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Signature Localization and Signature Classification

Manjula N[1], Navyashree S[2], Nikitha C[3]
[1, 2, 3]*Dept. ISE, Global Academy of Technology, Bangalore, VTU, Belagavi, Karnataka, India*

Abstract: Signature is one of the most important and widely accepted biometric. It is the most common biometric used in documents like financial transactions, legal documents, contracts, and others. The security requirements demand the classification of the signatures. In real-world scenarios, signatures are not always available separately. The signatures are to be extracted from the documents and are then to be processed for other applications. In the first stage, the scanned document images are fed to the system and the signatures from the documents are extracted using various morphological operations. Features are extracted using DenseSIFT and these extracted features are stored in a database for further processing. In the later stage, Support Vector Machines (SVM) are employed to classify the signatures. The testing signatures are extracted from the documents and are then classified against the stored documents in the database. For the purpose of this project, we have considered around 500 documents. But, can be extended to work with as much as 1000-2000 documents.
Keywords: Signature segmentation, Dense SIFT, SVM classifier.

I. INTRODUCTION

Signatures provide information and unique behavior of a person and are thus used as the most common biometric feature. With the advancements in technologies, many methods for the extraction of signatures from the documents and their classification are presented. The handwritten signature is the most accepted biometric feature and is a basic source of representation. Most of the formal and financial documents still demand the signatures. The modern-day technologies and security requirements demand user authentication in every step. In forensic science, the document containing the signature is used to establish genuineness or non-genuineness, or to expose forgery, or to reveal alterations of the signatures of any type. Most signature classification and identification methods require the pre-segmented form of the signature from the document. In reality, the documents that are present may be a sheet of paper containing mechanically-produced text with the signatures. In such cases, the signatures are to be extracted and processed further. The handwritten text or the signatures can be differentiated from the other contents in the documents. The signatures exhibit diversity in sizes and poor alignment of each line of text, whereas the typewritten text, is consistent in the character shapes and the alignment. This property of the type-written text is helpful in eliminating the useless and text part of the document. The dataset for signature localization and classification is a sample formal document with a varied number of signatures in varied positions. These collected documents with signatures are scanned and fed to the system for further processing.

Various morphological operations such as grey scale conversion, median filter, dilation is applied to the document and all the signatures in the document are localized and extracted. The features of these extracted signatures are collected using the denseSIFT algorithm and stored for classification purposes. The test document is inputted, signatures are localized, features are extracted and the signature is classified using the Support Vector Machine (SVM) classifier.

II. LITERATURE SURVEY

This survey discusses about the approaches and limitations of the existing methods. A simple two-stage approach proposed [1][9] is towards automatic signature segmentation and recognition from scanned document images. The methods used [1] for segmentation and localization are 74%-84% precise. The technique used on extracted signatures [2], uses several pre-processing steps, even though currently available tools work with a highest accuracy of ca. 80%, which is not reliable in the verification task. The pre-processing step of binarization [3] involves base line removal and enhancement of noisy images. This requires prior knowledge of the location of signature. The signature retrieval strategy implemented in [4] is indexing and the algorithm used for generating these processes is region growing algorithm. This is difficult in the presence of noise and text overlapping. The proposed system used to detect and localize the signature pixels [5] is robust and very effective but the method used for signature segmentation from documents is hyperspectral imaging. So, the Key point detection based method performs with very high precision but the recall is low meaning that there are many signature pixels that are missed in the final segmented signature. In [6] the system verifies the handwritten signatures by taking a boundary of the entire signature and do the pixel wise comparison, which gives 80% accuracy but signatures acquired should be consistent in manner and similar enough that the system can locate large percentage of common characteristics. The Image retrieval process used [7] includes distance metrics, using multilevel DWT features for binary images. In

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has greater complexity and more iterations are required to retrieve a signature. The segmentation of signatures from machine printed documents [8] is processed using conditional random field and the results obtained [8] are very encouraging. The verification of offline signatures using local interest points and descriptors [10] is based on a general-purpose wide baseline matching methodology. The final verification is carried out using a Bayes classifier. The proposed system [10] is validated using the GPDS signature database, where it achieves a FRR of 16.4% and a FAR of 14.2%.

III. PROPOSED METHODOLOGY

The design of the system is divided into three phases:

1) Localization and segmentation
2) Feature extraction
3) Classification

In the training process, segmented signatures from the document are extracted and their features are collected using the feature extraction process. These extracted features are trained and stored in the knowledgebase. While in the testing process, the testing document is inputted and the signature is segmented, features are extracted and the SVM classifier is used to classify these test signatures from the ones present in the knowledgebase. The result of these processes gives the classification of the signature from the previously stored data. The architecture for the methodology is as shown below:

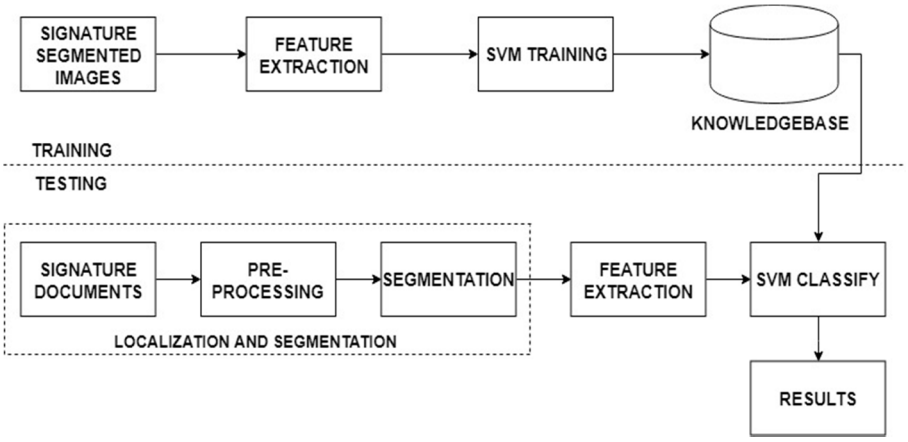

Fig1: System Architecture

A. Localization And Segmentation

The dataset containing documents with different signatures in different positions is taken as input for the segmentation process. Before proceeding to the segmentation process, the image is prone to a few pre-processing methods. First, the input image which is in the RGB image format sometimes referred to as a tricolor image is stored in MATLAB as an m-by-n-by-3 array that defines red, green, and blue color components for each individual pixel is converted to gray image. The MATLAB tools convert RGB images to grayscale by eliminating the hue and saturation information while retaining the luminance.

A 2-D Median Filtering technique is applied to the converted gray image. Median filtering of the matrix A is performed in two dimensions. Each output pixel contains the median value in the M-by-N neighborhood around the corresponding pixel in the input image. Median filtering pads the image with zeros on the edges so the median values for the points within [M N]/2 of the edges may appear distorted.

The image is then converted to black and white in which all the text and signatures are in white and the background is in black.

Clear border functions are applied that suppresses structures that are lighter than their surroundings and that are connected to the image border. The output image is intensity or binary, respectively. The default connectivity is 8 for two dimensions. For intensity images, clearing the border tends to reduce the overall intensity level in addition to suppressing border structures.

A morphological structuring element is taken as one of the inputs for the dilation process. When dilation is applied, it dilates the grayscale, binary, or packed binary image, returning the dilated image. A structuring element object, or array of structuring element objects, returned by the structuring element function is applied.

To measure the properties of image regions regionprops method is applied which measures the set of properties for each connected component (object) in the binary image, which must be a logical array; it can have any dimension. The input for the same is the

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dilated image and the properties are mentioned as 'all'. It returns all of the shape measurements. To locate the signatures, the bounding box is applied which defines an area by two longitudes and two latitudes, where: latitude is a decimal between -90.0 and 90.0 and longitude is a decimal number between -180.0 and 180.0.

After applying the bounding box, we were able to identify a single signature in the document. To locate all the signatures in the document a range for height and width of the bounding box is given and we observed that the signature's height and width are different from the rest of the text in the document. A rectangle box is created around the signature which adds a default red rectangle to the current axis. After

locating all the signatures in the document, the signature is cropped using the cropping function and this image is used for feature extraction process for classification purpose.

Steps for Signature Localization:

1) *Step 1:* The image of the document is taken as an input
2) *Step 2:* The input image is converted to a grayscale image
3) *Step 3:* Median filtering is applied on the image
4) *Step 4:* Dilation is applied
5) *Step 5:* Localized signatures are extracted.

B. Feature Extraction

Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps. Feature extraction is related to dimensionality reduction. The selected features are expected to contain the relevant information from the input data so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the number of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to overfit to training samples and generalize poorly to new samples.

Feature collection step will collect the features from the database. The extracted features are stored in a data file. The output of the signatures are stored in the output data file against the respective signature documents. This is followed by the feature extraction part, which extracts the features from the database with pre-processing and feature extraction methods. The algorithm DenseSIFT is used applied to extract the features.

DenseSIFT is derived from the SIFT algorithm which is based on keypoint detection. For the given document the SIFT algorithm finds all the key points. Each keypoint contains information of its location, local scale, and orientation. SIFT computes a local image descriptor based on each key point which shows the gradient features of the same. The complete features of the segmented images are obtained by combining all the local descriptors.

Following the SIFT algorithm, DenseSIFT has made a few assumptions:

1) The location of each key point is based on a pre-designed location.
2) The scale of each key point is also pre-designed.
3) The orientation of each key point is zero.

With the above assumptions, DenseSIFT can acquire more features in less time than compared to SIFT.

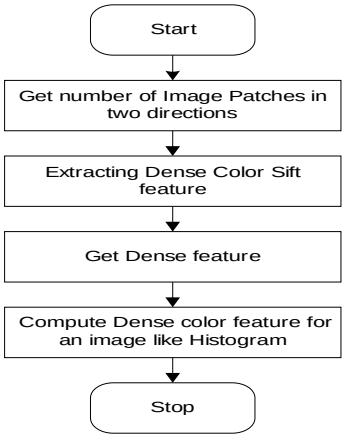

Fig 2: Flow diagram of DenseSIFT

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C. Classification

The first step in the classification process is SVM Training. The feature files and the output files that are extracted in the Feature Extraction process is loaded and is used in the SVM Training function. A SVM classifies by separating hyperplane. Given supervised training data, the algorithm outputs a separating hyperplane which helps in classifying new documents. The kernel trick is used to classify the non-linear data using a non-linear SVM Classifier, which transforms the linearly inseparable data into a linearly separable one by projecting it to a higher dimension.

The kernel used in this classification purpose is Radial Bias Function (RBF) kernel as it is non-linear, optimal and accurate. The Radial Bias Feature contains six parameters: AlphaY, SVs, nSVs, nlabels, bias, parameters. Radial Basis Function is a commonly used kernel in SVC:

$$K(x, x') = exp(-||x - x'||22\sigma2)$$

where $||x - x'||2||x - x'||2$ is the squared Euclidean distance between two data points xx and x′x′.

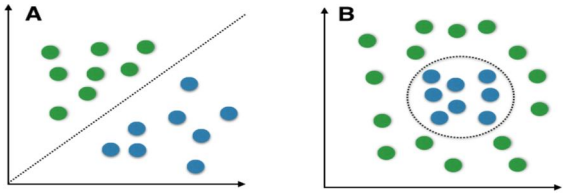

Fig3: Linear and non-linear SVM

SVM is flexible in choosing a similarity function and sparseness of solution when dealing with large data sets. Only support vectors are used to specify the separating hyperplane. Ability to handle large feature spaces is one of the salient features of SVM.

IV. DATA SETS

A dataset is a collection of data and a set that is organized into some type of data structure. The dataset document used for the implementation of the process consists of different signatures. These signatures are positioned in different formats and in different positions. The positions of these signatures are not standardized and can be present anywhere in the document. These positions of the signatures are not known before hand as is to be localized accordingly. Since there are more than one signatures present in the document, all the signatures are localized and extracted from the given document.

The documents that are considered are as shown below. These documents contain varied signatures in varied numbers as shown in the Fig4 below. The documents are considered in a number of 500 for the purpose of this project. But, can be extended to work with as much as 1000-2000 documents. Localization and segmentation does not hold a restriction on the number of documents that can be used for signature segmentation. However, above this number could cause problems in classification as it might not provide efficient classification and can cause misclassification.

Fig 4: Sample Document

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V. RESULTS

The signature segmentation and classification is a content-based task where the signatures are extracted using an efficient approach for the processes. The original document and the signature localized document image are as shown below Fig 5 :

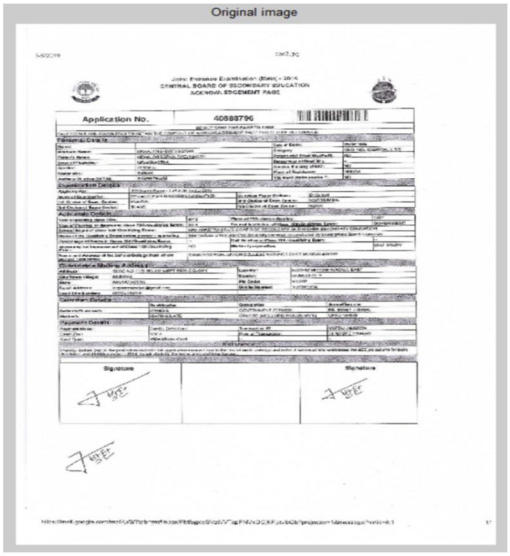

Fig 5: Document with signatures

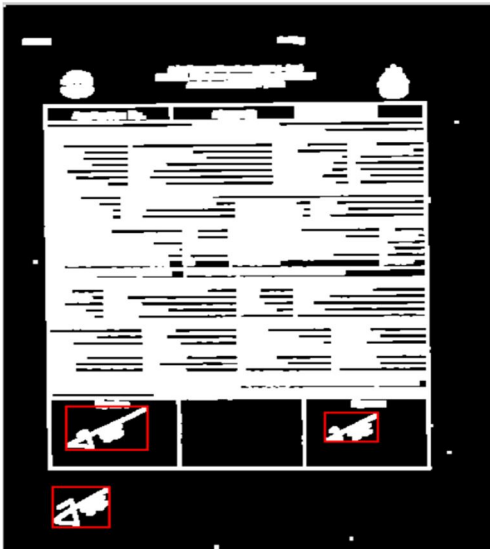

Fig 6: Document with Localized Signatures

The result of the processes is the extracted signature from the inputted document and the classified message. Its output is as shown below in figure 7:

Fig 7: Segmented signature

When a set of 100 documents are considered, trained and tested, all the docuemnts are localized and segmented efficiently whereas, only 96 documents are classified. The flaws in this classification is done as a future enhancement work.

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VI. CONCLUSION

Signatures are a large amount of biometric modality and are hence needed to be extracted from the real-time documents. Since most people are accustomed to signing in the interactions, this technology plays a vital role. This project helps in extracting all the signatures from the real-time documents and classifying the same. During classification, the features of the signature must not change in order to classify the signature of a person.

In future, we are planning to extend this method to include documents in which the signatures overlap the textual content in the document and extract the same. The SVM classifiers are efficient and powerful classifier that works well on a wide range of classification problems but still hold a few drawbacks. It cannot be used for larger data sets and contains several key parameters. Hence we plan to implement deep-learning neural networks for the classification purpose.

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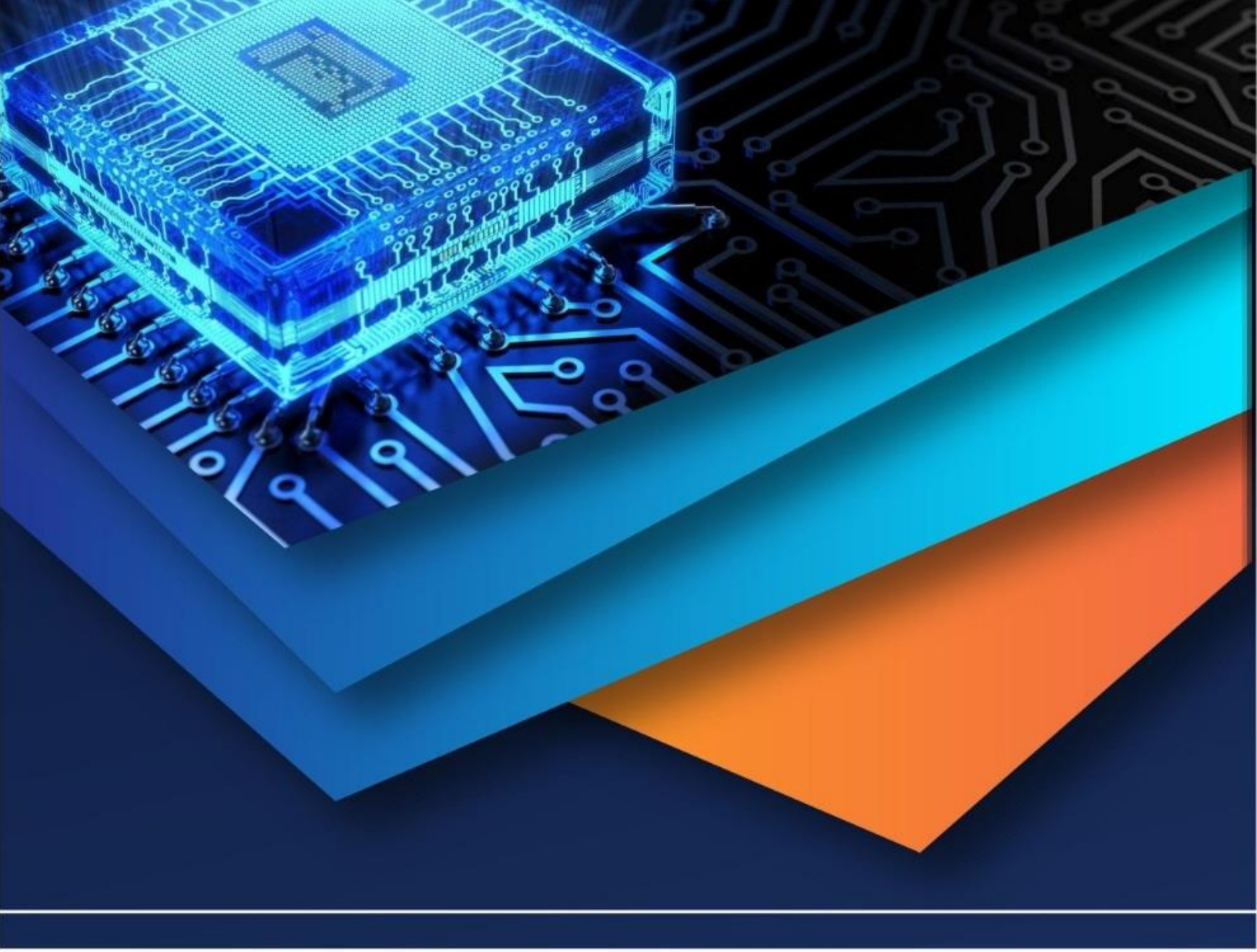

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