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CHARACTER ANALYSIS BASED ON HANDWRITING USING MACHINE LEARNING: CLASSIFICATION OF MANAGERIAL TRAITS OF TOP EXECUTIVES

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ABSTRACT

This study aims to classify the managerial characteristics of top executives through character traits inferred from handwriting samples using a machine learning approach. A dataset of handwriting samples was analyzed using decision tree algorithms to identify patterns linked to leadership competencies. The methodology includes preprocessing of handwriting features, selection of relevant attributes, and application of supervised learning techniques. The results revealed a classification accuracy of 57%, suggesting that while the model can detect some managerial patterns, further improvement is needed. Limitations such as small sample size, limited feature diversity, and data quality may have influenced the results. Future studies are encouraged to use larger datasets and integrate advanced models such as deep learning techniques and multidimensional handwriting features. This study contributes to the growing literature on biometric indicators in organizational research by demonstrating a novel intersection between graphology and machine learning.

Keywords: *Human Resources Management, Artificial Intelligence, Machine Learning, Handwriting*

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MAKİNE ÖĞRENMESİ İLE EL YAZISINA DAYALI KARAKTER ANALİZİ: ÜST DÜZEY YÖNETİCİLERİN YÖNETSEL ÖZELLİKLERİNİN SINIFLANDIRILMASI

Fetullah BATTAL[1], Tuğba CİĞAL[2]

ÖZ

Bu çalışma, makine öğrenimi yaklaşımı kullanılarak el yazısı örneklerinden çıkarılan karakter özellikleri aracılığıyla üst düzey yöneticilerin yönetimsel özelliklerini sınıflandırmayı amaçlamaktadır. El yazısı örneklerinden oluşan bir veri kümesi, liderlik yeterlilikleriyle bağlantılı örüntüleri belirlemek için karar ağacı algoritmaları kullanılarak analiz edildi. Metodoloji, el yazısı özelliklerinin ön işlenmesini, ilgili niteliklerin seçilmesini ve denetlenen öğrenme tekniklerinin uygulanmasını içerir. Sonuçlar, %57'lik bir sınıflandırma doğruluğu ortaya koydu ve modelin bazı yönetimsel örüntüleri tespit edebilmesine rağmen daha fazla iyileştirmeye ihtiyaç olduğunu gösterdi. Küçük örneklem boyutu, sınırlı özellik çeşitliliği ve veri kalitesi gibi sınırlamalar sonuçları etkilemiş olabilir. Gelecekteki çalışmaların daha büyük veri kümeleri kullanması ve derin öğrenme teknikleri ve çok boyutlu el yazısı özellikleri gibi gelişmiş modelleri entegre etmesi teşvik edilmektedir. Bu çalışma, grafoloji ve makine öğrenimi arasında yeni bir kesişim noktası göstererek örgütsel araştırmalarda biyometrik göstergeler üzerine büyüyen literatüre katkıda bulunmaktadır.

Anahtar Kelimeler: *İnsan Kaynakları Yönetimi, Yapay Zekâ, Makine Öğrenmesi, El Yazısı Analizi*

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1. INTRODUCTION

Writing, which has an important place in a large part of our lives, is not just about symbols written on paper but also contains many clues about our inner feelings. In this age, where technology is rapidly developing and advancing, it seems impossible to stop it, although tools such as the Internet, social media, and e-mail seem to have replaced handwriting, and handwriting still maintains its importance and existence. In addition to using technological tools in social or business life, everyone frequently performs transactions using handwriting. The traces left from the moment the pen tip touches the paper create clues that reveal the person's identity as patterns, shapes, and symbols that reflect our identity, and just like fingerprints or DNA sample sequences, it has the ability to reflect our personality in a unique way.

At the beginning of the 20th century, German Professor W. Preyer revealed that writing is not a psychomotor skill that occurs by exercising certain muscles, but is created by the brain. Later studies have shown that the brain is the most effective organ for the formation of writing is the brain (Robertson, 1991). Based on this, it has been shown that handwriting is an effective tool for reaching certain analyses and making inferences about the subject, in the case of psychology, directly to the human brain. Therefore, it was concluded that character analysis based on handwriting has the potential to be applied in many different areas. When the literature is examined, it is seen that it is effectively used in many areas such as judicial investigations, human resources (recruitment processes), psychological counseling and guidance services, and education.

When studies of personality analysis based on handwriting are examined, it is naturally seen that the science of graphology comes to the fore. Graphology is a field of study that includes steps such as making inferences about a person's personality and character based on handwriting samples and analyzing its structure (Sheikholeslami et al., 1997). It is defined as a branch of science that uses distinctive features obtained from handwriting for character analysis. The term graphology is formed by combining the Greek words "graphein" (writing) and "logos" (study). In linguistics, the term graphology is sometimes used synonymously with grapheme, the scientific study of traditional methods of transcribing spoken languages.

In management sciences, approaches to analyzing individual differences have long drawn upon insights from behavioral sciences. Personality traits and their relationship with leadership styles, decision-making patterns, and organizational performance have been extensively examined, particularly using the Big Five personality model and similar psychological assessment tools (Judge, Bono, Ilies, & Gerhardt, 2002). However, recent research in the management field has increasingly explored alternative and indirect methods for identifying personality characteristics. One such method is graphology or handwriting-based character analysis, which seeks to infer personality traits from the structure and features of an individual's handwriting (Jansen, 2002). Although handwriting analysis has historically been more common in fields such as psychology and forensic science, it also holds potential for applications in business and human resource management. Handwriting may provide useful insights into recruitment processes, such as assessing personality compatibility, leadership potential, and stress management capacity (Cohen, 2011). Nevertheless, for this method to gain broader acceptance within management science, it must be grounded in scientific rigor, moved away from subjective interpretations, and systematized through objective analysis.

Advances in artificial intelligence and machine learning have opened new possibilities for analyzing handwriting in a more objective and replicable manner. Machine learning algorithms are particularly proficient at detecting complex patterns within large datasets (Jordan & Mitchell, 2015). Accordingly, features extracted from handwriting samples, such as slant, pressure, spacing, and stroke width, can be analyzed using machine learning techniques to generate predictive models of personality traits (Singh, Dey, & Nagpal, 2020). Classification algorithms, such as decision trees, support vector machines (SVM), and artificial neural networks, are frequently employed in such analyses. Despite its potential, the integration of handwriting-based character analysis with machine learning remains relatively underexplored in management literature. For instance, Zhang et al. (2022) developed a model for predicting psychological resilience from handwriting samples, whereas Malik and Kaur (2021) focused on forecasting leadership tendencies using similar features. However, most of these studies emphasize general personality profiling rather than managerial competencies, such as decision-making, leadership behavior, or conflict resolution in organizational contexts. This reveals a clear research gap concerning the application of handwriting-based character analysis in the domain of management behavior.

Moreover, the existing body of research on the relationship between handwriting and personality is often limited to qualitative interpretations or small-sample statistical studies. These limitations challenge the reliability and generalizability of the findings (Eysenck & Furnham, 1993). Therefore, the quantitative association of measurable handwriting features with managerial personality traits may contribute to enhancing both the scientific validity of the method and its relevance to management literature. In summary, studies situated at the intersection of handwriting analysis, personality psychology, and machine learning represent a novel and emerging approach to management research. Linking character data derived from handwriting to managerial behavior patterns can open a new field of application, particularly in leadership assessment, managerial development programs, and potential analysis frameworks. Consequently, this study offers not only a methodological contribution but also a conceptual expansion in the field of management sciences.

2. EXPERIMENTAL METHOD

2.1. Conceptual Review

When the literature is reviewed, the following methods have generally been used to extract features from handwriting to predict human characters or behavior and perform personality analysis:

1- Slope of the text

2- Pen pressure

3- Features of some letters

4- Right, left, top and bottom margins of the page

5- Spaces between lines

6- Spaces between words

7- The adjacency of letters

8- The rectangle covered by the words

9- Slope of letters

10- Size of letters

The main machine learning algorithms used to automatically perform personality analysis using the aforementioned features are as follows:

1- Support Vector Machines

2- Artificial Neural Networks

3- Convolutional Neural Networks (Deep Learning)

4- Hidden Markov Models

In this study, the categories used in the analysis of handwritten characters were writing slope, right, left, top, and bottom margins of the page, interlinear spaces, interword spaces, and pen pressure. This is preferred because they are the most frequently used personality analysis categories in graphology. The machine learning algorithms used were the NB Classifier, Decision Trees, Random Forest, SVM and Logistic Regression. The decision tree method was preferred among these methods, and the decision tree results were obtained using the J48 algorithm with the help of the WEKA program.

When the literature is examined, it is observed that the decision tree method is used in several studies. Some of these studies are as follows: Çalış et al. (2014) made inferences about the computer and Internet security of people with different demographic characteristics. Data were collected through a survey and the decision tree method was used as the method. Şengür and Tekin (2014) predicted student graduation grades using artificial neural networks and decision trees. Bayır et al. (2016) used the decision tree method to predict voters' tendencies. Aksu and Güzeller (2016) classified mathematical literacy scores within the scope of an international student assessment program using the decision-tree method. Akbal et al. (2017) analyzed phone fraud data and conducted research on classification using the decision tree method. Using the decision tree method, Büyükarıkan (2020) attempted to determine the financial variables that affect financial performance. Okatan and Işık (2020) used the decision tree method to predict health expenditure. Koçak (2020) attempted to determine whether psychological contract and organizational commitment characteristics are effective in classifying and predicting organizational commitment using the CART decision tree method.

Decision tree algorithms have been used in many studies. In recent years, it has been observed that the method in question has also begun to be applied in the field of organizational behavior. In studies in the field of organizational behavior, regression and correlation analyses of the relationships between variables are mostly carried out using package programs such as SPSS, AMOS, and Lisrel. This research, unlike these studies in the literature, is original in that it addresses the variables that are the subject of organizational behavior through decision tree analysis, a data-mining method.

2.2. Studies on Handwriting

Champa and Ananda Kumar, in their study on the prediction of human behavior based on handwriting analysis, considered categories such as inclination, pen pressure, and the characteristics of letters y and t. Handwriting is often referred to in the literature as brainwriting. Each personality trait was represented using a neurological brain model. When the neurological brain model was examined, it was concluded that the model produces a unique neuromuscular movement that is the same for each person with a certain personality trait. These small movements occur unconsciously during writing. Each written movement or stroke results in a certain personality trait. Graphology is the science of identifying strokes based on reflections in handwriting and determining the corresponding personality traits. In this study, a method is proposed to predict a person's personality based on an analysis of handwriting.

When a person's handwriting is examined, the personality traits revealed by the baseline, pen pressure, the letter "t," the lower ring of the letter "y" and the slope of the writing are determined. Of these five parameters, the baseline, pen pressure and the height of the t line in the body of the letter "t," the lower ring of the letter "y" and the slope of the writing constitute the inputs of the rule. While the polygonalization method, which is one of the most widely used methods in the evaluation of the baseline, is used, the gray level threshold value is used in the evaluation of pen pressure. The height of the t line in the body of the letter "t" is calculated by the template matching method. While the shape of the lower ring of the letter "y" is calculated by the Generalized Hough Transform (GHT), which is one of the popular methods, the slope of the writing is also calculated by the template matching method. Based on these parameters obtained from handwriting, the existence of much correct information about the writer is revealed. The MATLAB program has been widely used in similar studies. Performance is measured by examining and analyzing multiple handwriting samples (Champa & Ananda Kumar, 2010).

Fatimah et al., in this path they set out to determine personality traits from handwriting, proposed to determine the analysis of an individual's personality, structure and symbolic features based on handwriting images with the study they conducted using convolutional neural networks. It was classified using the CNN method, which is a multistructure analysis based on symbol analysis. Margins, interlinear spaces, intra-word spaces, print and certain letter features, slope, and inclination, which were not included in previous studies and made a difference in the study, were examined (Fatimah et al., 2019).

Durga and Deepu comprehensively reviewed studies conducted on handwriting analysis using graphology methods between 1971 and 2017, and comprehensively evaluated the artificial intelligence and feature extraction methods used. The study was completed using a machine learning approach, where a few examples were used to learn the writer features and different examples were used to test the learned models (Durga and Deepu, 2018).

Prasetyo et al. designed a mobile application in 2017 that can be identified using graphology methods. In the application, the parameters of writing direction, slope, width, margin, pointed or rounded letters, and interlinear space were used for analysis. It was observed that the results obtained by testing 25 handwritings using the application were exactly the same as those evaluated by an expert (Prasetyo et al., 2017).

In 2018, Durga and Deepu conducted an Automatic Career Guidance study using graphology, aptitude tests, and personality tests. This study was conducted to guide and assist individuals in becoming acquainted with various career fields and choosing the right profession. The study was conducted by considering the basic aspects of human behavior analysis. When the basic aspects were examined, it was concluded that they included conscious and subconscious factors that help individuals make decisions about their attitudes and abilities. The methods used were the Aptitude Test, Psychometric Test (Myers–Briggs Type Indicator, MBTI), and handwriting analysis. While information about career and personality was obtained through conscious answers given by individuals through the question-answer module, the handwriting module focused on revealing the subconscious map of career and personality. By examining the handwriting samples taken, features such as the space between words, the size of the left and right margins on the page, the font, the slope direction of the letter, the size of the letter and the size of the letter "I" were calculated and by integrating the three modules, suitable career options were presented to individuals (Durga and Deepu, 2018).

2.3. Materials and Methods

2.3.1.Problem Definition

Character analysis comes to the forefront in many areas, such as recruitment, workplace performance, career management and development, education and academic success, personal development, and self-knowledge. As a result of the unforeseen situations encountered in these processes, wrong choices and irreversible decisions may have been made. Therefore, making the most accurate decision in the shortest time and re-establishing the operation are of great importance in terms of profitability. In this rapid decision-making process, revealing hidden or overlooked information using past data makes it easier to make new choices. Nowadays, analyzing past data and making inferences about the future has become quite useful for systems. In this study, character estimation was made from people's handwritings to create a structure that draws attention to important factors for managers, provides preliminary information on what to do, and thus speeds up. Thus, the theoretical information necessary for human resource management was converted into an algorithm using machine learning.

2.3.2 Application: Character analysis from handwriting

Previous studies have been conducted on character analysis based on human handwriting. While some studies used methods such as artificial neural networks and image processing to perform character analysis, other researchers performed this analysis using machine learning methods. In this study, human handwriting data were trained using traditional machine learning algorithms. However, to model character analysis using this information and use this model meaningfully, handwriting needs to be analyzed very carefully when converted into data.

For the classification of character analysis, a sample text was given, and handwriting samples were taken from 74 people in managerial positions residing in Bayburt Province. These handwriting samples were evaluated by taking into account criteria such as character, letter slope, space between lines, and type of printing of the text. The dataset created in Excel is a 75 × 13 matrix, and the first row contains the headings. A section of the dataset is shown in Figure 1.

harflerinegimi	Harflernasil	Kelimelerarasindakibosluk	Satiraralari	Basharfleringenisligi	tharfininasil	cizgisizbirsayfadayazi	Satiraralarindaencokboslukolusturanharf	Yazininkarakteri	Egimcesidi	Yaziboyutu	ustBolgeYuksekligi	Baski	ka
duz	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Duz bir sekilde	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	F	Orta	Uzun	Orta	
duz	tamamen bitisik	genis	Epey aralik var	Digerlerinden daha genis	t yi kesen cizgi t yi tam ortadan kesiyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	A	Buyuk	Uzun	Agir	
duz	tamamen ayri	genis	Epey aralik var	Digeriyle esit genislikte	t yi kesen cizgi t yi tam ortadan kesiyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	B	Orta	Uzun	Orta	
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duz	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digeriyle esit genislikte	t yi kesen cizgi t yi tam ortadan kesiyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	A	Kucuk	Uzun	hafif	
duz	kismen birlesik	genis	Epey aralik var	Digeriyle esit genislikte	t yi kesen cizgi t yi tam ortadan kesiyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	A	Kucuk	Kisa	hafif	
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ileri	kismen birlesik	genis	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	D	Orta	Kisa	Orta	
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ileri	kismen birlesik	genis	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digeriyle esit genislikte	t harfinin govdesinin sagina dogru oluyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	E	Kucuk	Kisa	Orta	
duz	kismen birlesik	genis	Epey aralik var	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	A	Buyuk	Kisa	Agir	
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geri	kismen birlesik	genis	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digeriyle esit genislikte	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	B	Orta	Kisa	Agir	
duz	kismen birlesik	genis	Epey aralik var	Digeriyle esit genislikte	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	A	Orta	Uzun	Orta	
duz	kismen birlesik	genis	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digeriyle esit genislikte	t yi kesen cizgi t yi tam ortadan kesiyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	C	Buyuk	Kisa	Agir	
ileri	tamamen bitisik	dar	Kelimeler birbirine degmeyecek kadar	Digeriyle esit genislikte	t yi kesen cizgi t yi tam ortadan kesiyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	C	Buyuk	Uzun	Orta	
geri	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digeriyle esit genislikte	t harfinin govdesinin sagina dogru oluyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	B	Kucuk	Uzun	Agir	
duz	tamamen bitisik	dar	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	B	Orta	Kisa	Orta	
ileri	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	C	Kucuk	Kisa	Agir	
geri	kismen birlesik	dar	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	D	Orta	Kisa	Orta	
ileri	kismen birlesik	dar	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	C	Orta	Kisa	Agir	
ileri	tamamen bitisik	dar	Epey aralik var	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	C	Buyuk	Kisa	Orta	
geri	tamamen bitisik	genis	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	D	Buyuk	Kisa	Agir	
ileri	kismen birlesik	genis	Epey aralik var	Digeriyle esit genislikte	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	D	Buyuk	Kisa	Agir	
ileri	tamamen bitisik	dar	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Kalin fakat duzgun yazarim	C	Kucuk	Kisa	Agir	
ileri	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t harfinin govdesinin sagina dogru oluyor	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	D	Buyuk	Kisa	Orta	
ileri	kismen birlesik	genis	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Asagi dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	D	Buyuk	Kisa	hafif	
geri	tamamen bitisik	dar	Asagi ve yukari uzanan harfler y ve g ya da h ve t gibi birbirine degmeyecek kadar yakin	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	C	Orta	Kisa	hafif	
ileri	tamamen bitisik	dar	Kelimeler birbirine degmeyecek kadar	Digerlerinden daha genis	t yi kesen cizgi t harfinin ana govdesinin soluna dogru	Yukari dogru	j ve y ve g gibi asagi uzayan harfler	Gayet ince ve bastirmadan yazarim	B	Orta	Kisa	hafif	

Figure 1. Example of Dataset

2.3.3 Model Selection and Data Processing in Weka Program

The WEKA (Waikato Information Analysis Platform) program, which is frequently used in machine learning studies, was used in the analysis of the decision tree method. The obtained data were categorized in an Excel file format and converted to CSV files to be compatible with the Weka software. The data in the CSV format were finally converted to the ARFF format and sent to the program. While the first 80% of the values in the file were used for the machine-learning process, the remaining values were separated to test whether learning had occurred, and the J48 algorithm was used as the method. Results were obtained using the branching criteria of the decision tree created using the Weka program. The performance of the algorithm was evaluated by calculating the accuracy levels, and it showed a success rate of 57%. A screenshot of the success rate is shown in Figure 2.

```
=== Summary ===

Correctly Classified Instances          34               57.6271 %
Kappa statistic                          0.2632
Mean absolute error                      0.3223
Root mean squared error                  0.4115
Relative absolute error                 79.2328 %
Root relative squared error             93.7128 %
Total Number of Instances               59

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0,541    0,318    0,741      0,541    0,625      0,216    0,646     0,716     Orta
                 0,933    0,409    0,438      0,933    0,596      0,458    0,812     0,501     Agir
                 0,000    0,000    ?          0,000    ?          ?        0,735     0,215     hafif
Weighted Avg.    0,576    0,304    ?          0,576    ?          ?        0,699     0,602

=== Confusion Matrix ===

  a  b  c   <-- classified as
 20 17  0 |  a = Orta
  1 14  0 |  b = Agir
  6  1  0 |  c = hafif
```

Figure 2. Success Rate of the Data Set Obtained from the Weka Program

2.3.4 Results of the Algorithm

```
Scheme:       weka.classifiers.trees.J48 -C 0.25 -M 2
Relation:     analizguncell-weka.filters.unsupervised.attribute.StringToNominal-Rlast-weka.filters.
Instances:    74
Attributes:   13
              harflerinegimi
              Harflernasil
              Kelimelerarasindakibosluk
              Satiraralari
              Basharfleringenisligi
              tharfininasil
              cizgisizbirsayfadayazi
              Satiraralarindaencokboslukolusturanharf
              Yazininkarakteri
              Egimcesidi
              Yaziboyutu
              ustBolgeYuksekligi
              Baski
Test mode:    split 20.0% train, remainder test
```

Figure 3. Program output of categories in the dataset

When Figure 3 is examined in detail, it is possible to see categories such as the slope of the letters in the dataset used for classification, the space between words, and pressure. In addition, when the "test mode " area at the bottom of the figure was examined, 20% of the data were used to test machine learning.

```
J48 pruned tree
------------------

Yazininkarakteri  = Kalin fakat duzgun yazarim
|   Harflernasil  = kismen birlesik
|   |   Satiraralari = Kelimeler birbirine degmeyecek kadar: Orta (10.0/4.0)
|   |   Satiraralari = Epey aralik var: Agir (3.0/1.0)
|   |   Satiraralari = Asagi ve yukari uzanan harfler  y ve g ya da h ve t gibi  birbirine degmeyece
|   Harflernasil  = tamamen bitisik: Orta (14.0/4.0)
|   Harflernasil  = tamamen ayri: Orta (1.0)
Yazininkarakteri  = Gayet ince ve bastirmadan yazarim: Orta (33.0/9.0)
Yazininkarakteri  = Kalin : Agir (5.0/1.0)
Yazininkarakteri  = Kalin: Agir (1.0)
```

Figure 4. Output of the pattern created as a result of the algorithm.

When Figure 4 is examined, it can be seen that the pressure variable in the algorithm is the most important analysis reason. Here, it is thought that most of the pressure is encountered compared to other categories related to character analysis. In addition, the space between the letters is considered according to the character of the text. In the next step, the space between the lines is evaluated, and it is concluded that the pressure is heavy, medium, or light. In addition, based on the information on the upper side of the figure, the J48 algorithm is used.

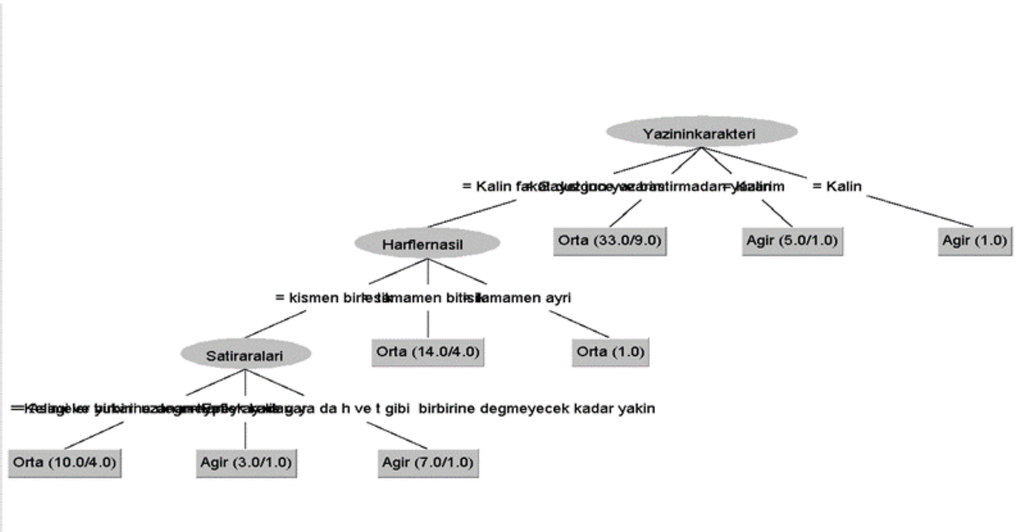

Figure 5. Decision Tree Created as a Result of the Algorithm.

Fig. 5 shows the decision tree formation of the logical pattern created in Figure 3. Here, the relationship between the root nodes that are important for analysis is clearly shown.

Table 1. The Equivalent of the Oppression Category in Character Analysis

Heavy	Medium	Light
Stressful Reliable	Fragile	Lacking
Nervous	Serious	Delicate
Frequent job changers	Responsible	Self-confidence

Table 1 shows the subcategories of the pressure categories (heavy, medium, and light). In light of the information obtained from the table, if the pressure type of the text is 'Heavy, ' it can be concluded that the person is 'Stressed, tense, and frequently changes jobs. Alternatively, if the pressure type of the text is 'Medium,' it can be concluded that the person is 'Reliable, serious. ' Finally, if the pressure type of the text is 'Light, ' it can be concluded that the person is 'Fragile, sensitive, and lacking in self-confidence.

3. DISCUSSIONS and CONCLUSIONS

Data mining is the analysis of (usually large) observational datasets with the aim of identifying unpredictable relationships and verbally summarizing them to make them understandable and useful for the data owner (Smith, 2002). Data mining is an interdisciplinary field that combines machine learning, pattern recognition, statistics, databases, and visualization techniques to extract information from large databases (Nayak, 2003). Data mining is the process of automatically discovering useful information from large data stores (Çiçek & Arslan, 2020).

Classification refers to the assignment of an object to a predefined class by examining its attributes. The class characteristics must be well-defined. Because the results are known in advance, the classification falls into the supervised learning group. The main techniques used in classification and regression analysis are as follows (Çiçek & Arslan, 2020):

- K-Nearest Neighbor,
- Genetic Algorithms,
- Artificial Neural Networks
- Naive- Bayesian,
- Linear Regression, Logistic Regression
- Can be given as Decision Trees.

Decision trees are the most widely used technique among classification models because they are easy to interpret, easily integrate with database systems, and have good reliability. Decision trees are an estimation technique in tree view (Özçakır & Çamurcu, 2007). In the algorithms used in the decision tree, which are used to classify data according to certain variable values, the inputs and outputs are the determined variables of the data, and the decision tree algorithm discovers the input data variables for the output data variables with data structures (Berry, 2000).

They can easily be translated into rule sets, work with continuous or discrete data, and make predictions with missing or erroneous data. They are also among the nonparametric methods. This means that decision trees do not have to comply with assumptions regarding the spatial distribution or classifier structure. However, they may also have disadvantages, as they are insensitive to missing or erroneous data and contain repetition at the leaf nodes (Maimon & Rokach, 2010).

The J48 algorithm is widely known as C4.5. Dichotomizer-3 (ID3) based machine learning model based on Quilan side; The model determines and predicts a new sample-based target value (dependent variable) on various feature values of existing J48 data, it is a very popular algorithm and ranks 1st in the "top 10" ranking. In data mining, algorithms follow a divide-and-conquer algorithm structure called the decision tree classifier. In the classification, a decision tree must first be created for each new element. It is based on the values of the features of categories created from the existing training data (Pelit et al., 2019).

The classification accuracy of 57% obtained in this study falls short of the targeted success level of machine learning applications. There may be several reasons for this finding. First, the limited sample size may have reduced the generalization capacity of the model. In high-variance areas, such as handwritten character analysis, training the model with larger and more diverse samples may increase classification performance. Second, considering only basic handwritten parameters in the feature selection may have been insufficient to represent managerial character traits. The quality level of the data used, especially the non-standardized scanning resolution and text format, may have also negatively affected model performance.

Several suggestions can be made to improve this model. Increasing the sample size and collecting diverse data from different groups of managers can improve the learning capacity of the model. In addition, more complex visual representations of handwriting can be processed with deep learning techniques (e.g., convolutional neural networks (CNN)) instead of just traditional features. Classification accuracy can be increased by integrating more advanced parameters, such as pressure, speed, and slope, in handwriting. Using such advanced methods can significantly improve scientific depth and model accuracy in this field in the future.

As a result of the study, artificial intelligence was used, and based on the machine learning method, managers were asked to write a certain text voluntarily without any pressure. Based on the results of this study, the pressure factor was taken as the determining factor based on the writings of the participating senior managers. Therefore, it can be said that managers who experience intense writing pressure are more stressed and tense, and may consider changing jobs frequently. In addition, according to the J48 algorithm suggestions obtained from machine learning, it can be said that managers who write with medium pressure are more reliable and serious than those who experience writing pressure. Finally, it can be said that managers who write with less pressure are fragile, elegant, and have low self-confidence. The results of this study reveal that there are many points where the modern world will soon be dominated by artificial intelligence. For example, such methods are now used for recruitment and human resources in Europe and the USA. In this respect, this study makes an important contribution to the management literature. Future studies can be expanded to text or images, or comparisons can be made between employees and managers in different countries. Thus, the relationship between the effect of organizational culture on employees and managers and writing style can be revealed.

Considering the limitations of this study, more comprehensive analyses should be conducted in line with various suggestions for future studies. First, a comparative examination of handwriting samples of managers with different cultural and institutional structures (e.g., public and private sector employees) can reveal how character traits are shaped in the institutional context. In addition, separately evaluating the effects of demographic variables such as gender, age, years of experience, and sector on both the formal characteristics of handwriting and the results of the character analysis will increase the distinctiveness of the model. In addition, correlating the personality traits obtained through handwriting with different organizational performance indicators (e.g., leadership styles, stress management skills, and organizational commitment levels) will make the potential applications of this approach in the fields of human resources and leadership development more visible. Such studies will provide important contributions in terms of testing the validity of the current model and expanding the application of handwriting-based analyses in management sciences.

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ETHICAL CONSIDERATION

The authors confirm that the ethical policies of the journal, as noted on the journal's author guidelines page, have adhered to.

In this study, all the rules specified to be followed within the scope of "Higher Education Institutions Scientific Research and Publication Ethics Directive" were complied with. None of the actions specified under the title of "Actions Contrary to Scientific Research and Publication Ethics", which is the second part of the directive, were not carried out.

Ethics committee permission information

As this study was conducted on secondary data using artificial intelligence, ethics committee approval was not required.

AUTHOR CONTRIBUTION

The contribution of the 1st author to the research is 60%, and the contribution of the 2nd author to the research is 40%.

Author 1: Duties and responsibilities of this study Presenting the subject and creating the theoretical framework through conceptual review, interpretation of the analysis, and evaluation of the results.

Author 2: Duties and responsibilities carried out in the research. Conducting analyses

CONFLICT OF INTEREST

The authors declare no conflict of interest.

GENİŞLETİLMİŞ ÖZET

Bu çalışma, insan kaynakları yönetiminde önemli bir yere sahip olan işe alım ve yönetim süreçlerini, makine öğrenmesi temelli yeni bir yaklaşımla değerlendirmeyi ve el yazısına dayalı karakter analizi ile desteklenmiş bir algoritma geliştirmeyi amaçlamaktadır. Araştırma kapsamında, Bayburt ilinde üst düzey yönetici pozisyonlarında görev yapan 74 katılımcıdan standart bir metni el yazısıyla boş bir A4 kâğıda yazmaları istenmiştir. Elde edilen el yazısı örnekleri, WEKA adlı makine öğrenmesi yazılımı aracılığıyla J48 karar ağacı algoritması kullanılarak analiz edilmiştir. Yapılan analizlerde, yazıların baskı düzeyi (ağır, orta, hafif) değişkeninin sınıflandırmada belirleyici bir rol oynadığı görülmüştür. Ağır baskı uygulayan bireylerin stresli, gergin ve iş değiştirme eğilimi yüksek kişiler olduğu; orta düzeyde baskı uygulayanların güvenilir, ciddi ve disiplinli bir yapıya sahip oldukları; hafif baskı uygulayanların ise hassas, zarif ancak özgüven eksikliği taşıyan bireyler olduğu sonucuna ulaşılmıştır.

Çalışmanın kuramsal temeli, yazının yalnızca psikomotor bir beceri değil, doğrudan beyin tarafından yönlendirilen nöromüsküler bir süreç olduğu görüşüne dayanmaktadır. Bu doğrultuda, el yazısında ortaya çıkan ince motor hareketlerin kişinin karakter yapısına ilişkin ipuçları barındırdığı varsayılmıştır. Grafikoloji biliminin sunduğu kavramsal çerçevede; harf eğimi, satır ve kelime aralıkları, yazı boyutu ve sayfa kenar boşlukları gibi değişkenler dikkate alınarak kişilik analizi yapılmıştır. Veriler Excel ortamında 75x13'lük bir matris hâlinde yapılandırılmış ve WEKA yazılımına uygun formatlara (CSV, ARFF) dönüştürülerek sınıflandırma işlemleri gerçekleştirilmiştir. Eğitim ve test veri kümeleri kullanılarak elde edilen model, %57 oranında doğrulukla sınıflandırma yapmıştır. Bu çalışma, insan kaynakları alanında yapay zekâ tabanlı veri madenciliği uygulamalarının etkili sonuçlar üretebileceğini ortaya koyması açısından önemlidir. Avrupa ve Amerika'da işe alım süreçlerinde kullanılmaya başlanan bu tür yapay zekâ destekli analizlerin Türkiye'deki insan kaynakları uygulamalarına da entegre edilmesi, süreci hem daha verimli hem de daha nesnel hale getirebilir. Ayrıca çalışmanın özgünlüğü, örgütsel davranış değişkenlerini klasik regresyon ve korelasyon analizlerinin ötesine taşıyarak, veri madenciliği yöntemlerinden biri olan karar ağaçları ile incelemesinden kaynaklanmaktadır. Gelecek çalışmalarda farklı kültürlerden çalışanlar arasında karşılaştırmalar yapılarak yazı stili ile örgüt kültürü arasındaki ilişkiler daha kapsamlı şekilde araştırılabilir.