

OFFLINE SIGNATURE VERIFICATION SYSTEM

GROUP DETAILS (B22PV03)

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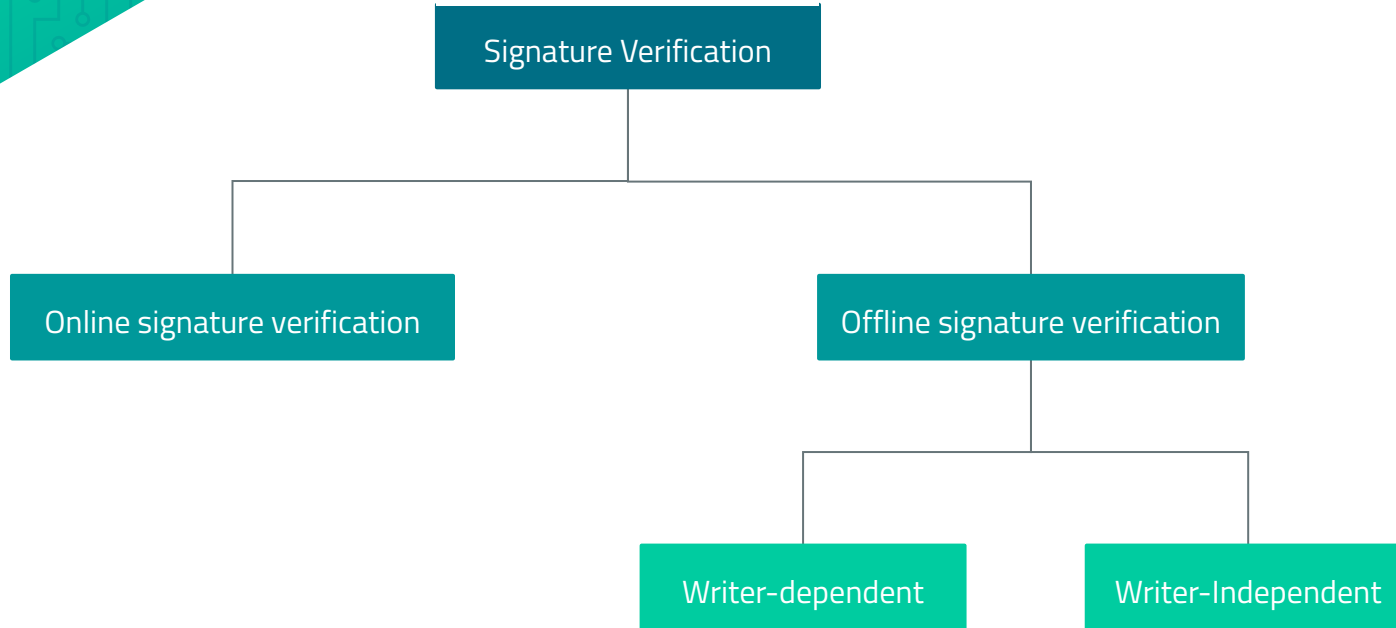
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Introduction



Approaches

The offline signature verification can be implemented in two ways.

1. Writer-dependent offline signature verification

In a writer-dependent approach, system uses a different set of features, a different thresholds, and also different classifiers for each user.

2. Writer-independent offline signature verification

In case of writer-independent approach, a common set of features, a common threshold, and also a same classifier have been used for all the users.

Motivation

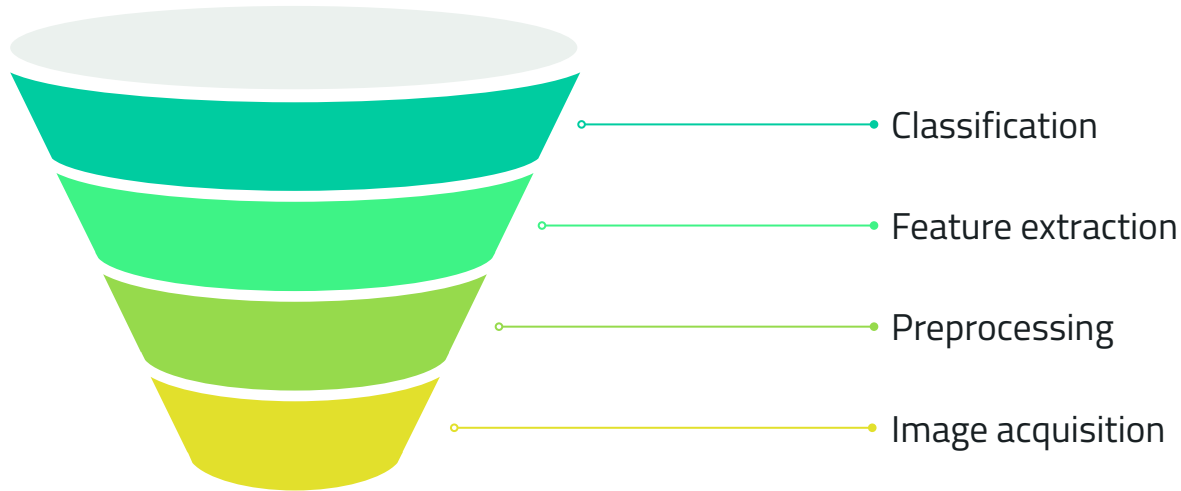
The offline signatures are the most widely used to verify the identity of a person, particularly in banking systems, administrative and financial applications.

Verifying the identity of a person using handwritten signatures has become challenging in the presence of skilled forgeries. It is difficult to distinguish between genuine and forged signatures as the dynamic information cannot be obtained in offline signatures. So, there is a need, to build a good model which is robust and accurate.

Problem Statement

Offline signature verification system using machine learning and deep learning techniques.

Methodology



Dataset

CEDAR signature database contains signatures of 55 signers belonging to various cultural and professional backgrounds. Each of these signers signed 24 genuine signatures 20 minutes apart. Each of the forgers tried to emulate the signatures of 3 persons, 8 times each, to produce 24 forged signatures for each of the genuine signers. Hence the dataset comprise $55 \times 24 = 1,320$ genuine signatures as well as 1,320 forged signatures.

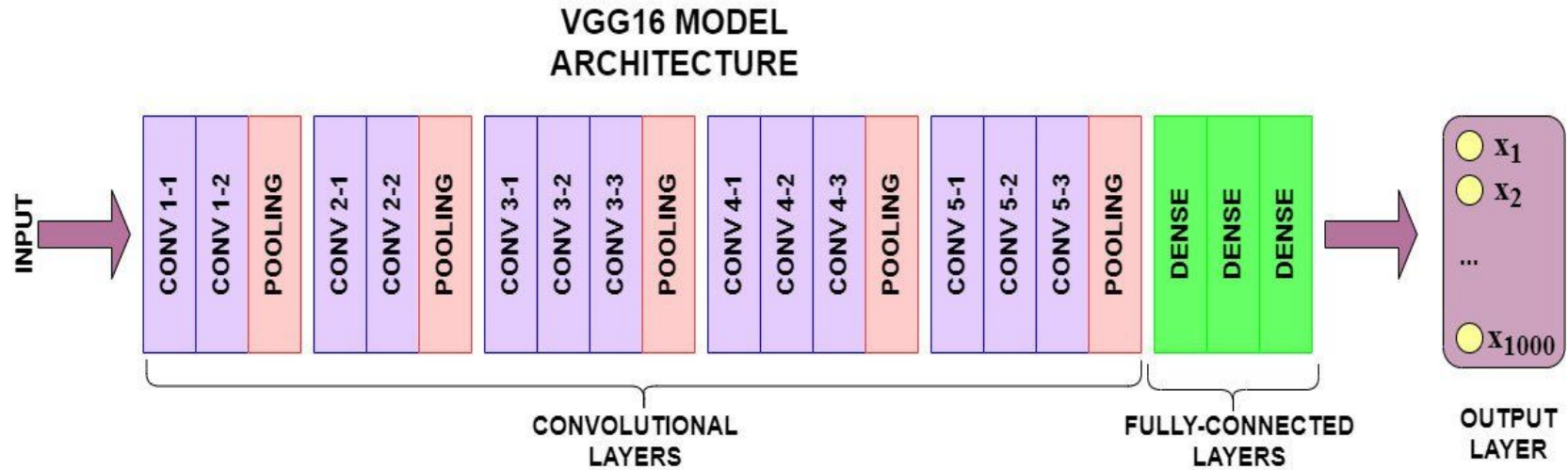
Preprocessing

The images in the dataset undergo several preprocessing techniques. They are

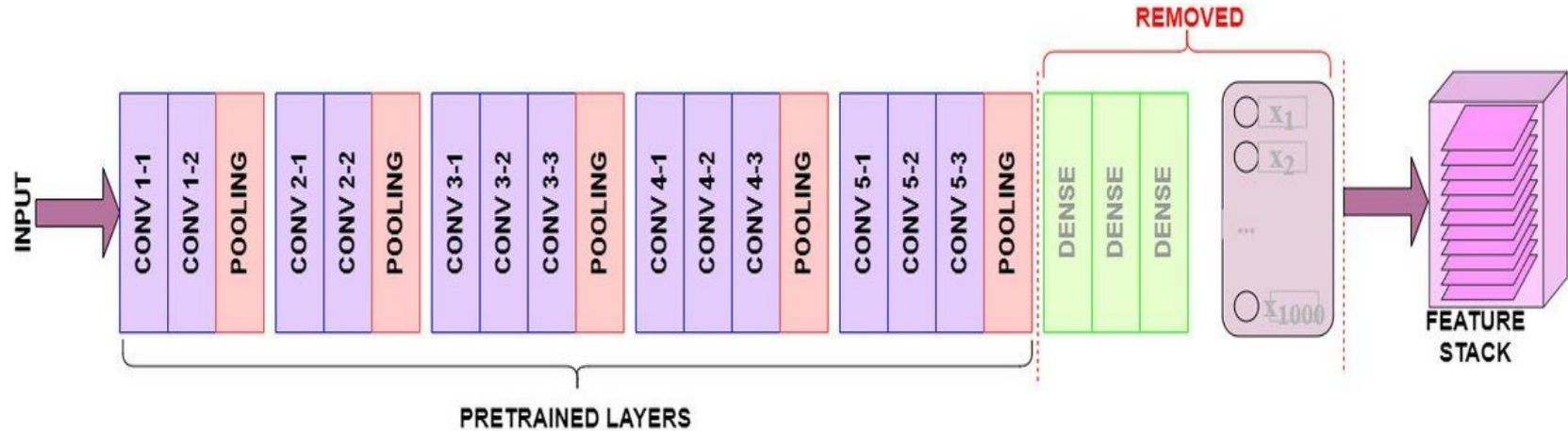
1. Binarization
2. Cropping
3. Resizing

Model - 1

VGG16 Architecture [3]



VGG16 Architecture



Feature Extraction

In this step, A convolutional neural network named VGG16 is used to extract features of the signatures. The dense layers of the neural network are removed from the architecture and the output of the remaining layers is given as features to Machine Learning algorithms.

Firstly, the signatures of size $(224 \times 224 \times 3)$ are given to the neural network. And for each image, a feature vector of size $(7 \times 7 \times 512)$ is obtained. This will be treated as feature vector of the image for further process.

Classification Methodology

- The obtained features are flattened and given to the machine learning algorithms.
- The signatures of 45 users are used for training and the remaining users signatures are used for testing.
- The classifier is trained using the training set and will be tested on the test set.
- The obtained model will be used for the classification of the signatures of a person.

Classification Algorithms

We have implemented the model using the below algorithms

1. K-Nearest Neighbours [1]
2. Support Vector Machine [2]
3. Logistic regression

Results

Algorithm	accuracy	FAR	FRR
SVM	71%	0.069	0.211
KNN	70%	0.067	0.20
Logistic Regression	72%	0.067	0.20

Model - 2

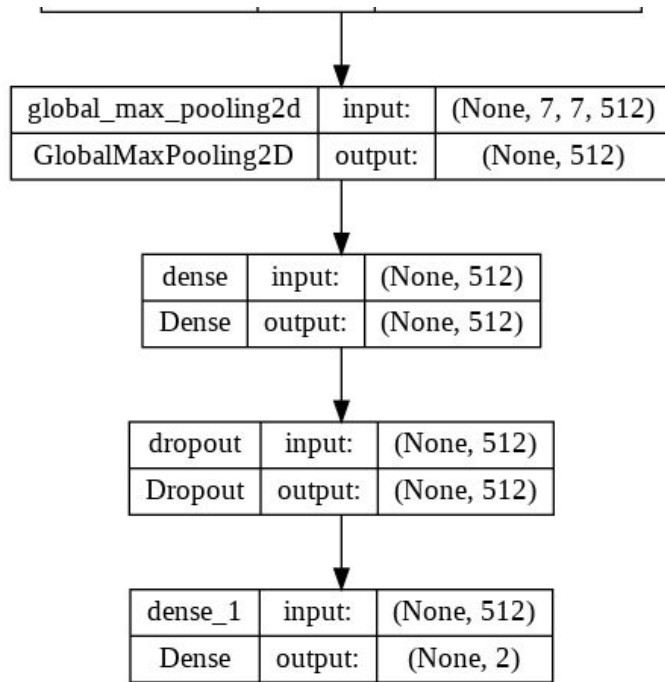
Model

- The VGG16 is built to classify the images in Imagenet dataset which consists of 22,000 categories.
- In this model we have used the VGG16 for binary classification.
- So, the dense layers of the neural network are removed and customized network is placed to support binary classification.

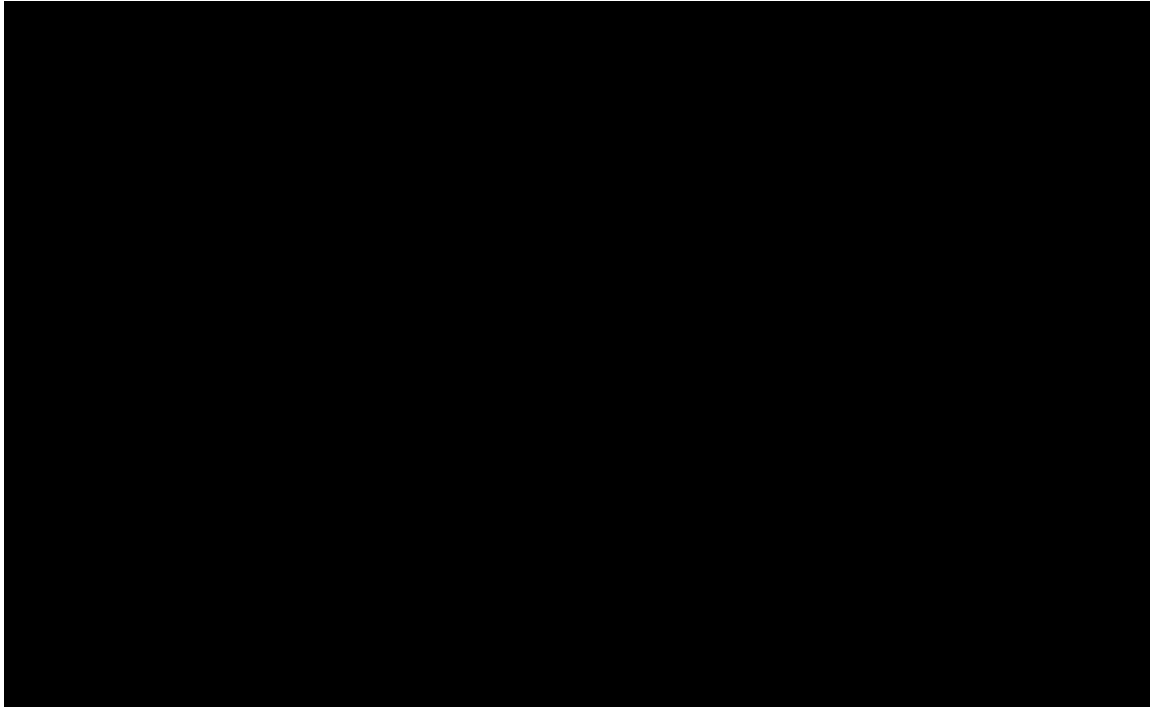
Model

- The features are extracted from remaining layers of the VGG16 and given to the customized network.
- Obtained an accuracy of 63 percent for this model.

Customized network



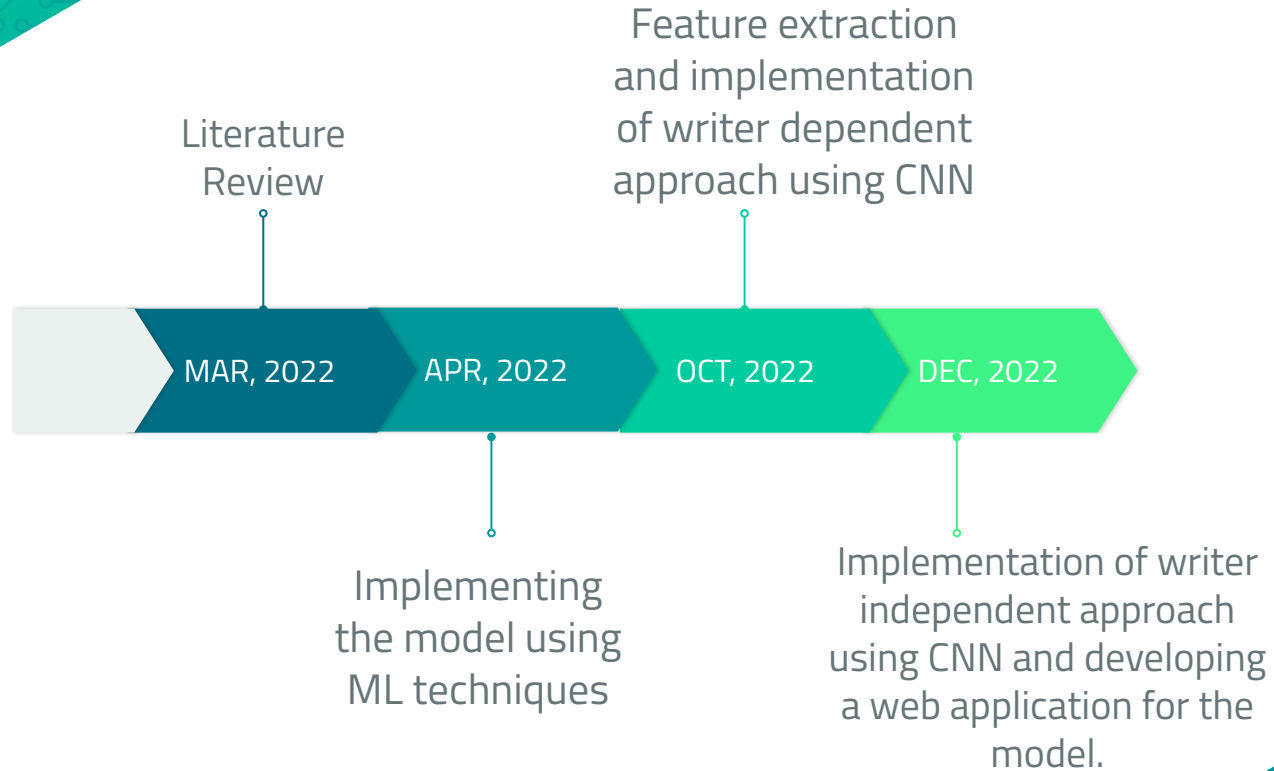
Web Application [\(Link\)](#)



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TIMELINE





Thank You...