Bangla Handwriting Based Person Identification Using Machine Learning Techniques

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Abstract. The increasing demand for personality identification based on handwriting processing in fields like resource management, criminal investigations, and mental health diagnostics has led to a flurry of research and experimentation in this area these days. Implicit information includes characteristics including writer identity, gender, age group, handedness etc. Additionally, handwriting has been used as a sign of neurodegenerative diseases, the evolution of writers' personalities, and their cognitive and emotional abilities. This paper aims to identify a person accurately using different machine learning models based on a person's Bangla handwriting. A lot of work has been done in this field, but more work is required in Bangla handwriting-based identification research. So, we feel motivated to do this work using Bangla handwriting. We have used the Wacom Tablet to collect data and used 1009 different Bangla words from 19 persons. We have used feature extraction and different feature selection methods and selected 27 features. Among Random Forest (RF), Support Vector Machine (SVM) and K-nearest Neighbors (KNN), the RF classifier identified persons with 99% accuracy and showed the best result over SVM and KNN. The actual outcomes confirmed that the suggested technique was successfully identifying personality traits from Bangla handwriting.

Keywords: Bangla Handwriting, Person Identification, Random Forest (RF), Support Vector Machine (SVM), K-nearest Neighbors (KNN), Machine Learning.

1 Introduction

In today's digital world, Bangla handwriting-based person identification by machine learning is extremely important. Large volumes of handwritten Bangla data may be analyzed by machine learning algorithms, allowing for accurate person identification and authentication. When it comes to online transactions involving textual elements

M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_66

and Bangla signatures, this technology helps with document verification, fraud prevention, and security measure enhancement.

Furthermore, by using machine learning techniques for Bangla handwriting analysis, sophisticated systems that quickly and precisely confirm identities can be developed. By automating identity verification duties, these solutions not only improve security protocols in the legal, financial, and government sectors, but they also expedite administrative processes. In addition, this technology helps to ensure the validity and accessibility of historical Bangla manuscripts for future generations by scanning and archiving them. In the end, using machine learning into the identification of Bangla handwriting strengthens security protocols while also promoting technological advancements and cultural heritage preservation in the Bangla language domain [1].

Our goal in this study was to correctly identify the individual utilizing several machine learning models based on their handwritten Bangla. Using a Wacom tablet, we have gathered data based on handwriting in Bangla from several individuals for this purpose. We used the Filter, Univariate, and Feature Important methods to pick features. To correctly identify the individual, Random Forest (RF), Support Vector Machine (SVM), and K-nearest Neighbors (KNN) were applied. The investigation's findings verified that personality traits could be discerned from Bangla handwriting using the recommended technique.

2 Literature Review

Person identification is required for a number of reasons, but it's crucial to weigh that need against concerns about individual rights, privacy, and ethics. To responsibly address these needs, it is imperative to implement identification methods that are secure, dependable, and ethical. Person identification is a broad field with a variety of approaches and procedures used to identify and authenticate people based on distinctive traits. This section reviews the body of research on person identification, highlighting important strategies, developments, and difficulties.

A study on personality detection through handwriting utilizing textural elements is presented by Gahmousse et al. [2]. This research investigates the ways in which handwriting texture can disclose personality traits. The study explores techniques for using these characteristics to identify personalities, adding to our knowledge of how handwriting analysis can be used to identify unique personalities. In their study, Lozhnikov, Sulavko, and Samotuga examine the use of signature writing for psychophysiological state assessment and personal identification [3]. Their study, which was published in the Information journal, probably looks at the ways in which identities and mental-physical states are reflected in signatures, emphasizing the connection between psychological states and signature writing. In Pattern Recognition, Said, Tan, and Baker (2000) report a study on handwriting-based personal identification [4]. Their research probably explores handwriting analysis approaches for individual identification, looking at handwriting patterns and traits to develop trustworthy ways for personal identification. He, Fang, Du, Tang, and You presented a novel method for offline handwriting-based writer identification. The article most likely describes a brand-new approach or strategy created especially for recognizing writers using offline handwriting samples. It might entail cutting-edge features, algorithms, or models designed to precisely identify the author of handwritten writings [5]. In 2018, Navya, Shivakumara, Shwetha, Roy, Guru, Pal, and Lu conducted research on gender recognition based on handwriting using adaptive multi-gradient kernels. The research, probably presents new methods for identifying gender based on handwriting patterns by using adaptive multi-gradient kernels. This method probably focuses on using different gradients and how they adapt to improve handwriting analysis's ability to determine gender [6]. A study on gender identification through handwriting utilizing an online approach is presented by Cordasco, Buonanno, Faundez-Zanuy, Riviello, Likforman-Sulem, and Esposito (2020). Their work probably presents real-time or online approaches to gender identification via handwriting analysis. In order to accurately categorize gender based on continuing handwriting input in an online scenario, the study may examine methods that make use of dynamic features or continuous handwriting samples [7].

Although a few publicly available datasets for handwritten text recognition exist, e.g. IAM [8], these are mostly tailored to the English and other European languages. Some speech datasets are also publicly available online [14]. To the best of our knowledge, very few Bangla online handwriting dataset is available in public containing characters only. This gap has been filled in the present work by introducing a new dataset for Bangla handwriting words which is hugely beneficial to the community.

Table 1. Brief comparison of the related works.

Authors	Focus	Methods	Contributions
Gahmousse et al. [1]	Personality detection	Textural analysis for personality traits	Identifying personality traits through handwriting
Lozhnikov, Sulavko, and Samotuga [2]	Psychophysiological state assessment and personal identification	Examination of signatures for mental-physical state assessment	Relating psychological states to signature writing for personal identification
Said, Tan, and Baker [3]	Handwriting-based personal identification	Handwriting analysis for individual identification	Developing trustworthy methods through handwriting
He, Fang, Du, Tang, and You [4]	Offline handwriting-based writer identification	Novel approach for recognizing writers	Precise writer identification through handwriting
Navya, Shivakumara, Shwetha, Roy, Guru, Pal, and Lu [5]	Gender recognition based on handwriting	Utilization of adaptive multi-gradient kernels	Innovating gender identification in handwriting
Cordasco et al. [6]	Gender identification	Gender identification	Using dynamic features in continuous handwriting
Proposed Model	Person Identification	Person Identification	Bangla Handwriting based person identification.

The Table 1 illustrates an overall comparison of related works which shows that the key difference of the proposed model with others is, in the proposed model has been run using the primary datasets of Bangla Handwriting.

3 Methodology

3.1 Working Principle and Datasets

We have gathered primary data from 19 different people. Using a Wacom tablet, the participants wrote ten different Bangla words. There are three to six writings of each word. After obtaining 1009 data, we worked on this main database. The Wacom tablet was used to calculate time, pen pressure, x-, y- as well as horizontal and vertical angles (see Fig. 1) that illustrated the pen tablet device [9]. We also obtained the person's name, age, and identity number to identify them. Following pre-processing, a csv file contains all the data.

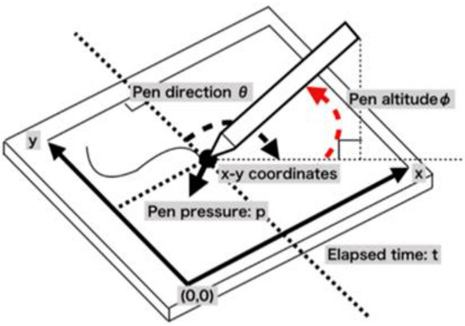

Fig. 1. Pen tablet device showing the pen pressure, x-y coordinates with horizontal and vertical angles.

In this process we use 10 Bangla words as a task. One person performs 7 tasks. One task is completed by writing 10 words. We Collect student data male; female both are performing these works. Ten Bangla words are illustrated in Table 2 and the summary of handwriting pattern dataset is illustrated in Table 3.

Table 2. The Bangla words we have used as handwriting.

Sl No.	Words	Sl No.	Words
1	আমার দেশ	6	ঘরে বাইরে
2	বাংলাদেশ	7	আরণ্যক
3	মাতৃভূমি	8	সোনার বাংলা
4	বিশ্ববিদ্যালয়	9	অর্ধমাত্রা
5	অধ্যাপক	10	আরশিনগর

Table 3. Summary of the handwritten text dataset.

Group	Age (Years)	No. of Subject	No. of Word	No. of Task	Total Sample
Male	21-26	13	10	7	13 * 10 * 7 = 910
Female	19-26	7	10	7	7 * 10 * 7 = 490

To obtain a uniform data format, we have prepared the dataset and used several pre-processing procedures, such as scaling and normalization. Following the application of the feature extraction procedure [15], we worked with 50 features and 1400 data points. Next, we used the feature important, univariate, and filter methods, and we evaluated the 28 best features for our processing—features that are shared by all three of the aforementioned methods. Subsequently, to validate the model on unseen writers and prevent overfitting, we split the dataset into training and testing sets (using an 80:20 proportion). The model took trained by the training set and was evaluated with the separate testing set, which included writers that did not overlap with those in the training set. Subsequently, we applied the RF, SVM and KNN techniques and calculated the confusion matrix. The analytic method of present study is depicted in Fig. 2.

3.2 Methods of Analysis

Data Preprocessing. Various data analysis has been carried out at this phase to create a reliable prediction model. Lack of value verification if we exclude the missing data, our conclusions will be skewed; therefore, the missing data is crucial. In general, missing data might reduce the model's strength and raise the likelihood of incorrect categorization. The dataset's data attributes are thoroughly examined to see if any missing or NA values exist. Ultimately, the dataset has no missing values.

One essential stage in the preprocessing of data for machine learning models is data normalization. It entails standardizing the feature value range to have a mean of 0 and a standard deviation of 1, or converting it to a common scale, usually between 0 and 1. This keeps features with higher values from controlling the learning process and guarantees that every feature contributes equally to the model. Rescaling numerical features to a common scale without distorting disparities in the ranges of values is known as normalization in data preprocessing. For gradient-based optimization techniques, feature scaling is especially crucial because it keeps the loss function from being excessively steep or too shallow in specific directions [10].

Feature Selection. Feature selection method includes filtering methods, univariate methods as well as feature importance that are discussed below:

Filter Methods. Filter methods are a kind of feature selection strategy that assesses features without reference to any machine learning algorithm. Based on each feature's inherent qualities—like variance, correlation with the goal variable, or information gain—they evaluate each one's importance. The Chi-square test, which evaluates the degree of independence between a categorical characteristic and the target variable, is one popular filter technique. The following gives the Chi-square test statistic:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i} \tag{1}$$

Where O_i denotes the category's observed frequency and E_i assuming independence, is its predicted frequency. A high chi-square score suggests that the characteristic is probably meaningful because it does not depend on the target variable.

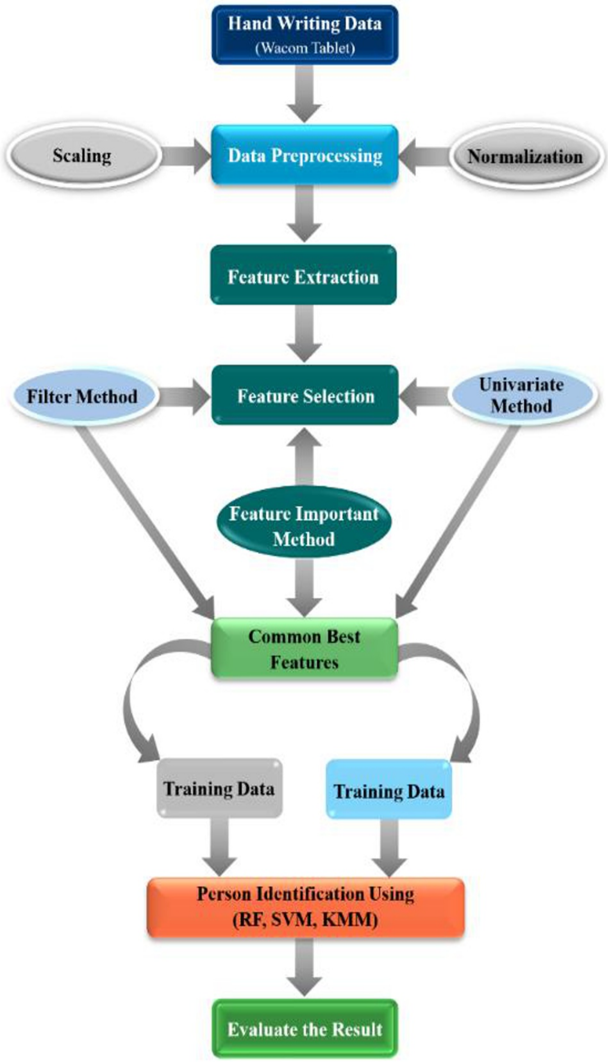

Fig. 2. Analytical approach of this investigation from data collection to result evaluation.

Univariate Methods. Univariate methods assess each feature separately to ascertain how strongly it correlates with the target variable. They are frequently used for exploratory data analysis and feature selection in high-dimensional datasets because to their ease of implementation and interpretation. The correlation coefficient, which quantifies the linear relationship between two variables, is one popular univariate technique. The following yields the correlation coefficient:

$$r = \frac{\Sigma((x_i - \bar{x})(y_i - \bar{y}))}{\sqrt{\Sigma(x_i - \bar{x})^2 \, \Sigma(y_i - \bar{y})^2}} \tag{2}$$

Where $\bar{x}$ and $\bar{y}$ are the respective means of the two variables, x_i and y_i are their values. Strong positive relationships are shown by correlation coefficients near to 1, and strong negative relationships are indicated by correlation coefficients near to -1. If there is no linear relationship between the two variables ($\bar{x}$ and $\bar{y}$), the correlation coefficient is 0.

Feature Importance. Feature importance methods assess how much each feature contributes to the overall effectiveness of a machine learning model. They need training a machine learning model and are more complicated than filter approaches, but they can offer more precise and situation-specific information about the relative value of each feature. The coefficients of a trained linear regression model serve as the foundation for one typical feature importance technique. With all other features held constant, the coefficients show how the predicted target variable changes with a one-unit change in the relevant feature. Greater relevant feature importance for predicting the target variable is indicated by larger coefficients. The permutation importance of a trained tree-based model serves as the foundation for yet another popular feature importance technique. When a feature's values are shuffled randomly, the model's performance decreases, which is measured by the permutation significance. The associated attribute is more significant for the model's predictions if there is a greater decline in performance. To choose features for tasks involving regression or classification, feature importance techniques can be applied. Features with high significance ratings are usually chosen for classification. High relevance features that are not redundant with other selected features are usually chosen for regression.

3.3 Prediction Techniques

Based on the individual's Bangla handwriting, several supervised machine learning approaches, including RF, SVM, and KNN, have been utilized to forecast them with accuracy. In this section, these methods are covered in brief.

Support Vector Machines (SVMs). Support Vector Machines are a type of supervised learning algorithm that are utilized for regression, outlier detection, and binary and multiclass classification. It is susceptible to outliers and can be computationally costly to train. To find a hyper plane that optimizes the margin—the distance between the hyper plane and the nearest data points for each class—they first choose which classes to use. Support vectors are the data points that are closest to the hyper plane. A linear SVM's decision function is as follows:

$$f(x) = w^T.x + b \tag{3}$$

Where x is the input data point, b is the bias, and w is the hyper plane's weight vector. A restricted optimization problem that reduces the margin while guaranteeing that the data points are accurately classified is solved to get the w and b parameters [7].

K Nearest Neighbors (KNN). K Nearest Neighbors is an additional ML classification method. Assigning a new data point to one of the many classes that already exist is the goal. As a result, k neighbors are selected, and either the Manhattan or Euclidean distances are used to find the k closest data points. A new data point's neighbors are counted to determine how many belong to categories A and B. A new data point is then allocated to a category by majority vote.

Random Forest (RF). Random Forest is an ensemble learning technique based on decision trees. In order to increase accuracy and decrease over fitting, it builds several trees and mixes their outputs for predictions. Choose subsets of the training data at random during the bootstrapped sampling phase. Consider a random subset of features for the feature randomness step at each node in the tree. Use these subsets to help decision trees grow throughout the tree-building phase so they can closely fit the data. Utilize averaging or voting for classification/regression to aggregate predictions from individual trees in the voting process. Consider the following function for RF classifier:

$$y = \frac{1}{N} \sum_{i=1}^{N} T_i(x) \tag{4}$$

Where, y is the predicted output, N is the number of trees and $T_i(x)$ represents the prediction of the i^{th} decision tree for input x. The final result is the combined forecast of several trees, each trained on a distinct subset, which improves accuracy and robustness [7].

3.4 Performance Evaluation

An essential component of a classification technique is performance evaluation. The optimal classification model can be found with the help of performance measures. A classification technique's effectiveness can be evaluated using the following metrics: F1 values, recall/sensitivity, accuracy, precision, and confusion matrix.

A confusion matrix is a tabular representation of the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions that provides an overview of a classification model's performance. Simple table layout for confusion matrix is represented in Table 4.

Table 4. Table layout for confusion matrix representing key components.

	Predicted Positive (P)	Predicted Negative (N)
Actual Positive (P)	True Positive (TP)	False Negative (FN)
Actual Negative (N)	False Positive (FP)	True Negative (TN)

True Positive (TP). Positive occurrences that were accurately predicted.

True Negative (TN). Negative occurrences that were accurately predicted.

False Positive (FP). When something is negatively expected but mistakenly anticipated as positive (Type I error).

True Negative (TN). When a positive result is mistakenly anticipated as a negative (Type II error) [11].
By computing metrics including accuracy, precision, recall, and F1-score—all important in determining the efficacy of a classification model—the matrix helps to evaluate model performance

Matrix for performance evaluation Based on the following metrics, classification accuracy, precision, recall/sensitivity, F1 score, and specificity—the effectiveness of the various approaches is assessed. Accuracy is defined as the ratio of the correctly predicted class to the whole class. Several performance evaluation methods such as, accuracy, precision, recall/sensitivity, f1-score, specificity are shown in Table 5. The accuracy can be defined as the ratio of all positive outcomes to accurately identified positive outcomes. Recall, commonly referred to as sensitivity, is a metric that quantifies the capacity to accurately recognize every real positive class as the true positive classes. Applying the weighted average over recall and precision yields the F1-score. F1-score is typically valued higher than precision in cases of unequal class appropriation. The number of true negative predictions (TN) divided by the total number of negatives (N) is the indicator of specificity.

Table 5. Performance evaluation metrics including accuracy, precision, recall/sensitivity, f1-score and specificity.

Metric	Formula
Accuracy	(TP + TN) / (TP + TN + FP + FN)
Precision	TP / (TP + FP)
Recall/ Sensitivity	TP / (TP + FN)
F1-score	(2 * Precision * Recall) / (Precision + Recall)
Specificity	TN / (TN + FP)

4 Result Analysis

4.1 Feature Importance

Feature importance analysis indicated that among the 28 selected features, pen-pressure and writing speed played major roles. More specifically, 'average pressure', 'maximum pressure' and 'writing speed' were the most relevant features according to the Random Forest model that interval computed as significant. This implies that how you write is a very good reflection of who you are.

4.2 Confusion Matrix

The performance of the classification models (SVM, KNN and RF) used to detect individuals based on their hand writing was evaluated using confusion matrices. Every classifier achieved profound accuracy in identifying a person individually according to their Bangla handwriting having no false positives and false negatives.

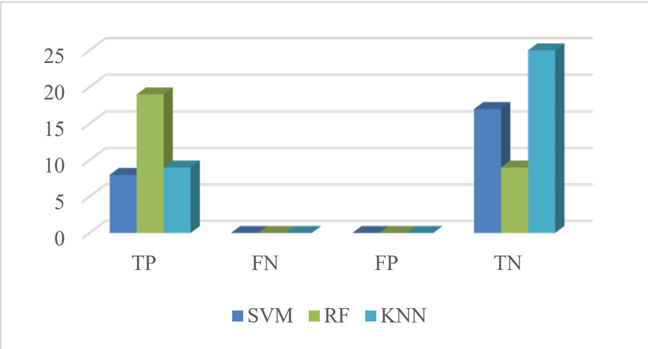

Fig. 3. Comparison of confusion matrices among SVM, RF and KNN models.

The above Fig. 3 shows the overall comparison of Confusion Matrices among classification models (SVM, RF and KNN) to examine the performance evaluation. SVM correctly predicted 8 instances as YES and 17 instances as NO. On the other hand, RF and KNN predicted 19 and 25 instances as YES respectively and both predicted 9 instances as NO correctly. The figure demonstrate that these models performed optimally with the high accuracy in predicting both YES and NO classes, particularly Random Forest, which showed the best balance between YES and NO predictions.

4.3 Accuracy Graph

We visualized the performance metrices (Accuracy, Precision, Recall, and F1-Score) of the classifiers (SVM, RF and KNN) with macro average and weighted average value using bar diagram for providing a clear comparison.

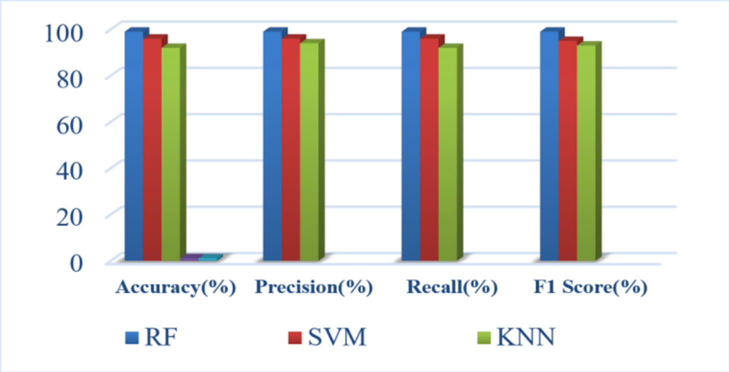

Fig. 4. Comparative representation among ML classifiers for macro average value.

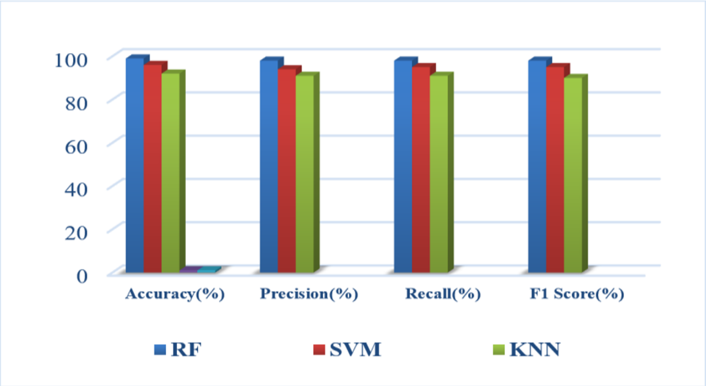

Fig. 5. Comparative representation among ML classifiers for weighted average value.

Fig. 4 and Fig. 5 illustrated the performance measurement of different machine learning classifiers with macro average and weighted average value accordingly particularly for SVM, KNN and RF. In the diagram blue, red and green bars indicate the RF, SVM and KNN classifiers respectively. Among all the metrices, RF consistently achieved the highest percentage with 99% accuracy, 98% precision, 98% recall and 98% F1-score. SVM followed RF closely with 96% accuracy and a balance precision-recall performance. On the other hand, though KNN slightly behind, but still achieved sound percentages with 92% accuracy and 90% F1-score

4.4 Performance Summary

A summary of the key performance metrices (Accuracy, Precision, Recall, and F1-Score) of the three classifiers (RF, SVM, and KNN) is given below:

Table 6. Summary of results (Accuracy, Precision, Recall, and F1-Score) of the key performance metrices.

Classifier	Accuracy	Precision	Recall	F1-Score
RF	99%	98%	98%	98%
SVM	96%	94%	95%	95%
KNN	92%	91%	91%	90%

Table 6. Summary of results (Accuracy, Precision, Recall, and F1-Score) of the key performance metrices.shows that RF demonstrated the most profound performance with minimum 98% or above percentages for all the performance evaluation metrices.

4.5 Real-World Applicability

Random Forest. RF is ideal for applications where high accuracy and minimal false positives is required like security systems. In a security system, identification of individuals with high precision is a must.

Support Vector Machine. SVM is appropriate for the environments that have the priority requirements of balanced performance and can accept a slight drop in accuracy while minimizing false positives.

K Nearest Neighbors. KNN can be well-suited for real-time applications where the main requirement is flexibility and a slight performance drop in accuracy is not so sensitive.

5 Discussion and Conclusion

This study demonstrates the feasibility study and performance evaluation of Bangla handwriting based person identification using machine learning models. From dataset selection and preprocessing to feature extraction, model development, and testing for real-world applicability, this research set out on a methodical journey. Using a Wacom tablet, we have gathered data based on handwriting in Bangla from several individuals and both static (letter shapes, slant etc.) and dynamic (pen pressure, spatial layout etc.) handwriting features have extracted. We have demonstrated that individuals writing traits can be effectively identified using Random Forest (RF), Support Vector Machine (SVM) and K-nearest Neighbors (KNN).

In this research we have extracted 50 features with 1400 data points and preprocessed data using the feature important, univariate, and filter methods. After that we evaluated the 28 significant features for model training, divided the dataset into training and testing sets, and ran RF, SVM, and KNN algorithms. Among the classifiers, Random Forest shows the best results with 99% accuracy showing its strength in high dimensional feature spaces. SVM also shows profound results with a balanced performance to detect individuals and KNN maintained a competitive results. Because of RF's efficiency in high dimensional spaces, SVM and KNN's deep learning capabilities were enhanced, producing identification models that were resilient and flexible.

Despite the promising results with primary dataset, this study has some limitations such as, limited number of subjects used to build and validate the data. This could potentially reduce the generalizability of the results. Also, cross validation with external dataset was not performed. Future study should focus on data collection of broad and diverse population. Additionally, there remains several challenges including heterogeneity of the dataset, on ongoing model adjustment, multimodal biometrics, and scalability for big data. To improve scalability exploring model optimization techniques, distributed computer methods, or parallel processing approaches can be considered [12]. On contrary, future research is required to overcome rest of the challenges. By tackling these issues, new directions for research can be explored, including the integration of more biometric modalities, model ensemble strategies, sophisticated feature extraction techniques, and the application of deep learning models [13].

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