).

$$\cos(\theta) = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \ X \ \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Where, $A_i \; and \; B_i$ are term frequency values in two text documents. Using student academic records including high school (10th and 11th grade scores), CGPA, extracurricular events, certifications and internship experiences we created a dataset for placement prediction. The dataset was gathered from previous student's recruitment records and university placement cells. Data cleaning and feature development methods, such as feature scaling, outlier removal and missing value imputation were used to guarantee good model performance. For categorical factors like department and course specialty we employed one-hot encoding; for numerical qualities like CGPA and prior academic performance we used standardization [24]. Using web scraping techniques [25], a dataset of questions for interviews from several domains was gathered in order to prepare for the interview. We extracted questions from online coding forums and interview experience platforms using Selenium. The dataset was then divided into technical fields (software development, data science, cybersecurity etc.) and difficulty levels (beginning, intermediate and advanced). Tokenization, stemming and the elimination of duplicate items were all part of the preprocessing procedure which produced a more polished dataset. The YouTube API [26] was used to gather data for course recommendations and instructional videos pertaining to several professional categories were examined. Video titles, descriptions, views, likes and comments were all included in the dataset. A collection of technical questions covering a range of topics including the development of software, machine learning, cybersecurity, business analytics and finance was assembled for the quiz and skill evaluation. Based on level of expertise and applicability to various career roles the questions were grouped. Questions were categorized into structured quizzes content was reformatted and redundant questions were removed using NLP-based text processing algorithms. The finished dataset was set up to deliver quiz evaluations in real time along with tailored feedback and suggestions for skill development. All module's data pretreatment pipelines included feature engineering, handling unbalanced data, leveling text inputs, removing missing values and putting pertinent NLP approaches into practice [27].

B.Resume Screening:

A critical phase in the hiring process is resume screening which aids in assessing applicants according to their experience, education and abilities. To improve and automate this procedure we used K-Nearest Neighbors (KNN) and Logistic Regression in our suggested method [28]. With over 40,000 resumes spanning more than 1,000 categories the collection guarantees a broad range of skills. To improve the raw resume material preprocessing techniques included text extraction, tokenization, stop-word elimination and normalization. Following that each resume was categorized into various domains according to education, work experience and talents. The KNN model was employed to classify resumes identifying the most relevant area by comparing each resume to comparable ones in the dataset. In contrast the KNN classifier obtained 89% accuracy, while the Logistic Regression technique was trained to predict with 95% accuracy whether a resume is appropriate for a given employment profile. Following resume processing the algorithm uses extracted skills to assign scores in each domain. These scores aid in determining a candidate's level of proficiency in several domains. The KNN model [29] rates the resume according to how similar it is to the best resumes in the dataset whereas the Logistic Regression approach forecasts a binary result (appropriate or not suitable for a specific area). A candidate is considered an appropriate match for related position descriptions if they score highly in a certain domain. If not, the system highlights talents that are lacking or underdeveloped and offers ideas for improvement. This methodical assessment directs applicants toward skill development while assisting recruiters in more effectively screening resumes.

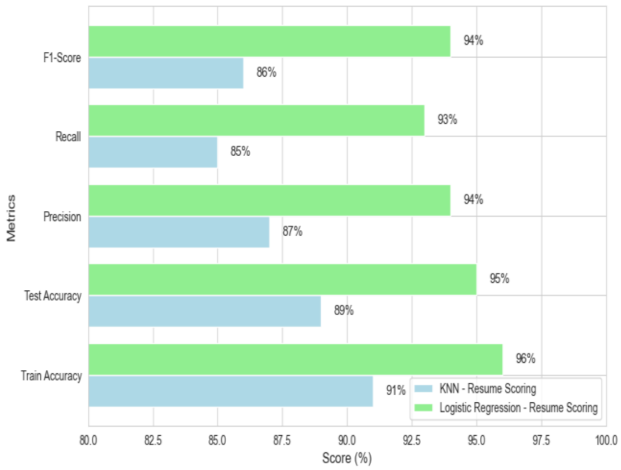

Fig.1 Comparison of Evaluation Metrics of KNN vs Logistic Regression

We used a variety of graphical representations such as word clouds, pie charts and bar charts to show the resume screening results. Candidates can see their advantages and disadvantages by seeing the skill rankings for each domain in bar charts. The distribution of abilities across several domains is shown in pie charts which offer insights into the industries for which people are most qualified. By highlighting the most often listed talents on resumes a word cloud graphic provides a concise summary of the most in-demand skills in the labor market. These graphic aids make it easier for recruiters and students to understand screening results. Candidates can upload resumes and immediately obtain domain-wise ratings, employment suitability rankings and suggestions for enhancement as part of the automated and interactive resume screening process. Instead of using keyword-based filtering our approach makes sure that applicants are matched with suitable job openings based on data-driven insights. We accomplish a high degree of screening accuracy by combining KNN with Logistic Regression which greatly increases the effectiveness of the hiring process (as shown in Fig.1). Additionally, candidates can make well-informed professional selections thanks to the representation of skill distribution and domain strengths which eventually improves their chances of landing a job.

C.Candidate Matching:

A crucial stage in the hiring process is candidate-job matching which makes sure that resumes are spatially aligned with the job postings in addition to being screened based on keywords. The BERT (Bidirectional Encoder Representations from Transformers) approach a cutting-edge NLP framework that comprehends contextual meaning in addition to precise keyword matching is used in our system [30]. The collection is made up of thousands of resumes and job descriptions that were gathered from public datasets, job boards and recruiting portals. Key elements including experience level, job role, necessary abilities and industry-specific terminology are extracted from each job description. Tokenization, stop-word elimination, lemmatization and vectorization are also used to preprocess resumes in order to ensure consistency. Following that the BERT model produces deep lexical embeddings for the job description, providing precise and significant candidate-job matching. Cosine similarity between resume embeddings and the job description is calculated as part of the matching procedure. The CV is shortlisted for subsequent hiring stages if its comparison score surpasses a predetermined threshold. The system labels the resume as not selected and moves on to an improvement analysis if its score is below the cutoff. The BERT approach (as shown in Fig.2) captures situational significance ensuring that applicants possess appropriate but differently stated experiences are not disregarded in contrast to standard keyword-based systems that may reject a resume because it lacks specific terms. By comprehending phrase frameworks, synonyms and job-specific jargon this deep learning method greatly increases the reliability of candidate-job matching.

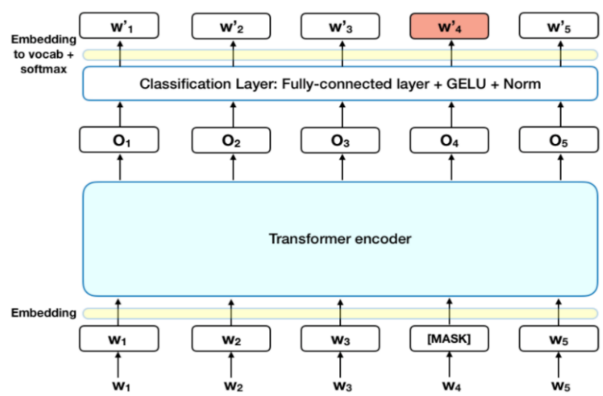

Fig.2 BERT Architecture for Candidate Matching based on Job Descriptions

The system offers thorough improvement recommendations according to NLP and analyzing texts for applicants who are not selected for further consideration. It emphasizes weak areas finds abilities that are lacking, and contrasts the resume with applications that have been accepted for comparable positions. Additionally, the system offers a skill gap evaluation highlighting areas in which the candidate's chances could be enhanced by extra projects, qualifications or experience. Named Entity Recognition (NER) [31], TF-IDF weighting and text similarity metrics are used to identify the most pertinent missing components in a candidate's profile and produce these recommendations. In addition to rejecting resumes the objective is to help

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applicants improve their profiles for subsequent applications. The technology also produces visualizations like resume-job pairing scores, missing ability heat maps and phrase importance rankings to help applicants understand how well their resumes are performing. A word cloud representation identifies the most crucial job description terms that were either included in or absent from the resume while a bar chart displays the CV's relevance score for various employment titles. The process of improvement is made more apparent and actionable by these visual aids. Our technology guarantees a data-driven intelligent hiring process that benefits both companies and job seekers by combining real-time resume enhancement suggestions with BERT-based candidate matching.

D. Interview Process And Preparation:

Different rounds of interviews are used by different firms to evaluate candidates on a variety of criteria including as technical knowledge, solving issues skills, communication ability and domain expertise. Through internet scraping and human gathering of information from sources like business websites, Glassdoor evaluations and job applicant forums, our technology offers an organized archive of interview procedures unique to each organization. The dataset contains comprehensive information about hiring processes including technical assessments, system design rounds, group discussions, online tests, coding challenges and HR interviews. Candidates can strategically prepare by using the structured framework that compiles each company's evaluation weighting, commonly asked questions and selection criteria. Our approach uses cosine similarity-based answer evaluation and TF-IDF to assess a candidate's comprehension level in order to improve interview readiness [32]. Domain-specific interview questions are given to candidates and the accuracy depth, and clarity of their responses are assessed by comparing them to ideal responses using natural language processing techniques. By classifying a candidate's performance into beginner, moderate or advanced levels the system provides learning tools and tailored feedback. The system suggests foundational courses and condensed explanations for candidates who have trouble understanding concepts. While advanced applicants receive case studies and challenging problem-solving tasks intermediate candidates are recommended real-world projects and programming practice assignments. The system also offers interactive mock interviews, behavioral question tactics and video recommendations (using the YouTube API) guaranteeing thorough preparation for every facet of the interview. The software offers a data-driven customized approach for job interview preparation by utilizing AI-driven assessment processes greatly increasing a candidate's chances of success.

E. Placement Prediction:

A thorough dataset comprising educational records, skill sets and additional achievement is the foundation of the placement prediction algorithm. The dataset covers characteristics including CGPA, subject-wise efficiency, attendance, projects, certificates, internships and involvement in technical events or hacking events. It includes study data from the 10th, 12th, and B. Tech semesters. To improve forecast accuracy non-academic elements including leadership positions, soft skills and involvement in clubs and organizations are also taken into account. The information is gathered via placement databases, university records and polls of students who have already been placed. In order to preprocess the data, categorical values (such sector and ability level) are captured, feature scaling is used to guarantee uniformity and mean/mode imputation is used to manage missing values. Students are classified as placement or not placement based on past records in the labeled data used to train the model. To forecast the chance of placement, the model is fed features including CGPA, technical skills, certificates, internships and topic proficiency. During training the Random Forest technique builds several decision trees. To ensure forecast robustness, a majority vote process is used to make the final prediction. To attain a high degree of accuracy, this model has been thoroughly adjusted through hyperparameter optimization. The Random Forest model's performance [33] rating shows how reliable it is at forecasting student placements. The model successfully differentiates between pupils who are placed and those who are not as evidenced by its remarkable accuracy of 99.87%. Precision, recall and F1-score are additional crucial evaluation criteria that guarantee equal performance in both groups. A low false negative rate is confirmed by the confusion matrix indicating that children with high employment potential are rarely incorrectly classified.

F. Course Recommendations Using YouTube API:

By utilizing YouTube videos and associated comments the course system of recommendations aims to assist students in locating the most beneficial learning materials. Our methodology evaluates user comments to assess a course's effectiveness rather than depending only on video titles or explanations which could not accurately represent the caliber of the content. Videos pertaining to a variety of topics, including programming, data science, cloud computing, artificial intelligence and more can be retrieved via the YouTube API. Title, description, likes, dislikes and most importantly user comments are among the video metadata that the API retrieves [34]. User comments are a crucial component in determining whether a material is interesting, educational and beneficial since they frequently offer insightful commentary regarding the caliber of a video. Before being examined using NLP

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approaches the gathered comments go through preprocessing steps like stemming, tokenization and stop-word removal. We use a BERT-based sentiment assessment model which has a 96.7% accuracy rate in classifying comments into a positive, a negative, feelings to evaluate the caliber of YouTube courses. In contrast to conventional sentiment analysis techniques, BERT is very good at figuring out whether a comment represents a real learning experience because it is aware of the context and subtleties of user input. Every video has thousands of comments each of which is given a sentiment score by the model. A comment receives a high emotion score if it is favorable (for example "This tutorial was extremely beneficial and well-explained!"). The video's score is lowered by negative remarks (such as "The teacher's style is confusing and the material is outdated"). Although they are taken into account neutral remarks (such as "This video covers Python basics") have little effect on the sentiment score as a whole.

$$Sentiment\ Score = \frac{Positive\ Comments - Negative\ Comments}{Total\ Comments}$$

This helps in ranking and recommending the most useful courses based on user feedback. The method calculates a video's total positivity by adding together sentiment scores. To assist students in rapidly identifying the most valuable content videos are rated with a star system based on positive scores after sentiment analysis is finished. The ranking algorithm takes into account a number of variables such as the overall quantity of comments, the proportion of favorable to unfavorable feedback and the degree of involvement (likes and views). Higher rankings and ratings of four to five stars are given to videos with a large percentage of positive feedback and significant levels of engagement whilst videos with mixed reviews are given ratings of two to three stars. To guarantee that only top-notch content is recommended videos with a large number of unfavorable comments are removed from consideration. This system's real-time video rating analysis and updating capabilities are among its main benefits. The technology periodically re-assesses videos and modifies rankings based on fresh sentiment patterns because YouTube videos are constantly receiving new comments. To guarantee that learners always receive the most recent and excellent courses, a highly rated video's ranking is automatically dropped if it begins to garner bad feedback because of out-of-date content or subpar instruction. Additionally, the system makes dynamic recommendations for online courses in areas where students need to improve based on their performance on quizzes and resume screening results. With the help of an AI-powered course suggestion system students are guaranteed individualized superior learning resources that enhance their technical proficiency and preparedness for the workforce.

G. Quiz Generation Using NLP Techniques:

The quiz system uses natural language processing (NLP) to create customized questions that evaluate a candidate's topic knowledge and skill proficiency. The quiz questions are created by preprocessing and examining big datasets including technical documents, inquiries during interviews, academic texts and job descriptions in order to guarantee thorough coverage. Web scraping methods and structured datasets are used to gather the text data which is further preprocessed using lemmatization, stemming, tokenization and stop-word removal. The system recognizes important subjects and extracts the most pertinent terms from a variety of areas including cybersecurity, data science, machine learning and programming [35]. Following that these extracted subjects are converted into fill-in-the-blank, multiple-choice and coding-related challenges. To ensure that the candidate is assessed on the most pertinent topics for their career path, the quiz is customized based on their resume screening findings and preferred employment role. Following the completion of the test the candidate's answers are assessed using scoring algorithms and similarity metrics based on natural language processing. Direct answer matching is used to assess correctness for both multiple-choice and objective questions. To compare the candidate's reply with an ideal answer template a more sophisticated cosine similarity and TF-IDF technique is used for description or coding-based questions. When a candidate gives a partially accurate response, the algorithm gives them a score that is proportionate to how relevant and accurate their response was. Additionally, descriptive responses are analyzed using word embeddings utilizing BERT to see if the candidate's argument is theoretically sound even if it is presented in a different way.

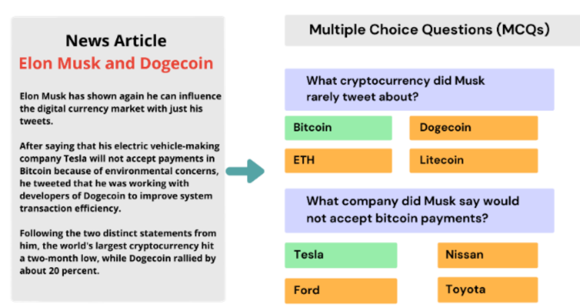

Fig.3 NLP based MCQ's Generation

RESULTS:

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The models employed in this study have proven to be accurate and efficient across a range of modules guaranteeing dependable outcomes for real-time applications. The K-Nearest Neighbors (KNN) model successfully analyzed skills and produced domain-specific scores while the Logistic Regression model for job screening reached 95% accuracy. With a remarkable 99.87% accuracy rate the placement prediction module which was developed using a Random Forest Classifier is a highly dependable tool for predicting student's employability based on their academic performance and extracurricular involvement. Classifying video responses into positive, negative and neutral feelings for the purpose of rating educational resources was accomplished with 96.7% accuracy using the BERT-based sentiment evaluation model used for course recommendations. Standard criteria including precision, recall, F1-score and matrix of confusion were used to assess each model's performance and determine how effective it was (as shown in Fig.4). The precision and recall values of the placement model for prediction were close to 1 indicating that it was reliable. ROC-AUC scores were used to validate the sentiment classification results of the BERT model, guaranteeing its robustness in identifying trends of video positivity. The accuracy of evaluation of skills scores and the relevance of responses were confirmed by manual cross-checking of the TF-IDF and cosine similarity methodologies used for quiz evaluation and interview preparation. Both recruiters and students can make data-driven decisions in real time because to the system's holistic integration of several AI-driven models.

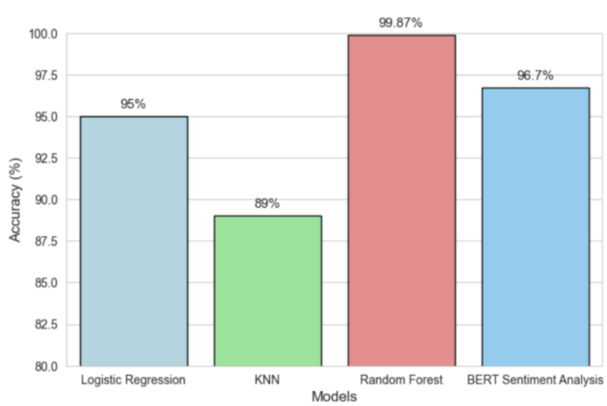

Fig.4 Comparison of Evaluation Metrics Models Used for Recruitment System

Streamlit is used to implement the resume assessment module in real-time giving candidates immediate feedback on the merits and faults of their resumes. After an applicant uploads their resume, the system uses natural language processing (NLP) to extract important skills and experience and then it uses BERT-based similarity in text analysis to match those abilities and experience to preset job roles (as shown in Fig.6). A depiction of the candidate's domain-specific skill score is shown, emphasizing both their strong points and places for development. The algorithm shortlists the applicant if the resume satisfies the requirements of the job description; if not it makes recommendations for improving the candidate's skills. In order to successfully advise the candidate, the interface also shows word clouds and bar charts which provide a clear visual depiction of the relevant and absent skills.

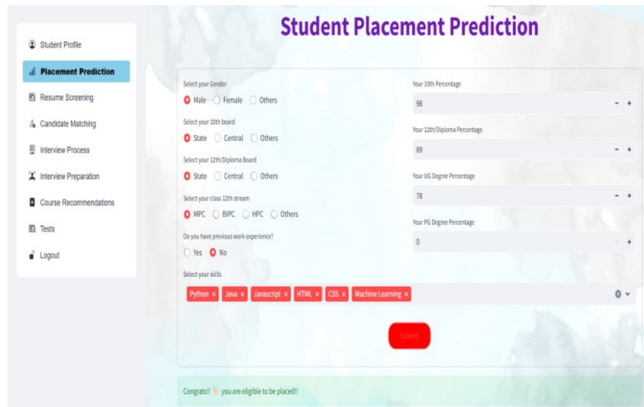

Fig.5 Student Placement Prediction using History of Education Data

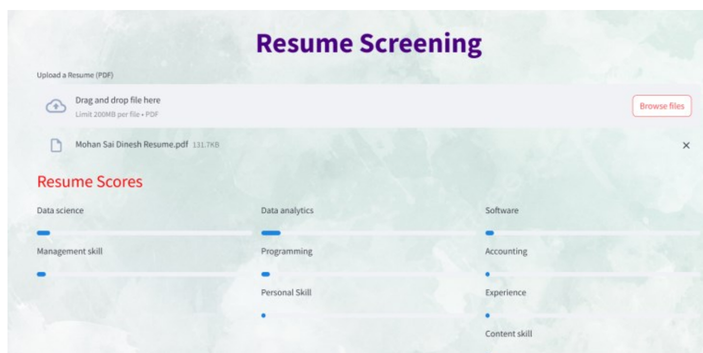

Fig.6 Resume Screening based on Skills and score generation system

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Fig.7 Mock Interview Preparation questions based on level of understanding of individuals

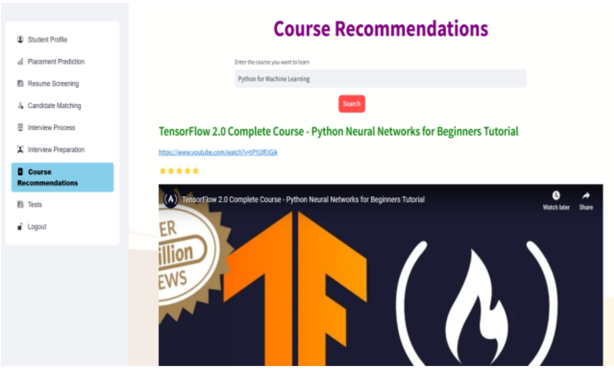

Fig.8 Course Recommendation System using YouTube API

Fig.9 MCQ's Generation system of various areas

In order to efficiently rank instructional films, the course recommendation engine (as shown in Fig.8) analyzes sentiment scores from thousands of real-time YouTube comments. In addition to their positive rating, sentiment assessment disintegration and engagement data (likes, views and comments) candidates are given a list of the top-ranked courses. Candidates can make well-informed judgments on which courses to take by using the Streamlit dashboard which shows graphical insights such word clouds of frequently used both positive and negative aspects in course reviews. The system's real-time functionality guarantees that only top-notch learning materials are recommended and that out-of-date or poorly evaluated courses are eliminated. The quiz module provides real-time grading and insights while assessing candidate's abilities in a variety of topics. Candidates get a domain-wise assessment of performance that highlights their strengths and shortcomings after finishing the question. The system produces heatmaps, pie charts and bar charts that show the candidate's performance in each ability category. The algorithm automatically recommends pertinent learning resources to assist the candidate improve if their score in a given domain is poor. By continuously improving their knowledge candidates are more equipped for interviews and placements thanks to this adaptive feedback mechanism. All modules are consolidated into the real-time Streamlit interface which enables dynamic result analysis for recruiters and candidates. In one location candidates may check their quiz scores (as shown in Fig.9), suggested courses, interview preparation insights, placement predictions and resume screening findings. Based on their career objectives users can evaluate various job roles, skill gaps and interview techniques thanks to the system's dynamic filters. Recruiters may make more informed and efficient hiring decisions by using the system's automatic application ranking, skill-based resume sorting and interview preparedness assessments.

CONCLUSION:

In order to improve student achievement, job recruitment insights and tailored recommendations the Intelligent Placement and Job Development Platform combines AI, NLP and deep learning methodologies. The system guarantees precise and data-driven decision-making by utilizing models like Random Forest (99.87%) for placement prediction, BERT for job matching and sentiment analysis (96.7%), and Logistic Regression (95%) and KNN (89%) for application screening. Candidates can access real-time resume evaluation, skill-based assessing, interview preparation tips, placement projections, personalized course suggestions and adaptive quizzes using the platform's Streamlit-based interface. While the applicant's matching system matches resumes with job postings and provides suggestions for improvement using natural language processing (NLP) the resume filtering module assesses domain-specific competencies. The placement prediction algorithm predicts applicability based on educational and extra data while the interview preparations tool evaluates responses and recommends learning materials. In order to guarantee access to top-notch instructional materials, the YouTube-based course suggestion engine also uses sentiment analysis to score learning videos. In order to assist applicants in strengthening their areas of weakness the quiz module assesses technical proficiency and offers recommendations for adaptive learning. All things considered our AI-powered technology guarantees that recruiters can effectively identify the best candidates, improves candidate preparedness and expedites the hiring process. This platform drastically improves placement results for students and job seekers by transforming the conventional recruitment and career development procedure into a more intelligent, automated and based on data experience through the combination of real-time analytics, modeling, prediction and personalized learning pathways.

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