In this paper, high intra-variable handwriting based writer identification/verification is done. Both handcrafted and auto-derived feature-based models are taken to study writer identification/verification performance.

Two offline Bengali intra-variable handwriting databases from two different sets of 100 writers are taken here. For writer identification, multi-class classification is done (the number of classes is equal to the total count of writers) where the task is to assign the writer-id to the unknown handwritten specimens. For write verification, a binary classification is made where the task is to answer yes or no to a questioned handwritten sample.

At-first two kind of patches are selected: patchchar (containing character-level information from the pre-processing stage) and patchallo (containing some key points on writing strokes). The process used for Handcrafter Feature extraction are: Macro-Micro Features (FMM), Contour Direction and Hinge Features (FDH) and Direction And Curvature Features At Key points (FDC). For Auto-Derived Feature Extraction Basic\_CNN, SqueezeNet, GoogLeNet, Xception Net, VGG16 and ResNet 101 are used. For writer identification id done on the basis of two things: Handcrafted Feature-Based Identification and Auto-Derived Feature-Based Identification. In Handcrafted Feature-Based Identification, SVM-RBF is used, where C = 22 and γ = 24 is taken for best performance, thus 5-fold-cross-validation is used. Two major strategies are used for Auto-Derived Feature-Based Identification: Strategy-Major (where identification is done on the basis of majority of the text-patches being identified by an author) and Strategy Mean (mean is calculated from each feature vectors to make a mean feature vector and classification is done on the basis of that). Writer verification is also done on the basis of Handcrafted Feature-Based Verification and Auto-Derived Feature-Based Verification.

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| **Model** | **Accuracy** |
| XN\_char\_mean | 76.07% |
| XN\_allo\_mean | 77.76% |

After experimentation on the databases, it is observed that by training and testing on similar writing variability, the system produces encouraging outcomes. However, the system performance is comparatively lower for training and testing on disparate types of handwriting variability. Cross learning is also attempted and it is observed that the system performance improves with pre-training. Here, a practical scenario is imitated, whereby a certain writing style of an individual is unknown (i.e., absent during training), and we note that the state-of-the-art methods do not perform well. The most promising result is obtained when Mean strategy is used for writer identification, with 76.06% accuracy in identifying patchchar and 77.76% accuracy in identifying patchallo. In case of writer verification, the accuracy using mean strategy, patchchar gave an accuracy of 83.68% whereas patchallo gives an accuracy of 84.02%.

**Writer Identification on enlarged writer set:**

**Writer Verification enlarged writer set:**

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| **Model** | **Accuracy** |
| XN\_char\_mean | 83.68% |
| XN\_allo\_mean | 84.02% |