# Data-driven Automatic Attribution of Azerbaijani Flat Woven Carpets

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## ABSTRACT

Carpet attribution is an important task for studying the carpets and textiles, and more generally the history and culture of the communities producing these carpets. However, this is not an easy task, often relying on experts' subjective opinion or complex chemical or radiographical analysis, often not available to many practitioners. In this work, building on the success of applying machine learning and artificial intelligence methods in different fields, we present another, data-driven approach for carpet attribution. Based on a large dataset of Azerbaijani flat woven carpets we have developed a novel machine learning based data-driven carpet attribution system, which successfully determines their types, schools and weaving century, achieving up to 98% accuracy of the attribution.

## CCS CONCEPTS

**• Computing methodologies → Supervised learning by classification**; **• Applied computing → Fine arts**; **Digital libraries and archives**.

## KEYWORDS

carpets, textiles, applied arts, attribution, machine learning, classification

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## 1 INTRODUCTION

The tradition of carpet weaving has ancient roots in the area which constitutes modern Azerbaijan[1]. The earliest information about carpets in the area corresponding to present day Azerbaijan dates to V Century BC, when Xenophon described the carpet weaving in Persian satrapy Media, although the analysis of the ancient tools found in the area as well as fabric prints on vessels suggest that carpet weaving can be traced to the Bronze age. Throughout the history, carpet weaving played an integral role in the lives of the people living in Azerbaijan with its products used in their everyday lives as floor and wall coverings, prayer mats, tablecloths, bag material etc. In XV-XVII centuries, with the increase in trade links, Azerbaijani carpet also gained prominence in Western Europe.[14, 15]

Currently Azerbaijani carpet is a major cultural heritage element of Azerbaijan. Its status is protected by the Azerbaijani Government, with Azerbaijani National Carpet Museum established in 1967 being the first carpet museum in the world. In Azerbaijani Republic the carpets are both hand-woven by individual weavers, as well as produced with the help of mechanised weaving tools in factories. In 2010 the traditional art of Azerbaijani carpet weaving in the Republic of Azerbaijan was inscribed in on the Representative List of the Intangible Cultural Heritage of Humanity by UNESCO[2].

Azerbaijani carpets is a prominent export in both Azerbaijan and Iran, and are valued both as utility as well as collector items. The examples of carpets are held in museum collections not only in Azerbaijan but also throughout the world in the UK, the US, France etc. Thus, carpets' attribution, this is the identification their defining characteristics, is a very important field for their study and preservation, with links to the culture and history of respective communities. It is necessary to correctly identify the type of carpet, its school and the weaving time to estimate the rarity and the value of the carpet. The attribution of the carpets is not an easy task and requires a deep background knowledge of carpet history, geography and weaving process. This is currently done manually by experts

[1]For brevity purposes, in this text, we will refer to the territory populated by Azerbaijani-speaking people as Azerbaijan and carpets produced there as Azerbaijani carpets. This territory mainly encompasses modern-day Azerbaijani Republic and Iranian Azerbaijan region in Islamic Republic of Iran
[2]https://ich.unesco.org/en/RL/traditional-art-of-azerbaijani-carpet-weaving-in-the-republic-of-azerbaijan-00389

in this area, which makes the process cumbersome and prone to human error.

To start addressing this problem, current work introduces Machine Learning techniques to identify the type of Azerbaijani flat woven carpets. We are concentrating on flat woven carpets which are one of two major carpet types (other type being piled carpets), and has arguably retained more traditional character. We are using the largest to our knowledge dataset of carpets' technical characteristics, which includes more than 600 carpets with more than 120 attributes, including their weaving technologies, colours, sizes, density and other data. We apply common ML methods on this dataset and also analyse the features behind the classification models and identify which ones contribute to the result the most.

The results are promising, achieving up to 98% accuracy rates. We believe that this is a correct first step towards fully automated attribution of Azerbaijani carpets, which can then also be extended to carpets from other areas as well. In addition to black-box predictive models, our work can help practitioners understand which features are the most relevant for carpet attribution, assisting related practical and academical activities.

This paper is structured as follows; Section 2 presents information on Azerbaijani carpets targeted in this work, as well as related work in ML-based attribution of carpets and similar cultural heritage items, Section 3 introduces the dataset, Section 4 presents the results of ML techniques and Section 5 gives concluding remarks.

# 2 BACKGROUND

## 2.1 Azerbaijani Carpet

The main characteristics of carpet attribution are its age, school, and type. These are our targets for automated attribution system. These characteristics mostly determine their weaving techniques, compositional structure, ornamentation, and color schemes, through which different flat woven carpets differ from each other. In sections below we provide more information regarding the schools, the types and the technical characteristics of Azerbaijani flat woven carpets.

*2.1.1 Types.* **Cicim** carpets are woven from wool, cotton and raw silk. The main feature of cicim is that its surface is not made of weft threads, but of colored (white, red, yellow, brown) warp threads that form strips of different colors and sizes. Uni-colored weft threads are interlaced through them very tightly. Thus, the wefts are hidden between the warps and the warps form the surface of the fabric. Often the warp is thicker than the weft. The front of cicim is also often convex. The width of the cicim does not exceed 25-30 cm, but its length can be more than 15 m. [16]

**Kilim** carpets are woven from from wool, cotton and linen. The structure of the rug consists of two thread systems: warp and weft. The weft threads are interlaced between the warp using a simple threading method. Thus, the weft covers the warp completely and constitute the structure of the front surface of the rug. The patterns of the rug are woven using different colored weft threads. When the border of a pattern changes, the weft is changed. Slot-like gaps are often formed at these borders, however, rugs without gaps are also woven. [16]

**Palas** is woven from wool, cotton, silk, camel wool, and linen, hemp and rope fibers. The structure of the palas is determined by two different threads - the warp and weft. By simple threading, the weft threads are interlaced through the warps one by one and cover them completely. Thus, the palas has a weft face surface. Patterned raw palas, in which the third thread was used, were also woven. [16]

**Shadda** carpets are woven from wool, cotton and silk. The structure of the carpet consists of two main threads - warp and weft - which form a balanced weave. There are several types of shadda: uni-colored, checkered, conceptual shadda and camel shadda. For conceptual shaddas, the background is constructed by a balanced interlacing. The thread that creates the pattern only participates in the creation of the ornament. The thread forming the pattern is wrapped around two pairs of warp threads, and then again around the last pair, forming a curved thread (4/2). This technique is called "boat". Shaddas usually consist of two pieces sewn together. However, whole shaddas are also found. [16]

**Soumak** carpets are woven from wool, or sometimes from silk. Its structure consists of warp, weft, and pattern-forming yarns. Soumak patterns are woven using the "boat" technique described above. The distinguishing feature of soumak is its unique structure: two closely woven slats of the carpet form patterns resembling a wheat or a braid, which completely covers the surface of the soumak. Soumaks' inner area is often dark-red and their area can range from 2 $m^2$ to 25 $m^2$. [16]

**Zili** carpets are woven from wool, cotton and silk. Zilis can have various structures. The methods used for zili or **verni** carpets are also used for shaddas. The background is constructed by a balanced interlacing, and the patterns are woven using a "boat" technique. [16]

*2.1.2 Schools.* The fundamentals of the scientific classifications of Azerbaijani carpets created by many researchers of the 19$^{th}$-20$^{th}$ centuries are comprised of regional geographic principles in accordance with traditional terminology of the people and market nomenclature. While there are different classifications of Azerbaijani carpets and carpet products to the regional groups or schools according to their artistic and technical characteristics, in this work we are following the classification proposed by Karimov[4, 8]. This classification 4 major groups; Guba-Shirvan, Ganja-Gazakh, Karabakh and Tabriz. For our attribution, we consider the sub-groups of the first two major groups, resulting in seven schools: Guba, Shirvan, Baku, Ganja, Gazakh, Karabakh, and Tabriz. These school generally differ by their weaving, colors, types of produced carpets, materials etc. [15]

**Guba** carpets are characterized with beautiful and delicate weaving, the gracefulness of decors and intense color gammas consisted of the alignment of color lines, which do not grab the attention separately. Small geometric images are based on stylized botanical and sometimes animal motifs. Medallion compositions are widespread. [15]

The carpets of **Shirvan** carpet school are distinctive with their density and ancient compositions where calm and monumental dyeing rhythm has been accurately created. Baku school is dominated by flat woven carpets such as rugs, zili and others. [15]

The different characteristics of the carpets of **Baku** school were their medium sizes, moderate density of knots, bright colors, geometric motifs, medallions comprised of stylized botanical elements and symmetric compositions. The softness of the fabric, intensity of colors and delicate images of beautiful motifs are specific for Baku carpets. [15]

The artistic-technical characteristics of **Gazakh** carpets are the intensity of colors, moderate format, usage of simple and large stylized geometric elements, and the special quality of the wool which gave brightness and velvetiness to the carpet. [15]

Almost every carpet of **Tabriz** school is individual and has an original tonal and color expression (sun golden, raspberry blue and yellow-red colors). The elastic system of spiral-shaped pattern developed with gently entangled forms and delicate and complicated botanical ornaments prevails in Tabriz carpets. Pattern is either densely shared in main area and cover its whole upper surface or structured in medallion style. [15]

The carpets of Guba, Baku, Shirvan and Tabriz cities are made of high quality wool with long and delicate fibers. They are woven with dense graceful embroideries and mainly with small, beautiful forms. Large abstract motifs characterize Ganja, Gazakh and Garabakh carpets with short and thick fibers and less knot density. [15]

## 2.2 Carpet Attribution Techniques

Attribution of Azerbaijani carpets is currently performed manually. To determine the age (century) of the carpet experts examine its condition, colours and colouring elements. For type of the carpet, experts examine the weaving technology. Finally, technology, material and the color can help to determine the school of the carpet.

Currently, the work concerning automated carped identification, attribution or tagging is scarce. The only work to our knowledge which deals with specifically Azerbaijani carpets is [1], where authors automatically identify patterns using statistical methods. More widely, [6] use traditional ML methods as well as Convolutional Neural Networks to detect colour and pattern of carpets. To our knowledge, this is the only research work which has applied Deep Learning methods on carpet patterns. Conversely, [11] propose using SVM with hand-crafted features for Persian pattern type classification. Both approaches achieve promising results. It should be noted that all of these approaches are based solely on the patterns of the carpet, that is images. While on one hand this is the easiest, quickest and the least invasive approach as it requires only taking a picture of the carpet for analysis, it does not consider the technical features such as the weaving style, number of knots, density and others which are very characteristic to particular types and origin areas. Purely pattern based identification of Azerbaijani carpet type can be flawed as the same patterns can be used for different types. As opposed to the works above, [17] investigates the most important technical characteristics, such as area, density etc. of piled Caucasian carpet schools. It shows the similarity of technical characteristics' distributions of carpets belonging to different schools, motivating a multi-variate machine learning approach.

On a different side of the spectrum in terms of ease and invasiveness are the laboratory based tests of carpet material. Common techniques to attribute and authenticate the carpets include chemical and physical analysis using ultraviolet reflectance and fluorescence photography, ultraviolet and visible spectrometry, x-radiography, and particularly radiocarbon dating [7, 12]. Another method includes utilising techniques such as raman spectroscopy combined with liquid chromatography – mass spectrometry to determined the dyes, and then using background knowledge about the dates of the availability of identified dies for getting more information about carpet and its dating [13]. These methods are obviously complex, time-consuming and require advanced expert knowledge, normally not available to the museum staff. While arguably the most accurate to determine the used dyes, the date and potentially (although not seen in literature) the origin of the carpet, these approaches lack the background knowledge to identify more specialised traits such as types of carpets, patterns or weaving schools.

In terms of ease of use, our proposed approach is placed between these two analysis types. We are proposing a purely ML based approach based on technical features of the carpet. This requires (a) having a dataset for training of the models, which is available for Azerbaijani carpets and (b) an ability to identify all or the most of these features for the carpets needed to be attributed. While the identification of the features is not necessarily straightforward and requires some expert knowledge as well, it is certainly easier than lab analysis. ML based approach also has the potential to attribute all of carpets traits.

Finally, it is not unreasonable to suggest that pattern, lab and technical features based approaches can be combined for the increased attribution accuracy.

# 3 DATASET

The used dataset was provided by the Azerbaijani Carpet Makers' Union. It consist of 637 samples each representing a real traditional Azerbaijani flat woven carpet.

## 3.1 Target labels

In this work we are focusing on prediction of carpet type, school and century. The breakdown by types and schools is given in Figure 1. Among the schools, most of the carpets belong to Karabakh school followed by Shirvan and Guba. While Karabakh has relatively balanced distribution of carpet types, Shirvan has predominantly kilims and Guba nearly only soumaks. Among types, most of the carpets are kilim, which are found mainly among Karabakh, Shirvan, Baku and Tabriz schools. The next common type is soumak which is mainly in Guba school and zili, mainly found in Karabakh and Gazakh schools. Our dataset also includes some carpets of non-traditional origin. It is apparent that the distribution of school/type combination is not balanced, as weavers of different schools had preferences for particular carpet types.

The data distribution is broken down by age; woven in XX century (517 carpets) and before XX (119 carpets) in Figure 2 A and B respectively. For most of the schools relative number of carpets and their breakdown by types is similar for both age groups. Noticeable differences are that for Shirvan school, soumak only appears before XX and cicim appears only in XX, zili type carpets of Baku school appear only before XX, shadda in Gazakh school appear only in XX, palas in Karabagh school only appear in XX, cicim in Guba school only appear in XX.

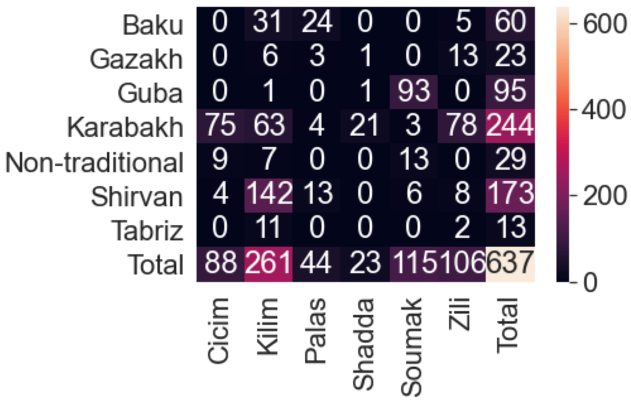
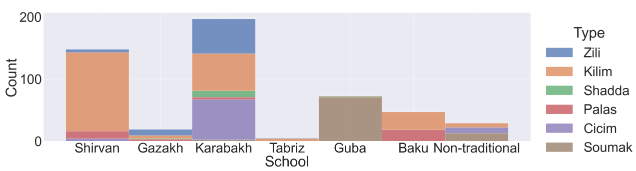
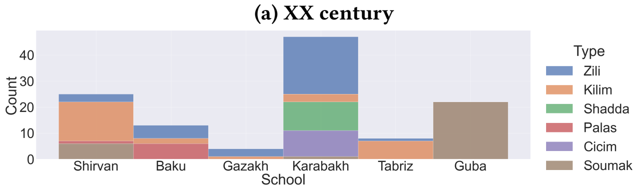



**Figure 1: Distribution of carpet types and schools.**




**(a) XX century**




**(b) Before XX century**

**Figure 2: Distribution of carpet types and schools by century of weaving.**

## 3.2 Input features

In addition to target label columns the dataset consists of 129 input features, which can be grouped into several categories given in Table 1. These features cover the main parts of Azerbaijani carpet; weft, warp, selvage, skirt, fringe including the information regarding colours, colouring type, materials, weaving patterns, weaving construction etc. Information regarding the dimensions, density, thread counts, of the carpet is also available.

# 4 RESULTS

## 4.1 Predicting Carpet Types

We have experimented with classifiers such as LightGBM [9], XGBoost[3], SVM and Nearest Neighbour[5] classifiers for the classification of carpet type. All the experimentation was done using **scikit_learn**, **xgboost** and **lightgbm** libraries in Python. The algorithms were evaluated using 10-fold cross-validation and the results of experiments are given in the Table 2, where the classifiers' hyperparameters optimisation included grid or random search. They are shown in Appendix A.1. Pre-processing included imputation of missing values with median for numerical features and mode for categorical,

**Table 1: Input features for automatic attribution**

| Feature Type | Number of features | Examples of features |
|---|---|---|
| Dimensions | 2 | Width, length |
| Warp | 5 | Yarn, material, colouring |
| Weft | 5 | Yarn, material, colouring |
| Colours used | 35 | Maroon, indigo, burgundy |
| Density dimensions | 2 | Density width and length |
| Carpet front | 7 | Type, material, colouring |
| Weaving technique | 5 | Interlacing, braiding, wrapping |
| Weaving patterns | 32 | |
| Side selvage | 8 | Technique, form, colouring |
| Finishing selvage bottom | 6 | Yarn, material, colouring |
| Finishing selvage top | 6 | Yarn, material, colouring |
| Fringe bottom | 8 | Colouring, construction, form |
| Fringe top | 8 | Colouring, construction, form |

standard scaling of numerical features and one-hot encoding (except for LightGBM) of categorical features. LightGBM achieves top result of 0.984 accuracy and F1-score, which strongly outperforms the naive majority benchmark of 0.409 accuracy, and is therefore a very positive result.

**Table 2: Results of prediction of carpet types**

| Classifier | Accuracy | Weighted F1-Score |
|---|---|---|
| LightGBM | 0.984 | 0.984 |
| SVM | 0.934 | 0.934 |
| XGBoost | 0.934 | 0.933 |
| Random Forest | 0.928 | 0.928 |
| Nearest Neighbours | 0.898 | 0.896 |

We further investigate the results of LightGBM classifier by examining the confusion matrix (Figure 3). It is seen that all the instances of cicims and soumaks are classified correctly, while other carpet types have a few misclassifications each.

An important aspect of our work is not only developing predictive models, but also trying to understand which features contribute to the predictions. For this, we employ SHAP TreeExplainer[10], which reveals the features with the highest contribution to the best model on Figure 4. Analysis of the top 5 features with the most contribution to the model reveals that the front weaving technology contributes to the classification of the most types, especially cicim and shadda, different weaving patterns contribute to soumaks and zilis, side selvedge yarn contributes mostly to kilims, and other (not one of the most popular 34) colours contribute to kilims. These

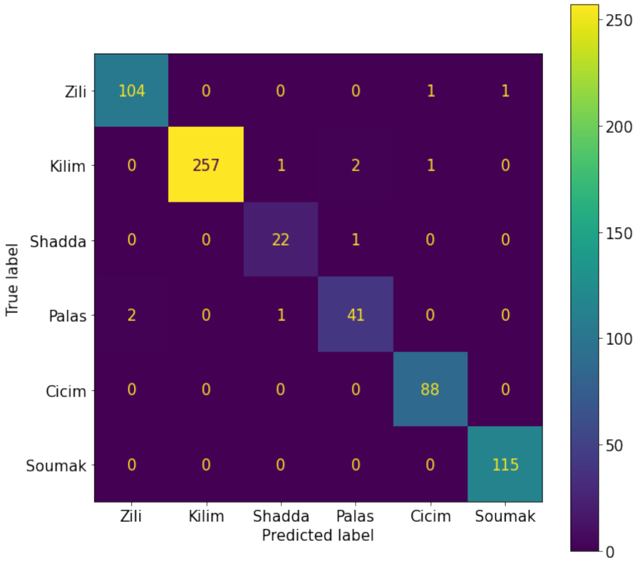



**Figure 3: Confusion matrix of carpet type predictions using LightGBM.**

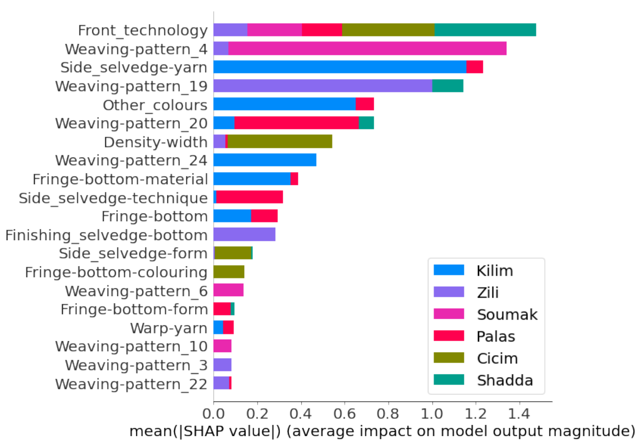



**Figure 4: The most contributing features to carpet type predictions using LightGBM according to SHAP.**

results mostly conform to the expectations, except the surprising emergence of side selvedge yarn as an important factor.

## 4.2 Predicting Carpet Schools

For predicting carpet schools, the same methodology was followed as in Section 4.1. The hyperparameters are shown in Appendix A.2. XGBoost achieves top result of 0.73 accuracy and 0.712 F1-Score. which outperforms the naive majority benchmark of 0.384, and is therefore a highly positive result. The results of experiments are given in the Table 3.

We further investigate the results of the XGBoost classifier by examining the confusion matrix (Figure 5). It is seen that while most of the carpet schools are predicted fairly well, all Gazakh carpets are predicted as Karabakh and most of the Baku carpets are predicted as Shirvan. This is likely caused by the similarity between the respective schools, and the fact that there are much more Karabakh and Shirvan carpets in the dataset comparing to Gazakh and Baku.

**Table 3: Results of prediction of carpet schools**

| Classifier | Accuracy | Weighted F1-Score |
|---|---|---|
| XGBoost | 0.73 | 0.712 |
| Random Forest | 0.726 | 0.686 |
| SVM | 0.714 | 0.701 |
| LightGBM | 0.675 | 0.645 |
| Nearest Neighbours | 0.669 | 0.646 |

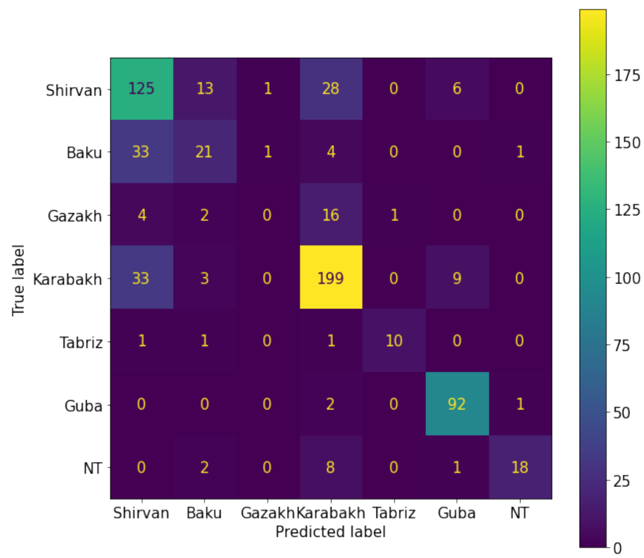



**Figure 5: Confusion matrix of carpet school predictions using LightGBM.**

The most important features contributing to the model as identified by SHAP library are shown in Figure 6. Analysis of the top 5 features with the most contribution to the model reveals that the various weave patterns contribute to classification for the most schools, especially Karabakh, Shirvan and Baku, width-wise density contributes mostly Karabakh and non-traditional schools, usage of cotton in the weft contributes to Tabriz and Shirvan and the width of the carpet contributes to the most of the schools. Also in this case, most of the features identified as important by SHAP conform to experts' expectations, with the exclusion of width of the carpet.

## 4.3 Predicting Carpet Century

The prediction of carpet creation century was somewhat more challenging than the previous two use cases. The reason for this is a pronounced class disbalance. In order to avoid the bias of the model towards the majority class (XX century), the re-balancing of the dataset was undertaken combining over- and under-sampling using

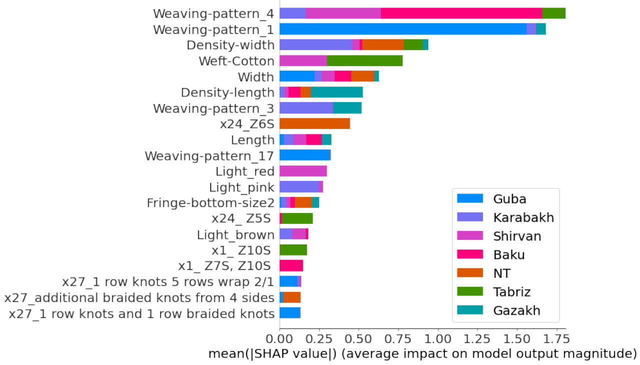



**Figure 6: The most contributing features to carpet school predictions using XGBoost according to SHAP.**

SMOTE with Edited Nearest Neighbours[2]. Subsequently, the train-test set evaluation was used to assess the chosen algorithms, with train set constituting 70% of the dataset and the test set the remaining 30%. In addition, we have included Balanced Random Forest without artificial dataset rebalancing in our experiments, results of which are given in the Table 4. The hyperparameters are shown in Appendix A.3. XGBoost achieves top result of 0.781 accuracy and 0.674 F1-Score[3]. The confusion matrix of the predictions is given in Figure 7. While, unsurprisingly, the majority class is predicted well (recall=0.828), even the minority class (before XX) is more likely to be predicted correctly (recall=0.57). Thus, the performance of the classifier is generally positive. It should be noted that the most important indicators of carpet's age - its condition, does not exist in our dataset, thus we surmise that inclusion of this data would further improve the results.

**Table 4: Results of prediction of carpet century**

| Classifier | Accuracy | F1-Score |
|---|---|---|
| XGBoost | 0.781 | 0.674 |
| LightGBM | 0.771 | 0.665 |
| Balanced Random Forest | 0.688 | 0.609 |
| SVM | 0.641 | 0.553 |
| Nearest Neighbours | 0.604 | 0.547 |

The most important features contributing to the model as identified by SHAP library are shown in Figure 8. The top 5 features with the most contribution to the model are the different weaving and knot patterns, existence of color white in the carpet and whether the top fringe material is wool.

## 5 CONCLUSIONS AND DISCUSSION

This work is focused on data-driven automated attribution of Azerbaijani flat woven carpets. While statistical approaches have been previously used for classification of carpets, this work is unique by using machine learning approaches on a dataset with significantly larger feature set as compared to other works. We have successfully addressed three use cases; identification of carpet's type, school and age. Hereby, the identification of the carpet type can be considered largely solved.

There are multiple academical and practical implications of our research. For Azerbaijani flat woven carpets, we have shown that the technical characteristics can be used to determine its main attributes. Along confirming the known factors for the attribution of carpets, we have also identified features which were previously not thought to be important for attribution. Further research is necessary to look into this and identify the reasons, why these features appear to be major contributors to the classification.

In practice, the results of our research, particularly the explanations behind the models, can be used by practitioners in attribution

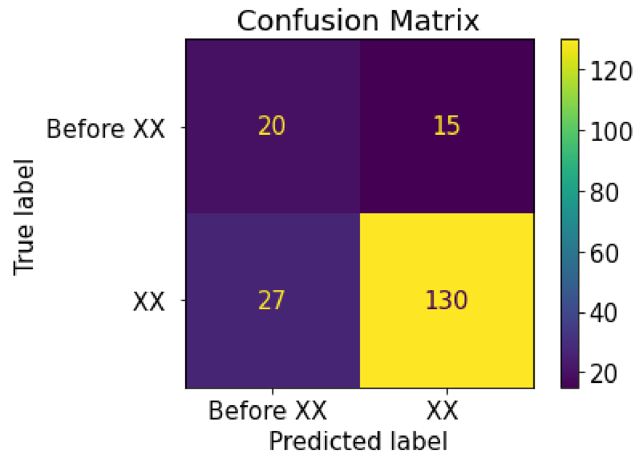



**Figure 7: Confusion matrix of carpet century predictions using XGBoost.**

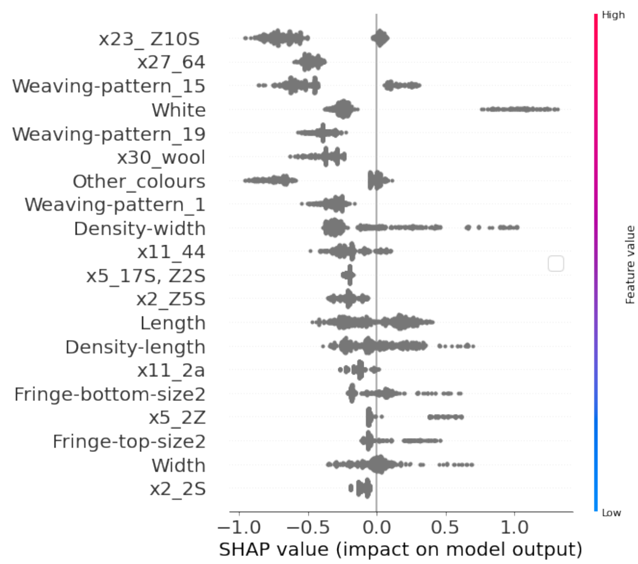



**Figure 8: Confusion matrix of carpet century predictions using XGBoost.**

[3]We are using unweighted F1-score for this case to have a fair evaluation for both classes.

of previously un-attributed flat woven carpets or for the confirmation of already existing attribution. Current limitation of our approach is the number of features required to provide in order to attribute a carpet. This can be addressed in the future by identifying the minimum set of features which is necessary to attribute carpets with sufficient accuracy and either developing new models based solely on this set or providing default values for other features. Future work will also include an app which will make it possible to make the direct use of our models via a web-interface.

It is likely that our approach can be successfully extended to the same types of carpets originating from other regions, e.g. Persian, Afghan, Anatolian etc. carpets. Furthermore it would make sense for the attribution of other types or schools of carpets as well, starting from Azerbaijani piled carpets. In fact, a popularity of some of these carpet types can result in more available data, which would increase the performance of the automated attribution. Inclusion of the features not available in this work, such as the images of the carpets or the information about the condition of the fabric can also improve the results and will be addressed in the future.

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# A HYPERPARAMETERS' SELECTION FOR CLASSIFIERS USED IN EXPERIMENTS

## A.1 Type Classification

**LightGBM**: colsample_bytree=0.7076074093370144, min_child_samples=105, min_child_weight=1e-05, num_leaves=26, reg_alpha=5,reg_lambda=5, subsample=0.7468773130235173;
**XGBoost**: colsample_bytree=0.6, gamma=0.5, learning_rate=0.05, max_depth=5, min_child_weight=5, subsample=0.8;
**SVM**: C=100, gamma=0.001, kernel='rbf';
**KNN**: leaf_size=10, metric='minkowski
**Random Forest**: bootstrap=False, criterion='entropy', max_depth=None, min_samples_leaf=1, min_samples_split=10.
Other hyperparameters were kept at default values as defined in respective libraries.

## A.2 School Classification

**LightGBM**: colsample_bytree=0.7076074093370144, min_child_samples=105, min_child_weight=1e-05, num_leaves=26,reg_alpha=5,reg_lambda=5, subsample=0.7468773130235173;
**XGBoost**: colsample_bytree=1.0, gamma=1.5, learning_rate=0.05, max_depth=5, min_child_weight=1, subsample=1.0;
**SVM**: C=100, gamma=0.001, kernel='rbf'
**KNN**: n_neighbors=7;
**Random Forest**: bootstrap=False, criterion='entropy', max_depth=None, min_samples_leaf=1, min_samples_split=10.
Other hyperparameters were kept at default values as defined in respective libraries.

## A.3 Century Classification

**LightGBM**: num_leaves= 15, max_depth=-1,random_state=314, metric='None',n_jobs=4,n_estimators=1000,colsample_bytree=0.9, subsample=0.9,learning_rate=0.1;
**XGBoost**: colsample_bytree=0.6, gamma=0.5, learning_rate=0.1, max_depth=3, min_child_weight=1, subsample=0.6;
**SVM**: C=100, gamma=0.001, kernel='rbf'
**KNN**: n_neighbors=3;
**SMOTEENN**: SMOTE(k_neighbors=1), EditedNearestNeighbours(n_neighbors=2).
Other hyperparameters were kept at default values as defined in respective libraries.