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Sekazu: an integrated solution tool for gender determination based on machine learning models

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Abstract

Gender determination is the first stage of identification used in forensic investigation, anthropology, archeology, and bioarchaeology, which helps accelerate the process of narrowing possible matches in a medical-legal context. Without DNA analysis, the dimorphic property of bones comprises a basis for gender determination with measurements taken on only bones. In this work, 9 different bones such as cranium, mandibula, femur, patella, calcaneus, condylus occipitalis, sternum, hand bones, and foot bones were used for gender determination. Machine learning methods and artificial neural networks, especially linear and quadratic discriminant analysis, while determining the gender, machine learning also were technically adopted. 13 different machine learning algorithms were used as a model for gender determination. Many tools were designed to perform processes like designing necessary bookmarks to try models, designing measurements where machine learning algorithms are used as features, determining coordinates of designed bookmarks, and computation of features. A software named Sekazu was developed by presenting an integrated solution proposal. Thanks to the developed software, models used in gender determination were developed and tried in a fast way and researchers can obtain results reported based on performance metrics flexibly.

Keywords: Gender determination, image labeling, bone measurement, machine learning models, GUI

Introduction

Determining unidentified human remains in forensic investigations is crucial in the analysis of severely shattered or burnt cadavers or skeletal remains. In such cases, gender determination from the evaluation of skeletal remains is a priority since determining gender is often used as a basis to estimate other biological profiles such as height, age, and ancestry [1–4]. Gender determination is the primary component of the biological profile, which plays an important role in identifying human remains to help accelerate the process of narrowing possible matches in medical-legal context [5].

The skeleton is one of the important elements in genetic, anthropological, odontological, and forensic investigations in living and non-living individuals [6]. Gender can be determined by analyzing adult bone with an accuracy of 100% [7].

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The accuracy of gender determination depends on available bones to analyze and judge [8]. While the pelvis and skull are the most suitable skeletal regions for accurate gender determination, these bones may be damaged, fragmented or missing, especially in cases of mass disasters and human rights research [1]. Besides, recent research has shown that the appendicular skeleton can differentiate higher between the genders [9]. In gender determination, various bones like femur [10,11], patella [9], mandible [12], calcaneus [13], condylus occipitalis [14], sternum [15] and hand bone [16,17] were examined. Alternatively, it has been reported that tarsal bones have a special value for forensic analysis on missing or fragmented human remains especially in gender determination because tarsal bones have a resistive, robust and compact structure against taponomic factors [18-21].

Gender determination can be performed by morphological or metric methods [17]. Morphological methods are subjective, and accuracy depends on the observer's experience [22]. Metric methods use measurements and statistical analysis to validate results objectively. These methods eliminate observer's prejudices for the presence, absence, or importance of features used in morphological methods. Metric methods can also detect dimorphism in skeletal features that can be characterized as ambiguous at morphological evaluations [20,22]. On the other hand, osteometry is an effective tool preferred to determine gender since it is easy and repeatable, low cost, high accuracy and does not require special expertise [23,24].

The radiological description was first introduced in 1926 by Culbert ad Law. It has been widely used in skeletal pathology, diagnosis of trauma, and identification since 1926 [25]. Besides, classical radiographic methods have been used in skeletal identification [26]. Radiography is a less invasive method that can be used for both living and dead individuals [27]. Anthropologically, Computerized Tomography (CT) has been used as an additional resource in the skull study and forensic identification process [6]. CT is an imaging method that can show all tissues and especially bone tissue with sharp borders [28]. When a thin section is taken, image orientation can be directed to three dimensional and it can be taken on the orthogonal plane. Thus, length and angle measurements can be calculated such that orientation affects less.

In forensic anthropology and bioarchaeology, most methods for gender determination are based on statistical models created through osteometric data collected from identified populations [29]. Discriminant analysis has obtained a high accuracy when it has been used for gender determination. The obtained accuracy rates change between 83% and 88% for skull with visual evaluation and classical measurements and change between 92% and 100% for pelvic bones [30-32]. Recent studies have uncovered that discriminant function is population-specific [33-35]. Therefore, the best accuracy for any discriminant function can be obtained by using population-specific methods based on national standards.

Machine learning (ML) is a scientific field that combines disciplines such as artificial intelligence, computational statistics, mathematics, and information theory [36]. ML methods generally classify using collected data about a case after obtaining an essential learning level. The fact that classes are known and the learning process is done according to classes is called supervised learning. 70% of ML methods are to apply supervised learning [37]. The main difference between ML methods and conventional statistical learning methods is that ML methods use training data more comprehensively. ML methods work on not only group parameters like means and covariance matrices. Instead of them, most ML methods iteratively solve optimization problems to find tree structure that provides a nonlinear decision point by using the best neuron weight set or maximum classification rate. Because ML methods are based on data, it is not required to use certain statistical assumptions like normality [38].

In the literature, there are few papers where ML techniques are applied to forensic anthropological problems and biological profile estimation. McBride et al. [39] applied Bootstrap methods based on the pelvic bone for gender determination. Turan et al. [21] appliedan artificial neural network method based on first and fifth phalanx and metatarsal for gender determination. Oner et al. [15] applied an artificial neural network method based on the sternum for gender determination.

In this study, with the use of data obtained from measurement studies on bones, a software application including a graphical user interface (GUI), specialized to determine the gender of the case was developed and named Sekazu. Thanks to the developed software, researchers have been given the ability to quickly search the data in terms of gender, test the suitability of different ML models for the problem, adapt the model to the problem by making detailed changes to the arguments of the tested model, obtain results as both reported way and form of tables, and store results. With the developed GUI, advantages like working without writing code and obtaining results quickly have been provided to researchers.

Materials and Methods

Sekazu, a tool for gender determination based on the results obtained from bone measurements, includes five tools such as bookmark management tool to describe bookmarks, feature management tool to create features using bookmarks, labeling management tool to label collected coordinates of features by positioning features on case images, calculation tool to convert features of collected coordinates to distance, angle, area, and perimeter measurements and ML model tool. Sekazu was developed using Python programming language with the version of 3.5.8 based on 64-bit architecture. Packages used to develop Sekazu, their version, and the purpose of usage are given in Table 1.

Table 1. Name, versions, and purpose of usage of packages (40–48).

Package name	Version	Purpose of Usage
NumPy	1.9.3	Numeric calculations
Pandas	1.1.4	Processes on data
SciPy	1.5.4	Statistical analysis
Matplotlib	3.3.2	Graphic visualization
Scikit-learn	0.23.2	Building ML methods
PyQt5	5.13.1	Designing GUI

In this section, the developed tools of Sekazu as bookmark management tool, feature management tool, labeling management tool, calculation tool, and ML model tool were described. The flow chart of Sekazu was given in Figure 1.

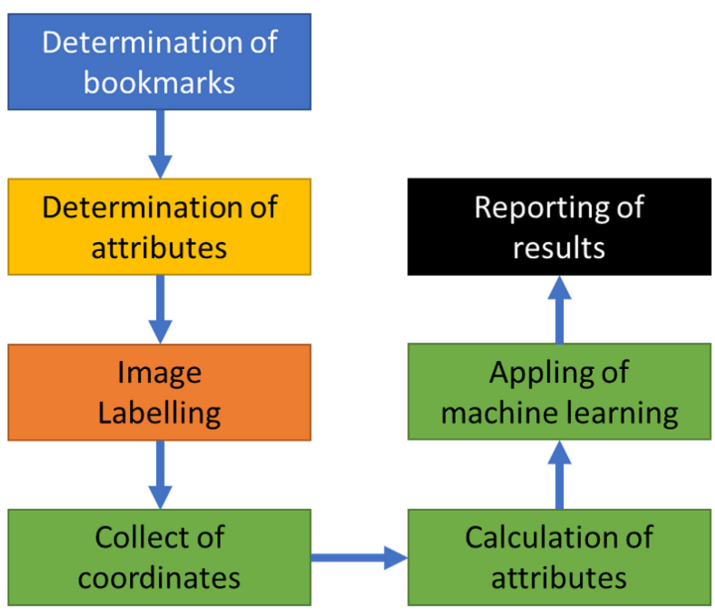


Figure 1. The flow chart of Sekazu.

Bookmark Management Tool

A bookmark management tool was developed to describe bookmarks used during labeling. Each bookmark composes of Id number, bookmark name, tag, plan, background color, font color, and explanation. An id number is a unique number. A bookmark name is a special name as the name of a bookmark or anatomical name. Tag is an abbreviation of bookmark name which consists of 3 characters, without space character and without starting a number. Tag is used as a visual indicator during labeling. The plan is used to determine the orientation of the bookmark since all bookmarks may not be observed on images obtained from specific orientations like horizontal, vertical oblique, etc. Background color and font color are visual indicators to make the tag more understandable during the labeling process. The explanation is a text containing explanations about bookmarks (Figure 2).

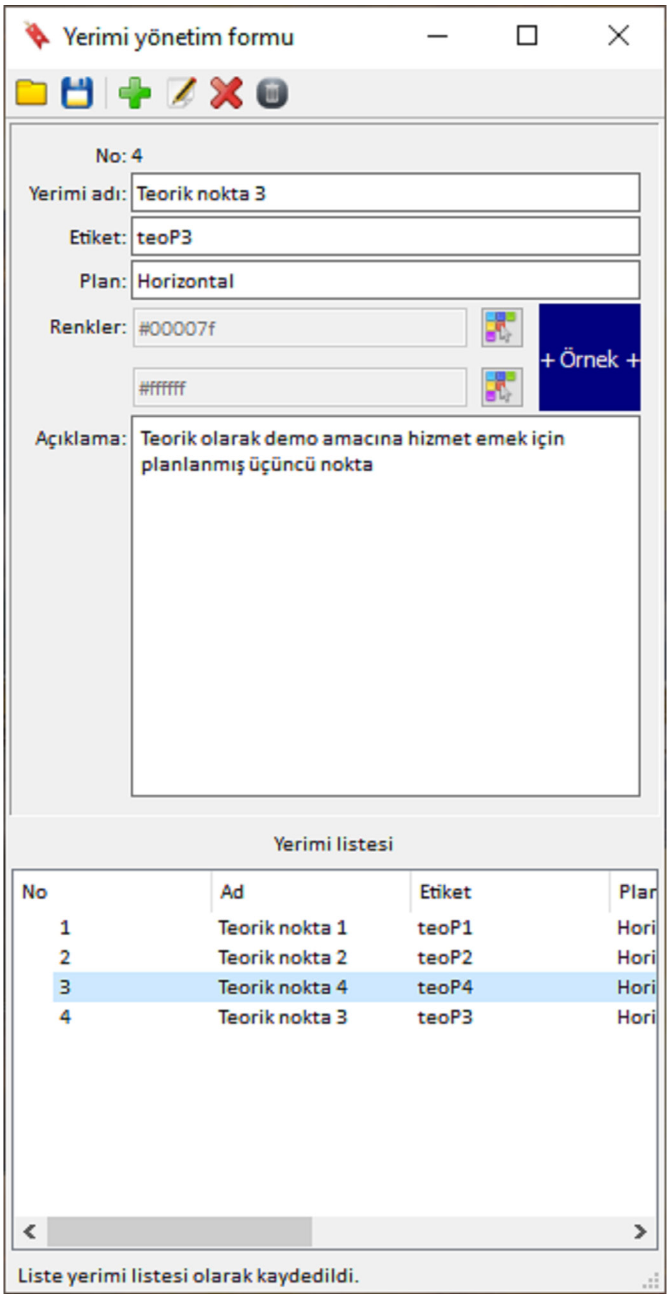


Figure 2. Bookmark management tool view.

Feature Management Tool

The feature management tool is used to create calculated features by using bookmarks. Features created by the feature management tool are used by using the calculation tool in the next steps. Calculated features are length, angle, area, perimeter, circular area, circular perimeter. A feature composes of source, name, tag, type, bookmark list, and explanation. As a source, a bookmark file that includes bookmarks belonging to features is indicated. Name and tag represent the name of features and abbreviation of feature, respectively. Like tag bookmark, it is an abbreviation that does not contain spaces and does not start with a number. Type includes the type of feature. The feature can have one of length, angle, area, perimeter, circular area, circular perimeter as a type. Bookmark list includes a list of bookmarks which are necessary to calculate feature. Only two bookmarks for length, only three bookmarks for angle, at least three bookmarks for area and perimeter, at least two bookmarks for the circular area and circular perimeter should be included in a bookmark list. The explanation is a text that includes explanations about the feature (Figure 3).

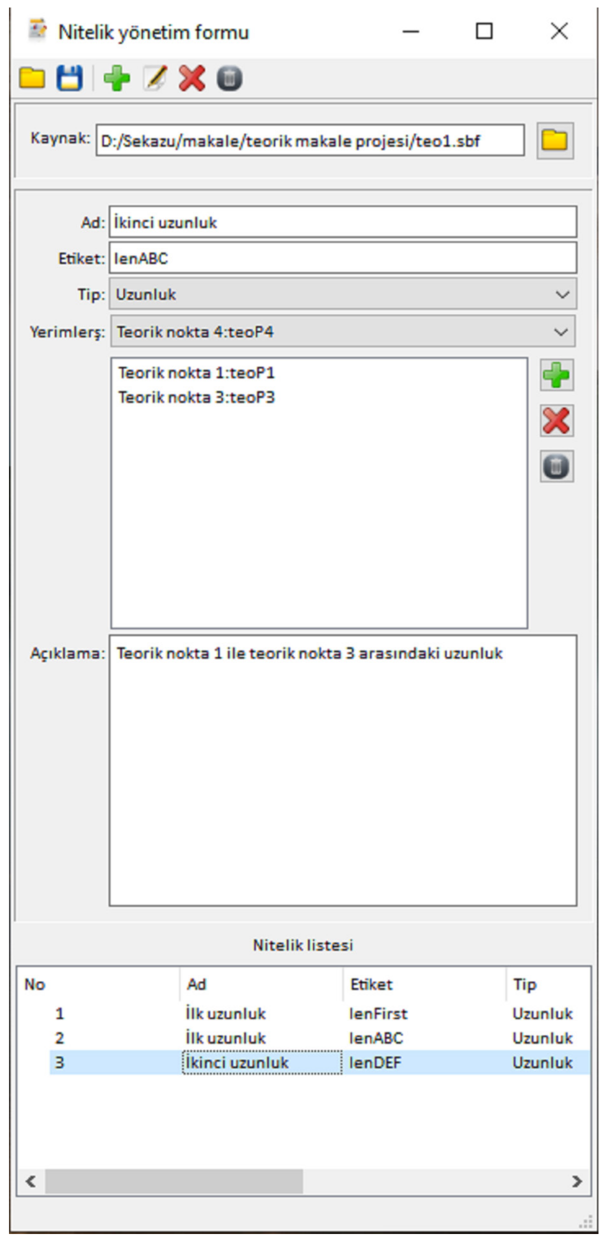


Figure 3.Feature management tool view.

Labeling Management Tool

The labeling management tool is used to collect x and y coordinates of bookmarks belonging to the case and draw out bookmarks on images obtained according to the required plan. A tag contains the protocol number, case name, age, length, gender, and coordinates of all bookmarks belonging to the case. The source file of the labeling management tool is a bookmark file. Measurement order belonging to bookmark is defined by a protocol number. It is used to obtain coordinates from a case by drawing out bookmarks a lot of times, increase the number of data, and provide the required flexibility for ML methods (Figure 4).

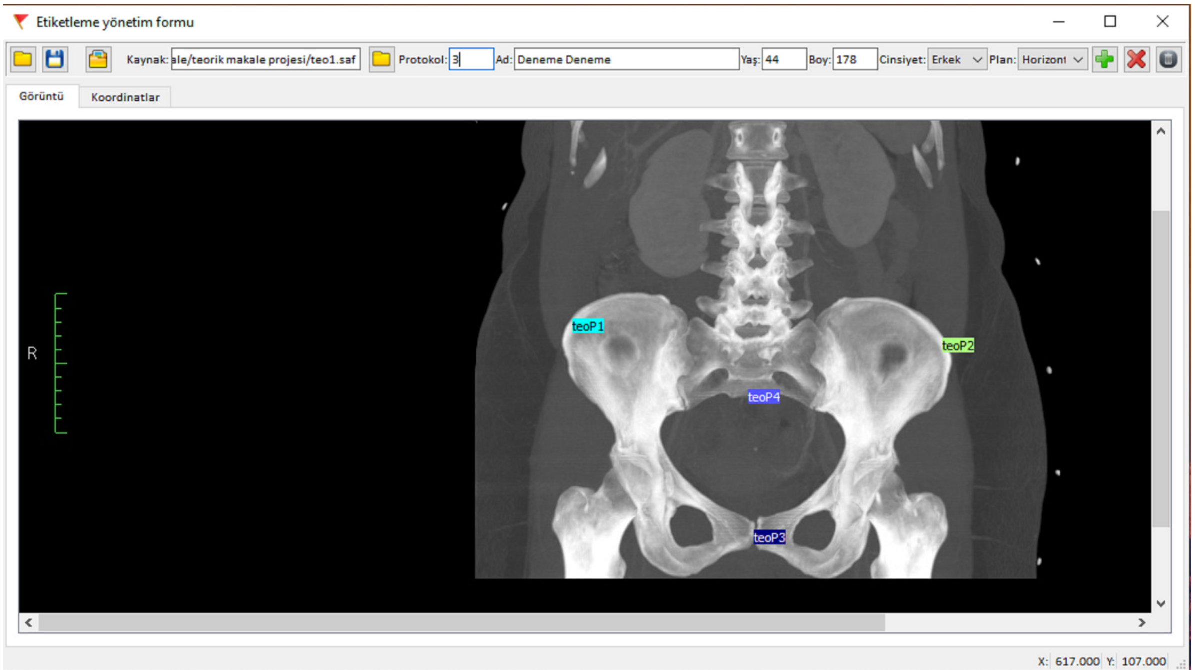


Figure 4. Labeling management tool view.

Calculation Tool

X and y coordinates of bookmarks are used to calculate length, angle, area, perimeter, circular area, circular perimeter. It is presented in Equation 1.

$$L(p1,p2)=\sqrt{(p1_x-p2_x)^2+(p1_y-p2_y)^2}$$

$$A(p1,p2,p3)=\operatorname{acos}\left(\frac{L(p1,p2)^2+L(p2,p3)^2-L(p1,p3)^2}{\sqrt{4L(p1,p2)^2L(p2,p3)^2}}\right)$$

$$Area(p1,p2,\ldots,pn)=\left|\frac{(p1_xp2_y-p1_yp2_x)+(p2_xp3_y-p2_yp3_x)+\cdots+(pn_xp1_y-pn_yp1_x)}{2}\right|$$

$$Perimeter(p1,p2,\ldots,pn)=L(p1,p2)+L(p2,p3)+\cdots+L(pn,p1)$$

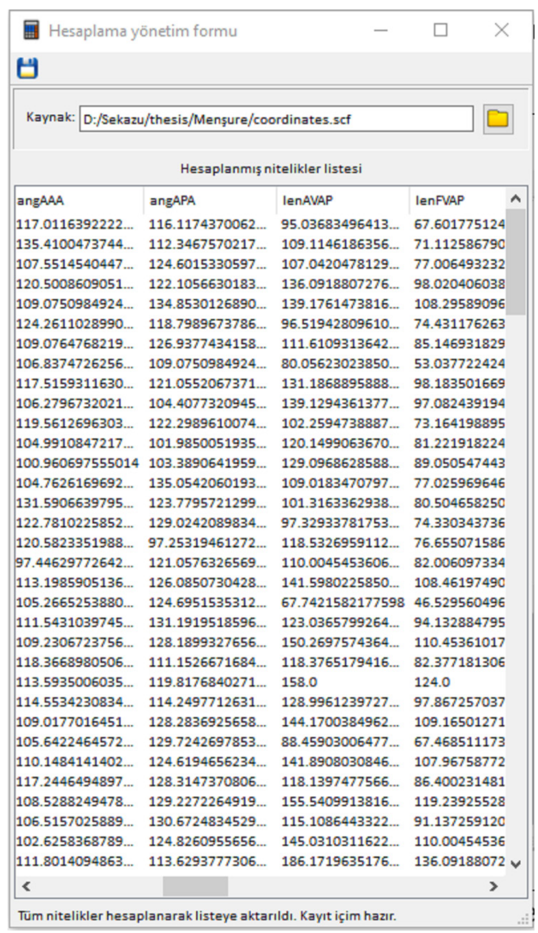
$$Area_{Circular}(p1,p2)=\pi L(p1,p2)^2$$

$$Perimeter_{Circular}=2\pi L(p1,p2)$$

Equation 1. Formulas of length, angle, area, perimeter, circular area, and circular perimeter (L: distance between two points, A: median angle among three angles, p1: point 1, p2: point 2, pn: point n, x: x coordinate of a point, y: y coordinate of a point).

Calculated data are created without using preprocessing operations, statistical filtering, any inclusion and exclusion criteria. If these processes are necessary, they can be performed on data by Sekazu users before ML calculations. Sekazu tools will consider the data to be used in ML calculations as completely ready for use.

The calculation tool is designed to calculate features specified by the feature management tool and present results in table form (Figure 5).



angAAA	angAPA	lenAVAP	lenFVAP
117.0116392222...	116.1174370062...	95.03683496413...	67.601775124
135.4100473744...	112.3467570217...	109.1146186356...	71.112586790
107.5514540447...	124.6015330597...	107.0420478129...	77.006493232
120.5008609051...	122.1056630183...	136.0918807276...	98.020406038
109.0750984924...	134.8530126890...	139.1761473816...	108.29589096
124.2611028990...	118.7989673786...	96.51942809610...	74.431176263
109.0764768219...	126.9377434158...	111.6109313642...	85.146931829
106.8374726256...	109.0750984924...	80.05623023850...	53.037722424
117.5159311630...	121.0552067371...	131.1868895888...	98.183501669
106.2796732021...	104.4077320945...	139.1294361377...	97.082439194
119.5612696303...	122.2989610074...	102.2594738887...	73.164198895
104.9910847217...	101.9850051935...	120.1499063670...	81.221918224
100.960697555014	103.3890641959...	129.0968628588...	89.050547443
104.7626169692...	135.0542060193...	109.0183470797...	77.025969646
131.5906639795...	123.7795721299...	101.3163362938...	80.504658250
122.7810225852...	129.0242089834...	97.32933781753...	74.330343736
120.5823351988...	97.25319461272...	118.5326959112...	76.655071586
97.44629772642...	121.0576326569...	110.0045453606...	82.006097334
113.1985905136...	126.0850730428...	141.5980225850...	108.46197490
105.2665253880...	124.6951535312...	67.7421582177598	46.529560496
111.5431039745...	131.1919518596...	123.0365799264...	94.132884795
109.2306723756...	128.1899327656...	150.2697574364...	110.45361017
118.3668980506...	111.1526671684...	118.3765179416...	82.377181306
113.5935006035...	119.8176840271...	158.0	124.0
114.5534230834...	114.2497712631...	128.9961239727...	97.867257037
109.0177016451...	128.2836925658...	144.1700384962...	109.16501271
105.6422464572...	129.7242697853...	88.45903006477...	67.468511173
110.1484141402...	124.6194656234...	141.8908030846...	107.96758772
117.2446494897...	128.3147370806...	118.1397477566...	86.400231481
108.5288249478...	129.2272264919...	155.5409913816...	119.23925528
106.5157025889...	130.6724834529...	115.1086443322...	91.137259120
102.6258368789...	124.8260955656...	145.0310311622...	110.00454536
111.8014094863...	113.6293777306...	186.1719635176...	136.09188072

Figure 5. Calculation management tool view.

ML Model Tool

ML methods such as Decision tree classifier (DTC), Random forest classifier (RFC), Extra tree classifier (ETC), Gaussian process classifier (GPC), Gradient boost classifier (GBC), Gaussian naive bayes classifier (GNB), Linear discriminant analysis (LDA), Quadratic discriminant analysis (QDA), Support vector machines (SVM) were used in ML model tool. Different GUIs were used for each ML method. These methods have usually been preferred to determine gender using results obtained via bone measurement [49,50]. The calculated features are composed of input vectors of ML. In this case, it was very difficult to estimate which feature set achieves more accuracy for gender determination. To overcome this difficulty,all possible subsets were identified and all of them were tested from a subset with one element to a subset with n elements. K-fold cross-validation method was used to test the subsets. To uncover which subset is more effective for gender determination, performance metrics were used.

The developed GUI for the machine learning model tool is shown in Figure6. As a sample view of GUI, the source file composed of the calculated features belonging to one of the analyzed cases was shared. LDA was selected and arguments specified for LDA and fold value were designed to use as input vectors of LDA. In the report part, performance values and the best feature list is shown.

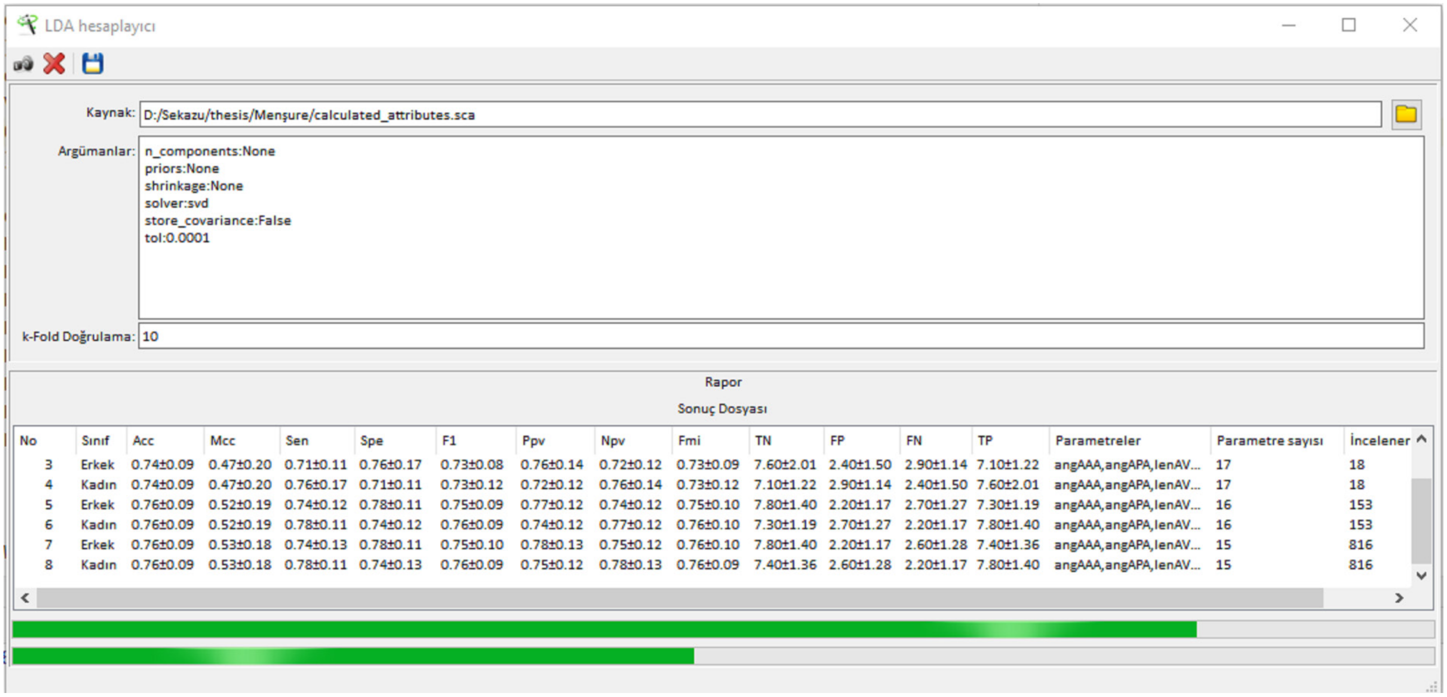


Figure 6.The developed GUI of the machine learning model tool is specified for LDA.

The k-fold cross-validation method was preferred for performance measurement in Sekazu. The k-fold cross-validation method divided the set into k different subsets. Then, the first 80% records of subsets were assigned as a training set and the last 20% records of subsets were assigned as a test set. ML methods were trained with training sets. After that, trained ML methods were tested with a test set that was not used during the training process. These training and test processes were performed for each k different subsets. Thus, performance metrics were calculated more consistently and realistically way [51]. Any k-fold value can be written in Sekazu. 3, 5, and 10 values as a k-fold value were used in this study.

Accuracy (Acc), Sensitivity (Sen), Specificity (Spe), F1 score (F1), Positive predictive value (Ppv), Negative predictive value (Npv), Matthews correlation coefficient (MCC), Fowlkes–Mallows index (FMI), and confusion matrix that composes of True positive (TP), True negative (TN), False positive (FP), False negative (FN) were selected as performance metrics for ML methods. These performance metrics are calculated by the formulas shown in Equation 2. MCC can take values between -1 and +1 and uncovers the similarity between sets (predicted conditions and true conditions). When similarity between predicted conditions and true conditions is increased, MCC approaches +1. When similarity between predicted conditions and true conditions is decreased, MCC approaches -1. When random results are obtained, MCC approaches 0. Like MCC, a high FMI value indicates that greater similarity exists between predicted conditions and true conditions. A low FMI value indicates that less similarity exists between predicted conditions and true conditions [52].

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Sen = \frac{TP}{TP + TN}$$

$$Spe = \frac{TP}{TP + TN}$$

$$F1 = \frac{2TP}{2TP + FP + FN}$$

$$NPV = \frac{TN}{TN + FN}$$

$$PPV = \frac{TP}{TP + FP}$$

$$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

$$FMI = \sqrt{(\frac{TP}{TP + FP})(\frac{TP}{TP + FN})}$$

Equation 2: Performancemetrics.

Equation 2: Performance metrics.

Discussion

Sekazu includes tools that obtain ability such as creating, listing, reporting, and storing bookmarks, features, calculated features, coordinates. A composite solution that provides to test ML methods was presented for the gender determination based on bone measurements calculated features by using these tools.

Sekazu is open-source and open to improve for other problem solutions. The fact that NumPy, SciPy, Pandas, and Scikit-learn packages were used is an advantage in comparison with studies in the literature.

The data transfer problem was kept to a minimum level because Sekazu includes bookmark management tool, feature management tool, labeling management tool, calculation tool, ML model tool, and supports popular file formats. In addition to this, data transfer can be done quickly and it can be used as a source without the need for massive code editing.

Sekazu provides users to draw out bookmarks on images based on a plan by labeling management tools and collect coordinates. Besides, because Sekazu gives different protocol numbers for collected coordinates, it provides users to perform multiple measurements at different times on the same cases.

The selection of k-fold cross validation supplies to more easily evaluate performance metrics of test sets applied on trained ML models. The fact that users can select a fold value is an advantage to work on small or large datasets.

Measurement of performance metrics supported by 8 different parameters based on confusion matrix provides users to compare their studies with studies in the literature. Besides, Sekazu provides friendliness for users by reporting confusion matrix parameters and measurement metrics.

Conclusion

Sekazu has different GUIs with the same design for each ML method. This is an advantage such that different arguments can be tested by different ML methods. Moreover, users can add new tools and features to Sekazu.

Conflict of interests

The authors declare that they have no competing interests.

Financial Disclosure

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Ethical approval

This study does not require an ethics committee report.

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