Research Article

NLP-Semantic Machine Learning-Based System for Intelligent Classification of Professional Skill-Sets for Efficient Human Resource Management Process

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Abstract: Skill sets can improve individual professional proficiency and enable individuals to perform better at work. Professional skill sets create opportunities to aid in advancement in job classification of individual skill advantage resulting in good human resource management to efficiently present employers with adequate and qualified candidates for a given job offer. Classifying the right people for the right skills is a common task in human resource management. This research work presents a mechanism for classifying individual extracted Summary page texts of Curriculum Vitae (CV) through the application of the Semantic Machine Learning Model. First, data was gathered by mining different summary page curriculum vitae both online and offline. Second, preprocessing of datasets, by undergoing data cleaning, text normalization, and feature extraction and splitting data sets into training and test sets in the ratio of 80:20% for train and test set. Thirdly, exploratory data analysis was carried out to visualize different variables to determine how each metrics (parameter) interact with each other regarding Skill Sets classification based on the five topics concerns (Goal Oriented, Emotional Intelligence, Good Communication Skills, Problem Solving, and Leadership skills). Fourthly, Using an Artificial Neural Network for the classification of the text vectors, ANN gave an accuracy of 94% on the 10-epoch used in the model. Performance evaluation on the model was carried out and results show a precision of 82%, 76%, 40%, 66%, and 57 % respectively for Goal Oriented, Emotional Intelligence, Good Communication Skills, Problem Solving, and Leadership skills classifications. The proposed system served as an efficient Human resource management process.

Keywords: Human Resource, Goal Oriented, Emotional Intelligence, Semantic Machine Learning Model, data analysis

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1. Introduction

The strategic approach to managing people in a company or organization effectively that contributes to a firm's ability to compete favorably is known as human resource management (HRM or HR). Its goal is to boost staff performance in support of a company's strategic goal [20]. Also, the development of the qualities that businesses are looking for in employees involves training in management and leadership, which increases chances in the business sector that are created by Human resource (HR) experts who have a broader understanding of pertinent subjects and better practical abilities. An organization's human resources department manages human resources, keeping an eye on a variety of employment-related matters, including compliance with labor, laws, employment standards, administration of employee benefits, and some aspects of hiring and firing [14].

Consequently, increased opportunities in the business sector are produced by HR professionals who have a broader understanding of relevant subjects and stronger practical abilities. The development of the qualities that employers are looking for in employees entails training in management and leadership which looks at the individual skill sets of the different employees. A person's variety of skills and abilities that they can use to learn and complete a profession is referred to as their skill set. Both interpersonal and professional abilities might be part of this. Anyone can attain professional objectives like getting a promotion or becoming an authority in a particular industry by taking the time to comprehend their capabilities, grow them, and improve them. Since businesses including healthcare industries depend on their Supply Chains to provide them with what they need to survive and thrive [16] there is validation to develop a framework that could ensure a more efficient supply chain [37]; [36].

Nevertheless, a skill set entails the collection of knowledge, character traits, and aptitudes that are acquired over life and career. In most cases, it incorporates both soft skills and hard skills. In the twenty-first century, skills are a crucial enabler for national success and better lives for individuals. Increased productivity from skills-based labor promotes economic growth both directly and indirectly by enabling people and businesses to adopt new technology and methods of operation [25]. However, more skill sets can improve individual professional proficiency and help individuals perform better at work. Since each skill is unique, expanding skill sets might enhance individual advancement in a job, and also classifying individual skill sets will help human resource management to better and efficiently present employers with adequate and qualified candidates for a particular job offer. Possessing strong learning and abilities (skill sets) will ensure that an individual stands out from other job applicants and demonstrates to employers that he/she is eager to learn and adapt as needed. Collaborative learning, communication, and critical thinking are a few examples of skill sets that an individual must have.

Hence, there is a need for strategic a framework by human resource management that will help in the correct classification of individual skillset to help match the suitable job with their skills [46]. Based on this need a semantic natural language-based system is proposed for the classification of Professional Skill-Sets for Efficient Human Resource Management Process.

The NLP-Semantic Machine Learning approach is a strategic methodology for implementing the study goal of classification of professional skill-sets for efficient Human Resource Management Process. By leveraging Natural Language Processing (NLP) and semantic understanding, this approach enhances the classification of professional skill sets by accurately interpreting job descriptions, resumes, and workforce requirements. Semantic analysis ensures that context-aware relationships between skills and job roles are identified, thereby improving the efficiency of talent acquisition and workforce planning [47]. The integration of machine learning models further refines classification accuracy [49] through continuous learning from structured and unstructured textual data. This methodology aligns with NLP-driven classification in various domains, including where semantic processing significantly improved categorization and decision-making [48].

2. Literature Review

The difficulty of finding job applicants with the necessary abilities, experience, school credentials, and credentials to be successful has long been a source of concern for Human Resources (HR) and other corporate leaders. Given that some people have difficulty finding employment, a variety of skills play a significant role in the availability of career alternatives for individuals. Finding the right people for the right jobs is a common task in human resource management. Finding the correct expert to learn from or obtain information within a business, choosing team members based on various skills and qualities, and recruiting human resources are a few examples of such jobs. In most professions, more than a third of the necessary core skill sets in 2020 may consist of abilities that are not currently seen as essential to the work [41]. Consequently, it's challenging to find the appropriate people for the right jobs. Changes in Technology are causing a quick change in the requirements for certifications or abilities, but it is not a problem to have many highly skilled personnel; rather, a better distribution of work resources is essential for firms looking to improve performance and be competitive. Adequate classification of individual skill sets leads to job mismatch and imbalance between an employee's attributes with the rest of the knowledge domain or field of expertise, or competencies and abilities. Often, knowledge, abilities, and competencies may be in excess or insufficient for a job. Therefore, it entails human resource management to intelligently classify individuals with the required skill sets to fit required job requests for efficient job provisioning. The advent of information and communication technology offers an opportunity for industries to change their operations, ways of doing business, and customers [45].

A skill set is a list of aptitudes or capacities to carry out a particular task successfully. Performing a specific job or conducting business in the tumultuous modern business market, requires a certain level of abilities [18]. The Association for Talent Development (ATD), formerly the American Society for Training & Development (ASTD) and U.S. Department of Labor study demonstrated how technology is altering the workplace and identified 16 fundamental skills that workers must possess to keep up with it. The three suggested broad skill types are technical, human, and conceptual [27]. The first two can be replaced by hard and soft skills. Consequently, Employability skills have been defined as "individual assets possessed by workers and job searchers, and the measure to which they fit in with the urgent demands of employers," are crucial for a wide range of parties involved [30]. Human capital is highly valued by organizations around the world and is essential to the health of an economic system [26] & [29], Three recognized levels of analysis are taken into consideration when discussing human capital: "The knowledge, skills, abilities and other traits embodied in individuals or groups of persons acquired during their life and used to produce commodities, services, or ideas in market situations" is how the individual (micro) is described [39]. It encapsulates the collective fundamental competencies of the people working for an organization [24].

As a result, it is believed that the nature and compatibility of a person's hard and soft skills in a certain environment are crucial for the longevity and quality of a labor market [45]. Hard skills are described as a unique ability to do a certain task [5]. Hard skills are observable abilities that may be developed by study and practice; It require formal education and practical experience [9]. It entails having a thorough understanding of and being skilled at a particular task involving methods, processes, procedures, or techniques [8]. These skills may be measured, as opposed to soft skills, which are personality-related. These are also abilities that may be tested or already have been, and they might require some kind of professional, technical, or academic background [3]. While different vocations demand various levels of hard skills [13]; [33]; [40]. For the data analysts or scientists, the hard skills may include the use of particular tools, forms of systematic work with data and the use of appropriate software [38], software development and/or programming, statistical knowledge, quantitative analysis, the ability to use a variety of analytical, statistical, and modeling tools, or specialized industry knowledge encapsulates hard skills [32]. Again, soft skills are also required which are personality qualities and social abilities that define a person's interactions with others. It encapsulates all of a person's innate talents, which are inextricably tied to personal characteristics and are extremely valuable in all professions. It is used in "handling others and managing one's self and one's emotions in a manner appropriate with specific workplaces and organizations [17].

Soft skills should be taken into account within the context and type of job in which they are employed, according to both academics and practitioners [17], and their application can be highly particular in some circumstances. However, research does venture to suggest that common core soft skills, such as leadership, problem-solving, initiative, self-regulation, expertise, know-how, ambition, and ethics, could be grouped within the skill categories of learning and innovation, digital literacy, and life and career [1]; [7]; [15]. [34]. Again, soft skills are considered a benefit in the context of one's employment and can be perceived as complementing hard skills [2]. [12]. Furthermore, Professional skills are aptitudes that can aid in career success. A habit, personality quirk, or skill that enhances your productivity at work. People in almost all employment roles, industries, and work environments can benefit from having these talents. Professional skills, often known as soft skills, are abilities that may be used in a variety of jobs. Some categories of soft skills that can advance one professional career are; Communication, Problem-solving, Emotional Intelligence, Organization, and Openness to Learning, Human resource management (HRM) is the process of hiring individuals, providing them with the necessary training and compensation, creating policies about them, and creating retention plans. The human resource management (HRM) function can play a key role in promoting organizational change by utilizing several Human Resource Management (HRM) approaches to supply businesses with human resources who possess the necessary knowledge, skills, abilities, and behavioral tendencies to implement change strategies [35]. The main strategy for every change attempt is to manage employee attitude toward change with more preparedness and less opposition [22]. A significant correlation between HRM procedures and employee behavior [23], and the HR department can play a significant role in facilitating organizational change [22]. The summary of the related literature in this research work is presented in Table 1.

Table 1. Summary of the related literature

Author	Aim	Methods	Objectives	Results	Research gap (Limitation)
[6]	Revising the standard occupational classification system for 2010	A review was conducted.	To describe the process used to revise the 2000 SOC system for 2010, the scope and nature of changes incorporated, new and improved features, and plans for implementation and future revisions	According to the number of comments received, one topic that attracted a lot of attention was the suggestion to include clinical nurse specialists as a separate specialized employment. Hundreds of organizations and individuals made similar demands.	Focuses on occupational classification updates but lacks an intelligent machine-learning-based approach for professional skill-set classification and automation in HR processes.
[21]	A graph-based approach to skill extraction from text	Using Spreading Activation algorithm	Skill extraction from text documents	The number of initially activated nodes can be customized by the system's user. By	Focuses only on skill extraction but does not classify or intelligently process skill sets based on

Author	Aim	Methods	Objectives	Results	Research gap (Limitation)
				assessing Precision and Recall concerning the relevant skills and examining the target skill's average position on the list of final activations, they looked into the impact of this decision.	NLP-semantic models for HR applications.
[43]	A system for skill identification and normalization	Using Wikipedia API.	an automated approach for skill entity recognition and optimal normalization	Their current system achieves 91% accuracy on taxonomy generation and 82% accuracy on skills tagging tasks through sampling-based end-user evaluation.	Handles skill identification and normalization but lacks deep NLP-semantic learning for contextual skill-set classification in HR processes.
[19]	Large-scale occupational skills normalization for online recruitment	Discussions were carried out.	SKILL, a named entity normalization (NEN) framework for occupational skills, will be explored.	Building client feedback loops will eventually improve the system of occupational skill normalization.	Discusses skill normalization but does not use machine learning or NLP-based models to classify skills efficiently for HR management
[28]	Learning representations for soft skill matching	Uses neural network-based Approaches	To provide a phrase-matching-based strategy that distinguishes between soft skill expressions about a candidate and other expressions.	On the employment dataset, the proposed tagging-based input representation using LSTM had the highest recall (83.92%) when the precision was increased to 95%.	Focused only on soft skills without integrating hard skills and does not incorporate a structured NLP-semantic framework for HR optimization.

Author	Aim	Methods	Objectives	Results	Research gap (Limitation)
[31]	Syntax-based skill extractor for job advertisements	Syntax-based method	To extract meaningful skills from job advertisements by analyzing the syntactic patterns of the textual content	It was demonstrated that the vocabulary expands greatly when the same 100 labeled jobs are used to produce labels for 10,000 unlabelled jobs, even when only a small sample size is used. Based on a scant amount of initial data, the findings show that these new labels were mainly accurate.	Focuses on extracting skills from job advertisements but lacks machine learning classification for professional skill-sets in HR systems.
[42]	Hard and soft skill extraction from English job	Using language models	To explore language model-based skill and knowledge extraction from job listings	Results reveal that single-task learning performs better than multi-task learning and domain-adapted models significantly outperform their non-adapted counterparts.	Extracts skills but does not integrate a structured classification framework based on NLP-semantic machine learning for HR management.
[4]	Design and Implementation of a Human Resource Management System Based on B/S Mode	Analysis was conducted and the design and development of the system were presented.	This study examines the needs for a human resource management system from the perspectives of system role, function, and non-function, among others, and	The findings demonstrate that the system satisfies the requirements of businesses, its user interface is attractive and simple to use, its operation is quick and convenient, and its functions are	Focuses on HRM system development but does not address the intelligent classification of professional skill sets using NLP and machine learning.

Author	Aim	Methods	Objectives	Results	Research gap (Limitation)
			elaborates on the system's design and implementation process from the perspectives of system role, function, and non-function.	comprehensive and strong.	

Unlike existing studies that focus on skills extraction or normalization in Table 1, our study focuses on intelligent classification of professional skill sets based on NLP-semantic machine learning models to enhance the efficiency of human resource management processes. Our approach includes context-aware classification, skill categorization through deep learning, and semantic similarity analysis to optimize recruitment and workforce management in HRM systems.

3. Material and Method

3.1 Conceptual Framework

The proposed system framework is shown in Figure 1 which identifies the flow of the method employed in this study.

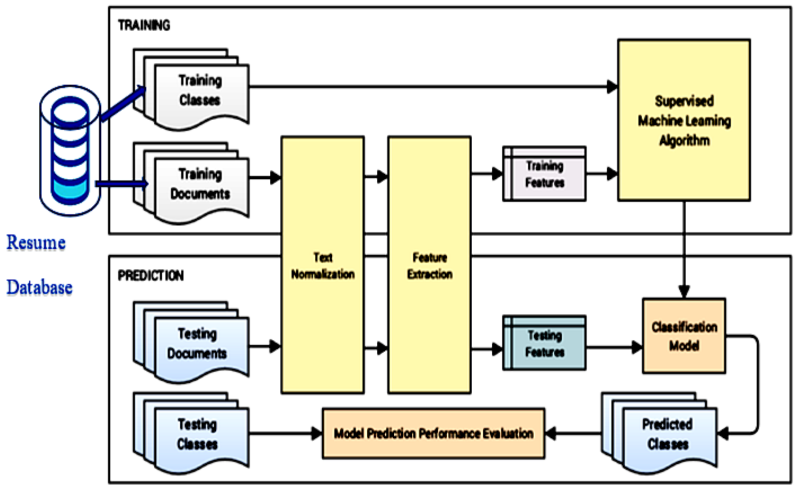


Figure 1. Proposed Conceptual Framework

3.2 Algorithm of our Proposed Framework

i. Extract text from the summary page of the Curriculum Vitae to form a resume database.
ii. Extract the keywords from the resume database
iii. Carried out Pre-processing
iv. Perform Text Tokenization
v. Perform word vectorization (transform words to vectors of numbers to be understood by the computer)
vi. Checked for stop words
vii. Feature extraction
viii. Split data into train and test classes in a ratio of 80:20% respectively

ix. Apply artificial neural network for classification of the text data
x. Conduct a Performance Evaluation of the model using Classification Metrics.

The pre-processed for the model is shown in Table 2 Preprocess data. Table 3 provides the cross-section of the selected sample of the data set for training the model.

Table 2. Preprocess data

Id	topic	text	topic_encode	Goal_Oriendnted	Emotional_Intelligence	Good_Communication_Skills	Problem	Leadership_skills
0	Goal_Oriented	To develop the world through information communication	0	0	1	0	0	0
1	Emotional_ intelligence	I am a passion-driven	1	1	0	1	0	0
2	Good_Coordination	Excellent Communication and Interpersonal skills.	2	2	0	0	1	0
3	Problem	Highly proactive, logical, analytical, self-motivated, Dilger	3	3	0	0	0	1
4	Leadership	Responsible for workforce planning	4	4	0	0	0	0
5	Goal_Oriented	To offer excellent solutions that will enhance the accomplish	0	0	1	0	0	0
6	Goal_Oriented	maintain the effective, ardent, and smooth running of the c	0	0	1	0	0	0
7	Goal_Oriented	A self-motivated human resources administrator with expert	0	0	1	0	0	0
8	Goal_Oriented	Willingness to take on added responsibilities to meet team	0	0	1	0	0	0
9	Goal_Oriented	To work in an organization where hard work is celebrated and innovative ideas are welcome towards the attainment of	0	0	1	0	0	0

Id	topic	text	topic_encode	Goal_Orientednted	Emotional_Intelligence	Good_Communication_Skills	Problem	Leadership_skills
		organizational goals and achievement of its vision.						
10	Goal_Oriented	To effectively and efficiently work hard to impact my	0	0	1	0	0	0
11	Goal_Oriented	To be a part of a result-driven organization, that is ardently al	0	0	1	0	0	0
12	Goal_Oriented	Where team spirit, positive competition, and opportunities	0	0	1	0	0	0
13	Goal_Oriented	A positive-minded, focused, and purpose-driven person, wi	0	0	1	0	0	0
14	Goal_Oriented	To work in an organization that provides me with ample	0	0	1	0	0	0
15	Goal_Oriented	Ability to recognize and source for needed information,	0	0	1	0	0	0
16	Goal_Oriented	Ability to plan and organize own work, working with minim	0	0	1	0	0	0
17	Goal_Oriented	Commitment to maintenance of accounting principles.	0	0	1	0	0	0
18	Goal_Oriented	Successfully maintain relationships with clients by	0	0	1	0	0	0
19	Goal_Oriented	established personal networks; benchmarked	0	0	1	0	0	0

Table 3. Selected Sample of the Training Sets

ID	Topic	Text	Topic encode	Goal Oriented	Emotional Intelligence	Good Communication Skills	Problem solving	Leadership skills
0	Goal_Oriented	To develop the world through information communication Technology	0	1	0	0	0	0
1	Emotional_ Intelligence	I am a passion-driven	1	0	1	0	0	0
2	Good_ Communication Skills	Excellent Communication and Interpersonal skills.	2	0	0	1	0	0
3	Problem_ solving	Highly proactive, logical, analytical, self-motivated, diligent, innovative, and initiative	3	0	0	0	1	0
4	Leadership skills	Responsible for workforce planning	4	0	0	0	0	1
5	Goal_ Oriented	To offer excellent solutions that will enhance the accomplishment of your organization's goal	0	1	0	0	0	0
6	Goal_ Oriented	Maintain the effective, ardent, and smooth running of the organization.	0	1	0	0	0	0
7	Goal_ Oriented	A self-motivated human resources administrator with experience in consistently adopting innovative strategies	0	1	0	0	0	0
8	Goal_ Oriented	Willingness to take on added	0	1	0	0	0	0

ID	Topic	Text	Topic encode	Goal Oriented	Emotional Intelligence	Good Communication Skills	Problem solving	Leadership skills
		responsibilities to meet team goals.						
9	Goal_ Oriented	To work in an organization where hard work is celebrated and innovative ideas are welcome towards the attainment of organizational goals and achievement of its vision.	0	1	0	0	0	0
10	Goal_ Oriented	To effectively and efficiently work hard to impact my acquired skills to enhance organizational goals.	0	1	0	0	0	0

4. Result and Discussion

Result evaluation refers to a systematic and objective appraisal of a current or completed activity. The goal is to identify the amount of significance of project objectives being met, as well as development effectiveness, efficiency, impact, and sustainability. The semantic-based approach through artificial neural network is used in this study to classify professional skill sets. Hence in this section of the study, we will take a look at exploratory data analysis, result, and model performance respectively.

4.1 Exploratory Data Analysis

In this section, some of the EDA performed on the data are presented alongside charts.

4.2 Number of Text documents per Topic

This chart presents the total number of text documents belonging to each of the classes of topic arranged from highest to lowest. From the chart, we can observe that our data has some level of imbalance where the topic of leadership skills has more text documents than the rest of the topics.

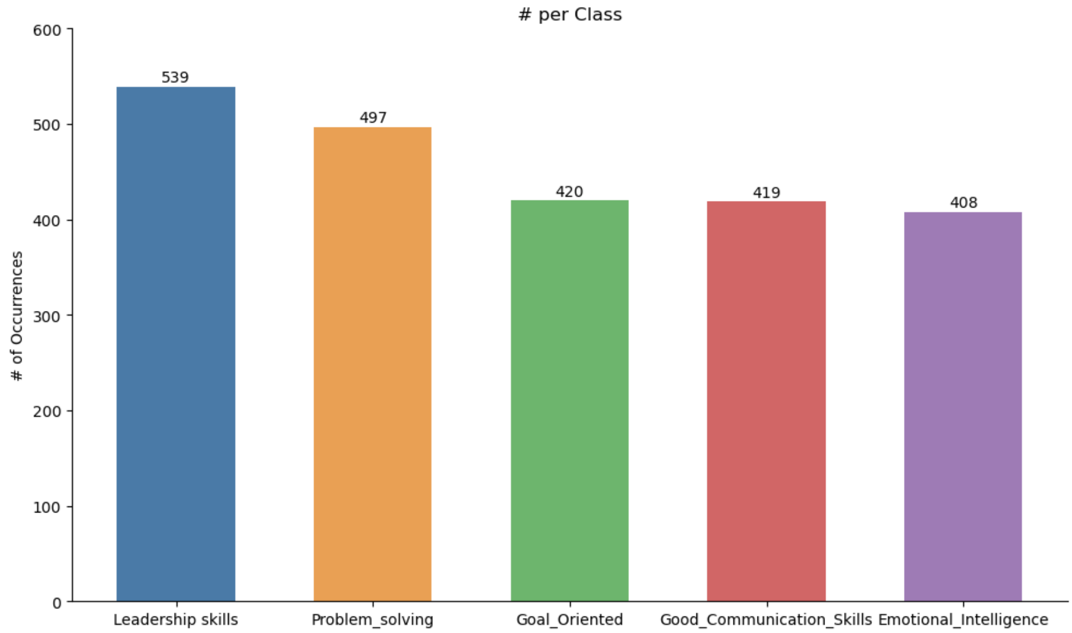


Figure 2. Number of text document

4.3 Topic Correlation

The chart below shows a Pearson correlation of topic labels based on the content of the text document for each topic.

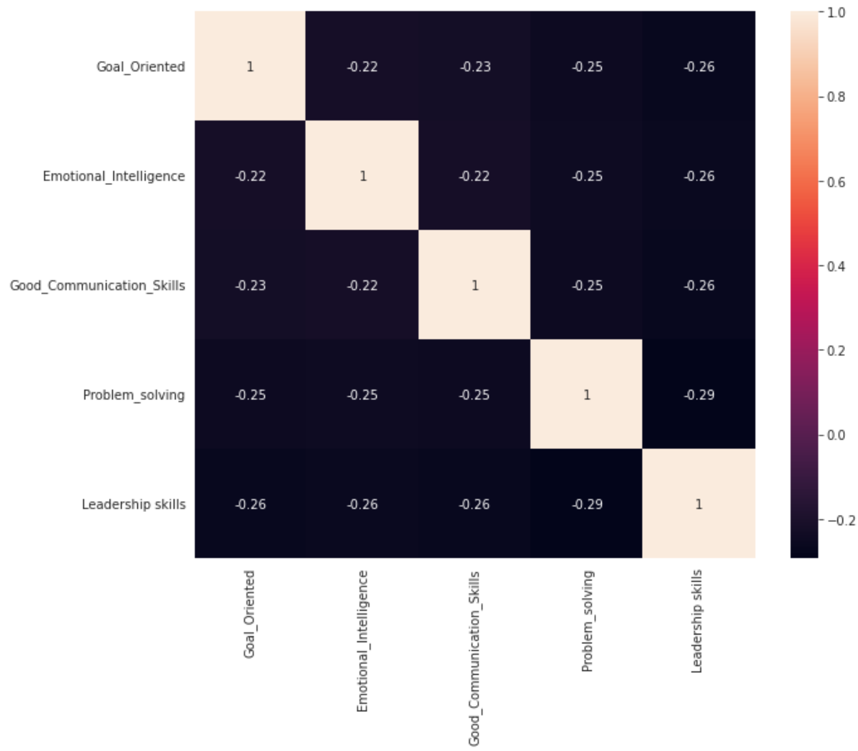


Figure 3. Topic Correlation

4.4 Word Cloud

Word cloud is used to demonstrate an emphasis on the most frequent words in a corpus. Different word cloud was implemented in our work including using custom shapes to highlight the most frequent words in the text documents.

Figure 4. A Custom shape word cloud

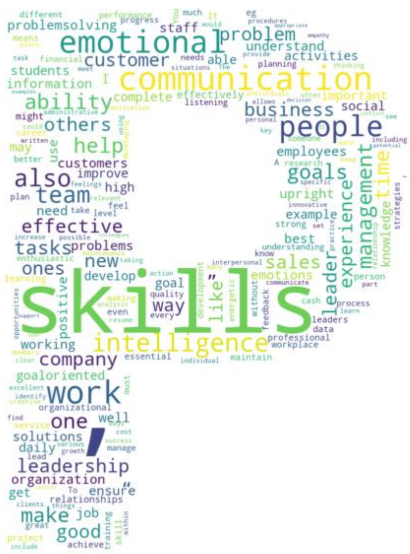


Figure 5. Custom shape word cloud

From the two-word cloud figures shown above, we can observe the most frequent words in our dataset emphasized.

4.5 Impact of Number of Sentences and Words

Part of our feature extraction included the determination of sentences and number of words in each of the texts and the impact on each of the topics. The figure below shows the effect of several sentences and words on the class of Goal-oriented topics. The chart uses a violin plot, an alternative to a box plot. The inner markings show the percentiles while the width of the violin shows the volume of text at that level/instance.

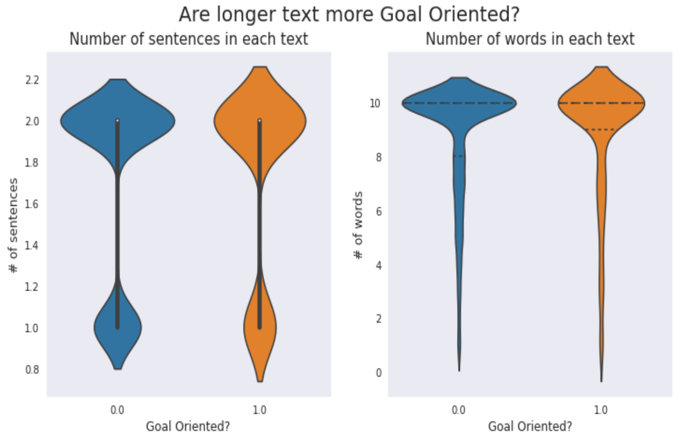


Figure 6. Impact of number of sentences and words

4.6 TF-IDF (Unigram)

As explained and illustrated in detail in Figure 7 on the use of TF-IDF as a feature extraction technique in text classification. The following figure shows the TF-IDF score for all five classes and highlights the top words in each of the topic classes.

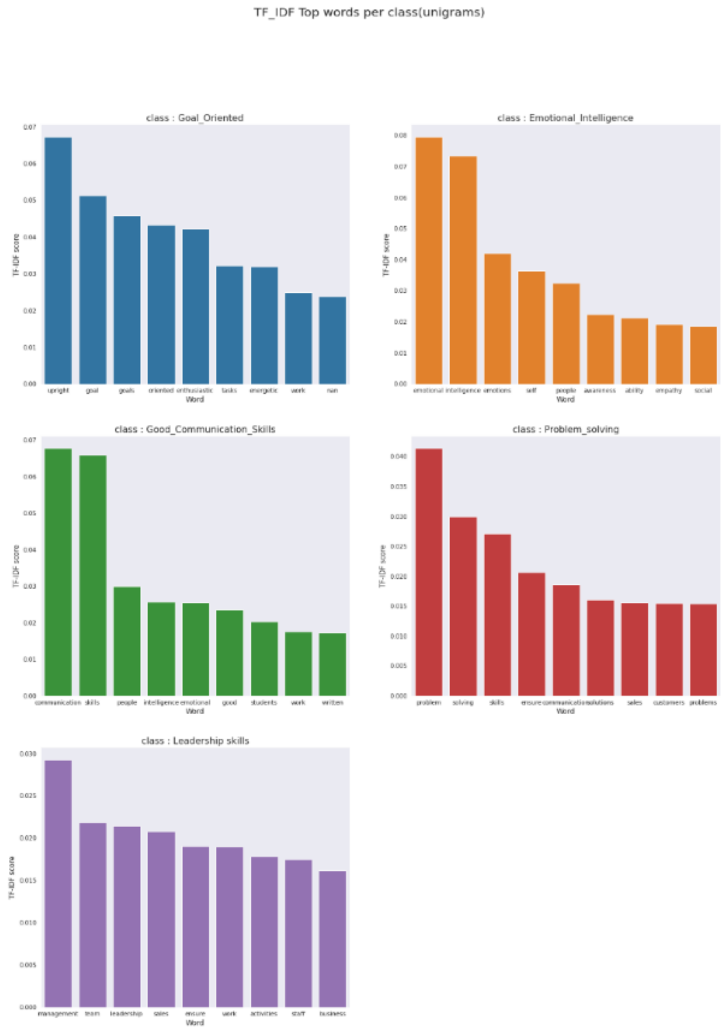


Figure 7. TF-IDF (Unigram *Smart Dispenser Design)*

4.7 Performance Evaluations

It is common in predictive modeling to train several different models, apply each to a holdout sample, and assess their performance. Sometimes, after a number of models have been evaluated and tuned, and if there is enough data, a third holdout sample, not used previously, called the test data, is used to estimate how the chosen model will perform with completely new data. Fundamentally, the model assessment process attempts to learn which model produces the most accurate and useful predictions. The following are some of the methods that were used to evaluate the performance of these classification algorithms used in this research:

4.7.1 *Accuracy*: Accuracy is a simple measure of total error and is expressed as the percentage of cases classified correctly. The accuracy formula can be seen in Equation 1.

$$accuracy = \frac{\sum True\ Positive + \sum TrueNegative}{SampleSize} x\ 100\% \tag{1}$$

4.7.2 *Confusion Matrix:* The confusion matrix is a table showing the number of correct and incorrect predictions categorized by type of response. It is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. This includes true positives and negatives. Also, to measure the selectivity or recall the ratio of true negative to the false negative and true negative. This provides the fact that how many relevant cases have been detected by the classifier and how many of them are correctly guessed. This ratio of recall gives a measure of inclusiveness.

4.7.3 *Precision:* This is the proportion of true positives among instances classified as positive. Thus, any false positives are also included. A true positive is when the outcome is positive and the actual value is also positive. The true negative is when a condition (a disease in this case) exists but the classifier outcome is absent. The ratio of the positives gives the performance resolute of a classifier based on the number of correct guesses to the no of guesses it made. The formula for this equation is shown in Equation 2.

$$precision = \frac{\sum TruePositive}{\sum TruePositive + \sum FalsePositive} \tag{2}$$

4.7.4 *Sensitivity:* Sensitivity, also known as the recall measures the strength of the model to predict a positive outcome the proportion of the 1s that it correctly identifies. It is expressed as equation 3.

$$sensitivity = \frac{\sum TruePositive}{\sum TruePositive + \sum FalseNegative} \tag{3}$$

4.7.5 *Specificity:* Specificity measures a model's ability to predict a negative outcome and is expressed as equation 4.

$$specificity = \frac{\sum TrueNegative}{\sum TruePositive + \sum FalsePositive} \tag{4}$$

Hence, Figure 8 depicts the flow of Our Artificial neural network model built in this research

ANN Model structure

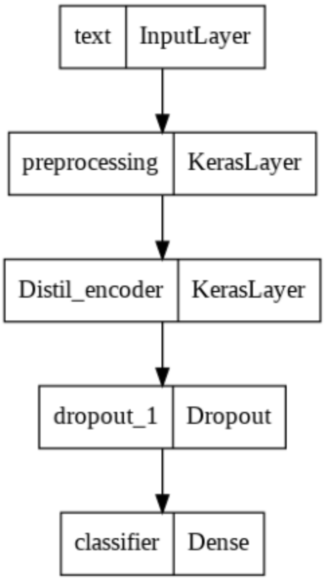


Figure 8. ANN model build Process.

Furthermore, Model training loss and accuracy from our ANN model are presented in Figure 9.

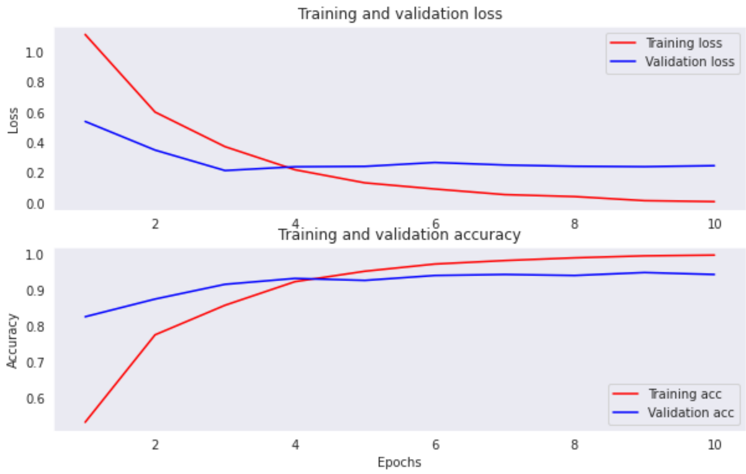
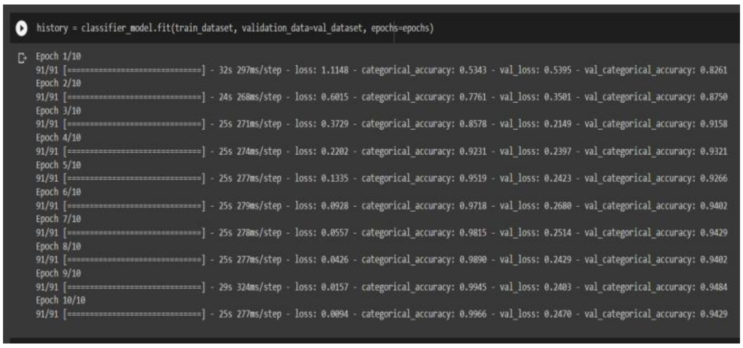


Figure 9. Training vs validation

Again, figure 10 depicts the training accuracy using 10 epochs of our neural network model.

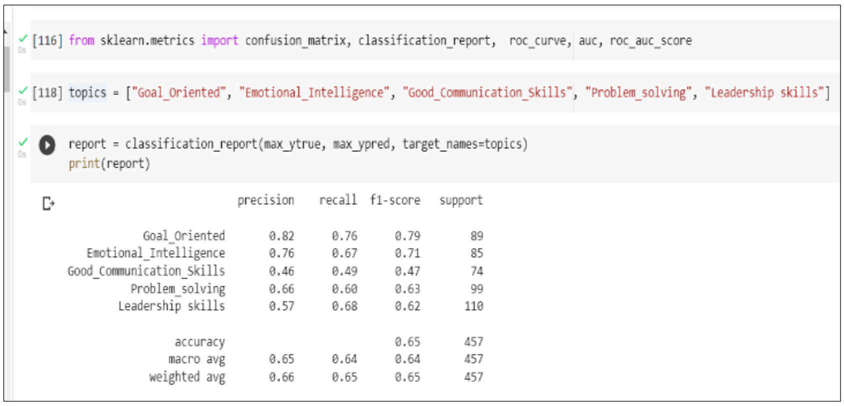


```
history = classifier_model.fit(train_dataset, validation_data=val_dataset, epochs=epochs)

Epoch 1/10
91/91 [==============================] - 32s 297ms/step - loss: 1.1148 - categorical_accuracy: 0.5343 - val_loss: 0.5395 - val_categorical_accuracy: 0.8261
Epoch 2/10
91/91 [==============================] - 24s 268ms/step - loss: 0.6015 - categorical_accuracy: 0.7761 - val_loss: 0.3501 - val_categorical_accuracy: 0.8750
Epoch 3/10
91/91 [==============================] - 25s 271ms/step - loss: 0.3729 - categorical_accuracy: 0.8578 - val_loss: 0.2149 - val_categorical_accuracy: 0.9158
Epoch 4/10
91/91 [==============================] - 25s 274ms/step - loss: 0.2202 - categorical_accuracy: 0.9231 - val_loss: 0.2397 - val_categorical_accuracy: 0.9321
Epoch 5/10
91/91 [==============================] - 25s 277ms/step - loss: 0.1335 - categorical_accuracy: 0.9519 - val_loss: 0.2423 - val_categorical_accuracy: 0.9266
Epoch 6/10
91/91 [==============================] - 25s 279ms/step - loss: 0.0928 - categorical_accuracy: 0.9718 - val_loss: 0.2680 - val_categorical_accuracy: 0.9402
Epoch 7/10
91/91 [==============================] - 25s 278ms/step - loss: 0.0557 - categorical_accuracy: 0.9815 - val_loss: 0.2514 - val_categorical_accuracy: 0.9429
Epoch 8/10
91/91 [==============================] - 25s 277ms/step - loss: 0.0426 - categorical_accuracy: 0.9890 - val_loss: 0.2429 - val_categorical_accuracy: 0.9402
Epoch 9/10
91/91 [==============================] - 29s 324ms/step - loss: 0.0157 - categorical_accuracy: 0.9945 - val_loss: 0.2403 - val_categorical_accuracy: 0.9484
Epoch 10/10
91/91 [==============================] - 25s 277ms/step - loss: 0.0094 - categorical_accuracy: 0.9966 - val_loss: 0.2470 - val_categorical_accuracy: 0.9429
```

Figure10. Model Training and Accuracy Using ANN

Nevertheless, since we were saddled with a classification problem, in this research, we evaluated our model using a confusion matrix to determine the precision, recall, f1-score, and support of our model Figure 11 depicts our classification report.



```
[116] from sklearn.metrics import confusion_matrix, classification_report,  roc_curve, auc, roc_auc_score

[118] topics = ["Goal_Oriented", "Emotional_Intelligence", "Good_Communication_Skills", "Problem_solving", "Leadership skills"]

report = classification_report(max_ytrue, max_ypred, target_names=topics)
print(report)

                           precision    recall  f1-score   support

            Goal_Oriented       0.82      0.76      0.79        89
   Emotional_Intelligence       0.76      0.67      0.71        85
Good_Communication_Skills       0.46      0.49      0.47        74
          Problem_solving       0.66      0.60      0.63        99
        Leadership skills       0.57      0.68      0.62       110

                 accuracy                           0.65       457
                macro avg       0.65      0.64      0.64       457
             weighted avg       0.66      0.65      0.65       457
```

Figure 11. Classification Report

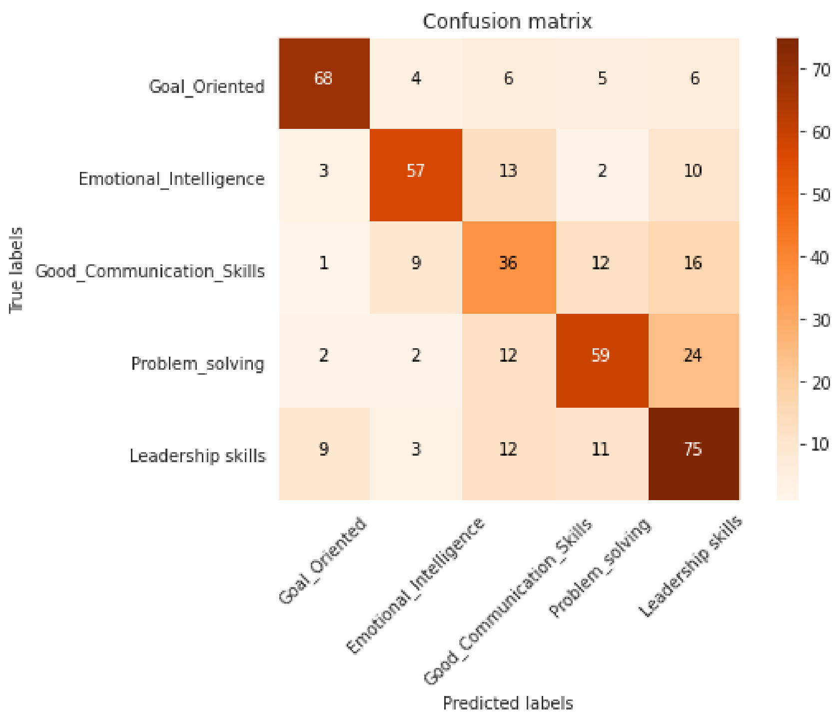


Figure 12. Confusion matrix

5. Conclusion

Presently, professional skills in the workplace enable firms to utilize their technical expertise and knowledge effectively and efficiently, without being constrained by interpersonal conflicts, internal strife, and negative public and market impressions. It requires a deliberate and strategic approach to recruit the correct mix of soft skills. Soft skills, also known as professional skills, are a combination of people skills, social skills, communication skills, character or personality traits, attitudes, career attributes, social intelligence, and emotional intelligence quotients that help employees perform well and accomplish their goals while utilizing complementary hard skills. Soft skills are a crucial but elusive set of skills to look for since they are non-quantifiable professional qualities that can be challenging for hiring managers and other participants in the hiring process to evaluate in potential employees. In addition, in today's world, information has become the most valuable resource. Modern corporations, schools, governments, healthcare agencies, and even individuals must be able to obtain daily information in real-time. Despite the obvious benefits that automation, in general, and Machine learning (ML), in particular, would bring to the decision-making process, progress in implementing Machine learning (ML) applications and the extent of Machine learning deployment in human resource management is still insufficient. Hence, this research considered the development of an intelligent human resource classification system through a Semantic-NLP approach with Artificial Neural Network (ANN). Data was obtained by mining different summary page curriculum vitae both online and offline and pre-processing the datasets, through a data cleaning process, text normalization, and feature extraction in order for effective utilization of the data in a semantic machine learning model. Exploratory data analysis was carried out based on visualization of our different variables as regards skill set classification based on the five (5) topics (Goal-oriented, Emotional Intelligence, Good Communication Skills, Problem-Solving, and Leadership skills) used in the classification procedure. Using an Artificial neural network for classification of the text vectors, an accuracy of 94% was obtained on the 10-epoch used in the model. The performance evaluation on the model demonstrated a classification precision of 82% for Goal Oriented, 76% for Emotional Intelligence, 40% on Good Communication Skills, 66% for Problem Solving, and 57 % on Leadership skills respectively. This work served as a valuation instrument for an efficient human resource management process.

6. Future Research

Future research can explore enhancing the classification accuracy of skill sets in CV summaries by integrating advanced deep learning techniques such as Transformer-based models (e.g., BERT or RoBERTa) for better contextual understanding. Additionally, expanding the dataset with more diverse professional backgrounds and refining feature extraction methods can improve model generalization. Further studies could also investigate the integration of explainable AI (XAI) to provide transparency in classification decisions, enabling human resource managers to interpret results effectively. Lastly, incorporating real-time CV analysis and recommendation systems could streamline recruitment processes, making skill classification more adaptive and dynamic.

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