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Morse code Digits Recognition through different features and classifiers

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Abstract: *In this study, we classify synthetic images of Morse code digits using various classifiers. Our objective is to assess the efficiency of different features extracted from the images when combined with different classifiers. To evaluate the performance, we employ accuracy as the metric for comparing the results. The classification experiments are conducted using Matlab functions, which are utilized in our work. Through this investigation, we aim to gain insights into the effectiveness of different feature-classifier combinations for the classification of Morse code digits in synthetic images.*

1. Introduction

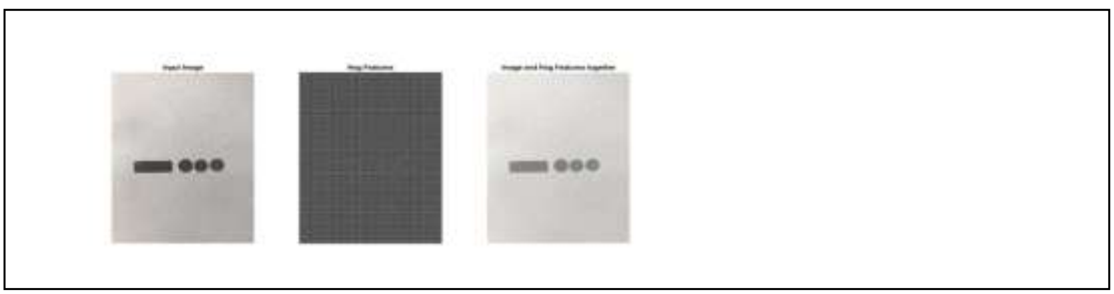
Image recognition, a subcategory of machine learning [1], involves the use of artificial neural networks to perform automatic learning tasks. These networks are trained on specific datasets to enable them to classify and recognize images. This capability extends to building automatic recognition systems, such as intelligent video surveillance [2], and automating business processes to improve productivity [3]. For instance, in the telecommunications field, an image recognition system is utilized for quality control automation, ensuring the quality of installations. The applications of image recognition are diverse, spanning industries such as construction and pharmaceuticals [4].

In this study, we focus on four specific image features for classification within the context of neural networks. These features play a crucial role in enabling accurate image recognition and classification.

1.1 Color Features

In image analysis, extracting color information is essential to determine the color value of each pixel in an image, irrespective of its semantic meaning. Color images are commonly represented as a combination of three color channels: red, green, and blue. Each channel is typically stored as a matrix with pixel values ranging from 0 to 255, representing different levels of intensity.

1.2 Histogram of Oriented Gradients (HOG)



Figure(1) Hog features on Morse code image

Gradients play a crucial role in detecting image edges and corners, as they capture intensity changes within regions. To leverage this information effectively, we employ the Histogram of Oriented Gradients (HOG) feature. In this approach, the image is divided into small connected regions called cells, and the gradients within each cell are computed. By creating a histogram of these gradient orientations, we capture the distribution of intensity changes in the image. This technique has been widely used for feature extraction in various applications [5].

1.3 SURF (Speeded Up Robust Features):

SURF is a fast and robust algorithm introduced by Herbert Bay in 2008 [6]. It enables local, similarity-invariant representation and comparison of images. This algorithm extracts features that describe the local texture features of key points in the grayscale image across different directions and scales. It achieves invariance to rotation, scaling, and brightness changes by applying an approximate Gaussian second derivative mask to the image at multiple scales and orientations. SURF exhibits excellent stability against affine transformations and noise, surpassing other methods in terms of uniqueness and robustness. Furthermore, it significantly improves computational efficiency, making it an attractive choice for various image processing tasks.

1.4 Shape Features

Shape features play a crucial role in image analysis as they closely resemble human perception. Various techniques have been proposed for shape matching in computer vision, as highlighted in the comprehensive survey by Loncaric in 1998 [7]. The selection of shape features depends on the characteristics of the images under consideration, and different measures can be employed for distinguishing between shapes. Some common shape features include the calculation of center of gravity, circularity ratio, and ellipse variance, among others. These measures capture the geometric properties of the image and contribute to the accurate analysis and discrimination of shapes.

2. Morse Code

Morse code is an ancient method of encoding messages, where each alphabetic character is represented by a unique arrangement of dots and dashes (._). This encoding scheme assigns a specific code to each character.
The distribution of dots and dashes in Morse code is based on the frequency of occurrence of letters in the English language. For instance, the letter "E," being one of the most common letters, is represented by a single dot (.), while letters like "I" and "S" are encoded with two and three dots, respectively. On the other hand, letters with lower frequency, such as "Q," are encoded with a more complex sequence like (.._.).
The assignment of more dots to frequently occurring letters aims to reduce the overall length of the message [8]. Numerous researchers have addressed the development of automatic recognition systems for Morse code. This includes the creation of software systems to generate images representing Morse code symbols [9], as well as systems focused on decoding these encoded symbols [10]

3. Proposed System

The proposed system is illustrated in Figure 2, which depicts the system diagram.

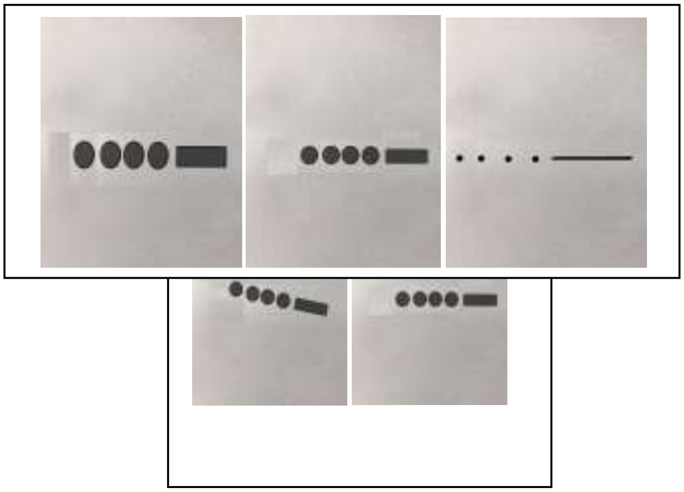
Figure (2): proposed system diagram

3.1 Synthetic Images

The synthetic images used in this research are Morse code digits created using the ibis Paint X application. A total of 10 colored images representing the ten digits of the English language were generated, with 5 examples of each digit, resulting in 50 different images. The images were drawn at a resolution of 1280x1280 pixels, as shown in Figure 2(a). These images were collected, labeled, and stored on the hard disk.

3.1.1 Evaluation Dataset

To evaluate the classification system on the synthesized dataset, an evaluation dataset was prepared. This dataset includes images with pepper and salt noise added at specific ratios (0.1, 0.01, 0.001) and rotation applied at specific angles (10, 45, 60 degrees) to all the images in the training dataset. This resulted in a total of 300 images in the evaluation dataset. An example of rotation applied to digit 4 is illustrated in Figure 2(b).



(b) original and rotated image
Figure(2): sample of synthetic Morse code

3.2 Feature Extraction
Various types of features were considered for comparison in our study.
3.2.1 Color Features
The RGB image was reshaped and considered as features after resizing it to 64x64 pixels.

3.2.2 HOG Features
The function "extractHOGfeatures" was used with a cell size of 32x32 pixels to extract HOG features.

3.2.3 SURF Features
The grayscale image was used as input to the "detectSURFFeatures" function to extract SURF features.

3.2.4 Shape Features
Binary images were utilized to describe circles and rectangles present in the images. We considered features such as area, centroid, and bounding box using the "regionprops" function.

3.3 Classification
We compared two different classifiers in our study:

3.3.1 Perceptron
The perceptron is a type of backward neural network classifier. In our work, we applied the perceptron using the "train" function as a single-layer network with a hard limit activation function. The model was trained as follows:
net = train(net, X, Y),
where X represents the training data and Y represents the given binary labels of the 10 classes. We evaluated the classification performance using the accuracy metric Equation (1).
Accuracy = (Number of correct matches / Total number of samples) x 100….(1)

3.3.2 SVM
Support Vector Machine (SVM) is another classifier model that aims to find a hyperplane between classes. We used the "fitcecoc" function to implement this classifier, with X representing the training data and Y representing the given decimal labels of the 10 classes.
4. Results and Discussion
As a result of the proposed classification system, a comparison table (Table 1) was generated to evaluate the performance on the rotated and noised dataset. The neural network was trained for 2000 iterations.

Table(1): classification results

features	Percepetron Acc%	SVM Acc%
Color	90.1	91.2
Hog	78.1	78.2
SURF	19.3	20.3
Shape	40.2	40.1
Color+Hog+Surf+Shape	91.3	92.1

From the table, it is evident that the Perceptron neural network demonstrates the ability to recognize images with varying levels of noise and different rotation angles. The recognition accuracy varies based on the types of features used during network training. Therefore, incorporating all the image features into the training process yields the best results. Additionally, we observed similar levels of efficiency between the two compared classifiers, indicating comparable performance.

5. Conclusion

Our practical demonstration has shown that the effectiveness of training a neural network to classify images is directly influenced by the method of image description, specifically the type of features used during network training. By improving the efficiency of image description, the training process becomes more effective, enhancing the network's learning capabilities and ultimately improving the accuracy of image classification. This holds true even when the images being classified have varying levels of noise and rotation angles, highlighting the robustness of the trained network.

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