Research Article / Araştırma Makalesi

Machine Learning Based Investigation of Relation Between Patient and Glabellar Wrinkle Characteristics

Hasta Özellikleri ile Glabellar Kırışıklık İlişkisinin Makine Öğrenimi Tabanlı İncelenmesi

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Abstract

Background: The skin around the glabella area is the region most affected by the underlying muscle activity during facial expressions and wrinkling. Although glabellar lines or wrinkles are commonly considered a cosmetic concern in the facial region, objective clinical assessment of this condition remains important. This study investigated the relationship between various patient characteristics, potentially reflecting lifestyle and physiological factors, and glabellar wrinkle patterns, which were categorized according to distinct muscle contraction types described in the literature.
Materials and Methods: Data were collected from a total of 870 patients. One of the study's primary objectives was to explore the potential of using multiple patient-related variables in a machine learning-based prediction system while identifying the most influential characteristics associated with glabellar wrinkles. Multiple supervised machine learning algorithms were employed to uncover potentially nonlinear associations and identify the most informative predictors, including Naïve Bayes, Random Forest, Logistic Regression, and K-Nearest Neighbors. Each model was tested across all possible feature subsets to evaluate their predictive performance.
Results: The study aimed to demonstrate that a machine learning-based approach could be functional for the early prediction of glabellar wrinkles. The analysis revealed significant associations between patient characteristics, such as age, gender, education, marital status, and occupation, and distinct glabellar wrinkle patterns. Furthermore, the machine learning models demonstrated that these characteristics could be used to predict wrinkle types with considerable performance. In the best scenario, separating the U-type pattern from others, an F1 score of 0.71 was achieved using K-Nearest Neighbors, supporting the potential for early identification and personalized intervention planning.
Conclusions: The study confirmed that specific patient characteristics are strongly related to the formation of different glabellar wrinkle types. In addition, machine learning-based predictive systems showed promising performance, indicating their potential use in supporting clinicians with personalized cosmetic assessments and early intervention strategies.

Keywords: Artificial Intelligence, Skin Aging, Machine Learning, Demography

Öz

Amaç: Glabella bölgesindeki deri, yüz ifadesi ve kırışıklık oluşumu sırasında alttaki kas aktivitesinden en çok etkilenen alanlardan birisidir. Glabellar çizgiler veya kırışıklıklar genellikle kozmetik kaygı nedeni olabilmekle birlikte, bu çizgi ve kırışıklıkların klinik açıdan nesnel değerlendirilmesi önem taşımaktadır. Bu çalışmada, hastaların yaşam tarzı ve fizyolojilerini yansıtabilecek çeşitli özellikleri ile literatüre göre sınıflandırılmış glabellar kırışıklık karakterleri arasındaki ilişki araştırılmıştır.
Materyal ve Metod: Bu araştırmada toplam 870 hastadan veri toplanmıştır. Çalışmada öncelikli olarak hastaları karakterize eden birden fazla değişkenin makine öğrenmesi tabanlı bir tahmin-teşhis sisteminde kullanılabilirliğinin araştırılması hedeflenmiş, bu doğrultuda glabellar kırışıklıklarla ilişkili olabilecek en etkili özelliklerin belirlenmesi amaçlanmıştır. Naïve Bayes, Rastgele Orman, Lojistik Regresyon ve K-En Yakın Komşular gibi farklı kılavuzlu makine öğrenmesi algoritmaları kullanılarak, doğrusal olmayan potansiyel ilişkilerin ortaya çıkarılması hedeflenmiş, en ilintili değişkenler belirlenmiştir. Her modelin tahmin performansı, tüm olası özellik alt kümeleri üzerinde test edilmiştir.
Bulgular: Çalışmada, glabellar kırışıklık karakterinin önceden tahmini için makine öğrenimi temelli bir yaklaşımın işlevsel olabileceğinin gösterilmesi amaçlanmıştır. Analiz sonuçları; yaş, cinsiyet, eğitim, medeni durum ve meslek gibi hasta özellikleri ile glabellar kırışıklık karakteri arasında önemli ilişkiler olduğunu göstermektedir. Ayrıca çalışmada, bu özelliklerle kırışıklık tiplerinin öngörülebilirliği araştırılmış, U tipi desen için K-En Yakın Komşu algoritmasıyla 0.71 F1 skoru elde edilmiştir. Bu sonuç, erken teşhis ve kişiselleştirilmiş planlama açısından yöntemin potansiyelini ortaya koymaktadır.
Sonuç: Çalışma, belirli hasta özelliklerinin farklı glabellar kırışıklık türlerinin oluşumuyla önemli derecede ilintili olduğunu doğrulamıştır. Ayrıca makine öğrenimi tabanlı potansiyel bir teşhis ve kestirim sisteminin bu özellikler ile yüksek performanslı sınıflama yapması otomatik sınıflayıcıların kişiselleştirilmiş kozmetik değerlendirme ve erken müdahale için destek potansiyeline işaret etmektedir.

Anahtar Kelimeler: Yapay Zekâ, Cilt Yaşlanması, Makine Öğrenmesi, Demografi

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Introduction

The glabella region between the eyebrows is subject to increased muscle activity during facial expressions associated with emotions such as anger and irritation (1). Due to its anatomical location and underlying muscular dynamics, this area has become a focal point in cosmetic dermatology (2). One widely used treatment modality is botulinum toxin injection, which requires careful planning and precise application (3). A clear understanding of its anatomy, combined with identifying patient characteristics that contribute to wrinkling, forms the basis for aesthetic procedures targeting this region and a critical foundation for proactively preserving its cosmetic integrity.
In one study, authors noted that age and gender significantly influence the formation of glabellar lines due to anatomical and physiological differences, which may impact the treatment approach (4). Additionally, it has been highlighted that age, gender, ethnicity, and skin sensitivity play a significant role in facial aging and should be considered when planning cosmetic procedures (5). Moreover, an extensive twin study by Rexbye et al. demonstrated that various lifestyle-related factors, such as smoking, sun exposure, body mass index, and social status, significantly influence perceived facial aging, with distinct patterns observed between genders (6).
At this point, computer-aided investigation holds excellent potential for identifying the most influential attributes. Accordingly, numerous previous studies have implemented automated classification and estimation methods to make predictions related to facial wrinkles, aging, and cosmetic outcomes. For instance, Shah et al. showed that machine learning can effectively analyze facial features to predict cosmetic treatment needs, underscoring the potential of computer-aided methods in facial assessment (7). Recent surveys have further supported the potential of automated systems for facial wrinkle detection and analysis, highlighting the broader role of machine learning in cosmetic evaluation tasks (8). In another study, Kim et al. proposed a semi-automatic labeling and deep learning-based detection system for facial wrinkles, demonstrating the capability of AI models to extract wrinkle-related patterns from facial images reliably (9).
In recent years, computer-aided methods have shown strong potential for identifying important factors in facial aging and wrinkle formation. Several studies have used machine learning techniques to analyze facial features and predict cosmetic needs. Although the present study does not involve facial images or image processing, machine learning was applied to evaluate patient-related characteristics. The goal was to identify the factors most strongly associated with glabellar wrinkle types based on muscle contraction patterns defined in previous research. The analysis pipeline involved balancing the class distributions, trying out different feature combinations, and evaluating performance using F1 scores. This allowed us to identify which feature-method setups performed best in distinguishing wrinkle patterns and to explore whether such predictions could have clinical value.

Materials and Methods

Original Data

The data analyzed in this study were collected from 870 participants, including male and female volunteers aged between 18 and 74. Based on predefined criteria, individuals who had undergone any surgical or medical procedures (such as botulinum toxin injections) in the facial region or who had a history of facial trauma were excluded.
Glabellar wrinkle types were determined based on the classification proposed by Lima et al. (10). Accordingly, participants were asked to frown, and five distinct wrinkle patterns were identified: V-shaped, U-shaped, omega-shaped, converging arrows, and inverted omega-shaped lines.
All procedures, assessments, and data collection processes were carried out in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Non-Interventional Clinical Research Ethics Committee of the Faculty of Medicine at Çukurova University on June 2, 2023 (approval number 134/44).
This study is also supported by the Çukurova University Scientific Research Projects Unit under project number TSA-2024-16787 and is derived from this project.

Analyzed Attributes

This study examined several patient-related attributes to explore their potential association with the severity of glabellar wrinkles. The dataset comprised the following variables:
Age: A normalized continuous variable ranging from 0 to 1, representing the patient's age. Although age is often assumed to be normally distributed, a Shapiro-Wilk test (W = 0.943, $p < .001$) showed a significant deviation from normality. The corresponding histogram in Figure 1 illustrates this skewed distribution
No transformation was applied since all possible feature combinations were tested during model evaluation. Age is considered one of the key factors in wrinkle formation due to long-term muscle activity and decreasing skin elasticity with age.

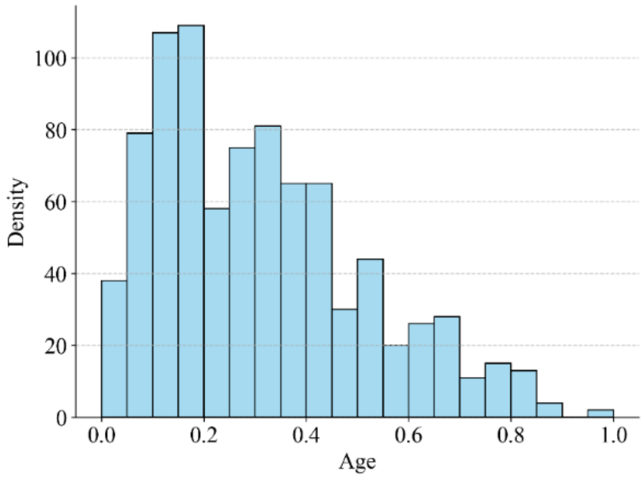

Figure 1. Histogram of the normalized Age variable. The distribution is right-skewed, indicating a deviation from normality.

Gender: A categorical binary variable (Female, Male). Gender-based anatomical and hormonal differences are known to influence the pattern and depth of facial wrinkles.
Education: A categorical variable denoting the level of education, categorized as primary school and below, high school, university, and postgraduate education. It was included as a potential lifestyle-related indicator, reflecting differences in health awareness, stress exposure, and access to skincare practices.
Marital Status: A categorical binary variable representing the individual's marital status (Single, Married). Social and emotional factors related to marital status have been suggested to influence aging processes and perceived stress, which may, in turn, affect skin health.
Occupation: A categorical binary variable corresponding to the patient's occupational status (Employed, Unemployed). It was considered due to its potential relevance to environmental exposure (e.g., sunlight, stress, or physical activity), which are recognized factors in facial aging.
Glabellar Contraction Pattern: The target variable in this study represents the pattern of muscle contraction in the glabellar region, classified based on facial expressions observed during animation. Following the classification proposed by Lima et al., this categorical variable includes five primary types: "U", "V", "Omega", "Inverted Omega", and "Converging Arrows". Each pattern is associated with a different combination of muscle activity involving the corrugator supercilii, depressor supercilii, procerus, and orbicularis oculi muscles (10). This classification system has allowed us to group the facial dynamics within our region of interest accurately.
These attributes were selected due to their potential role in wrinkle formation, either directly through biological mechanisms or indirectly via lifestyle and environmental influences. Subsequently, the contribution and predictive importance of each variable were assessed using various machine learning algorithms. Figure 2 visualizes the distribution of glabellar contraction patterns across four demographic characteristics to provide an overview of the dataset.

Machine Learning Based Investigation

An experimental algorithm was implemented to determine the most effective subset of features for each classification scenario. Accordingly, all possible non-empty combinations of the available features were evaluated. For each feature subset, every classifier was trained and tested using a stratified 80/20 train-test split. The accuracy of each model was recorded, and the combination yielding the highest performance was reported for each scenario. It should be noted that, to transform the multi-class glabellar contraction pattern into a machine learning-compatible structure, several binary grouping scenarios were defined. These scenarios grouped glabellar types based on different clinical perspectives. The four binary grouping scenarios were created to explore glabellar wrinkle classifications based on clinical relevance. These groupings reflect variations in wrinkle symmetry, distribution, and severity. For example, comparing type 1 with types 2–5 allows investigation of the most distinct contraction pattern, while other splits (e.g., 1–2 vs. 3–5) reflect increasing asymmetry or complexity in wrinkle formation. Such divisions may inform personalized treatment strategies or early signs of muscular imbalance. The following split strategies were applied:

- Types 1 and 2 vs. Types 3, 4, and 5
- Types 1, 2, and 3 vs. Types 4 and 5
- Type 1 vs. Types 2, 3, 4, and 5
- Types 1 to 4 vs. Type 5

For each scenario, a binary variable was created and balanced using random under-sampling to ensure equal class representation. The balanced datasets were used to evaluate the classification performance of multiple models. The overall workflow of the implemented experimental classification scheme is visualized in Figure 3.
This approach has allowed a comprehensive exploration of the interactions between demographic variables and glabellar pattern classification.

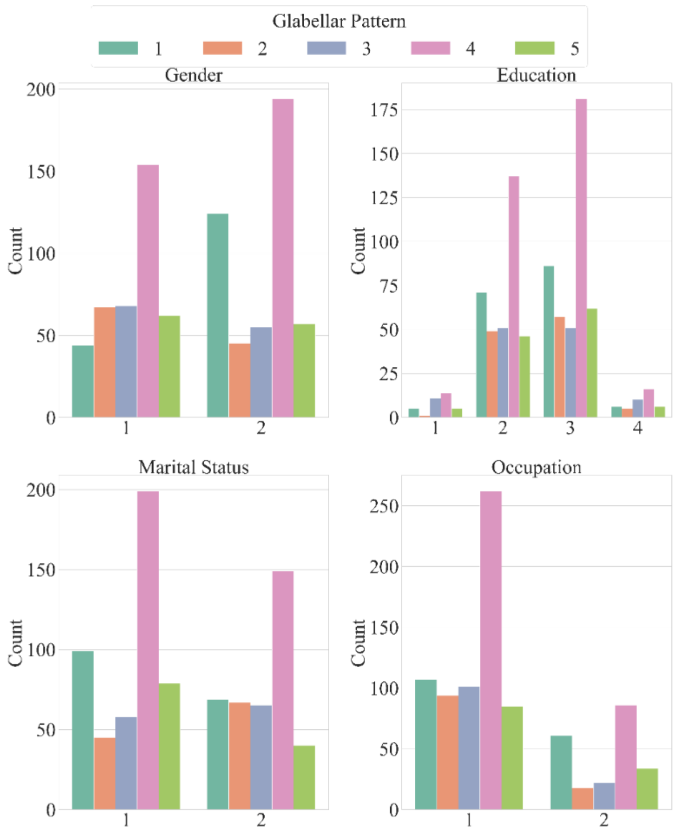

Figure 2. Glabellar contraction types shown by gender, education, marital status, and occupation.

Implemented Classifiers

This study used four supervised machine learning methods to classify glabellar wrinkle types. Each classifier was specifically chosen because of its proven performance in similar prediction tasks and suitability for the type of data collected. Naive Bayes is a probabilistic classification method grounded on Bayes' theorem (11). It assumes that predictor variables (patient characteristics in this study, such as age, gender, education, marital status, and occupation) independently contribute to wrinkle type (12). While this assumption may not always hold perfectly true in reality, Naive Bayes often performs effectively in practice, especially with categorical and relatively small-sized feature sets.

Random Forest is an ensemble learning method that constructs multiple decision trees using random subsets of data and features (13). Combining predictions from these trees reduces the risk of overfitting and often achieves higher accuracy (14). This robustness makes it particularly valuable for identifying the most critical patient characteristics contributing to wrinkle patterns.

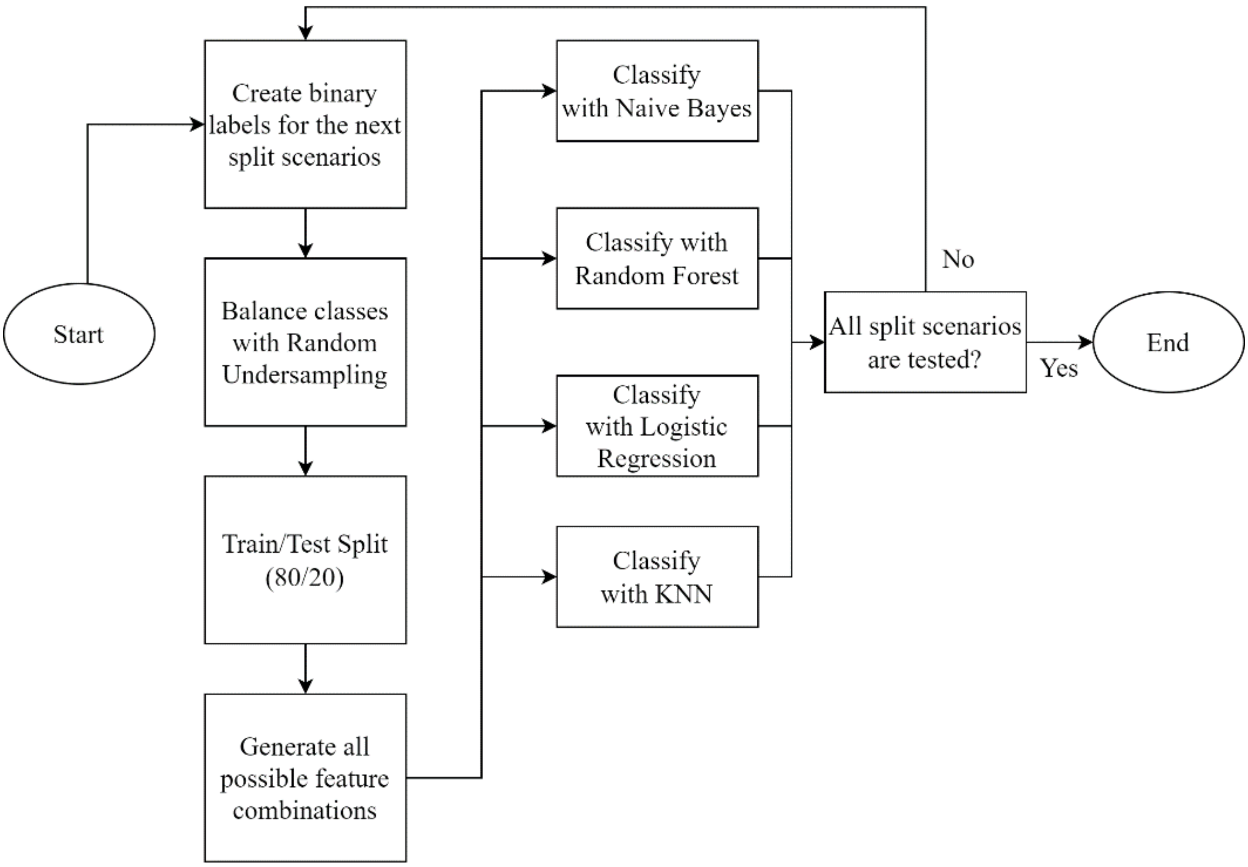

Figure 3. Workflow of the classification process applied to glabellar wrinkle patterns.

Logistic Regression is a widely used linear classification method primarily suited for binary prediction tasks (15). This method calculates the probability of an observation belonging to a specific category based on its predictor variables (16). Due to its straightforward nature and interpretability, Logistic Regression can provide insights into linear relationships between patient characteristics and glabellar wrinkle patterns. However, it performs best when predictor variables have linear relationships with the outcome and when categorical variables are numerically appropriately encoded. In this study, categorical variables were represented numerically without specific encoding methods, such as one-hot encoding, which might influence the interpretability and predictive performance of the Logistic Regression model.

Lastly, K-Nearest Neighbors (KNN) is a classification method that assigns the class label of an observation by examining the labels of its closest neighbors in the feature space. The final prediction is based on the majority class among these neighbors (17). KNN relies heavily on distance calculations, which typically perform best with numerical data (18). In this study, categorical variables were used directly in numeric form without special preprocessing. This approach can potentially impact the accuracy of the distance calculations and, consequently, reduce the predictive performance of KNN compared to other methods. Nonetheless, KNN serves as an intuitive and simple comparative baseline to evaluate how effectively wrinkle types can be predicted based solely on the direct numerical similarity of patient characteristics.

All classifiers were evaluated under identical conditions, using the same training-test splits and feature subsets, to ensure comparability of results and provide reliable conclusions about which patient characteristics best predict glabellar wrinkle patterns.

Results

Four binary classification scenarios, each representing a different grouping of contraction patterns, were tested to evaluate the predictive capability of demographic attributes on glabellar wrinkle classification. For each scenario, all possible non-empty combinations of five features (Age, Gender, Education, Marital Status, and Occupation) were evaluated using four supervised learning methods: Naive Bayes, Random Forest, Logistic Regression, and K-Nearest Neighbors. Random under-sampling was applied to ensure class balance before training.

To make sure the evaluations were fair and not affected by class imbalance, each scenario was tested using training and test sets that included equal numbers of positive and negative samples. This balancing was done separately for each scenario. Model performances were compared based on their F1 scores, and the best feature-method combination for each setup was recorded. Table 1 shows the classification results and related details for all scenarios.

Table 1. Best performing classification split scenarios are presented

Split	Train Size	Test Size	Best F1 Score	Best Method	Best Features
[1, 2] vs [3, 4, 5]	448	112	0.597	NB	('Education', 'Occupation')
[1, 2, 3] vs [4, 5]	644	162	0.667	KNN	('Gender',)
[1] vs [2, 3, 4, 5]	268	68	0.710	KNN	('Gender', 'Occupation')
[1, 2, 3, 4] vs [5]	190	48	0.694	KNN	('Age', 'Gender', 'Occupation')

In addition to the F1 score, other performance metrics were calculated for the best-performing classification scenario. The model achieved a sensitivity of 0.97, indicating a strong ability to detect positive cases. However, specificity was relatively low (0.24), which reduced the overall accuracy (0.60) and MCC (0.30). These results suggest that while the model is highly responsive to U-type wrinkles, its ability to identify non-U types correctly is limited.

To confirm the consistency of the best-performing setup, a 5-fold stratified cross-validation was applied using the K-Nearest Neighbors algorithm with Gender and Occupation as predictors. The model achieved F1 scores ranging from 0.66 to 0.89 across folds, with an average F1 score of 0.84. These results support the generalizability of the model beyond a single train-test split.

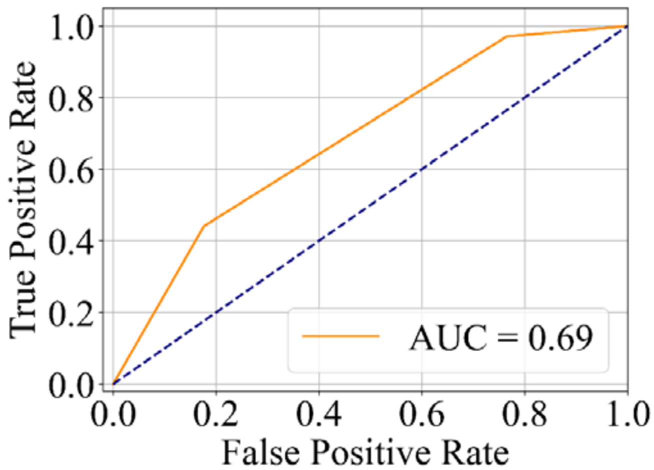

Figure 4. ROC curve for the best resulted feature combination and classifier in the one-versus-rest classification of glabellar type 1.

The ROC curve for the best-performing scenario, where glabellar wrinkle type 1 was compared against types 2 to 5 using the KNN classifier, is shown in Figure 4. The model achieved an F1 score of 0.71 and an AUC of 0.69 using only Gender and Occupation as features.

To further investigate the discriminative power of each feature in the most successful split scenario, a principal component analysis (PCA) was performed for all features. The loadings of the first principal component (PC1), which captures the maximum variance in the data, are visualized in Figure 5. The highest positive contribution to PC1 was observed from the Occupation variable, followed by Gender, whereas Education exhibited a strong negative loading. This pattern supports the classification results obtained in Scenario 3 ([1] vs [2, 3, 4, 5]), where the best F1 score was achieved using Gender and Occupation as predictors.

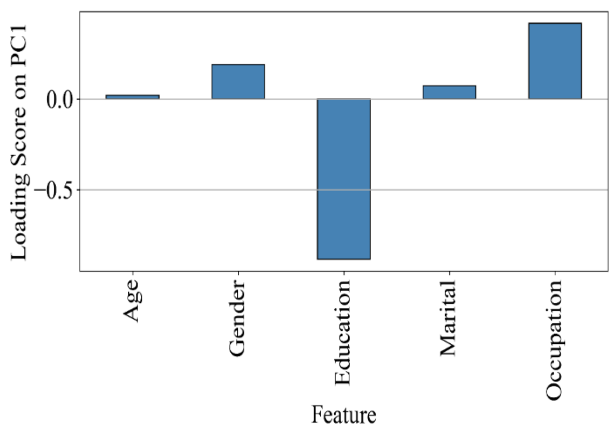

Figure 5. PC1 loadings from PCA applied to the most successful classification scenario, showing the contribution of each feature to the main variance axis.

Discussion

The present study aimed to exploit the predictive relationship between patient characteristics and glabellar wrinkle patterns through supervised machine learning algorithms. While previous clinical studies have focused primarily on descriptive or comparative statistics to understand muscle contraction patterns in the glabellar region, supervised classifiers were implemented in our study to investigate the degree of relation between wrinkle characteristics and individual-level attributes such as age, gender, and lifestyle indicators while evaluating the different grouping scenarios.

Our findings indicate that best resulting classification was performed with one-versus-rest scenario where the "U-type" contraction was separated from others (Table 1). With this scenario, gender and occupation emerged as the most influential predictors in differentiating glabellar wrinkle types, particularly in the one-versus-rest scenario where the "U-type" contraction was separated from others. The predictive capacity of these features is supported by PCA results, where they demonstrated high contributions to the main variance component.. This is consistent with prior research indicating gender-related anatomical and hormonal influences on facial muscle behavior. For instance, Luebberding et al. revealed that wrinkle formation patterns differ significantly between males and females, with men exhibiting earlier and more pronounced glabellar lines, while women experience an accelerated development of wrinkles post-menopause, likely due to hormonal shifts (19). Additionally, occupational status may reflect cumulative exposure to environmental factors like stress or UV radiation, which are known contributors to facial aging (20). Moreover, the ROC curve analysis for this scenario showed an AUC of 0.69, reflecting a moderate but meaningful ability to distinguish the "U-type" contraction from other wrinkle patterns.

The best classification performance (F1 = 0.71) was achieved using the KNN algorithm, suggesting that nonlinear relationships and local proximity in the feature space are relevant when modeling facial muscle dynamics. To check the consistency of the results, a 5-fold stratified cross-validation was applied to the best-performing scenario. The model showed stable performance across folds, with an average F1 score of 0.84, supporting that the results are not dependent on a single train-test split. However, the overall moderate F1 scores across all models and scenarios suggest that patient characteristics alone may only partially explain glabellar wrinkle patterns. Other factors, such as genetic predisposition, emotional expressivity, or skin type, may also play significant roles and merit further exploration.

In this study, a set of supervised classifiers including Naive Bayes, Random Forest, Logistic Regression, and K-Nearest Neighbors was implemented. While these algorithms provided meaningful results, future studies incorporating a broader range of classifiers may help improve the generalizability and robustness of the findings. The model demonstrated strong sensitivity in detecting U-type wrinkles; however, its relatively low specificity suggests a tendency to overpredict this class, which should be addressed in future improvements.

The research presented by Lima et al. highlights the complexity of facial muscle interactions and the need for individualized evaluation. It emphasizes that contraction patterns in the glabellar, forehead, and periocular regions are interconnected and influenced by demographic factors (10). Our findings complement these observations by demonstrating that such contraction groupings can be partially predicted based on basic demographic and lifestyle characteristics.

One major strength of our study is the comprehensive evaluation of all feature subsets across multiple classifiers, allowing for an unbiased investigation into variable importance. Nevertheless, limitations include the lack of facial imaging data, which could have enriched the analysis with direct morphological cues. Moreover, excluding skin phototypes and sun exposure levels may have prevented a more complete understanding of extrinsic aging effects.

The step-by-step analysis pipeline implemented in this study enabled a systematic examination of how patient characteristics are associated with different types of glabellar wrinkles. By balancing the dataset in each scenario, testing all possible feature combinations, and evaluating models with consistent performance metrics, the approach ensured fairness and comparability across setups. This structure also enabled the identification of the most informative features and the selection of suitable algorithms for each grouping. While relatively simple, the pipeline offers a practical framework for exploring classification problems where the underlying relationships may vary across clinically meaningful subgroups.

Future research should consider integrating facial imaging with structured patient data, using deep learning architectures to improve prediction accuracy. Additionally, expanding the dataset to include ethnically and geographically diverse populations could enhance the generalizability of the findings.

Conclusion

This study demonstrates that glabellar wrinkle patterns are influenced by demographic factors such as gender and occupation and that machine learning can serve as a valuable tool in predicting these patterns with reasonable accuracy. By identifying key individual attributes associated with specific contraction types, our findings may contribute to a more personalized approach in cosmetic dermatology, where individualized treatment planning is increasingly emphasized. Furthermore, this study offers a data-driven perspective on the behavioral dynamics of facial muscles, which may complement clinical observations and support future research aiming to optimize aesthetic interventions.

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Ethical Approval: This study was performed in line with the principles of the Declaration of Helsinki. Ethical approval was obtained from the Non-Interventional Clinical Research Ethics Committee of the Faculty of Medicine at Çukurova University on June 2, 2023 (approval number 134/44).

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Design : Ç.C., A.G.K., D.M.B., E.E.S., YT., M.G.B.
Data acquisition: Ç.C., A.G.K., D.M.B., E.E.S., YT., M.G.B.
Analysis and interpretation: Ç.C., A.G.K.
Writing manuscript: Ç.C., A.G.K.
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