Evolving with Klinkenberg's Idea (EKI) Algorithms for Automatic Identification of Sa Huynh Antique Glass Artifacts

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Abstract. This research focuses on the challenge of comprehensively identifying Sa Huynh glass jewelry in Vietnamese archaeology based on new SEM gemological analysis. We propose the implementation of a system, called Recognition Automatic System for Sa Huynh Glasses (RAS-SHG), motivated by the unique conditions in archaeology, that aims to employ evolving continuous learning algorithms on our Sa Huynh Culture archaeological databases. This research develops new evolving continuous learning algorithms, so called Evolving with Klinkenberg's Idea (EKI) algorithms, based on a combination of different classic machine learning algorithms with the "*sliding windows*" approach and Klinkenberg's optimized window size. We compare these algorithms to select the most suitable model that aligns with the performance requirements of the Sa Huynh Culture archaeological dataset. This Recognition Automatic System for Sa Huynh Glasses (RAS-SHG) has been developed to accurately distinguish between Sa Huynh and non-Sa Huynh glass ornaments and is now utilized at the Vietnam Institute of Archaeology and the UNESCO Centre for researching and preserving Vietnamese antiquities.

Keywords: Sa Huynh antique glass identification, Vietnamese glass classification, machine learning in archaeology, evolving machine learning, continuous machine learning.

1 Introduction

Ancient Vietnamese glass artifacts, such as those from the Dong Son, Sa Huynh, and Oc Eo cultures, have been extensively traded throughout history, leading to their wide distribution in Vietnam and across the world. However, in private antiquities collections, misclassification and confusion of these ancient jewels are pervasive and intricate. The Sa Huynh culture, in particular, faces the challenge of jewelry being sold under different names, and artifacts from other cultures, such as Dong Son and Oc Eo, being mislabeled as Sa Huynh. To address this issue, this paper employs a combination of gemological methods and evolving continuous learning algorithms to analyze the unique identification characteristics of Sa Huynh glass jewelry. The background of this study is rooted in the complexity of classification studies in archaeology, stemming from the unique characteristics of stream data in the field. Here, data gradually accumulates over time as new discoveries emerge from excavations. The significance of this research lies in enhancing a recently published system by integrating additional learning methods through evolving approaches. This research question poses significant challenges due to data scarcity, which can be attributed to several main factors of real-life scenarios encountered in archaeological investigations make it.

In this research, we present our study through three main sections. Firstly, we provide an interdisciplinary overview of the intersection of evolving continuous learning applied for identification of antique artifacts by using gemological analysis, for setting the context of archaeology. Next, we offer comprehensive insights into our archaeology dataset, the gemological measuring equipment, and the experimental procedures adopted. Subsequently, we outline our Evolving with Klinkenberg's Idea (EKI) learning algorithms, our evaluation metrics, and our experimental protocols, followed by a detailed discussion of the results obtained. Ultimately, we conclude by emphasizing the significance and value of our findings in advancing the identification of Sa Huynh glass jewelry.

2 State-of-Art

2.1 Identification of Antique Glass artifacts by Gemological Analysis

The investigation of ancient glass through gemological methods commenced in the 1990s, with significant contributions made by J. Henderson's work on Roman glass in England [1]. Gemological analysis involves categorizing ancient glass artifacts based on their distinctive characteristics and composition-related components [2, 3]. Categorizing ancient glass artifacts into distinct groups may appear simplistic at first glance; however, this approach does not fully meet the requirements of modern research. Upon closer examination, each group of ancient glass can be further subdivided into smaller subgroups, displaying unique variations despite sharing common characteristics within the broader category. The complexity of this classification becomes particularly apparent when different types of glass are produced within the same cultural tradition but in different regions, leading to significant archaeological variations. From a gemological standpoint, these subtle differences might not be discernible using rudimentary mathematical tools. In the present era, the application of artificial intelligence technologies for the classification, appraisal, assessment, and judgment of antiquities, archaeological sites, and cultural heritages has experienced considerable popularity. Notably, studies conducted by Bickler on antique porcelain [13], Jones on the classification of ancient plants [14], and Ngo Ho on the categorization and evaluation of ancient documents [15, 16, 17] have contributed to this trend. As a consequence, some Vietnamese researches have been progressively establishing the initial automatic identification systems for Vietnamese antiquities, leveraging advanced technologies [18, 19].

In previous works [18, 19] on Vietnamese Oc Eo antique glass, the research employed a neural network artificial intelligence system that applied MLP functioning:

extracting feature sets from the scanning electron microscope (SEM) system, comprising 36 features, the system trained the neural networks for recognition, comparing and selecting the most suitable network. The selected network for this application encompassed 36 input values, 120 hidden layer neurons, and one output layer neuron. Through the training process, the research obtained a set of networks optimized for identification. During the identification process, the application continuously gathers user-entered data, extracts features, and feeds them to the network for further identification. Consequently, the outcomes and efficiency progressively improve through continuous learning, leading to enhanced accuracy in the final results. The attributes of the analyzed rays are chosen based on characteristic properties, vectorized, and transformed into a *36*-dimensional vector $\{x_1, x_2, ..., x_{36}\}$. Although the research have established a system MLP that constructs a single network for specimen recognition, its capability can be expanded to handle multiple types of specimens concurrently. The neuron set comprises three layers: the input value layer, the hidden neuron layer, and the output neuron layer. Two sets of neuron weights correspond to the links from the input layer to the hidden layer and from the hidden layer to the output layer. In consideration of the attributes of artifact identification, the system opted for the feedforward neural network architecture combined with the error backpropagation algorithm as the network architecture type. However, this method is adapted only for a static environment based on the hypothesis that all data is collected and labeled correctly throughout the entire archaeological process.

The complexity of classification studies in archaeology is underscored by the fact that previous research data, such as gemological analyses, can be significantly different labelling, rendering earlier studies irrelevant for subsequent categorization efforts. These challenges also extend to data science disciplines, particularly concerning the phenomenon known as "*concept drift*", which will be elaborated upon in the following sections.

2.2 Evolving Continuous Approaches in Concept Drift

In this research, our primary objective is to enhance a recently published system by integrating additional learning methods through the utilization of evolving approaches. Our inspiration stems from the unique characteristics of stream data in the field of archaeology, where data is gradually accumulated over time as new discoveries emerge from excavations. This presents significant challenges due to data scarcity, which can be attributed to some main factors. The real-life scenarios of archaeological investigations make it difficult to find artifacts, and conducting experimental excavations for feature extraction can be prohibitively expensive. Consequently, data is acquired sporadically and in limited quantities. So on, the field of archaeology occasionally experiences reclassification of artifacts initially assigned to a particular group based on new data and discoveries. The classification of artifacts into specific categories relies on various interdisciplinary factors, some of which can be unexpected. As explained in the preceding section, this poses challenges for data science disciplines, particularly concerning the phenomenon known as "*concept drift*", which will be explored further here.

Therefore, the required system must demonstrate their effectiveness under these unique circumstances of archaeology.

Due to the limitations of traditional learning methods, evolving continuous learning methods become more relevant and intriguing for addressing this problem. Given the specific context of archaeology and the comprehensive state-of-the-art review of evolving learning methods as extensively studied in [15], we recognize that the system can effectively utilize lightweight methods based on data selection approaches due to the limited samples obtained from archaeological excavations. This ensures that critical information is not lost due to the generalization concept employed by many evolving methods. To achieve this, we propose employing a simple "*sliding windows*" approach, akin to the FLORA method [23]. This principle involves updating the model at each moment '*t*' using the most recent training data, defined by a "*sliding windows*" of a predetermined size (either based on time scale or the number of data points). This approach can involve either batch retraining using the selected data within the "*sliding windows*" or updating the model if an online learning method allows for it. Typically, these methods consist of three steps [23], see Fig.1: 1. Detecting concept changes using statistical tests on different windows; 2. If a change is observed, selecting representative and recent examples to adapt the models; 3.Updating the models. Recently, several researchers have explored the adaptation of "*concept drift*" using "*sliding windows*" techniques [20], [21], [22], all aiming to capitalize on its advantages.

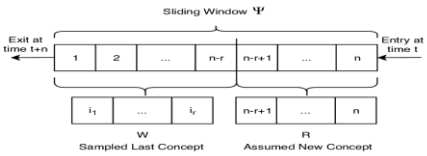

Fig. 1. Sliding windows algorithms, following [28].

The window size in the evolving approaches is determined a priori by the user, and each window overlaps the previous one by sharing a batch of data. At each step, a new model is learned, representing an updated set of classes. The key challenge in these approaches lies in determining the appropriate window size. While many methods use a fixed-size window tailored to specific real-world problems, there are approaches that aim to automatically detect the optimal size of the analysis window. For example, in [24] with ADWIN (ADaptive WINdow), the author tests a range of window sizes by dividing each window into sub-windows of minimal size. If these sub-windows exhibit significantly different distributions, a statistically significant size is considered suitable. In [25], the authors propose utilizing two models at each step, trained with different window sizes: *S* (a predefined standard size) and *2S*. The smaller window with size *S* is employed to detect new concept spaces using a statistical test, while the larger window with size *2S* is used to update the model when a new concept space is detected. In [26] with OLIN (On Line Information Network), the authors suggest dynamically adjusting the window size based on the performance achieved on a validation dataset. The new data is divided into two parts: one for training and the other for validation. Multiple windows with varying sizes are independently applied for learning and testing, and the

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size that yields the best result on the validation data is chosen for the current step. However, the effective implementation of this approach requires conducting learning phases on sufficiently large batches of data. Finally, in [27], Klinkenberg’s paper employs a consecutive increment of window sizes. At each step, the performance (in terms of error rate) is calculated for different window sizes, and the size that yields the best performance is selected (e.g., size No_1 represents the last batch, size No_2 represents the last two batches, size No_3 represents the last three batches, and so on). In this study, we will explore evolving approaches based on Klinkenberg's idea [27], applied to our archaeological dataset, to dynamically detect the best window size for analysis. Hence, it is essential for the algorithms utilized in the experiments to demonstrate their efficacy within these exceptional conditions. Considering the specific context of archaeology, as explained previously, we recognize the potential effectiveness of employing lightweight methods that leverage data selection approaches. This is particularly important due to the limited number of samples obtained from archaeological excavations. The underlying rationale is straightforward: we can exercise control over information loss by managing the "*density*" of learning data within the selected optimal size. Utilizing Klinkenberg's methods, with a simple parameter '*n*' representing the size of the batches, allows us to control the loss of valuable information caused by the generalization concept commonly employed in various evolving techniques.

Consequently, we develop nine new evolving continuous machine learning algorithms, by applying the "*sliding windows*" approach with the incorporation of Klinkenberg's idea for dynamically detecting the optimal window size on nine classic algorithms [4, 5, 6, 7, 8, 9, 10, 11, 12], so called Evolving with Klinkenberg’s Idea (EKI) algorithms. This research will compare the performance of these EKI algorithms on the archaeological dataset to explore the effectiveness of these methodologies under the evolving data conditions encountered in Sa Huynh Culture archaeological datasets.

3 Archaeological Sa Huynh Dataset

The Oc Eo, Sa Huynh, and Dong Son specimens employed in this study have been exhibited in multiple national exhibitions, authorized by the National Appraisal Council, and sourced from the UNESCO Center for Research and Conservation of Vietnamese Antiquities. The gemological characteristics of these ancient specimens were extracted using the gemological Scanning Electron Microscope (SEM) technique, which has been previously described in our studies [2, 3, 18, 19] and conducted by Hanoi University of Mining and Geology.

In summary, this technique relies on Energy Dispersive X-ray Spectroscopy (EDXS) or Wavelength Dispersive X-ray Spectroscopy (WDXS) analysis to determine the chemical composition of solids. During this analysis, X-ray spectra are recorded when the solid interacts with radiation, typically high-energy electron beams in electron microscopes. The SEM machine, combined with the EDS exploitation machine (Model: Quanta 450; Manufacturer: FEI-USA), was utilized in this study to facilitate the physical technique. The results of the SEM technique provide 10 values for each chemistry element. The effective reflectance (Net Int) indicates the reflectance of the electron beam, while Weight and Atomic Mass (%) and Atoms (%) represent the composition of the specimen. The Kratio value signifies the ratio of the reflected electron density, and R represents the resolution in microns after determining the reflected electron density. To calibrate the elemental composition, the spectrum of the standard sample is compared with the spectrum of the measured sample. Calibrating values, such as Z (atomic calibration), A (absorption correction), and F (fluorescence calibration), are utilized to ensure accuracy and account for specific factors.

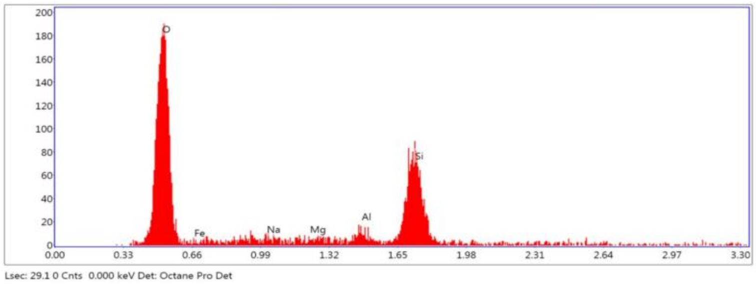

Fig. 2. The result of SEM method.

In this specific experiment, the antique Sa Huynh glass specimens comprise eight chemical elements: Calcium (Ca), Potassium (K), Iron (Fe), Sodium (Na), Magnesium (Mg), Aluminium (Al), Silicon (Si), and Oxygen (O), see Fig.2. The location and number of analytical processing times are crucial for accurate identification. Due to the costliness of each analysis shot, only necessary positions are analyzed to avoid data redundancy. Hence, specific conditions are followed in our measurements: based on the sample quality, each sample is analyzed five times at different locations on the specimen. By selecting distinct sites for analysis, we aim to achieve maximum variation. Homogeneous samples may require fewer analyses, while larger samples may undergo fewer shots. For Sa Huynh specimens, we analyze four different specimen, with five shots at each specimen. For other non-Sa Huynh antique specimens, we analyze one position in each specimen with five shots or less, depending on the specificity of the artifacts. Currently, our dataset is exclusively comprised of specimens obtained from the UNESCO Center for Researching and Conservating of Vietnamese Antiquities.

In summary, the archaeological dataset comprises a total of 108 samples, with 19 attributed to the Sa Huynh culture and the remaining assigned to other cultures and antique imitations. These samples collectively exhibit 40 characteristics, including eight chemical elements: Calcium (Ca), Potassium (K), Iron (Fe), Sodium (Na), Magnesium (Mg), Aluminium (Al), Silicon (Si), and Oxygen (O), each characterized by five indications ('W,' 'R,' 'Z,' 'A,' and 'F'). Due to the small size of the dataset, it has been decided to skip any normalization procedures before classification to avoid potential distortion of the inherent class structure within the data.

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4 Experiments and Discussion

The algorithms employed in this study were implemented using version 0.24.2 of the *scikit-learn library*, in conjunction with the "*sliding windows*" technique and Klinkenberg's optimized window size method, developed in *Python*. The implementation was processed in a streaming manner, utilizing mini "*sliding windows*" that encompassed the last n samples. We initiated the process with $n = 1$, corresponding to classic online learning, and progressively increased $n > 1$ to represent batch learning. For each evolving algorithms, we selected only the best results of n for comparison with other Evolving with Klinkenberg's Idea (EKI) algorithms. The nine Evolving with Klinkenberg's Idea (EKI) algorithms developed in this research are EKI k-Neighbors Classifier, EKI Extra Tree Classifier, EKI Adaboost, EKI Bernoulli Naive Bayes Classifier, EKI Random Forest Classifier, EKI MLP Classifier, EKI Decision Tree Classifier, EKI Bagging Classifier, and EKI Gaussian Naive Bayes Classifier. The EKI classifier algorithms has the complexity of $O(n-m)$ where n is the current number of data batches and m is the best_no_of_data_batch.

The dataset was partitioned into a training dataset (70%) and a testing dataset (30%) with the classic cross-validation. For each experiment, the positions of the data in the training and testing datasets were randomly assigned, a process repeated 10 times. Furthermore, the training dataset was shuffled randomly 10 times, generating diverse scenarios of stream learning to evaluate the adaptability of the model to evolving data. As a result, each learning method with each parameter variation underwent 100 random experiments, ultimately leading to the collection of final comparison data. The achieved results were averaged to ensure the reliability and generalizability of the experiments. To evaluate the performance of binary classifiers, especially in the presence of class imbalance, all attained results were based on Balanced Accuracy (BA). The formula of Balanced Accuracy (BA) is as follows: *Balanced Accuracy (BA) = 1/2 (Specificity + Precision)*. In situations characterized by highly imbalanced data, where one class significantly outweighs the other (e.g., 1 data point in group A, 999 data points in group B), conventional accuracy calculations become unreliable. In such cases, metrics like the Area Under the Curve (AUC) and Balanced Accuracy (BA) are preferred. Balanced Accuracy (BA) is a fundamental metric used to assess the performance of binary classifiers when dealing with imbalanced classes, especially in comparison tasks [15, 16, 17], providing a simpler, more realistic, and optimal assessment of classification.

In general, all evaluated methods demonstrated favorable performance, with the average Balanced Accuracy exceeding 80% for each method, and most of them achieving close to or above 90% accuracy (with the exception of EKI Gaussian Naive Bayes Classifier). The rankings based on Balanced Accuracy are as follows: EKI k-Neighbors Classifier (91.92%), EKI Extra Tree Classifier (89.57%), EKI Adaboost (88.93%), EKI Bernoulli Naive Bayes Classifier (88.53%), EKI Random Forest Classifier (88.10%), EKI MLP Classifier (88.04%), EKI Decision Tree Classifier (87.66%), EKI Bagging Classifier (87.02%), and EKI Gaussian Naive Bayes Classifier (83.47%). Notably, Ensemble Learning's EKI methods, such as EKI Random Forest Classifier, EKI Adaboost, EKI Extra Tree Classifier, and EKI Bagging Classifier, achieved similarly good results, with an average accuracy of around 88%. It is essential to highlight that the Balanced

Accuracy of the last step is not consistent with the Average results due to the influence of weaknesses in the initial steps. Focusing solely on the Average of the final steps, certain methods with weaker performance, such as EKI Gaussian Naive Bayes Classifier, still achieved remarkably good results compared to other methods, as well as the Naive Bayes family, like EKI Bernoulli Naive Bayes (which attained 89.59% compared to EKI Gaussian Naive Bayes's 89.70% in the last 20 steps). Therefore, on the whole, the tested methods showed relatively minor differences in performance, except for the unexpectedly superior performance of the EKI k-Neighbors Classifier, indicating a substantial and easily distinguishable difference between Sa Huynh glass and other types of glass. In terms of overall results, the EKI k-Neighbors Classifier displayed the best performance, although the EKI Extra Tree Classifier also proved to be the top-performing method among all Ensemble Learning's EKI techniques in our experiments.

Table 1. Table of experiment results.

Evolving with Klinkenberg's Idea (EKI) Algorithms with its best *n*	**Average (%)**	**Last Step (%)**	**Std (%)**
EKI k-Neighbors Classifier *(n=74)*	91,92	96,57	4,71
EKI Extra Tree Classifier *(n=69)*	89,57	95,63	3,23
EKI Adaboost Classifier *(n=69)*	88,93	88,64	3,33
EKI Bernoulli NB Classifier *(n=73)*	88,53	89,59	6,31
EKI Random Forest Classifier *(n=71)*	88,10	89,33	3,02
EKI MLP Classifier *(n=74)*	88,04	94,05	5,11
EKI Decision Tree Classifier *(n=55)*	87,60	91,94	5,39
EKI Bagging Classifier *(n=74)*	87,02	87,77	3,70
EKI Gaussian NB Classifier *(n=71)*	83,47	89,70	3,09

Upon examining the results, it is important to note the differences in rankings between the data from all steps and the data from the last 20 steps (see Table 2 and Table 3). The methods can be categorized into three main groups: Group 1 includes EKI k-Neighbors Classifier, Group 2 consists of all Ensemble Learning's EKI methods, and Group 3 encompasses the remaining EKI methods. The substantial superiority of the EKI k-Neighbors Classifier over the methods in Group 2 (Ensemble Learning's EKI methods), which are generally strong classifiers, suggests that the Sa Huynh data is quite uniform in range. This characteristic enables the EKI k-Neighbors Classifier to perform favorably compared to Group 2, regardless of the distribution of non-Sa Huynh data. Group 2 obtained weaker results due to the impact of the diverse distribution of non-Sa Huynh data, where each weak classifier within the Ensemble Learning's EKI methods lacks sufficient detail to accurately classify non-Sa Huynh data, although they accurately classify Sa Huynh data (resulting in a significantly higher False Positive rate compared to the True Negative rate). Consequently, the Ensemble Learning's EKI methods, which rank based on voting from multiple weak classifiers, provide inaccurate results overall. The EKI Multi-layer Perceptron (MLP) did not achieve satisfactory results due

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to the limited number of Sa Huynh data and the excessive diversity in non-Sa Huynh data, which led to insufficient details for accurate classification, consistent with its theory. Keep in mind that all deep learning algorithms, which have been very trendy recently and are based on the neuron-network concept, share the characteristic of sensitivity to limited data. Regarding the Naive Bayes's EKI family, which includes EKI Gaussian Naive Bayes Classifier and EKI Bernoulli Naive Bayes, there seems to be a difference in the Average (table 1); however, both methods have comparable capabilities in the last steps. The uniformity of Sa Huynh data also explains why the EKI Decision Tree Classifier outperforms Naive Bayes's EKI (in the last 20 steps). The natural structure of the Decision Tree Classifier allows it to achieve good results by correctly classifying one class in one branch of the tree, which naturally results in the accurate classification of the other class. In contrast, for Naive Bayes, both classes must have similar predictions to achieve accurate results, as the probability of one class depends on the presence of the other class.

Table 2. Table of experiment results (in 20 last steps).

Evolving with Klinkenberg's Idea (EKI) Algorithms *(in 20 last steps)*	**Average (%)**	**Last Step (%)**	**Std (%)**
EKI k-Neighbors Classifier	96,50	96,57	0,14
EKI Extra Tree Classifier	92,86	95,63	1,79
EKI Decision Tree Classifier	90,36	91,94	1,13
EKI Adaboost Classifier	89,90	88,64	0,80
EKI Random Forest Classifier	89,61	89,33	0,30
EKI Bernoulli NB Classifier	89,59	89,59	0,00
EKI MLP Classifier	88,99	94,05	2,92
EKI Bagging Classifier	88,79	87,77	0,42
EKI Gaussian NB Classifier	83,72	89,70	2,62

Observing the plotted learning progression of the methods, four main groups can be identified. After an initial period, the groups stabilize, with most of them achieving stability around step 20 (except for EKI MLP Classifier), with results hovering upper than 80%. Subsequently, the groups gradually diverge and distinctly separate into four groups: One group steadily increases and reaches high levels of stability, becoming one of the most effective methods (EKI k-Neighbors Classifier); One group shows very unstable progress (EKI Extra Tree Classifier, EKI MLP Classifier, EKI Decision Tree); One group decreases in performance (EKI Gaussian NB Classifier, EKI Adaboost); the rest maintain stability.

The EKI k-Neighbors Classifier shows consistent and good performance due to the uniformity of the Sa Huynh data range, see Fig.3. Most methods in the stable group belong to Ensemble Learning's EKI. Among the Ensemble Learning's EKI, EKI Adaboost is the only method that experiences a decrease in performance. The reason lies in the difference between the Boosting technique (used in EKI Adaboost) and the Bagging technique (used in EKI Extra Tree Classifier, EKI Random Forest Classifier, EKI Bagging Classifier) in Ensemble Learning's EKI. Bagging technic uses bootstrap samples with replacement from the dataset to train each weak learner, reducing sensitivity to outliers. Boosting technic, on the other hand, gives more weight to misclassified instances in subsequent training rounds, focusing more on them during training. Boosting combines multiple simple classifiers to make predictions, making it robust to overfitting. However, it may focus on the diversity of the non-Sa Huynh data instead of the uniformity of the Sa Huynh data, leading to a decrease in performance. The instability of the EKI MLP Classifier can be attributed to its nature, as it is highly sensitive to limited data. The instability problem of decision tree classification algorithms is due to small changes in input training samples causing large changes in output classification rules, especially with limited data. The EKI Extra Tree Classifier also shows high instability compared to the EKI Bagging Classifier and EKI Random Forest Classifier due to its nature. EKI Extra Trees randomly select values to split features and create child nodes, ensuring sufficient differences between individual decision trees, unlike bagging and random forest classifiers, which randomly select datasets. As a result, each weak classifier in the EKI Extra Tree Classifier is significantly affected by the diversity of non-Sa Huynh data, leading to different views of the uniform Sa Huynh data. This causes the EKI Extra Tree Classifier to become unstable from these diverse views. EKI Bagging and EKI Random Forest Classifiers, by randomly selecting subsets of the datasets, ensure the presence of all types of diversity within the non-Sa Huynh data. As a result, each weak classifier observes a global view of all the diversity within the non-Sa Huynh data, rather than just focusing on a specific subgroup within the non-Sa Huynh data.

Overall, the EKI k-Neighbors Classifier, despite having a relatively high overall standard, outperforms all other methods with high stability and distinctively superior results.

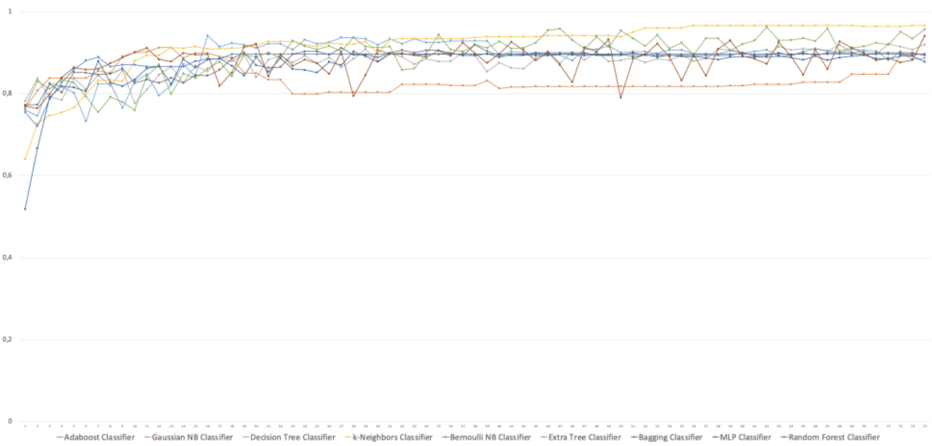

Fig. 3. The line graph of learning process of nine EKI's algorithms.

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5 Conclusion

The study was conducted under the unique constraints of the archaeology field, which presents challenges due to data scarcity. This scarcity is primarily caused by the difficulty in locating artifacts in real-world contexts, the high costs associated with conducting excavations for feature extraction, and the sporadic nature of data acquisition over time. An additional factor complicating the classification of artifacts is the possibility of reclassification based on new data and discoveries, as artifacts initially classified under a specific group belonging to a culture may be subject to revision. This paper presents an advanced system, called Evolving with Klinkenberg's Idea (EKI) algorithms, designed specifically for the automatic identification of Sa Huynh glass jewelry, utilizing SEM gemological analysis parameters, to adapt this unique constraints of the archaeology. The study's results have been integrated into a software suite called the Recognition Automatic System of Sa Huynh Glass (RAS-SHG), which is already utilized at the Vietnam Institute of Archaeology and the UNESCO Centre for researching and preserving Vietnamese antiquities.

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