Performing DISC Personal Inventory Analysis in Job Postings Using Artificial Intelligence Methods

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***Abstract*— One of the application fields of DISC self-evaluation analysis was introduced to predict people's performance and orientation in their working life. Each letter in the word DISC represents an essential personal characteristic, dividing the profiles of people in business life into four essential parts. In the current study, DISC analysis is conducted on job postings to match the person with the job posting. The current study was based on the analysis of 3 different datasets with job postings in English, Turkish and Romanian prepared by using web scraping methods and then labeled in accordance with DISC criteria. Several different machine learning algorithms have been performed on the DISC analysis outputs, and they reached the best results with accuracy values of around over 96% on the English dataset, around over 95% on the Turkish dataset, and around over 96% on the Romanian dataset, for both D, I, S, C models.**

***Index Terms*— DISC, self-evaluation, job postings, XGBoost, LSTM.**

I. INTRODUCTION

Hiring qualified candidates in the company's recruitment process directly improve the company's performance, productivity, and efficiency. For this reason, the evaluation of candidates and the recruitment process have gained importance daily. In order to identify and recruit the people the organization needs; profiling analysis is necessary for industrial recruitment [1]. Various psychometric tests are applied to candidates to realize an effective recruitment process and narrow the candidate pool. These tests reveal the strengths and weaknesses of the candidates and measure whether the candidate in question is suitable for the open position in the organization. Several models are used in the industry for personality assessment, but this study used the Dominance, Influence, Stability, and Conscientious (DISC) Assessment Framework, which focuses directly on behavioural preferences.

DISC Assessment is a questionnaire-based personality test based on the classification of certain personality traits into D (Dominance), Influence (I), Steadiness (S), and Conscientiousness (C) personality types. Type D personalities are described as task-oriented, fast-mover, and bottom-line-oriented. In contrast, type I personalities are people-oriented, energetic, and desire popularity and praise, while S-type personalities are very people and family-oriented, motivated by loyalty and security, and slower-moving. Finally, type C personalities are task and detail-oriented, want all information, and are slower-moving [2]. Personality assessment consists of procedures for determining how people are and how they think, feel and act. For this reason, applying personality assessments in the recruitment process can shed light on predictive applications that can be made about how the candidate will behave in the company.

Artificial intelligence, which is developing daily and integrating into our lives, currently offers recruitment process solutions in many companies. Especially in HR Management, it contributes significantly to the acceleration of the recruitment process and the narrowing of the candidate pool [3]. In this study, the processed text data is used to classify job postings based on the DISC framework. The long-Short-Term Memory approach has been used to classify the collected texts by DISC scores.

Considering the academic literature, artificial intelligence studies aimed at facilitating the recruitment process aimed to reduce the number of candidates and shorten the process [4]. However, studies on selecting the right candidate based on personality traits are insufficient. In this study, machine learning and deep learning algorithms were used to classify candidates based on the DISC personality inventory.

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II. METHODS

A. Data Collecting and Pre-processing

The job posting data used in the study were collected from websites such as Linkedin [5], Indeed [6], and Kariyer [7], in three different languages, English, Turkish and Romanian, by web scraping method. Web scraping was performed using the Selenium [8] and BeautifulSoup [9] libraries of the Python [10] programming language. All job postings will be tokenized and trained by artificial intelligence models. Therefore, all job posting data is free of punctuation. In addition, all letters in job postings have been converted to lowercase letters so that the same words can be tokenized in the same type. In addition, the words that serve as conjunctions in each language were determined and removed from job postings because the words that serve as conjunctions can be found in more numbers than other words in the sentence and can play a dominant role in the models. In addition, repetitive data, and sentences with less than 20 words were removed from the dataset to increase the generalizability of the model. After the pre-processing, a total of 252090 job postings remained in the English dataset, 22713 job postings in the Turkish dataset, and 1418 job postings in the Romanian dataset.

B. DISC Analysis

In order to distinguish the Dominance, Influence, Steadiness, and Conscientiousness classes in the DISC evaluation, the words belonging to each class were determined. In addition, the determined words are common words for all the languages entioned in the study. D, I, S, and C scores were created according to the number of words in the job advertisement. Then, in order to normalize and binarize these scores, they are labeled as 0 if less than 2 and 1 if greater than 5. Intermediate values are not considered in order to increase the decision-making ability of the model and to produce more generalizable models. After the processes, 138737 to represent D, 139877 to represent I, 142252 to represent S, and 129818 to represent C were found in the English data set. For the Turkish data set, 8348 job postings were found to represent D, 7369 to represent I, 8492 to represent S, and 7153 to represent C. Finally, for the Romanian dataset, 1132 to represent D, 978 to represent I, 1029 to represent S and 1096 to represent C were found. Additionally, some DISC words for Dominance, Influence, Steadiness, and Conscientiousness are listed in Tables I and II.

TABLE I. SOME WORDS FOR DOMINANCE AND INFLUENCE

(D)ominance	**(I)nfluence**
Decision making	Communication
Risk taking	Sociability
Creativity	Motivation
Innovation	Impact
Strategic planning	Empathy

TABLE II. SOME WORDS FOR STEADINESS AND CONSCIENTIOUSNESS

(S)teadiness	**(C)onscientiousness**
Project management	Attention on details
Information research	Quality control
Teamwork	Analytical
Service	Time management
Customer oriented	Diplomacy

C. Machine Learning Models

Six different machine learning algorithms were tested for all D, I, S, and C values of the datasets created for English, Turkish and Romanian. These 6 machine learning algorithms are XGBoost, Logistic Regression, Decision Trees, Extra Trees, K-Nearest Neighbours (KNN), and Random Forest. A total of 72 different machine learning algorithms were created with 4 different personal inventory analysis values and 6 different machine learning models for 3 different languages. Before the models, the dataset containing each language and DISC class is divided into 80% for training and 20% for testing. In addition, since machine learning algorithms cannot process non-numerical data, it has been vectorized with the Term Frequency Inverse Document Frequency (TF-IDF) method. You can see the mathematical calculation of the TF-IDF method in equation 1. In addition, to get the highest performance in all the models created, the best parameters were found on the dominant parameters of each model with the Grid Search method. After all these processes, machine learning models were created.

$$TF(t,d) = \frac{(number\ of\ times\ term\ t\ appears\ in\ document\ d)}{total\ number\ of\ terms\ in\ document\ d}$$

$$IDF(t) = \log\left(\frac{N}{(1\ +\ df)}\right) \tag{1}$$

$$TF-IDF(t,d)\ =\ TF(t,d)\ *\ IDF(t)$$

Deep Learning Models

Deep learning refers to neural network-based methods that use current optimization methodologies and training objectives [11]. LSTM, one of the deep learning models used for Natural Language Processing (NLP), was used. The LSTM algorithm was used because it contains a retrospective short and long-term memory model and is widely used in the literature for NLP methods [12]. Since the GRU and RNN algorithms have forward-looking memories, it has caused the vanishing gradient problem because it brings the weights learned beforehand to 0 during backpropagation. Since LSTM networks are the solution to this, only LSTM has been studied. A total of 12 models were created for 4 different DISC methods in 3 different languages. Before the models were created, the words were tokenized and digitized. In order to increase the dominance of certain words in the tokenization method, the first 10000 words were selected. While creating the LSTM model, 4 layers were used with 120 batch sizes. A 0.2 dropout was used between layers to avoid overfitting. Since we made a binary classification, sigmoid was used as the activation function. In addition, the Adam optimizer, which is frequently used in NLP studies, was used with a learning rate of 0.001. The LSTM model structure can be seen in Figure 1.

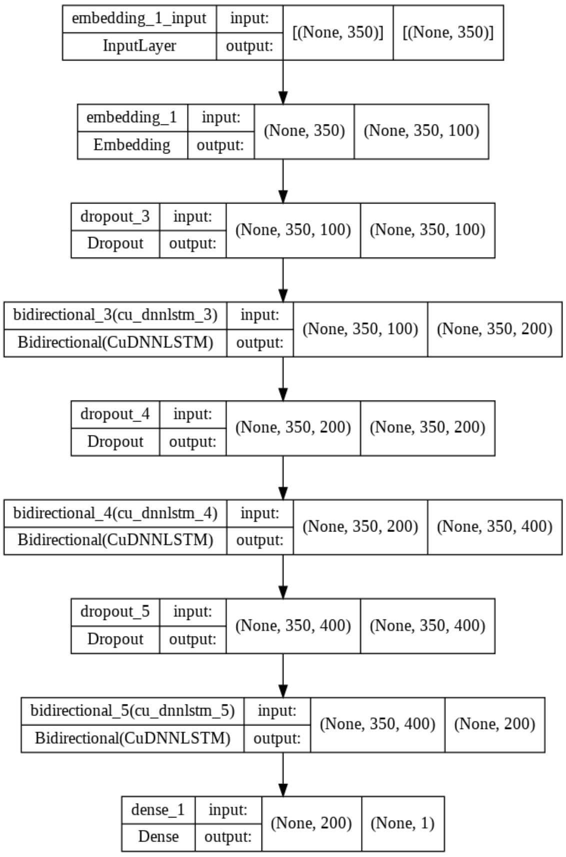

Figure 1. The architecture of the CuDNNLSTM Model

D. Test Environment

All tests were conducted on Google Collaboratory Pro using the Python programming language. Machine learning models were built using the Sklearn [13] framework, and deep learning models were built using the Keras [14] framework.

III. RESULTS

A. Machine Learning Results

1) English Results

The accuracy, F1, precision, and recall scores of the models for Logistic Regression, XGBoost, Decision Tree, Extra Tree, Random Forest, and KNN algorithms for all

DISC personality types for English are shown in Table III. The best models have been selected for each DISC personality type, marked in bold on the table. The scores given in the table were taken as a basis for selecting the best models.

The selected models for the English language are Extra Tree and Random Forest for D type with 97.14% and 97.09% accuracy scores with a given order, Random Forest for I type with 97.10% accuracy, Extra Tree and Random Forest for S with 97.36% and 97.23% accuracy scores and finally, Random Forest for C type with 95.96% accuracy score is the best performing models. Confusion Matrixes for selected models are shown in Figures 2-7.

TABLE III. ENGLISH DATASET MACHINE LEARNING RESULTS.

Type	Model	Accuracy	F1	Precision	Recall
D	Log. Regression	0.9516	0.9736	0.9610	0.9865
D	XGBoost	0.9291	0.9614	0.9466	0.9767
D	Decision Tree	0.9630	0.9795	0.9789	0.9802
D	**Extra Tree**	**0.9714**	**0.9844**	**0.9730**	**0.9960**
D	KNNeighbors	0.6894	0.7948	0.9882	0.6647
D	**RandomForest**	**0.9709**	**0.9841**	**0.9736**	**0.9948**
I	Log. Regression	0.9482	0.9717	0.9578	0.9861
I	XGBoost	0.9285	0.9610	0.9465	0.9758
I	Decision Tree	0.9604	0.9780	0.9783	0.9778
I	Extra Tree	0.9692	0.9831	0.9708	0.9957
I	KNNeighbors	0.6945	0.7983	0.9879	0.6697
I	**RandomForest**	**0.9710**	**0.9841**	**0.9738**	**0.9946**
S	Log. Regression	0.9500	0.9729	0.9604	0.9856
S	XGBoost	0.9318	0.9631	0.9488	0.9777
S	Decision Tree	0.9652	0.9808	0.9809	0.9808
S	**Extra Tree**	**0.9736**	**0.9856**	**0.9752**	**0.9963**
S	KNNeighbors	0.6842	0.7921	0.9884	0.6608
S	**RandomForest**	**0.9723**	**0.9849**	**0.9745**	**0.9956**
C	Log. Regression	0.9225	0.9561	0.9379	0.9749
C	XGBoost	0.8916	0.9390	0.9144	0.9650
C	Decision Tree	0.9402	0.9654	0.9655	0.9653
C	Extra Tree	0.9557	0.9748	0.9583	0.9918
C	KNNeighbors	0.7097	0.8004	0.9870	0.6732
C	**RandomForest**	**0.9596**	**0.9770**	**0.9630**	**0.9914**

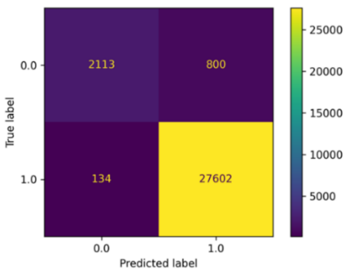

Figure 2. Extra Trees confusion matrix for D in English

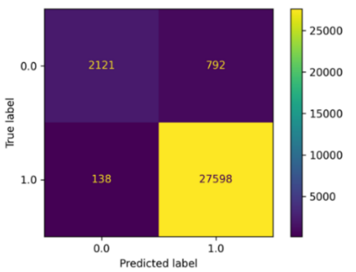

Figure 3. Random Forest confusion matrix for D in English

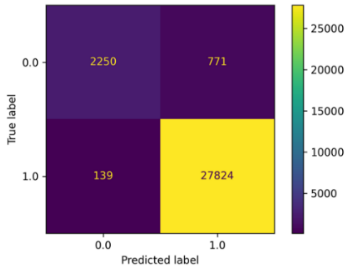

Figure 4. Random Forest confusion matrix for I in English

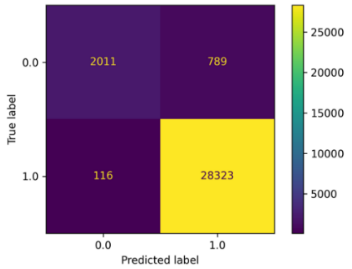

Figure 5. Extra Trees confusion matrix for S in English

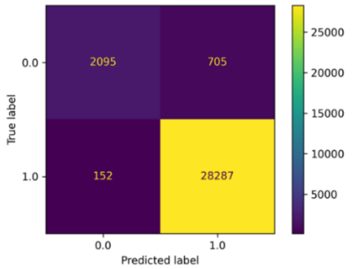

Figure 6. Random Forest confusion matrix for S in English

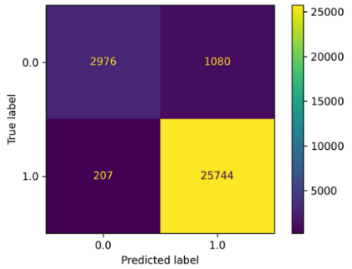

Figure 7. Random Forest confusion matrix for C in English

2) *Turkish Results*

The accuracy, f1, precision, and recall scores of the models for Logistic Regression, XGBoost, Decision Tree, Extra Tree, Random Forest, and KNN algorithms for all DISC personality types for Turkish are shown in Table IV. The best models have been selected for each DISC personality type, marked in bold on the table. The scores given in the table were taken as a basis for selecting the best models. The selected models for the Turkish language are Decision Tree for D type with a 95.07% accuracy score, XGBoost for I and S type with 94.29% and 96.11% accuracy scores in a given order, and finally, and XGBoost for C type with 94.75% is the best performing models. Confusion Matrixes for selected models are shown in Figures 8-11.

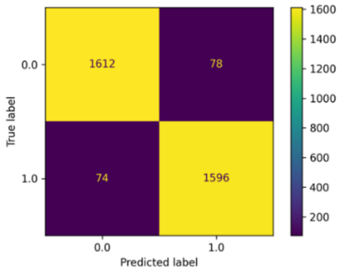

Figure 8. Decision Tree confusion matrix for D in Turkish

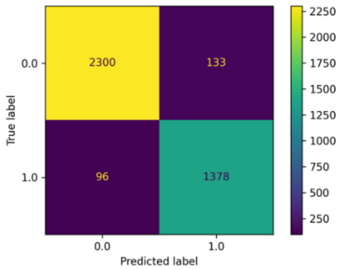

Figure 9. XGBoost confusion matrix for I in Turkish

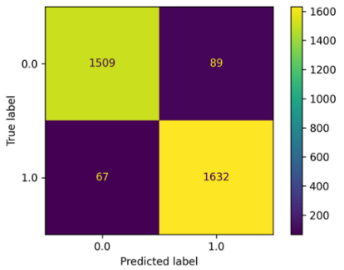

Figure 10. XGBoost confusion matrix for S in Turkish

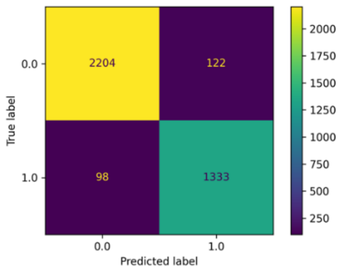

Figure 11. XGBoost confusion matrix for C in Turkish

TABLE IV. TURKISH DATASET MACHINE LEARNING RESULTS

Type	Model	Accuracy	F1	Precision	Recall
D	Log. Regression	0.8851	0.8798	0.9163	0.8461
D	XGBoost	0.9523	0.9522	0.9499	0.9544
D	**Decision Tree**	**0.9507**	**0.9604**	**0.9621**	**0.9586**
D	Extra Tree	0.9089	0.9100	0.8937	0.9269
D	KNNeighbors	0.7306	0.7154	0.7531	0.6814
D	RandomForest	0.9133	0.9132	0.9096	0.9167
I	Log. Regression	0.8871	0.8408	0.8982	0.7903
I	**XGBoost**	**0.9429**	**0.9249**	**0.9172**	**0.9328**
I	Decision Tree	0.9362	0.9155	0.9158	0.9151
I	Extra Tree	0.8804	0.8235	0.9292	0.7394
I	KNNeighbors	0.7225	0.5982	0.6593	0.5474
I	RandomForest	0.9035	0.8654	0.9133	0.8222
S	Log. Regression	0.8838	0.8853	0.9007	0.8705
S	**XGBoost**	**0.9611**	**0.9623**	**0.9612**	**0.9635**
S	Decision Tree	0.9560	0.9573	0.9575	0.9570
S	Extra Tree	0.8993	0.9048	0.8816	0.9293
S	KNNeighbors	0.7073	0.7048	0.7337	0.6780
S	RandomForest	0.8923	0.8975	0.8805	0.9152
C	Log. Regression	0.8802	0.8335	0.8853	0.7875
C	**XGBoost**	**0.9475**	**0.9316**	**0.9249**	**0.9385**
C	Decision Tree	0.9446	0.9268	0.9327	0.9210
C	Extra Tree	0.8738	0.8207	0.8944	0.7582
C	KNNeighbors	0.7146	0.6044	0.6403	0.5723
C	RandomForest	0.9028	0.8663	0.91	0.8266

3) *Romanian Results*

The accuracy, f1, precision, and recall scores of the models for Logistic Regression, XGBoost, Decision Tree, Extra Tree, Random Forest, and KNN algorithms for all DISC personality types for Romanian are shown in Table V. The best models have been selected for each DISC personality type, marked in bold on the table. The scores given in the table were taken as a basis for selecting the best models.

The selected models for the Romanian language are XGBoost for D type with 100% accuracy score, Random Forest for I type with 100% accuracy score, XGBoost for S with 98.80% accuracy score, and finally, XGBoost and Extra Tree for C type with 96.42% and 97.61% in a given order are the best performing models. Confusion Matrixes for selected models are shown in Figures 12-16.

TABLE V. ROMANIAN DATASET MACHINE LEARNING RESULTS

Type	Model	Accuracy	F1	Precision	Recall
D	Log. Regression	0.8851	0.8798	0.9163	0.8461
D	XGBoost	0.9523	0.9522	0.9499	0.9544
D	**Decision Tree**	**0.9507**	**0.9604**	**0.9621**	**0.9586**
D	Extra Tree	0.9089	0.9100	0.8937	0.9269
D	KNNeighbors	0.7306	0.7154	0.7531	0.6814
D	RandomForest	0.9133	0.9132	0.9096	0.9167
I	Log. Regression	0.8871	0.8408	0.8982	0.7903
I	**XGBoost**	**0.9429**	**0.9249**	**0.9172**	**0.9328**
I	Decision Tree	0.9362	0.9155	0.9158	0.9151
I	Extra Tree	0.8804	0.8235	0.9292	0.7394
I	KNNeighbors	0.7225	0.5982	0.6593	0.5474
I	RandomForest	0.9035	0.8654	0.9133	0.8222
S	Log. Regression	0.8838	0.8853	0.9007	0.8705
S	**XGBoost**	**0.9611**	**0.9623**	**0.9612**	**0.9635**
S	Decision Tree	0.9560	0.9573	0.9575	0.9570
S	Extra Tree	0.8993	0.9048	0.8816	0.9293
S	KNNeighbors	0.7073	0.7048	0.7337	0.6780
S	RandomForest	0.8923	0.8975	0.8805	0.9152
C	Log. Regression	0.8802	0.8335	0.8853	0.7875
C	**XGBoost**	**0.9475**	**0.9316**	**0.9249**	**0.9385**
C	Decision Tree	0.9446	0.9268	0.9327	0.9210
C	Extra Tree	0.8738	0.8207	0.8944	0.7582
C	KNNeighbors	0.7146	0.6044	0.6403	0.5723
C	RandomForest	0.9028	0.8663	0.91	0.8266

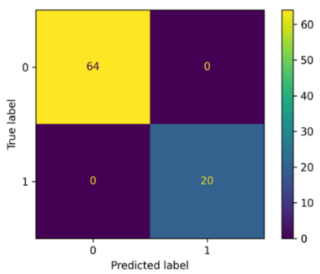

Figure 12. XGBoost confusion matrix for D type in Romanian

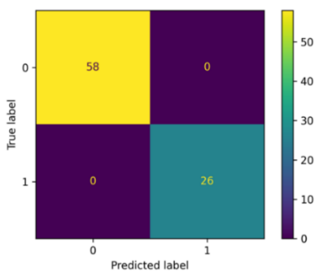

Figure 13. Random Forest confusion matrix for I type in Romanian

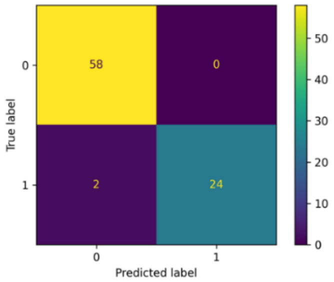

Figure 14. XGBoost confusion matrix for S type in Romanian

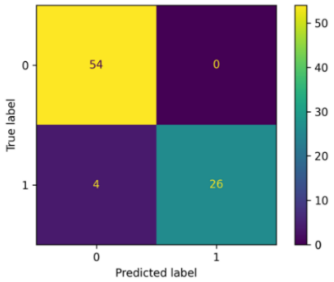

Figure 15. XGBoost confusion matrix for C type in Romanian

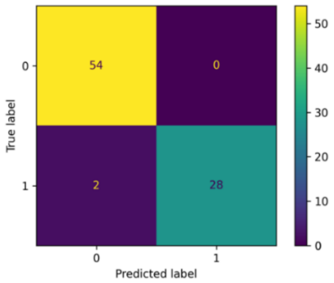

Figure 16. Extra Trees confusion matrix for type C in Romanian

B. *Deep Learning Results*

1) *English Results*

As mentioned in Figure 1, LSTM deep learning architecture is used for the English language. Train accuracy, validation accuracy, loss, and validation loss history plot for each of D, I, S, and C for DISC personality types are shown in Figure 17-20. Confusion matrices of the models are shown in Figures 21-24.

For the D model, 98.98% accuracy and 96.89% validation accuracy scores were obtained, while 99.17% accuracy and 96.64% validation accuracy values for the I model, 99.24% accuracy and 97.25% validation accuracy values for the S model, and finally, accuracy value of 98.59% and a validation accuracy value of 95.20% were obtained for model C. As a result, the validation accuracy value for the English language was above 95% in all models.

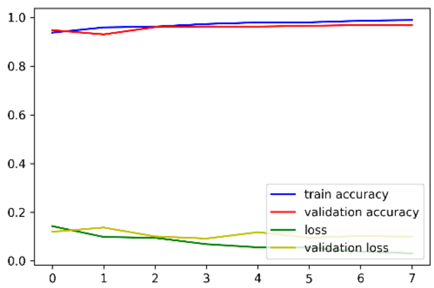

Figure 17. History plot for D in English

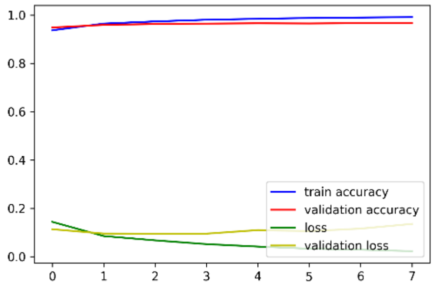

Figure 18. History plot for I in English

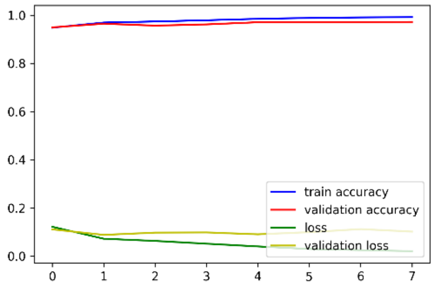

Figure 19. History plot for S in English

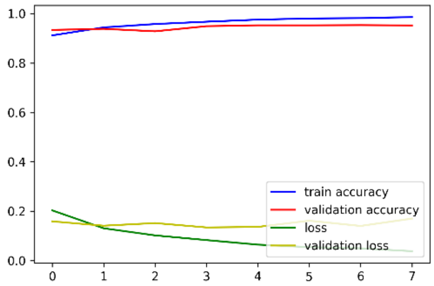

Figure 20. History plot for C in English

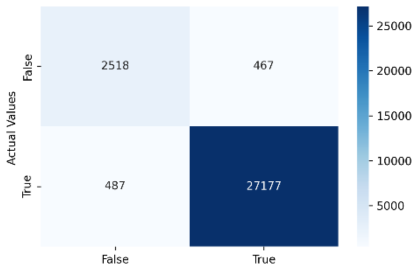

Figure 21. Confusion matrix for D in English

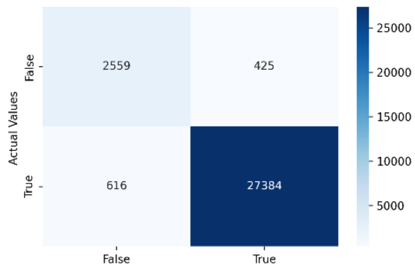

Figure 22. Confusion matrix for I in English

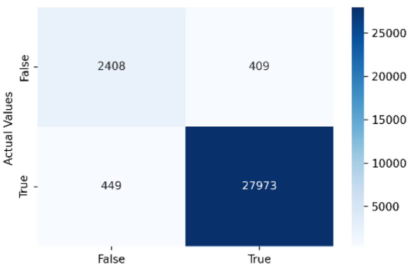

Figure 23. Confusion matrix for S in English

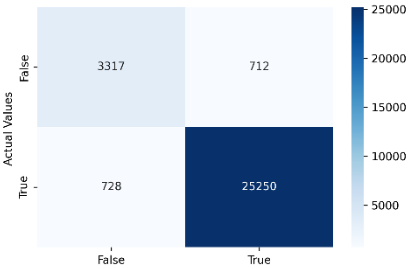

Figure 24. Confusion matrix for C in English

2) *Turkish Results*

As mentioned in Figure 1, LSTM deep learning architecture is used for the Turkish language. Train accuracy, validation accuracy, loss, and validation loss values for each of D, I, S, and C for DISC personality types are shown in Figure 25-28. Confusion matrices of the models are shown in Figures 29-32. For the D model, 99.97% accuracy and 99.55% validation accuracy scores were obtained, while 99.10% accuracy and 97.62% validation accuracy values for the I model, 99.39% accuracy and 99.21% validation accuracy values for the S model, and finally, accuracy value of 99.93% and a validation accuracy value of 99.15% were obtained for model C. As a result, the validation accuracy value for the Turkish language was above 97% in all models.

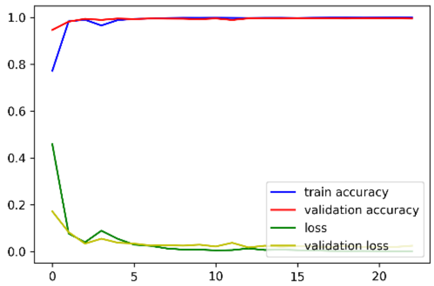

Figure 25. History plot for D in Turkish

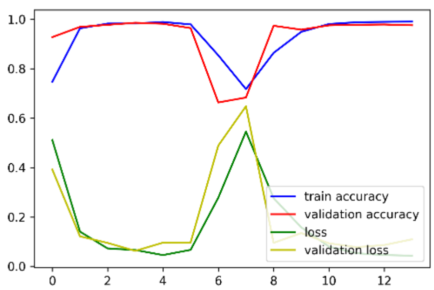

Figure 26. History plot for I in Turkish

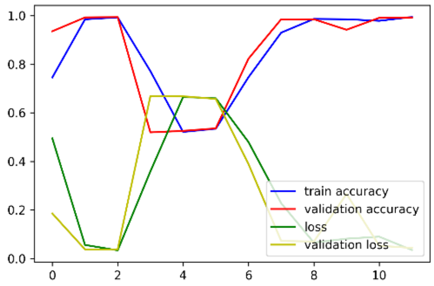

Figure 27. History plot for S in Turkish

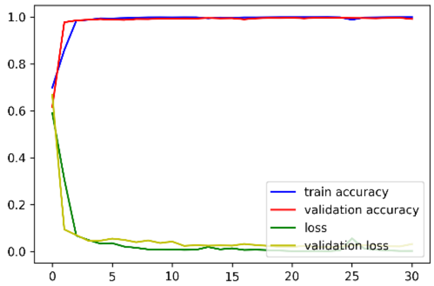

Figure 28. History plot for C in Turkish

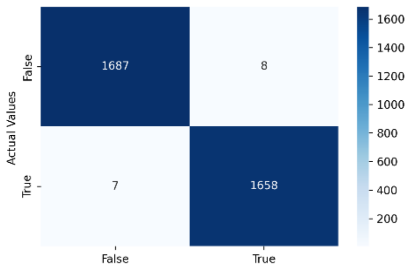

Figure 29. Confusion matrix for D in Turkish

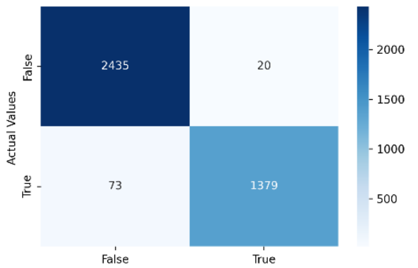

Figure 30. Confusion matrix for I in Turkish

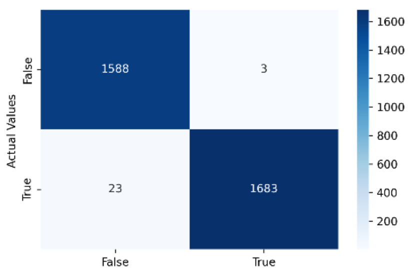

Figure 31. Confusion matrix for S in Turkish

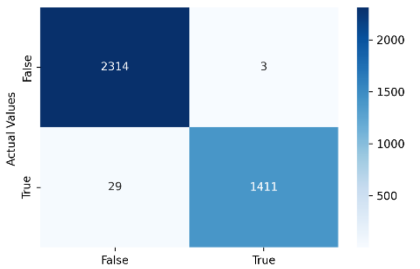

Figure 32. Confusion matrix for C in Turkish

3) Romanian Results

As mentioned in Figure 1, LSTM deep learning architecture is used for the Romanian language. Train accuracy, validation accuracy, loss, and validation loss values for each of D, I, S, and C for DISC personality types are shown in Figures 33-36. Confusion matrices of the models are shown in Figures 37-40. For the D model, 98.80% accuracy and 98.81% validation accuracy scores were obtained, while %100 accuracy and 94.05% validation accuracy values for the I model, 98.19% accuracy and 86.90% validation accuracy values for the S model, and finally, accuracy value of 99.40% and a validation accuracy value of 85.71% were obtained for model C. As a result, the validation accuracy value for the Romanian language was above 85% in all models.

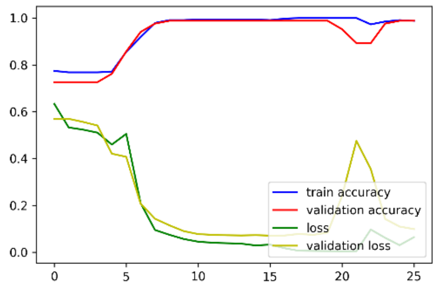

Figure 33. History plot for D in Romanian

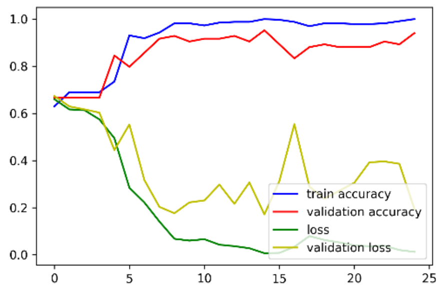

Figure 34. History plot for I in Romanian

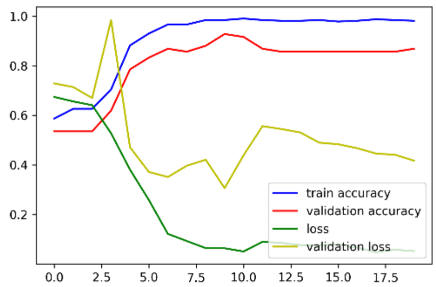

Figure 35. History plot for S in Romanian

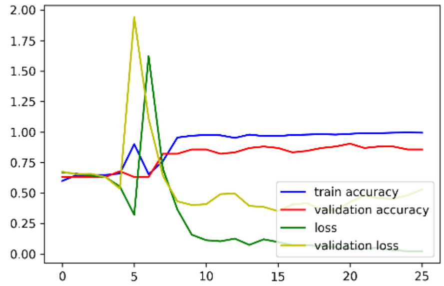

Figure 36. History plot for C in Romanian

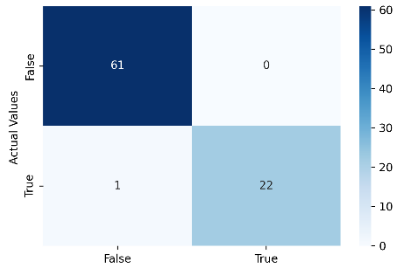

Figure 37. Confusion matrix for D in Romanian

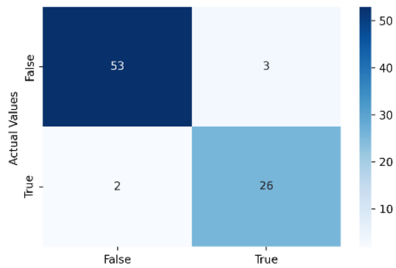

Figure 38. Confusion matrix for I in Romanian

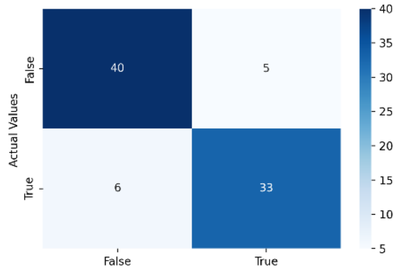

Figure 39. Confusion matrix for S in Romanian

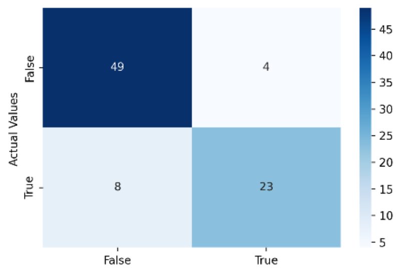

Figure 40. Confusion matrix for C in Romanian

IV. DISCUSSION AND CONCLUSION

This study aimed to classify job postings in the DISC personality inventory with their keywords and select the proper candidate using modern artificial intelligence applications.

In addition, in similar studies in the literature, the DISC personality inventory aimed to measure the success of candidates according to their personality traits [15, 16]. In contrast, our study aimed to determine the candidate profile that the company needed.

In our study, both machine learning models and deep learning models were used. Models have gained superiority over each other according to DISC type and language. Machine learning in some parts and deep learning models in some parts gave good results. However, there are no huge differences between them. The difference between them is about 3% maximum. Considering the low power consumption and faster prediction ability of machine learning models, it is more beneficial to use machine learning algorithms for this problem in terms of efficiency.

In the future, considering training and testing on millions of data, it is predicted that the deep learning model will work better. However, from time to time, a choice can be made between deep learning and machine learning models. The performance of traditional machine learning techniques becomes steady, whereas the performance of deep learning techniques rises as the amount of data increases [17].

Prior to this study, it was unclear whether the organizations could find the right candidate based on the personality traits of the candidates they were looking for. Our study fills this gap in the literature, it has been tested with various tree-based and classifier machine learning algorithms and deep learning algorithms in three different languages (Turkish, English, and Romanian), with a score of over 98% in Turkish and English, and 81% in Romanian.

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