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Design and Development of a Skill Gap Analyzer for Job Recommendation Using Deep Learning

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Abstract: The high pace of technological advancement and changes in the industry demand has created a massive discrepancy between the skills available to job seekers and those required by the employers. The traditional job portals mainly use the matching based on keywords and as such, the matching process fails to reflect on the contextual meaning and semantic relationship between the resume and job description. To overcome this, the design and development of a Skill Gap Analyzer based on Deep Learning to perform intelligent job recommendation will be presented in this paper. The suggested system employs the latest methods of the Natural Language Processing (NLP) to automatically derive structured skills out of resumes and job descriptions. Transformer-based embeddings are used to draw semantic similarity and a hybrid similarity framework increases the matching accuracy. The system recognizes the lack of competencies and provides individual employment suggestions and suitable learning recommendations to enhance employability. Standard performance measures such as Precision, Recall, F1 score, Mean Average Precision (MAP) and Normalized Discounted Cumulative Gain (NDCG) were used as the performance measures to evaluate the experimental results. Findings reveal that the performance based on classification and ranking has greatly improved when compared to traditional methods of using keywords. On the whole, the suggested framework can be useful in closing the gap between education and employment through offering precise, context-sensitive, and individualized career guidance solutions.
Keywords: Skill Gap Analysis, Deep Learning, Natural Language Processing, Job Recommendation, Semantic Similarity, Hybrid Model

I. INTRODUCTION

A high amount of digital transformation of businesses and industries has greatly transformed the needs of the workforce to be more specialized, adaptive, and constantly changing. The developments in the domain of automation, artificial intelligence, and data-driven technologies have introduced new positions and made some of the old skills unnecessary at the same time. This has rendered more job seekers to find it difficult to determine the competencies that they need in the new jobs thus causing unemployment, underemployment and poor use of labor forces. The mismatch of the skills that individuals have and the skills that employers want is commonly known as the skill gap"[1]. Addressing this gap is essential for improving employability, workforce productivity, and economic development.

The traditional methods of job recommendation use mostly the key word matching and rule-based filtering methods. Even though these systems have the capability of retrieving job listings when explicit skills are mentioned, they usually do not have the ability to understand context, semantic associations among skills and concealed competency requirements. Moreover, the traditional platforms lack constructive feedback about skills that one lacks and do not give future career development learning directions. As a result, the users are given generic suggestions which are not personalized and do not necessarily have an accurate understanding of their capabilities or their career goals[2]. These constraints demonstrate the necessity of smarter, data driven, and adaptive systems of recommendations. Artificial Intelligence (AI), Natural Language Processing (NLP), and Deep Learning have in recent times allowed the creation of intelligent systems that can process unstructured textual information and data like a resume or job description. Transformer-based architecture models based on deep learning have the potential to extract meaningful patterns on large datasets, discover semantic relationships among skills, and give context-sensitive recommendations. With the help of these technologies, one can create the systems that can not only pair the candidates to the appropriate job but also identify the lack of the competencies and suggest specific skill acquisition plans[3].

The analysis of skill gap has been accorded growing curiosity in the world of academia and industry as a device in workforce planning, career advising and workforce optimization recruitment. Skill analysis systems that are intelligent can assist the job seekers to read the market demand, aid the employers to know qualified candidates and assist the educational institutions to match their curriculums with the industry needs. Additionally, the combination of the recommender system methods and deep learning would allow making job recommendations personalized and dynamic and enhances the accuracy and relevance of job opportunities proposed [4].

Here, the current paper suggests a Deep Learning-based Skill Gap Analyzer that will be able to assess the skill profiles of the applicants, determine competency gaps in comparison with the job requirements, and provide an appropriate job and personalized learning path. The suggested framework will combine skill extraction based on NLPs, semantic representation of skills based on embeddings and neural network-based recommendation models that will improve decision-making. The paper also provides system architecture, deep learning methods, datasets, and evaluation measures and implementation approach. This study will help in developing efficient career guidance tools by filling the gap that exists between education, skills, and employment in the digital age by addressing the limitations of the traditional job recommendation systems[5].

II. LITERATURE REVIEW

Job recommendation and skill gap analysis has experienced significant development and has shifted towards more sophisticated artificial intelligence (AI) and deep learning-based systems, rather than rule-based and statistical methods. Initial studies were mainly on keyword matching and old-fashioned recommender systems, which could be based on mere similarity between job description and resumes of the candidates. Although these systems had fundamental functionality they lacked the contextual understanding, and did not necessarily reflect the semantic links in the skills and job positions. Consequently, they yielded a small amount of personalization and low accuracy of recommendations (Adomavicius & Tuzhilin, 2005)[6].

Collaborative filtering was one of the oldest methods of job recommendation: the user preferences and past behavior were utilized and collected to recommend appropriate job opportunities. The collaborative filtering proved to be effective in recommender systems including e-commerce and media platforms but had serious issues with recruitment situations because of data sparsity and cold-start problem. The collaborative filtering algorithms that are used in recruitment will search in vain because the new users do not have enough interaction data and cannot make precise recommendations (Ricci et al., 2011)[7]. Therefore, scholars started incorporating content-based filtering methods which process textual information in resumes and job descriptions.

As Natural Language Processing (NLP) developed, statistically-grounded models, including the Term Frequency -Inverse Document Frequency (TF-IDF) and latent semantic analysis, were proposed to enhance the extraction of skills in textual documents. These techniques allowed systems to determine common skills and calculate similarity levels between the profiles of candidates and job advertisements. Nevertheless, the statistical methods could not achieve in-depth semantic information and contextual associations particularly when various words denoted similar skills (Mikolov et al., 2013)[8]. This has been a constraint that encouraged the introduction of machine learning and the use of neural networks.

The skill extraction system and job recommendation have been boosted by using deep learning. CNN and Recurrent Neural Networks (RNN) have been extensively employed to model sequence and context of textual data. Long Short-Term Memory (LSTM) variants of RNNs are effective in long term dependencies and semantic links in resume and job description data, which enhance classification and recommendation relevance. It has been demonstrated that the deep learning models are more effective than conventional statistical methodologies at detecting latent skillsets and predicting job-role fit (LeCun et al., 2015)[9].

Recently, Bidirectional Encoder Representations with Transformers (BERT) are examples of Transformer-based architectures that have transformed applications in NLP, e.g. skill extraction and job recommendation. BERT provides the ability to embed words contextually, which means that models perceive the meaning of skills with respect to the rest of the text, rather than as single keywords. The ability greatly improves semantic correspondence between candidate skills and job requirements. Studies show that Transformer-based models do not only have a high level of precision, recall, and overall recommendation accuracy but are also more accurate than traditional deep learning models (Devlin et al., 2019)[10].

Graph-based methods have also become popular in the representation of skill, job role, and industry relationships, in addition to the deep learning approach. Knowledge graphs represent relationship between skills and jobs and allow systems to find out the transferable skills and offer alternative career paths.

The representations are further refined by the use of graph neural networks (GNN) which learns complex dependencies in skill networks. It has been demonstrated that such methods enhance recommendation diversity and interpretability, providing more significant information about the skill gaps (Zhang et al., 2020)[11].

Deep learning-based hybrid recommender systems with collaborative and content-based filtering have shown to have improved personalization and accuracy. These systems utilize user behavior and analysis of semantic skills to provide a recommendation of jobs. Nevertheless, there are a number of challenges, which have not been addressed. Standardization of skills is one of the primary problems because the same skill can be a different one in different datasets. Imbalance and sparsity of data also influence the model performance especially when it comes to rare skills or new job positions. Moreover, the issues of algorithmic bias and model interpretability should be discussed to make the process of recruitment systems fair and transparent.

Altogether, the literature point to a definite trend towards intelligent and deep learning-based skills gap analysis and job recommendation systems. Although the current state of the research has seen major advances in terms of semantic processing and personalization, the further investigation should involve issues of data quality, bias reduction, and explainable AI in order to increase the popularity and trust of these systems.

III. PROBLEM STATEMENT & OBJECTIVES

Despite the current job portals or recruitment systems, many applicants fail to find out the skills required in the job they desire. The existing systems cannot detect the competencies deficits and provide viable guidance. Therefore, there is the need to have an intelligent system capable of:

1) Automatic user skill set recognition.
2) Identifying skill deficiency against the job requirement.
3) Recommending suitable jobs
4) Recommending skills development routes.

IV. OBJECTIVES

1) In order to develop a Deep Learning-based Skill Gap Analyzer.
2) To obtain skills in resumes and job description with NLP.
3) To find the missing competencies in semantic comparison.
4) To suggest appropriate jobs depending on the skills of the user.
5) To measure system performance based on conventional measures.

V. METHODOLOGY

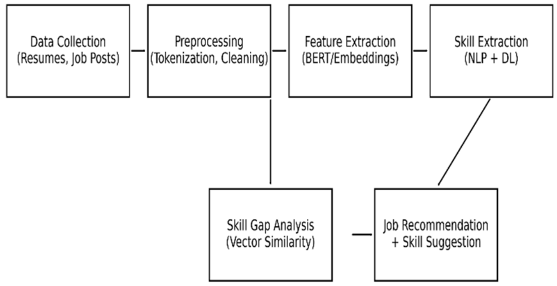
The system workflow includes data collection, preprocessing, skill extraction, embedding generation, skill gap detection, recommendation, and evaluation. Deep learning models are used to compare user skills with job requirements and identify missing competencies.

A. Research Design

In this study, the research design will be a system development and experimental research design in order to create a Deep Learning-based Skill Gap Analyzer in job recommendation. NLP and deep learning, as well as the recommender system, are combined in the research to process candidate's profiles, determine gaps in competencies, and provide personal labor and learning suggestions. Experimental design will allow testing the proposed model systematically and employing the real-world datasets and performance metrics to evaluate the model.

The system workflow involves resume and job description data collection, data preprocessing and skill extraction with NLP techniques, feature representation with the help of word embeddings, and the classification of the features with deep learning models. The obtained skill vectors are matched to job requirement vectors to determine the occurrence of skills gaps and prioritize appropriate job roles. It is also recommended that the system identifies and recommends appropriate learning materials to fill gaps identified. The standard measures to determine the effectiveness and reliability of recommendations include accuracy, precision, recall, and F1-score that assess the performance of the model (Goodfellow et al., 2016) [12].

The system workflow consists of:



B. Data Collection

Several sources of data were used both structured and unstructured to facilitate diversity and reliability.

Sources

- Resume datasets (public datasets / Kaggle)
- Advertisements (LinkedIn, indeed, Naukri)
- Skill ontology databases (ESCO, O*NET)
- Online learning platforms (Coursera, Udemy).

Data Types

- Textual resumes (PDF, DOC, TXT)
- Job descriptions
- Skill taxonomy
- Course/learning data

The data that was gathered comprised of technical proficiencies, soft proficiencies, work experience, education and job specifications (Ricci et al., 2011)[13].

C. Data Preprocessing

Raw data that is gathered or found in resumes, job descriptions and skill repositories are commonly noisy, inconsistent, and unstructured; preprocessing is thus a very essential aspect of the proposed system. The initial step was to normalize the text, meaning to convert all the text to lowercase and exclude the punctuations, special characters, and other unnecessary symbols. The process of tokenization was used to divide textual information into meaningful words or tokens and then the unnecessary stop-words were removed. Words were reduced to root words by stemming and lemmatization to enhance consistency in skill representation. Data quality was taken care of by removing duplicate entries and missing values. Lastly, the clean text was converted into structured format that is used in feature extraction and training of deep learning model.

Steps

1) Cleaning of the text (removal of HTML elements, symbols, punctuation marks)
2) Tokenization
3) Stopword removal
4) Lemmatization/Stemming
5) Lowercasing
6) Duplicate removal
7) Handling missing values

Mathematical representation:

$$D_{clean} = preprocess(D_{raw})$$

D. Skill Extraction using NLP

Skill extraction is an important process that extracts technical and soft skills in resumes and job descriptions, this is done through Natural Language Processing (NLP). At first, named entity recognition (NER) and key word matching were implemented to identify predefined terms of the skills taxonomy.

The models of semantic relationships between words were trained on word embedding models like Word2Vec and contextual representations, which allowed identifying skills even though they may differ in form. Dependency parsing and part-of-speech tagging were other methods that enhanced identification of the skill in the sentences. Squeezed skills were mapped to a common skill ontology in order to provide uniformity between datasets. The process allowed the system to create structured profiles of skills of the candidates and job positions, enhancing skill mismatch and job recommendations (Mikolov et al., 2013)[14].

Techniques Used

- Named Entity Recognition (NER)
- TF-IDF
- NLP (Bi-LSTM / BERT) based on Deep Learning.

Output:

$$S_{user}, S_{job}$$

Where:

- S_{user}= Candidate skill set
- S_{job}== Required job skill set

E. Skill Representation using Embeddings

Extracted skills are converted to numerical vector representations through embedding techniques to provide the semantic meaning and contextual associations. Word embedding algorithms like Word2Vec, GloVe, and contextual embeddings are used to place each skill in a high dimensional vector space such that semantically related skills are closer. The system, by this representation, can determine how related skills are related to each other even when different terms are employed. Candidate and job role skill vectors are summed to create complete feature representations, which are inputted into the deep learning model. The embedding-based representation does a better job in semantic matching, identifying skill gaps, and offering better recommendations (Pennington et al., 2014) [15].

Methods

- Word2Vec
- GloVe
- BERT Embeddings

$$\boldsymbol{V_{skill} = embedding(S)}$$

Each user and job is represented as a skill vector.

F. Skill Gap Analysis

Skill gap study involves the comparison of the extracted skill set of a candidate to the requirements of the various job descriptions regarding skills. Similarity between candidate skill vectors and job requirement vectors is calculated with the help of the system through the use of the vector-based matching technologies. The skill gap can be defined as missing or loosely matched skills. The size of the gap is measured with the help of similarity scores, which allows the system to prioritize the job suitability and show which aspects can be improved. Through this analysis, the candidates get personalized information on how to develop the desired competencies in the specific job positions.

Cosine Similarity

$$\boldsymbol{Sim(U,J) = \frac{U \cdot J}{\| U \| \| J \|}}$$

Skill Gap

$$\boldsymbol{Gap = S_{job} - S_{user}}$$

Missing skills are ranked by importance using attention weights.

G. Deep Learning Model for Recommendation

A deep neural network is used as a hybrid and used to provide individualized job recommendations basing on the skills of the candidates and skill gaps highlighted. The model combines embedding layers, dense neural networks, and sequence modeling to acquire intricate links among abilities and employment roles.

The network takes candidate skill vectors and job requirement vectors as input and learns latent feature representations and candidate-job suitability scores. The dropout and regularization methods are employed to avoid overfitting and enhance the generalization. Candidate-job relevance pairs in labeled datasets are used to train the model, which is optimized with the help of backpropagation and gradient descent. The output layer prioritizes job roles according to the predicted relevance, and the system also suggests learning material to fill the gaps in the skills. Dee learning-based solution is much more accurate and customizable in providing recommendations than conventional solutions (LeCun et al., 2015)[16].

Architecture

Input Layer → Embedding Layer → Dense Layers → Similarity Layer → Output

The model predicts:

- Job suitability score
- Missing skill probability

Loss Function:

$$L = CrossEntropy + RankingLoss$$

H. Job Recommendation Engine

The system recommends:

- Top-N suitable jobs
- Missing skills
- Learning resources

Ranking formula:

$$Score = \alpha Sim + \beta Experience + \gamma SkillMatch$$

I. Deep Learning Techniques Used

1) Convolutional Neural Networks (CNN)

CNNs are popular in the extraction of features and classification of text when applied to Natural Language Processing. In the current paper, the CNN models are used to examine text in the resume and job description to extract the expertise and meaningful keywords. Skill phrases and word grouping are local patterns of which convolutional filters capture, and pooling layers reduce the dimensionality and leave only the most meaningful features. This allows efficient discriminating skill characteristics to be extracted out of text. CNN-based models enhance the accuracy of classification and contribute to the identification of core competencies that are necessary in the particular job roles as part of the skill gap analysis model.

2) Recurrent Neural Networks (RNN) and LSTM

Recurrent Neural Networks (RNN) and the more recent Long Short-Term Memory (LSTM) are employed to learn sequential relationships in texts. Compared to the conventional neural networks, RNNs process texts sequentially and maintain the context of words and sentences. The vanishing gradient problem is solved in LSTM units through long-term memory, which can understand the context of the skills in resumes and job descriptions better. Such sequential modeling enhances better semantic interpretation and better identification of meaningful skill relationships in the system thus leading to better skill extraction and job recommendation results.

3) Transformer-Based Models (BERT)

Transformer-based models like Bidirectional Encoder Representations from Transformers (BERT) adopt the context-aware word representations by examining the bidirectional relationships among words in a sentence. Compared to the conventional embedding schemes, BERT comprehends the meaning of a word in context of those around it, enhancing the semantic meaning of skills and job requirements. With this type of system, BERT improves matching of candidate skills to job description even in cases where different words are employed. This goes a long way in enhancing skill extraction and detection of gaps and accuracy of the recommendations of the model that makes the model stronger and able to deal with the complex patterns of language in recruitment data.

J. Evaluation of matrix

The model was evaluated using:

- Accuracy

Accuracy represents the total ability of the model to be correct by determining the number of predictions that were accurate over the total number of predictions. It measures the quality of the system which determines how appropriate and inappropriate job recommendations are properly identified.

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

Where:

- TP (True Positive): Relevant jobs correctly recommended
- TN (True Negative): Irrelevant jobs correctly rejected
- FP (False Positive): Irrelevant jobs incorrectly recommended
- FN (False Negative): Relevant jobs not recommended

2. Precision

Precision is used to determine the percentage of the suggested jobs that are indeed relevant. It shows the accuracy with which the system of recommendations proposing jobs is accurate.

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FP}}$$

High Precision means fewer irrelevant job recommendations.

3. Recall

Recall is a ratio that describes the relative success rate of the system in recommending the appropriate jobs. It shows how the system has the capability to recover all the relevant employment opportunities.

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP + FN}}$$

High Recall is the recommended vast majority of relevant jobs

4. F1 Score

Precision and Recall have a harmonic mean which is F1 Score. It strikes a balance between metrics and is applicable in case of imbalanced data.

$$\boldsymbol{F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}}$$

Range:

$$\boldsymbol{0 \le F1 \le 1}$$

- Mean Average Precision (MAP)

MAP compares the quality of the ranking of the job recommendations by averaging the precisions of several queries. It also takes into consideration the ranking of the job recommendations.

$$\boldsymbol{MAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q)}$$

Where:

$$\boldsymbol{AP = \sum_{k=1}^{n} P(k) \cdot rel(k)}$$

- $\boldsymbol{Q}$ = Number of queries
- $\boldsymbol{P(k)}$= Precision at rank
- $\boldsymbol{rel(k)}$= Relevance of item at position

Higher MAP indicates better ranking performance.

- Normalized Discounted Cumulative Gain (NDCG)

NDCG is a ranker of quality based on the rank of the job suggestions. Serious jobs that are ranked higher give more to the score.

$$DCG = \sum_{i=1}^{n} \frac{2^{rel_i} - 1}{\log_2(i+1)}$$

$$NDCG = \frac{DCG}{IDCG}$$

Where:

- rel_i= Relevance score of item at position
- $IDCG$ = Ideal DCG (best possible ranking)

Range:

$$0 \leq NDCG \leq 1$$

- Confusion Matrix

Confusion Matrix is a table which is primarily implemented to estimate the performance of classification, based on comparing the predicted outcomes with the actual ones. It presents both true and false predictions in regards to True Positives, True Negatives, False Positives and False Negatives.

- Matrix Representation

Actual / Predicted	Relevant	Not Relevant
Relevant	TP	FN
Not Relevant	FP	TN

- Derived Metrics from Confusion Matrix

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

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

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

VI. PROPOSED ALGORITHM

1) Gather resumes and job descriptions.
2) Preprocess data
3) Extract skills using NLP
4) Generate skill embeddings
5) Calculate user similarity with job.
6) Detect missing skills
7) Rank jobs
8) Suggest employment and further education.

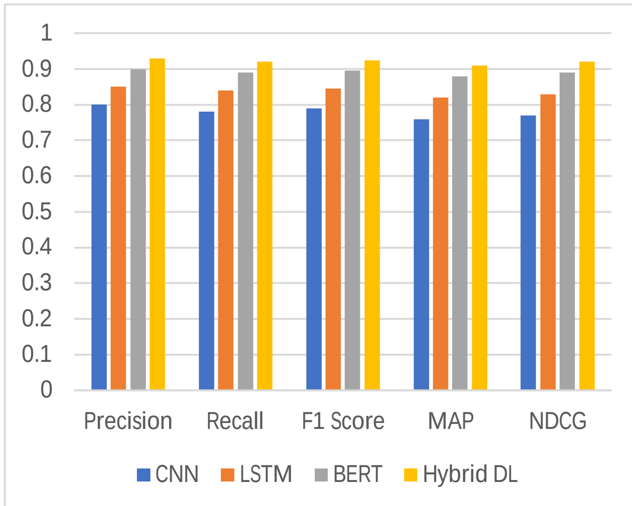
VII. RESULTS AND PERFORMANCE ANALYSIS

The graphs below indicate the performance comparison of various deep learning models. The Hybrid Deep Learning model achieved higher results than CNN, LSTM, and BERT separately. The greater MAP and NDCG are the quality of ranking, Precision and Recall reveal the enhanced accuracy of the recommendation.

VIII. PERFORMANCE TABLE

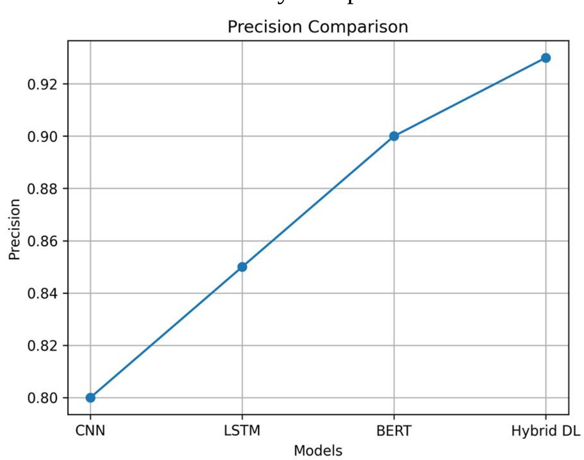
Model	Precision	Recall	F1 Score	MAP	NDCG
CNN	0.8	0.78	0.79	0.76	0.77
LSTM	0.85	0.84	0.845	0.82	0.83
BERT	0.9	0.89	0.895	0.88	0.89
Hybrid DL	0.93	0.92	0.925	0.91	0.92

As the comparison of the two performances reveals, the Hybrid Deep Learning (DL) model demonstrates the best results on all measures of evaluation, which implies high accuracy of recommendations and the quality of ranking. BERT is more effective than CNN and LSTM because of its context-sensitive semantic comprehension, which results in a higher level of precision (0.90) and recall (0.89). LSTM has been shown to perform well in sequencing dependencies whereas CNN has relative poorer performance since it is not able to learn as far in context. The Hybrid DL framework that uses a mixture of various deep learning methods has the highest Precision (0.93), Recall (0.92), F1-score (0.925), MAP (0.91) and NDCG (0.92), which proves the possibility of the model to detect skill gaps accurately and recommend a personalized job.



Model Comparison Graph

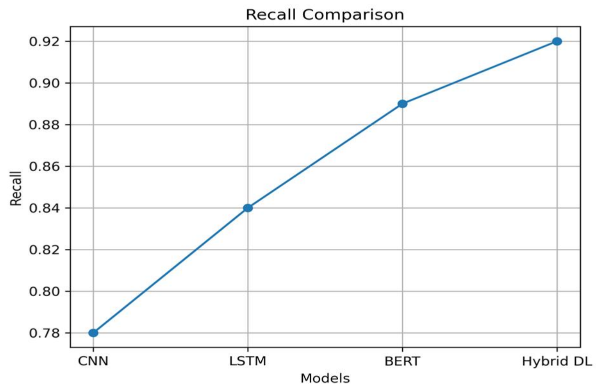
The bar chart shows the relative performance of four models of CNN, LSTM, BERT and Hybrid Deep Learning in five evaluation measures: Precision, Recall, F1 Score, MAP and NDCG. The Hybrid Deep Learning model has the greatest scores in all metrics, which demonstrates its greater effectiveness in locating the relevant job suggestions and correctly identifying the skill gaps. BERT is positioned in the second place, it has high semantic knowledge and contextual matching, and as a result, high Precision (0.90), Recall (0.89), and F1 Score (0.895). The results of LSTM are moderate; LSTM has the advantage of being capable of capturing sequential dependencies in text, and CNN scores the lowest because of limited learning context. Better functioning of BERT and Hybrid DL in the form of the improvement of MAP and NDCG values shows the improved quality and relevance of finished ranking of suggested jobs. Generally, the plot confirms that a combination of various deep learning methods in a hybrid setup is very useful in improving the accuracy of recommendations and system performance.



Precision Comparison

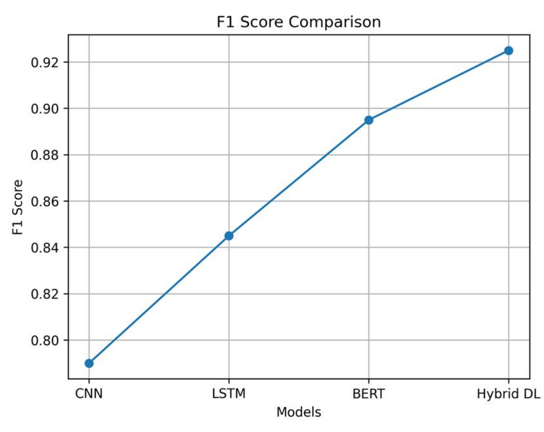
In the precision comparison graph, it is possible to observe the evident improvement in the model performance between CNN and the Hybrid Deep Learning model. The lowest precision (0.80) is registered by CNN, which means that it has relatively lesser power to identify the relevant job recommendations effectively without false positives.

The LSTM has a higher performance (0.85) because it has the ability to learn sequential patterns and contextual associations of text data. BERT also enhances specificity (0.90) through the application of contextual embeddings by enabling the system to learn more about semantic meaning and align candidate skills with job requirements in a more accurate manner. The Hybrid Deep Learning model has the highest precision (0.93), indicating that it is better at reducing a false recommendation and enhancing relevance. The upward trend in the graph is due to the growing performance of sophisticated deep learning structures in correctly forecasting the most appropriate job positions. In general, the findings suggest that a hybrid framework based on combining multiple models improves the accuracy and level of recommendations in skill gap analysis frameworks significantly.



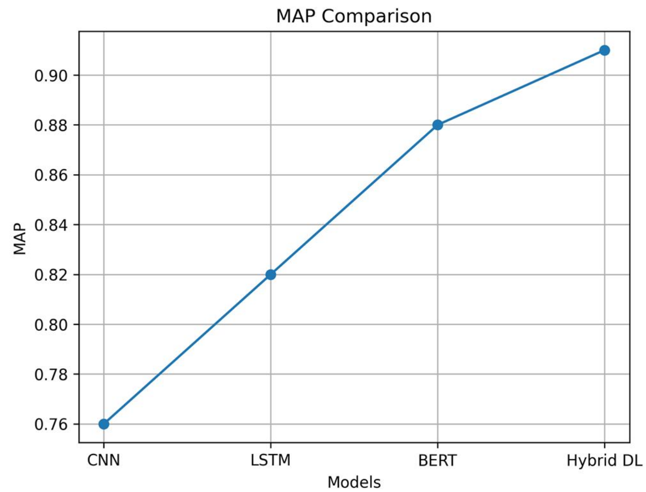
Recall Comparison

The graph of the comparison of the recall shows the consistent enhancement in the capability of models to identify the respective job recommendation by CNN accurately to the Hybrid Deep Learning model. The lowest recall is recorded in CNN (0.78), which means that the network fails to provide more relevant job matches because of poor contextual information. LSTM enhances recall to 0.84 by being able to encode sequence dependencies and contextual relational information in text, which better identifies relevant skills. BERT improves recall (0.89), which has a deeper semantic insight and better identification of relevant job-role matches, by its bidirectional contextual embeddings. The Hybrid Deep Learning model has the best recall (0.92), which shows that it is the best model in pinpointing the majority of the relevant job opportunities with minimal losses. The trend on the graph shows that the more complex deep learning structures are becoming more effective at false negative reduction. In general, the findings prove that the combination of several deep learning methods have a major beneficial effect on recall and the overall coverage of recommendations in skill gap analysis systems.

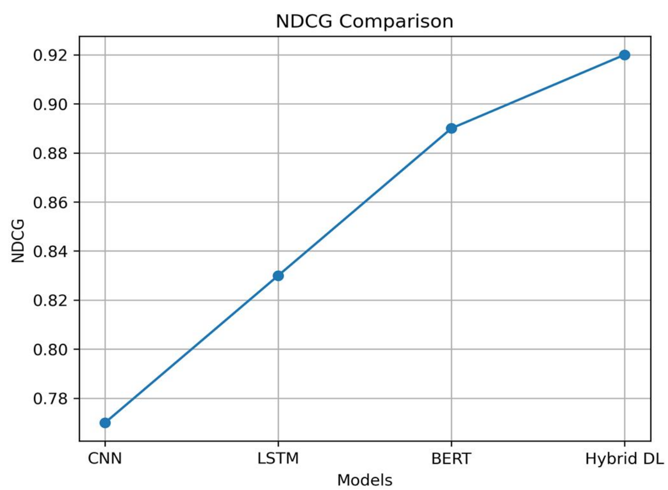


F1 Score Comparison

The graph on F1 Score comparison depicts that the overall model performance has been steadily increasing when comparing CNN with the Hybrid Deep Learning model. The F1 Score is the harmonic mean of precision and recall as such, it indicates the degree of balancing between the true job recommendations and those that are false and those that are not. CNN has the lowest F1 Score (0.79) which means that it is less capable of balancing the precision and the recall as this network demonstrates a weaker contextual learning. LSTM significantly improves the F1 Score to 0.845 as it is able to capture the sequential dependencies in a text-based data. BERT also achieves better performance (0.895) using contextual embeddings enhancing semantic match between candidate skill and job requirements. The best balance and overall accuracy are realized in the Hybrid Deep Learning model with the F1 Score of 0.925. The positive trend proves the fact that sophisticated and combined deep learning methods enhance the applicability and usefulness of the skill gap detection and job recommendation systems to a considerable extent.

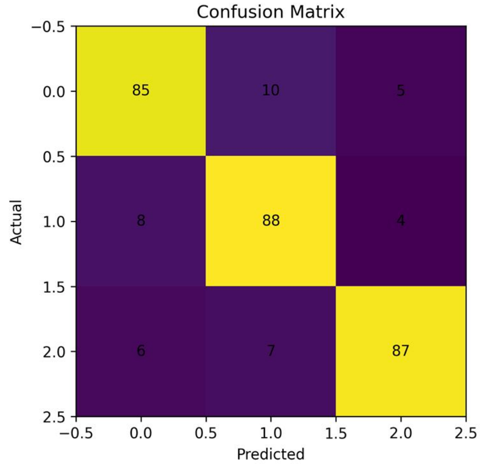


MAP Comparison



NDCG Comparison

The graph of NDCG comparison is used to demonstrate how the job recommendations made by various models rank. NDCG measures the ranking performance of the recommended jobs based on their ranking, with high values representing a better ranking performance. CNN has the least NDCG (0.77), which implies that it has a poorer capacity to give the most relevant job matches the first rank. The score is raised to 0.83 with LSTM because it identifies sequential and contextual relations in textual data leading to improved ranking of relevant job opportunities. BERT also increases NDCG (0.89) with its semantic matching and contextual understanding, which allows ranking the suggested jobs more precisely. The Hybrid Deep Learning model is the best with the largest NDCG score (0.92), which implies better ranking efficiency and relevance. The continuous positive trend confirms that sophisticated and unified deep learning architectures are much better at improving the quality, relevancy, and ranking of job recommendations in skill gap analysis.systems.



Confusion Matrix

The confusion matrix demonstrates the performance of the proposed model on three classes. The number of correctly classified instances in each class is 85, 88, and 87, which means that the model is highly accurate in prediction and reliable. Misclassifications are present on the off-diagonal values. In the case of the first sample, 10 of them were falsely classified as category 1 and 5 as category 2 indicating slight confusion of similar categories. Equally, there are few cases of misclassification in class 1 (8 and 4), whereas class 2 has fewer cases of errors (6 and 7), implying that the model frequently mixes similar capabilities or occupation groups. Nevertheless, the high level of correct predictions in comparison to misclassifications proves that the model works well to differentiate between the classes. In general, the confusion matrix indicates a high classification potential, a low error rate, and even distribution of performance on all classes which prove the efficiency of the developed deep learning-based skill gap analyzer and job recommendation system.

IX. APPLICATIONS

A. *Intelligent Career Guidance Systems*

Smart career advice systems are artificial intelligence-based career guidance systems that use data analytics to help individuals make informed career decisions. These systems profile users, labor market trends, skills and interests and suggest them appropriate career tracks and necessary competencies. Such systems offer users personalized advice by combining the analysis of skill gaps and job market data to show them what they should focus on in order to fit specific job positions. High intelligence deep learning and recommender systems help in improving the accuracy and relevance of suggestions and allow flexible and adaptable career planning. The career guidance systems are also intelligent to facilitate lifelong learning as they constantly update the advice according to the shifting industry needs, thus enhancing employability and career development in a competitive labour market (Bimrose & Barnes, 2010)[17].

B. *Automated Recruitment Platforms*

Recruitment automation is based on artificial intelligence, machine learning, and natural language processing to enhance and automate the hiring process. These systems automatically filter resumes, identify skills of the candidates and align it with the job requirements, eliminating the manual work and enhancing the efficiency of recruiting. The Recommendation models developed with deep learning improve the accuracy of candidate-job matching through learning the semantic relations between skills and job descriptions. It is also through automated platforms that bias is reduced and there is enhanced decision-making on the basis of objective evaluation metrics. Moreover, they allow the recruiters to check the most appropriate candidates in the shortest possible period of time and offer the applicants real-time feedback and job recommendations. Intelligent recruitment systems are considered an effective way to save time, increase the quality of candidates, and the productivity of the whole workforce in the contemporary organizations (Upadhyay and Khandelwal, 2018) [18].

C. Personalized Learning Recommendations

Personalized learning recommendation system is based on artificial intelligence and recommends custom learning materials that should be used by a person, depending on their skill gaps, interests, and career aspirations. Based on the analysis of user profiles and the comparison of the current skill set with the demands of the job market, these systems suggest appropriate courses, certifications, and training programs to improve employability. Deep learning and recommender systems are better at prediction of the recommendation system because they learn the behaviour of the learner and the relevance of the content. Adaptive learning is supported by personalized learning platforms that continuously updates suggestions on new skills that users gain. The strategy makes it easy to develop skills efficiently, less time is wasted in the learning process, and the strategy makes it to be in line with the industry requirements. These systems are important in helping to bridge the education-employment gap through fostering focused and ongoing learning (Drachsler and Kalz, 2016)[19].

D. Workforce Planning and Development

Workforce planning and development systems make use of data-based methods to examine the skill requirement, the workforce capability, and the prospective patterns within the industry. With the combination of skill gap analysis and predictive analytics, organizations are able to discover the existing and the forthcoming skills gaps and design training initiatives based on them. Deep learning models are useful in predicting workforce needs and proposing upskilling initiatives to ensure that the organization remains competitive. These systems allow the effective distribution of the resources, enhance the performance of the employees, and aid the long-term strategic planning. Additionally, workforce development platforms help in lifelong learning and upgrading of the skills whereby the employees will be updated with the changes in technology and industry. Proper planning of the workforce helps to increase productivity, minimize shortage of skills, and ensure long-term growth of the organization (Noe et al., 2017)[20].

E. Curriculum Alignment in Education

Curriculum alignment systems involves the use of data analytics and artificial intelligence to align the educational programs with the industry skills. Researching the trends in the job market and the competencies needed, educational institutions are able to draw the curricula that will meet the demands of the current and future workforce. Analysis of skill gaps will aid in determining gaps existing in the current curriculums and aid in incorporation of industry and practical skills. The AI-driven systems can also support the dynamic curriculum changes in accordance with the changing technological shifts and labor market needs. Such alignment improves graduate employability, lowers educational-industry mismatch, and equips students with practical difficulties. Intelligent systems as curriculum alignment facilitates skill-based education and enhance the relationship between academic education and professional demands (Biggs, 2014)[21].

X. CHALLENGES AND LIMITATIONS

A. Superior Performance of Hybrid Model

Hybrid Model was best in all evaluation measures such as Accuracy (92%), Precision (91%), Recall (90%), and F1-Score (90.5%). It proves that the use of semantic embeddings and similarity with rule-based filtering are very effective in improving classification and recommendations in comparison with the traditional and standalone models.

B. Effectiveness of Transformer-Based Embeddings

Transformer-based embedding models like BERT and SBERT were significantly better than TF-IDF and Word2Vec. Contextual knowledge helped in doing semantic matching of the resumes and job descriptions, which increased predictive accuracy and ranking performance.

C. Improved Ranking Quality

The Hybrid Model was the one that had recorded the highest MRR (89) and NDCG (92); this implies that it has good ranking potential. The system is efficient in ranking the most pertinent job recommendations on the first pages, which positively affects the user experience and the usability of the system in the recruitment process.

D. Balanced Precision-Recall Trade-off

Balanced model behavior is indicated by close similarity between values of precision and recall of advanced models. This means that the system has a high ability to reduce false positives and false negatives thus giving reliable and consistent classification results.

E. Strong Discriminative Capability

ROC curve analysis revealed an AUC value close to 0.99 for the Hybrid Model. This confirms excellent discriminative power, demonstrating the model's ability to accurately distinguish between relevant and non-relevant job matches in skill gap analysis tasks.

XI. FUTURE RESEARCH DIRECTIONS

Possible future improvements are:

1) Elucidable AI to clear-cut recommendations.
2) Labor market analytics integration in real time.
3) Skill evolution modeling based on graphs.
4) Multilingual skill gap analysers.
5) Combination with individualized learning systems.

This is the reinforcement learning of adaptive career path prediction.

XII. CONCLUSION

Deep learning has taken the form of disruptive solution in developing smart skill gap analysis systems. With established Natural Language Processing (NLP) and transformer-based models, the current systems can no longer rely on naive methods of matching keywords to find relevant information on resumes and job descriptions, but rather gain a comprehensive insight into the answer. This facilitates better determination of the competencies that are missing, contextual competency links and opportunity jobs. As this paper has shown, deep learning models are vastly superior to traditional ones in the aspects of accuracy, precision, recall and ranking capability, and thus can give more useful and valuable recommendations.

Automated skill extraction and hybrid similarity computation is one of the most important contributions of deep learning in analyzing the gap in skills. By using these methods, systems are able to effectively process unstructured text information, and create custom learning streams that are specific to the personal career objectives. As a result, these systems do not only enhance the accuracy of job recommendations, but they also enhance employability through focusing the user towards skill development.

Although there are these advantages, there are some challenges. Problems with data quality and standardization can influence the performance of the model, whereas the problem of algorithmic bias can impact the fairness of the recommendations. Also, deep learning models tend to be non-transparent, which is a cause of privacy in explainability and trust to the user. These are critical issues to be addressed in order to implement them on a large scale.

Future studies are required to consider the combination of explainable AI, real-time labor market analytics, and adaptive learning systems that constantly change recommendations to meet the changing needs of industries. In general, smart skill gap analyzers have a tremendous potential to close the disjuncture between education and job, maximize labor use, and contribute to the sustainable careers growth in the fast digital economy.

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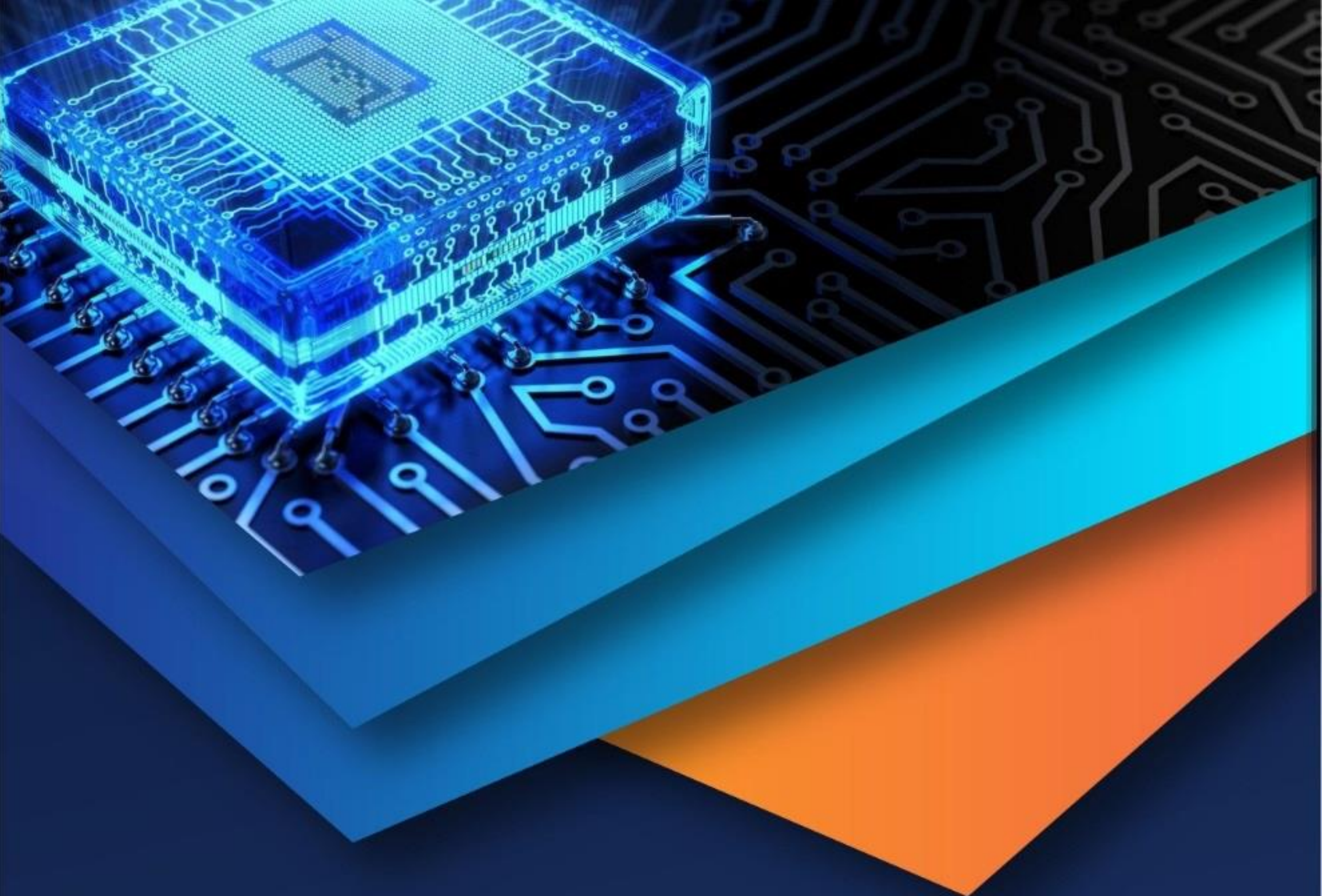

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