OFFLINE SIGNATURE VERIFICATION SYSTEM

GROUP DETAILS (B22PV03)

Guide : Dr. Viswanath P

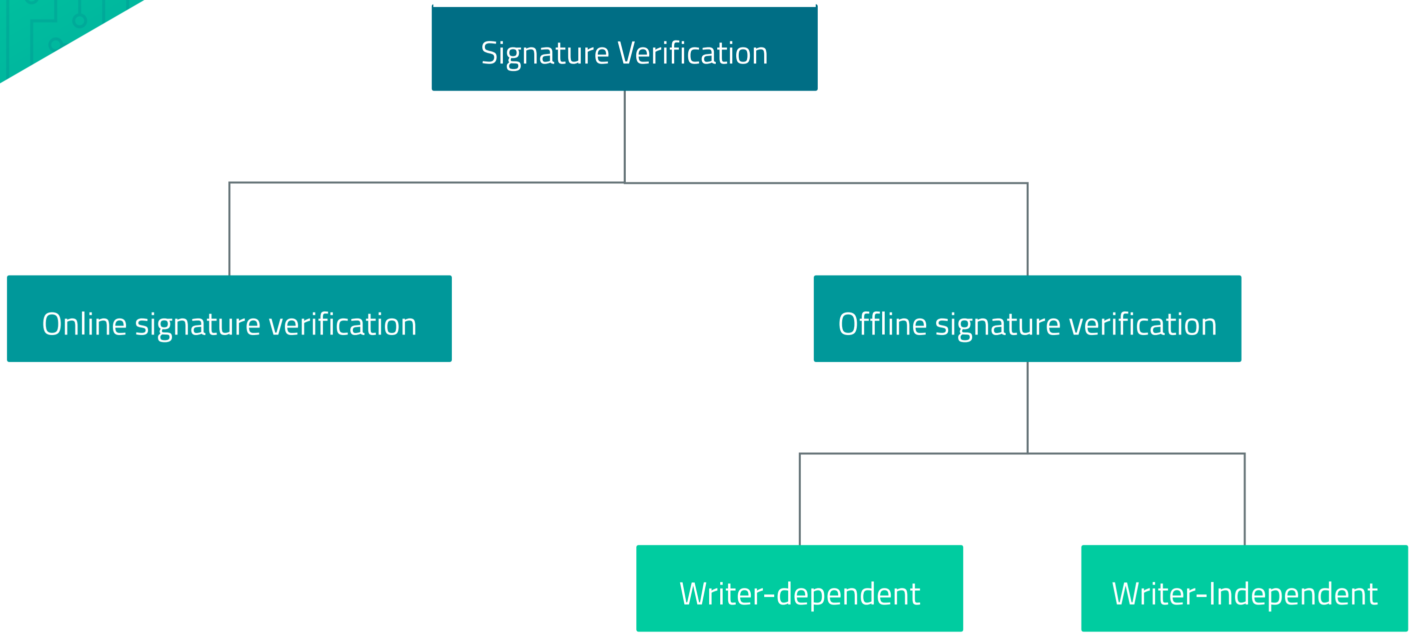
Tulluri Rakesh - S20190010182

Thorlikonda Lakshmi Sai Gopinadh - S20190010180

Veduruparthi Sai Bhaskar - S20190010188

TABLE OF CONTENTS

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.

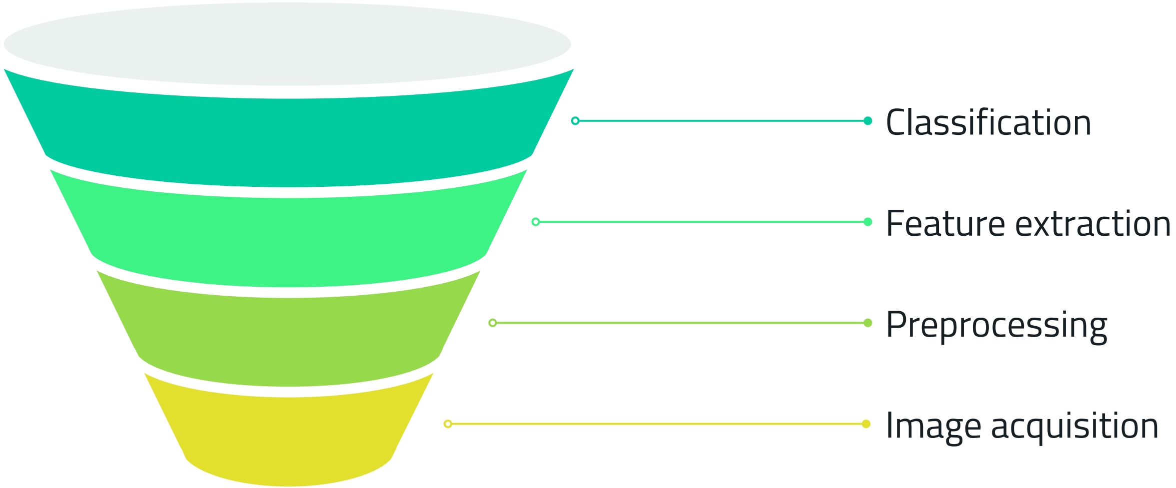
Motivation

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



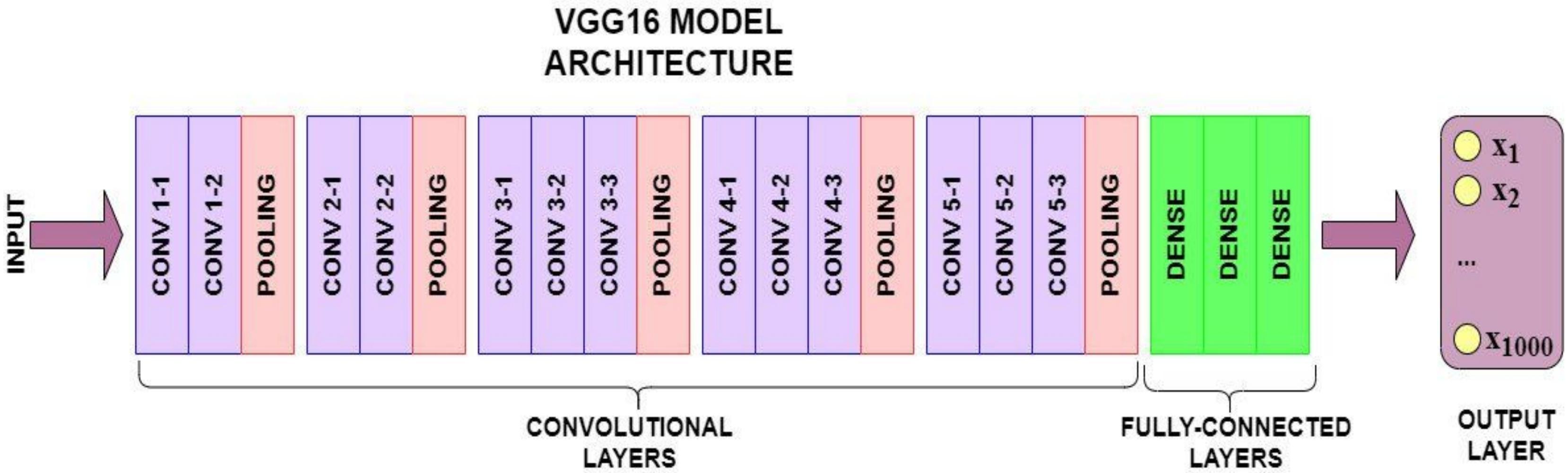
Dataset Used

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.

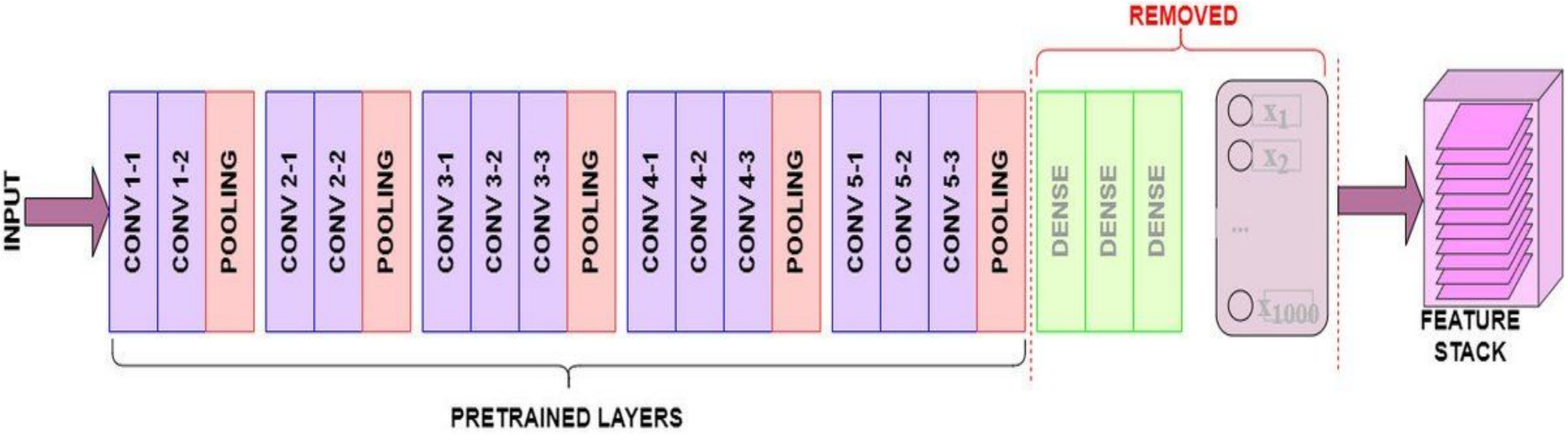
Work Done So Far...

Model - 1

VGG16 Architecture [3]



VGG16 Architecture



Feature Extraction

In this step, A convolutional neural network 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 x 224 x 3) are given to the neural network. And for each image, a feature vector of size (7 x 7 x 512) is obtained. This will be treated as feature vector of the image for further process.

Classification Methodology

- Here we will build classifier for each user in the dataset using the features obtained from the neural network.
- The original and forged signatures of the user are combined and splitted to form the train and testing set for the model.
- 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 particular user in the future.

Classification Algorithms

We have implemented the model using the below algorithms

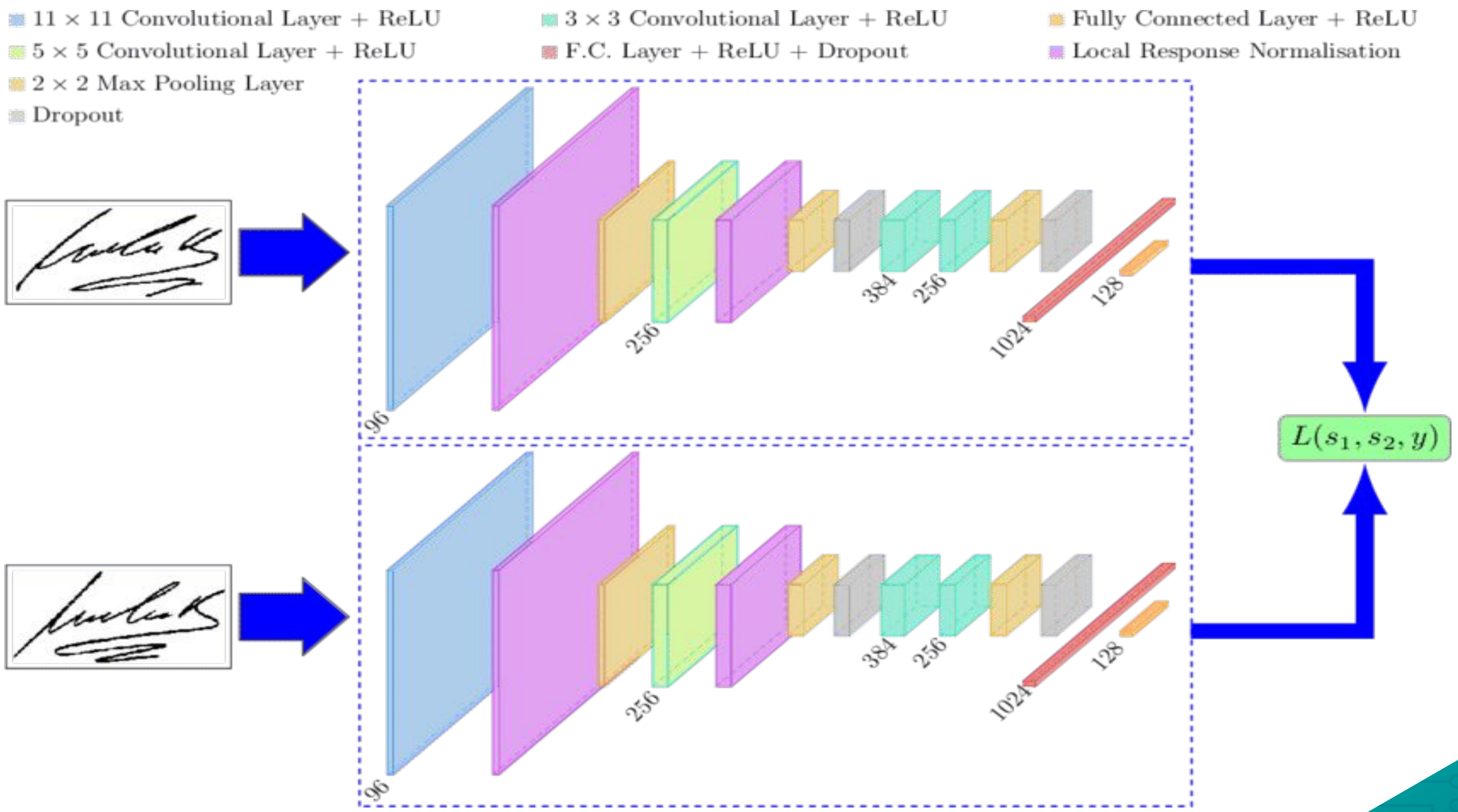
1. K-Nearest Neighbours [1]
2. Support Vector Machine [2]
3. Logistic regression

Results

Algorithm	Average accuracy	Max accuracy	Min accuracy
SVM	1.0	1.0	1.0
KNN	1.0	1.0	1.0
Logistic Regression	1.0	1.0	1.0

Model - 2

SigNet Architecture [5]



Siamese Network

- In this model, Siamese network is used to get the similarity measure between a pair of signatures.
- Each network computes the features of inputs and similarity of these features is measured using the loss function.
- The signatures will be classified based on the similarity measure obtained.

Siamese Network

- The genuine-genuine and genuine-forged pairs are generated for each user. These pairs are used in training and testing process.
- The signatures of 50 users are used for training the siamese network and remaining signatures are used for testing.
- Obtained an accuracy of 49 percentage.

Future Work

- Implementation of user-dependent siamese neural networks.
- Developing a web-application for this model.

References

1. Jadhav, T. (2019). Handwritten signature verification using local binary pattern features and KNN. Int. Res. J. Eng. Technol.(IRJET), 6(4), 579-586.(Link)
2. Kruthi, C., & Shet, D. C. (2014, January). Offline signature verification using support vector machine. In 2014 Fifth International Conference on Signal and Image Processing (pp. 3-8). IEEE.(Link)
3. Bonde, S. V., Narwade, P., & Sawant, R. (2020, March). Offline Signature Verification Using Convolutional Neural Network. In 2020 6th International Conference on Signal Processing and Communication (ICSC) (pp. 119-127). IEEE. (Link)
4. Sam, S. M., Kamardin, K., Sjarif, N. N. A., & Mohamed, N. (2019). Offline signature verification using deep learning convolutional neural network (CNN) architectures GoogLeNet inception-v1 and inception-v3. Procedia Computer Science, 161, 475-483.(Link)
5. Dey, S., Dutta, A., Toledo, J. I., Ghosh, S. K., Lladós, J., & Pal, U. (2017). Signet: Convolutional siamese network for writer independent offline signature verification. *arXiv preprint arXiv:1707.02131*.(Link)

TIMELINE

MAR, 2022 — Literature Review

APR, 2022 — Implementing the model using ML techniques

OCT, 2022 — Feature extraction and implementation using CNN

DEC, 2022 — Implementation using Siamese network and developing a web application for the model.

Thank You...