

Improving job matching with deep learning-based hyper-personalization

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ABSTRACT

This study introduces a novel approach to streamline the recruitment process, benefiting both employers and job seekers. It leverages real-time personality-based classification to match candidates with the most suitable roles in a scalable and precise manner. This is achieved through machine learning-driven hyper-personalization, employing deep learning models to create a predictive language model. The study encompasses two key tasks: binary classification, distinguishing sentences containing soft skills (1) from those that do not (0), and multi-class classification, categorizing positive sentences into five classes based on Big Five personality traits. The research involved a series of experiments. Initially, multiple machine learning algorithms were employed to establish baseline models. Subsequently, the study investigated the impact of deep learning versus these baseline models. The results demonstrated an accuracy of 0.79% and 0.68% for binary classification tasks, and 0.79% and 0.60% for multi-class classification tasks, using Support Vector Machines in the machine learning task, and Bidirectional Long Short-Term Memory in the deep learning task, respectively. This approach showcases promise in revolutionizing the job matching process, offering a more efficient and accurate means of connecting individuals with their ideal employment opportunities based on their unique soft skills and personality traits.

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1. INTRODUCTION

Technology today enables each engagement to be unique and personal, and customers expect a personal connection with the businesses with which they interact. Personalization is taking, in the digital world, a step further. Personalization is defined as a process designed to enhance an individual's experience [1]. It is based on the information companies and organizations learn about interacting with individuals and gaining trust and loyalty. In addition, new technologies have made it possible for businesses to collect and analyze data on a broader scale to identify and profile-specific persons [2]. As a result, companies can now directly contact a hyper-contextualized experience as they improve their strategies for acquiring customer knowledge [3].

One of the best ways to earn consumers' trust in a brand is by leveraging data for hyper-personalization. Hyper-personalization is generally defined as the concept of a real-time collection of behavioral data for users to customize experiences, services, and products according to their wants and needs. In other words, it means accompanying the client's journey all the way, by using all the data that of possessed for creating personalized content for each customer individually by linking content to the user or a user to user or a user to content [4].

Hyper-Personalization is a key enabler for many sectors such as the financial, marketing, public, health care, and employment and job seekers [5]. The power of hyper-personalization is customer engagement, relevancy, trust, and virality. Moreover, the process of hyper-personalization requires actionable data, academic and technical expertise, and excellent processing power [6].

The competition is not limited to obtaining consumers and their loyalty; it's also for attracting and employing people capabilities [7]. However, like other competitive conflicts between organizations, this one is the fiercest, most complex, and most disruptive to workflow; picking the wrong person can cost the company its market reputation as well as its audience. Most organizations now have a workforce spanning four generations, and this is a significant challenge since each generation has its lifestyle, requirements, education, and skills. It is no longer possible to rely on a one-size-fits-all model. When it comes to sharing between business and employees, both parties' expectations (employer and the appropriate candidate) differ. As the right job allows the employee to present the best of his talents and abilities, in other words, unleash his potential, as the word "potential" includes all the advantages and attributes that a person possesses of knowledge, skills, interests, and behaviors. This idea is essential for the individual and for organizations to understand the talent management process on the most talented individuals to manage their workforce [8]. Hyper-personalization technology, content, and requirements can be customized based on generational differences to suit Everyone's expectations from parties [9]. Delivering a hyper-personal experience can improve job satisfaction and employee retention and significantly reduce recruitment costs. This creates an interactive workforce with high efficiency and leads to a better customer experience and better income for all parties at work [10].

The increase in job seekers across sectors has made it increasingly necessary to assign candidates to their positions based on their true personalities and where they fit. Furthermore, hiring procedures at present focus on the level of the experience which refers to hard skills. Most studies and research have proven the impact of soft skills on the job site. Where soft skills play an important role in determining employee performance [11], [12]. "Soft" skills are defined as the ones that enable individuals to fit in at work, such as those relating to individual personality, traits, creativity, motivation, objectives, and interests [13]. In contrast, hard skills are teachable qualities associated with technical work [14].

The recruiters use tools and options to rank the most suitable candidates for face-to-face interviews. Besides the candidate's experience and qualifications, the candidate's personality traits are used to classify and shortlist candidates for interviews. However, existing methods of assessing personality traits, such as the standard set of candidate questionnaires, can contain misinformation and waste time, reducing the chance of putting the right person in the right place and can exacerbate the problem of non-compromise in the recruitment process. So, we try to highlight and improve this problem to devise a different approach to this process.

In our work, we relied on the expertise of psychology practitioners in understanding soft skills and major personality traits and HR administrators in understanding the appropriate functional areas of each candidate's personality to provide reliable predictive and an analytical model to detect people who are suitable for a job. The study aims to encourage companies to hire employees based on creativity, fairness, and diversity of personalities based on the functional area's needs, even if they do not have experience. In addition to the main aim of studying is to help employers find the fittest people for a given job and help job seekers find the most suitable and appropriate position.

Previous research has made significant contributions to job matching and skills detection. However, there has been little research into developing a comprehensive list of soft talents and smoothly linking them with applicable job categories while taking an individual's personality type into account. We present an innovative strategy that focuses on real-time personality-based classification to increase the interaction between job searchers and employers in this study. Our purpose is to connect the distance between individuals and their suitable job responsibilities by utilizing soft skills. This strategy represents a significant improvement in this field by addressing the difficulty of recommending functional domains based on an individual's unique personality traits. It also highlights findings of new skills rather than depending on defined skill lists. Machine learning (ML)-based Hyper personalization provides a more scalable and accurate way to link functional areas and candidate specifications smartly. By utilizing deep learning models to build a predictive language model to discover the right individual for a job to build a predictive language model to help deliver suitable employment to the right people based on their soft skills data. As a result, this study handled a critical research field and accomplished outstanding results with innovative approaches.

2. RELATED WORK

According to Deloitte [15], 80% of customers like to purchase from brands that offer personalized experiences. According to the same study, 90% of buyers said personalized advertisements piqued their interest. Several researchers have introduced hyper-personalization in their studies. Vavliakis *et al.* [6]

displayed a coordinated design for the conversational Web that can give hyper-personalized services such as UI/UX personalization, individual messages, and promos per client. It is displayed in two strategies for hyper-personalization, one for the recommendation of items and one for a search. The strategies were assessed on three diverse datasets. They find that the personalized search approach provides significant search results while being suitable for near-real search in commercial environments. The performance of personal recommendations improved in large datasets and outflanked the state-of-art strategies in little and medium datasets. Jeong *et al.* [16] implemented a system that uses deep learning as an adaptive recommendation system to link the type of tourism that fits the user's personality.

Hyper-personalization delivers a more individualized experience. According to the findings of this study [17], consumer innovativeness, attitude, and subjective norms all have a major impact on their engagement. This is the first work to investigate digital clienteling for hyper-personalization in the fashion industry using co-creation as a mediator.

Harmony between employee and organization is essential to employee satisfaction and turnover intentions [18]. For this reason, Companies seek someone who has the necessary qualifications and a personality that fits the position and the business. As a result, online and offline personality assessments have become crucial tools in staff selection [19]. Aside from inferring personality from a cover letter or CV, one may adequately guess a person's personality based on profiles on social networking sites like Facebook [20] or even predict such job performance [21]. Online personality forecasts are more closely aligned with actual personality than the profile owner's ideal personality [22].

This study [23], an integrated electronic recruitment system directed to companies proposed. Based on supervised learning and semantic skill matching, the system automates the filter pre-screening process and provides an overall filter rating. The application was evaluated using a specified set of objective criteria based on the applicant's abilities retrieved directly from their LinkedIn profile and personality traits extracted via textual analysis of blog posts. Finally, as a study In the Big Five model of personality is the most powerful way to describe personality differences. It was previously studied with job satisfaction in this work [24], They proposed and tested a method for automatically extracting applicants' personality attributes based on their use of social media. Utilizing web mining techniques, based on information gleaned from each candidate's social media behavior, such as how enthusiastic, kind, well-rounded, and influential they are. The outputs produced a top-25 list that coincided with the comparable ranking of human recruiters by at least 64% (for the well-rounded metric), with a correlation of 0.71 (for the passionate metric).

As a study of associate personality types with role skills this study [25] was used international personality inventory to associate personality types (Extraversion, Agreeableness, Conscientiousness, Openness to Experience) with software development role competencies by matching personality and role skills. An actual research was then conducted at a medium-sized software firm to validate the technique. Because they matched role skills with personality skills, the outcomes are more successful. However, none of them considered the idea of creating a list of soft skills to automatically link them to the appropriate functional area by personality type using job posting data or resume data by using deep learning algorithms to solve the problem of suitable functional area suggestions for people applying for a job. Our mission to extract skills aims to mine and extract new skills, rather than using a ready-made list of skills, revealing them, classifying them, and linking them in the appropriate functional area according to the personality.

3. DATASET

In this study, we use three datasets: the first is a set of vacancies (advertisements), the second is a set of resumes or CVs of people, and the third is a construction lexicon containing a list of soft skills with one of the big five based on what reasonable each skill with the help of experts. Both job postings and resumes contain simple candidate skills and descriptions. However, we relied more on job advertisements as they had more examples with cases where soft skills are used in different contexts and have no repetitions such as resumes and an unstructured pattern.

3.1. The Lexicon

The study's outcome is a Lexicon (HYPskill Lexicon) of terms and phrases that each reflect the soft skills and relate them to the attributes of the Big Five personality traits stated in the IPIP-NEO-120. The Lexicon has been studied and validated by three experts in relevant field grading, with highly standardized and deliberate efforts to match each term/phrase with the corresponding trait to assign the personality type. HYPskill Lexicon contains 2,189 terms, and each term is classified as a specific type of trait about the base form.

3.2. Dataset corpora

We depended on CVs and job descriptions as the primary source for real-time data for generating the dataset. Soft skills and applicant descriptions are included in both job postings and CVs. However, job

advertisements give more instances of how soft skills are employed in various circumstances and define the organization, team, environment, etc. Using a CV dataset allows us to evaluate our technique with new data from a different domain. Both datasets are used for soft skill annotation, which offers data for supervised methods. We collected 9802 sentences indicating soft skills. The total number of positive sentences was 6139, and the remaining were negative. The positive sentences were classified into five classes based on the terms linked with the Big Five personality traits features [26] mentioned in IPIP-NEO120 [27].

To annotate the data set, we drew on the experience of three field experts with relevant higher education degrees in Psychology (Ph.D. level). The procedures were classified at two levels; The first is Binary classification which aims to classify the dataset that indicates the presence of soft skills in the sentences with "1" if they contain on soft skills, and "0" if it does not contain soft skills. The second task is the multi-class classification. The positive sentences gained from the first task were classified into five classes based on the terms linked with the Big Five personality traits [26] (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism). Figure 1 shows the number of sentences per class. After completing the expert-assigned class assignment procedure, we fed the labeled dataset into different learning models to perform classification tasks, either binary or multi-class classifications.

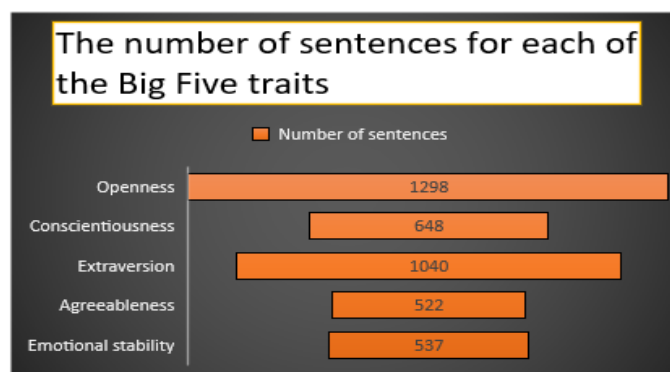


Figure 1. The number of sentences per class.

3.3. Functional Area Mapping with personality types

Assigning the right person to the correct task position is essential. Consequently, the study also established a relationship between the personality types and the primary functional areas within a business. It was confirmed two experts from human resources (HR) as mentioned in the definitions of an ERP solution [28]. Table 1 shows the personality types for each functional area.

Table 2 displays instances of these processes. More examples of what pre-processing processes were employed are as follows:

- Remove punctuation marks: Remove backslashes, commas, and other punctuation marks.
- Removing identifiers: In a language, identifiers and connecting words are deleted.
- Removing stopwords: removing the most widely used words in a language since they typically do not contribute meaning.
- Expanding abbreviations: when term shortcuts are enlarged to their corresponding words.
- Lemmatization: This minimizes word inflection to confirm that the term's root corresponds to the language.
- Removing duplicated sentences: To enhance the learning process and after that the classification process.

Table 1. The personality types for each functional area

Big five traits	Functional areas
Openness	Production
Conscientiousness	Finance
Extraversion	Marketing/Sales
Agreeableness	Human resources
Emotional stability	Operations

Table 2. Examples of pre-processing steps

Technique	Examples
Removing punctuations	“!, +, ., ;, ?, @”
Removing identifiers	“the”, “a” and “an”
Removing stopwords	“He”, “They”, “is” and “on”
Expanding abbreviations	“I’m”, “can’t” into “I am”, “Can not”
Lemmatization	“been”, “had” into “be”, “has/have”

4. METHOD

The work aims to link the functional area and candidate specifications intelligently that provides candidates with a suitable job based on their soft skills data. this enhances the accuracy of finding the fittest candidate for a particular job and the fittest job for the candidate's personality. The workflow architecture and methodology has been illustrated Figure 2.

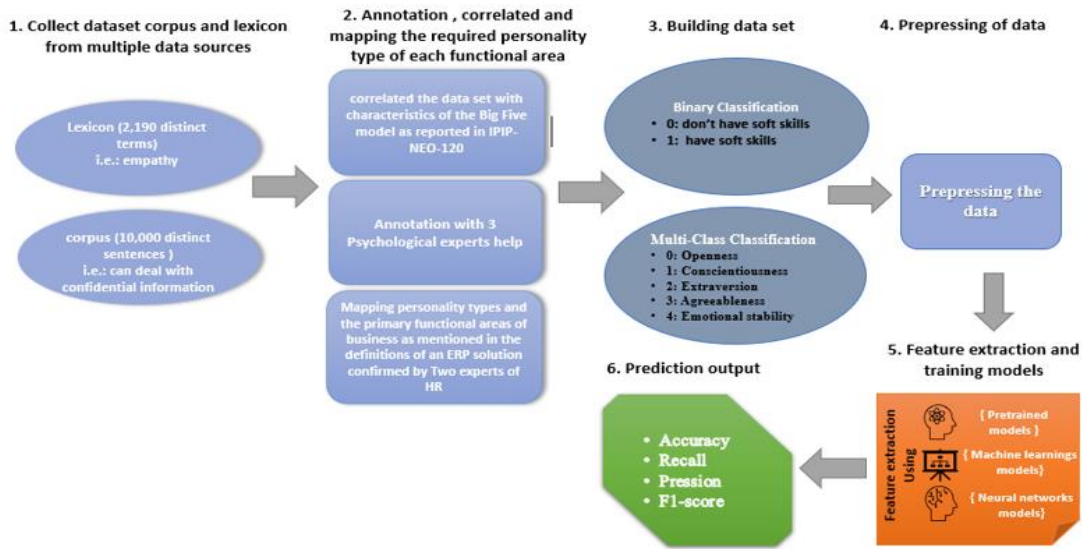


Figure 2. Shows the high overview of methodology

4.1. Classifications

This study encompassed two major classification tasks, each geared toward understanding the relationship between textual content, soft skills, and personality traits. In the first task (binary classification), our aim was to determine whether sentences contained soft skills or not, categorizing them as (0) for sentences without soft skills and (1) for sentences containing soft skills. We applied a range of models to achieve this goal. In the second task (multi-class classification), our focus expanded to predict text data into five distinct classes, each corresponding to a specific Big Five personality trait. By dividing our study into these two tasks, we were able to comprehensively investigate the presence of soft skills and their relationship with personality traits, providing valuable insights into job matching and recruitment processes.

4.1.1. Binary classification

The first classification is a binary classification that aims to classify the dataset into two categories (0/1); (0) indicates the sentence that does not contain soft skills, while (1) represents the sentences that have soft skills. The following models were applied in binary classification: baselines models Naïve Bayes, Logistic Regression, SVM, Random Forest, and XGBoost. In addition to using deep learning models CNN, CNN-LSTM, Bi-LSTM, and GRU. This task focused on determining the presence or absence of soft skills in the given text. Moreover, these models, when applied to this task, play a crucial role in determining the presence of soft skills within textual data.

4.1.2. Multi-class classification

The second classification is a multi-class classification. The number of predicted classes is (5) classes; each assigned to a particular type of Big Five personality traits where (0) represent Openness, (1) represent Conscientiousness, (2) represent Extraversion (3) represent Agreeableness, and (4) represent

Emotional stability. The following models were applied in multi-class classification: baselines models Naïve Bayes, Logistic Regression, SVM, Random Forest, and XGBoost. In addition to using deep learning models CNN, CNN-LSTM, Bi-LSTM, and GRU.

This task allowed us to understand how different personality traits could be associated with the content of text data. Moreover, the application of these models allowed us to effectively assign text data to their respective personality traits. This contributed significantly to enhancing our overall grasp of the intricate connection between language and personality within the multi-class classification context.

4.2. Models

Several experiments were conducted in this study to classify the dataset that contains soft skills or not, in addition to the data that defines a personality trait based on the Big Five personality traits. In the experimental work the dataset split into train and test sets with a ratio of 67:33, respectively. The 67:33 ratio was selected because it gave us the best result.

4.2.1. Baseline Models

As a starting point, we assumed the adoption of machine learning models as the baseline models to classify the sentences in two parts: Binary classification and multi-class classification. We used (naïve bayes, logistic regression, SVM, random forest, and XGBoost.) of machine learning algorithms. Many significant characteristics were recovered from the dataset, including (n-grams, TF-IDF, random oversampling, and stemming). In addition, the detection technique was carried out by combining multiple features. This step includes creating new features from the existing data for text (such as term frequency inverse document frequency (TF-IDF), Random over Sampling, stemming, and count vectorizer conditions).

4.2.2. Deep learning models

This study used four neural network models to detect soft skills in the first task (binary classification task) and determine a personality trait based on the Big Five personality traits in the second task (multi-class classification task). For the embedding, the experiment adopts Word2vec embeddings to extract a target word based on context or target context based on a word feature as the first layer with the input word of 300 input dimensions. With a two-layer neural network, Word2vec is a common approach for learning word embeddings. It takes a text corpus as input and outputs a set of vectors. The two major training strategies for word2vec are the continuous bag of words (CBOW) and skip-gram. The primary distinction between both algorithms is that CBOW predicts a target word from context, whereas skip-gram predicts a target context from a word. The skip-gram methodology surpasses the CBOW method in general because it can record two meanings for a single word [29].

a. CNN

We utilized pre-trained word embedding since it reflects the context in the document and then extracts features in the form of vectors from text to classify the sentences. Skip-gram embeddings were used using the input word and 300 input dimensions embeddings as the first layer. This layer's output vectors (i.e., altered sentences) were utilized to input the CNN classifier. The structure of the CNN model is shown in Figure 3.

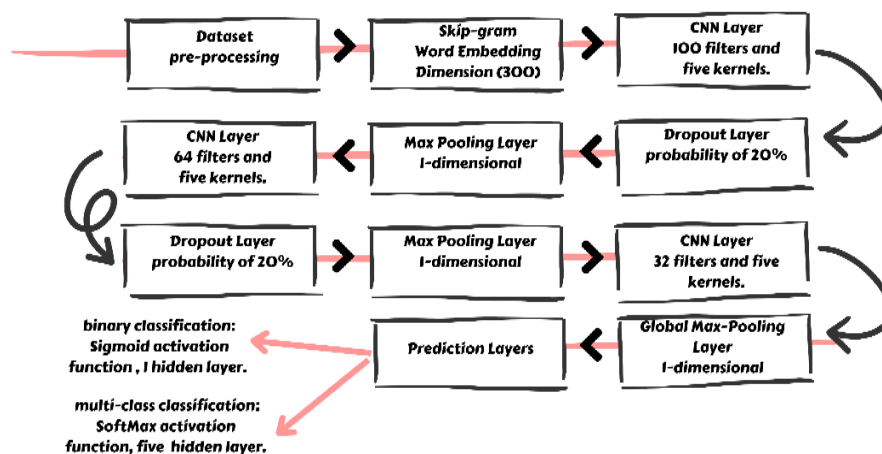


Figure 3. CNN model layers

The CNN classifier for both tasks (binary and multi-class) is built in a single layer, with 100 filters and five kernels, a ReLU activation function, and the same padding. Since in text data, the dot product is executed on the embedded vectors in the feature space. The filter/kernel is slid across these comparable embeddings to generate highly related words of a particular class. We applied a dropout layer with a dropout probability of 20% to minimize overfitting, and the high dimensional maps were reduced using the Max Pooling layers.

The second conv1d applied with the 64 filters and five kernels, followed by a dropout layer with a dropout probability of 20% and another 1-dimensional Max Pooling layer. A final conv1d with the 32 filters and five kernels, followed by a dropout layer with a dropout probability of 20%, and the global max-pooling layer on the feature map generated to extract the global abstract information. They were then routed via connected layers. For (the binary classification) comes the predictor layer that chooses one of two labels (0/1), with Sigmoid activation function. As for (the multi-class classification), the second dense layer is the prediction layer to predict the five classes, using the SoftMax activation function. This experiment was applied in a Colab environment using Keras API, with 32 batch sizes for both tasks, and the learning rate equals 0.001. In addition to using the Adam optimizer in the training phase for (multi-class classification), the best performance was achieved with 43 epochs. As for (binary classification) the learning rate equals 0.001. In addition to using the RMSprop optimizer in the training phase, the best performance was achieved with 15 epochs.

b. CNN-LSTM

In this experiment, we used as the first layer, CBoW embeddings were used using the context words and 300 input dimensions embeddings. These features were passed into a convolutional layer with 128 filters, five kernels, and the same padding. Then we applied a dropout layer with a dropout probability of 20% to minimize overfitting, and we then used max pooling on the feature map generated from the convolutional layer to extract abstract information. The structure of the model was then topped with LSTM layers with 64 units and Relu. The output was then flattened with the flatten layer and passed onto a fully connected layer with 1 unit for (the binary classification), with Sigmoid activation function. As for (the multi-class classification), the fully connected layer is the prediction layer to predict the five classes, using the SoftMax activation function. The structure can be followed in Figure 4. The hyperparameters are 32 batch sizes for both tasks, and the learning rate equals 0.001. In addition to using the Adam optimizer in the training phase for (multi-class), the best performance was achieved with 17 epochs. As for (binary) the learning rate equals 0.001. In addition to using the Adam optimizer in the training phase, the best performance was achieved with seven epochs.

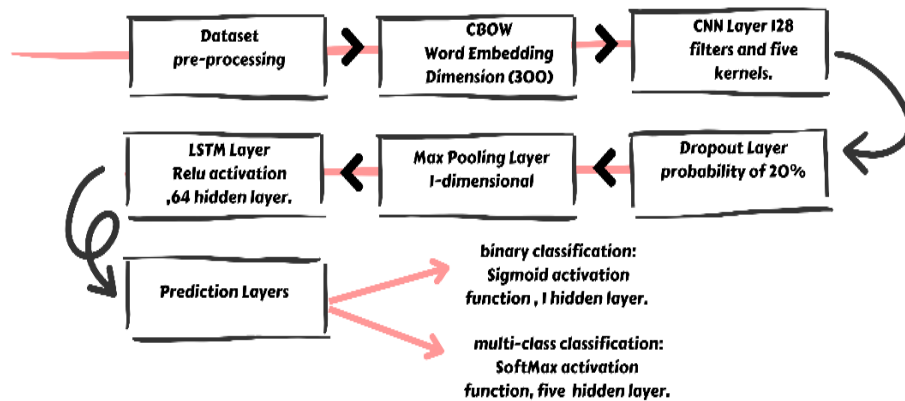


Figure 4. CNN-LSTM model layers

c. Bi-LSTM

To build the Bi-LSTM model, As the first layer, we used the input word of 300 input dimensions embeddings to initialize the Skip-gram embeddings to extract context features. We used Bi-LSTM layers with 64 units and Relu activation, stacked on top of Spatial Dropout probability of 20% layer. The output was then flattened with the flatten layer and passed onto three fully connected layers with 300, 200, and 1 unit for (the binary classification) and five for (the multi-class classification), respectively. The model was built using keras API with Adam optimizer with 0.01 learning rate, coupled with a batch size of 32 run for five epochs

for (the binary classification) and 13 epochs for (the multi-class classification). In Figure 5, a representation of the architecture of the Bi-LSTM model is presented.

d. GRU

Using the spatial dropout, we implicitly dropped an entire feature map to be fed into a GRU layer. Then we took the output from the previous GRU layer and fed it into a convolutional layer with 64 units and Relu activation, followed with global average pooling at first, then into global max pooling. The output from the two pooling layers was then concatenated. Finally, the vector generated from the concatenation operation was fed into dense layers, using SoftMax activation function for (the multi-class) and sigmoid activation function for (the binary). Figure 6 represents the structure of the model used.

The hyperparameters applied in the model were chosen 32 batch sizes for both tasks, and the learning rate equals 0.01. In addition to using the Adam optimizer in the training phase for (multi-class), the best performance was achieved with 12 epochs. As for (binary) the learning rate equals 0.001. In addition to using the Adam optimizer in the training phase, the best performance was achieved with six epochs.

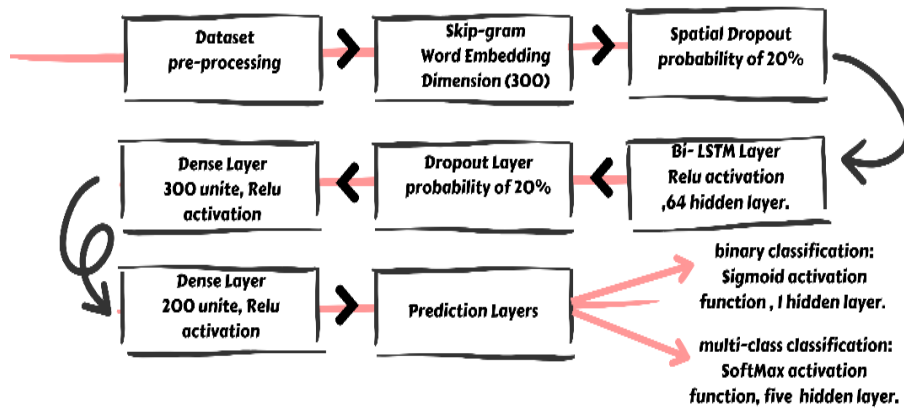


Figure 5. Bi-LSTM model layers

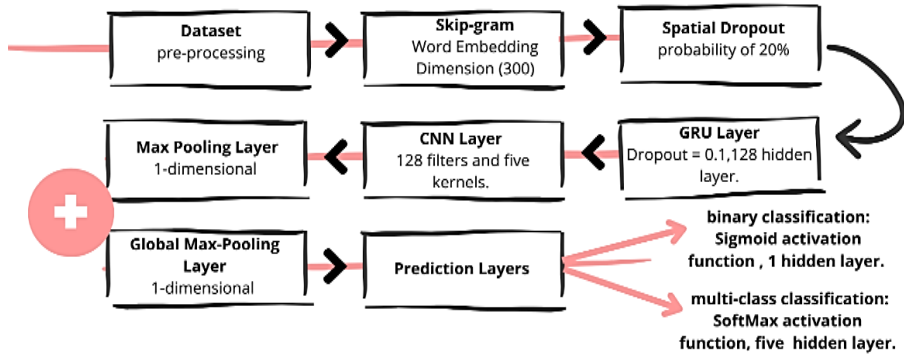


Figure 6. GRU model layers

5. RESULTS AND DISCUSSION

Our study introduces a novel methodology that distinguishes it from prior research in the recruitment and job matching domain. Through the integration of soft skills, personality types, and job matching using deep learning algorithms, we have achieved remarkable outcomes. In binary classification, our approach achieved a 79% accuracy rate for assessing soft skills. Additionally, our approach achieved a notable 60% accuracy rate in the multi-class classification of personality traits. These findings highlight the effectiveness and potential of our approach in revolutionizing the job matching process. While earlier studies laid the groundwork, our research takes a substantial leap forward by providing precise and efficient job matching solutions tailored to individual soft skills and personality traits. This section presents the results and

will discuss the performance evaluation results of the implemented classification models for both tasks (binary classification and multi-class classification tasks).

5.1. Baseline models

This section shows the outcomes of developing and testing the binary classification utilizing Machine Learning models as baseline models. We tested various machine learning models to establish a baseline model for future improvement in trials and testing. As a result, we needed to develop a baseline model to go ahead with NLP models. The evaluation measures for these classifiers are depicted in Figure 7.

Figure 8 displays that the highest result in accuracy was obtained from implementing the SVM poly, which exceeded the other models with an accuracy equal to 0.79 %, and Recall equals 0.79%, F1 measure equals 0.79%, and precision equals 0.78%. This can be justified due to the polynomial kernel SVM being suitable for non-linear problems such as text classification [30]. Furthermore, the poly kernel in SVM adds more features to the datasets to make them easier to separate and evaluate the use of machine learning classifiers in multi-class classification for identifying the various Big five personality traits. The evaluation measures for these classifiers are depicted in Figure 8. As shown in Figure 8 the SVM Poly obtained the highest results in Accuracy 0.68%, Recall 0.68%, and F1 measure with a result of 0.68%. While on the other hand, the XGBoost classifier obtained the highest Precision with 0.74%. Other classifiers obtained relatively close results.

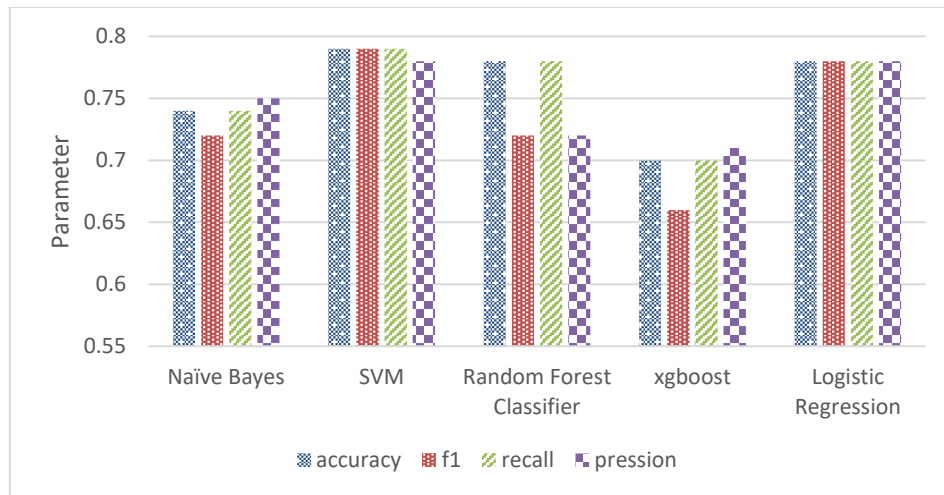


Figure 7. Evaluation measures for baseline models in binary classification

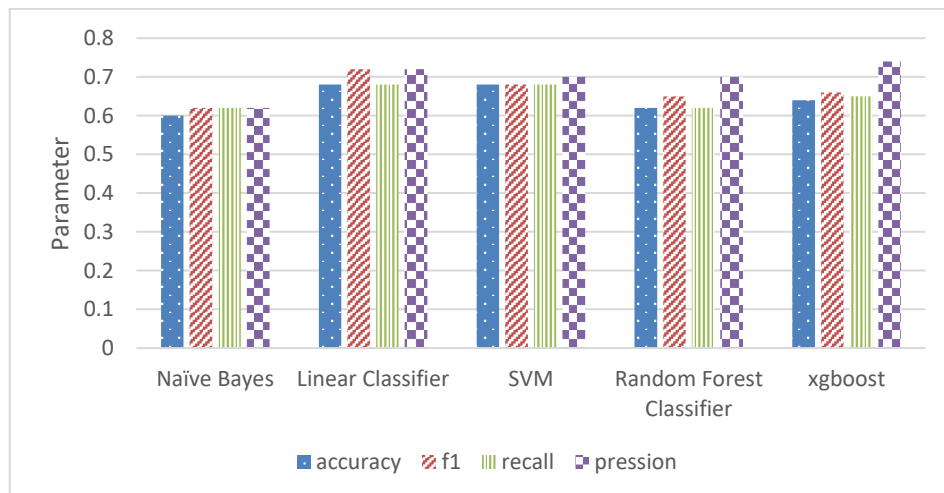


Figure 8. Evaluation measures for baseline models in multi-class classification

5.2. Deep learning models

This section discusses the results obtained from applying different architectures to the dataset (HYPskill dataset), using different features, learning experiments, and optimization measures, to detect the efficiency of using deep learning models in detecting the different personality traits in comparison to the baseline models. Table 3 displays the results of the binary classification challenge using deep learning models. In addition to evaluating the use of deep learning models in multi-class classification for identifying the various Big five personality traits. The evaluation measures for these classifiers are depicted in Table 4 and Table 5.

Table 3 The accuracy, precision, recall and F1-score for binary classification with deep learning

Models	F1-score	Precision	Recall	Accuracy
CNN	0.78%	0.78%	0.78%	0.78%
CNN-LSTM	0.76%	0.76%	0.76%	0.759%
GRU	0.75%	0.75%	0.75%	0.75%
Bi-LSTM	0.78%	0.78%	0.78%	0.79%

Table 4. The accuracy, precision, recall and F1-for deep learning models in multi class classification

Models	F1-score	Precision	Recall	Accuracy
CNN	0.56%	0.50%	0.60%	0.50%
CNN-LSTM	0.59%	0.55%	0.55%	0.55%
GRU	0.60%	0.57%	0.60%	0.57%
Bi-LSTM	0.60%	0.57%	0.66%	0.60%

Table 5. Evaluation measures results for the Bi-LSTM model for each class in multi-class classification task

Class	Precision	Recall	F1-score
Openness	0.67%	0.67%	0.67%
Conscientiousness	0.68%	0.70%	0.69%
Extraversion	0.72%	0.22%	0.34%
Agreeableness	0.68%	0.61%	0.64%
Emotional stability	0.54%	0.45%	0.49%

As shown in Table 3 for the binary classification task, the Bi-LSTM model exceeded the other models with an accuracy equal to 0.79 %, and Recall equals 0.78%, F1 measure equals 0.78%, and precision equals 0.78%. Furthermore, based on Table 3 and Table 4, it was evident that the Bi-LSTM model attained the maximum accuracy due to its bi-directional structure in both tasks (binary classification and multi-class classification). The dual training procedure on the input sequence is the foundation of bidirectional LSTMs. This structure enables the networks to extract features in both directions and information about the sequence at each time step. Table 5 summarizes the results of the evaluation metrics achieved by employing the Bi-LSTM model for each class in multi-class classification tasks. As per Table 5, it is shown that the conscientiousness trait has the highest score of F1-measure, Recall, and Precision. This can be explained by the fact that the soft skills and the qualities they express the conscientiousness trait are clear and do not overlap with any other trait.

6. CONCLUSION




The work in this study concluded was carried out systematically with consideration and constant effort. To deliver hyper-personalization to help employers find the most suitable people for a particular job and help job seekers find the most practical and qualified job based on their personality's traits. We have implemented experiments on sentences to detect traits using multiple Machine Learning algorithms to build the baseline models. The ML models are applied on two tasks: binary classification and multi-class classification. The experiments were carried out using several feature extraction techniques. The highest result in accuracy was obtained from implementing the SVM poly, with an accuracy of 0.79 % and 0.68% for binary classification task and multi-class classification task, respectively. The second step involved examining the impact of utilizing Deep Learning models vs. baseline models built using Machine Learning methods .it was evident that the Bi-LSTM model attained the maximum accuracy due to its bi-directional structure in both tasks (binary classification and multi-class classification) with an accuracy of 0.79 % and 0.60% for binary classification task and multi-class classification task, respectively. This work can be used as a starting point for further improvements, research, and comparisons. Where the work done in this study is

the first of its kind to extract new skills, instead of using a ready-made list of skills. Moreover, detecting, classifying, and automatically linking these skills to the appropriate job field according to the personality type through the use of job posting data or resume data classification using deep learning algorithms.




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