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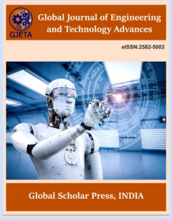

(Review Article)

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Detection of counterfeit images using SIFT and PNN

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Abstract

Manipulation of digital images presents a significant challenge, primarily due to the continuous advancement and sophistication of image enhancement tools. As a consequence, image feature extraction and matching have become pivotal areas of research in the field of image processing. Among the various techniques developed, the Scale-Invariant Feature Transform algorithm has gained widespread recognition for its robustness and superior performance in feature matching tasks when compared to other existing methods. In this context, our proposed method, which integrates the Scale-Invariant Feature Transform algorithm with a probabilistic neural network, offers a novel approach to digital image classification specifically aimed at counterfeit image detection. This integrated system not only enhances the accuracy of feature extraction but also leverages the probabilistic neural network to improve classification efficacy. Empirical results indicate that this hybrid approach achieves a remarkable relative error rate of just 0.666%, underscoring its potential as a reliable tool for combating digital image forgery. Such advancements are crucial for maintaining the integrity of digital media in various applications, from forensic analysis to digital content authentication.

Keywords: SIFT; PNN; Counterfeit; KNN; Matching

1. Introduction

Digital images enjoy widespread popularity and are utilized extensively across various domains, including scientific research, social contexts, media, and even in everyday photography. However, the proliferation of image editing software has led to an increase in digital image manipulation practices. As a result, distinguishing between authentic images and digitally altered ones has become increasingly challenging, often rendering it nearly impossible to identify manipulated images through visual inspection alone. To address this issue and ensure the authenticity of digital images, the detection of digital image manipulation has emerged as a critical field of study [1].

Image feature point matching is extensively utilized in various areas of image processing, including target tracking, picture tiling, and pattern recognition. As the foundation for numerous other image processing techniques, the development of image feature point matching technology is an active area of study within computer vision and related domains [2].

David Lowe first proposed the classic Scale-Invariant Feature Transform (SIFT) algorithm in 1999. The algorithm combines the Gaussian kernel with a scale-free spatial pyramid to enhance the stability of feature point detection across variations in scale, translation, rotation, and illumination. The fundamental principle of the SIFT algorithm is that its execution is divided into two stages: initially, the characteristic points of the image are identified, and subsequently, these points are described. This two-stage process allows for robust and reliable detection and description of features, making SIFT a cornerstone method in the field of image processing [3].

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Since its inception, the SIFT algorithm has been employed to address a variety of problems, including image matching [3-5], image forgery detection [6], ground-penetrating radar image analysis [7], encrypted image retrieval [8], retinal image registration [9], and the registration of synthetic aperture radar and optical images [10]. Its versatility extends to numerous other applications, demonstrating its broad utility across different domains.

Various techniques exist for feature point detection, with three of the most notable being the aforementioned SIFT, Speeded-Up Robust Features (SURF), and Oriented FAST and Rotated BRIEF (ORB). Comparative studies on these techniques highlight their respective strengths and weaknesses. Notably, the study in [11] demonstrates that while ORB is the fastest and SURF excels in handling rotations, SIFT offers the best overall performance, despite its higher computational cost.

According to the literature, employing the SIFT algorithm to detect modifications in images, such as identifying instances where a fragment, animal or a person has been extracted from one image and inserted into another, is a contemporary challenge. Optimal and rapid solutions are actively sought, necessitating the exploration of various computational methods to develop more robust algorithms and achieve superior results.

This paper presents an approach that integrates the SIFT algorithm with a probabilistic neural network (PNN) to address the problem of detecting alterations in which a person/animal has been inserted into an image from a different context. In this framework, the SIFT algorithm is responsible for extracting a cloud of feature points, while the PNN evaluates the probability that the person/animal has been extracted from one image and inserted into another. The implementation of this approach was conducted using the Python programming language.

2. Theoretical support

2.1. The SIFT Algorithm

The SIFT algorithm integrates feature selection with the Difference of Gaussian (DoG) and encompasses six principal steps: establishing the scale space, constructing the Gaussian pyramid, detecting extrema and positioning key points, determining the orientation of key points, and creating feature point descriptors [12].

- Scale Space: To simulate the multi-scale features of image data, a processing model is required, which involves continuously varying the scale parameters to obtain image representations at different scales. The scale space determines the degree of image blurring. Different scales can be represented as the convolution of images with Gaussian kernels, as outlined in (1) and (2) [12].

$$P(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad \text{……………………(1)}$$

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \quad \text{……………………(2)}$$

- Gaussian Pyramid: The construction of the Gaussian pyramid involves generating images at multiple scales. This process calculates the difference in pixel values between two adjacent scales, as shown in (3) and (4) [13].

$$(x, y, \sigma) = \big(G(x, y, k\sigma) - G(x, y, \sigma)\big) * I(x, y) \quad \text{…………….. (3)}$$

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \text{……………………(4)}$$

- Extreme Point Detection: In this step, pixels in the Difference of Gaussian (DoG) are compared with their adjacent pixels. Through this comparison, certain points, despite varying conditions such as brightness, darkness, or edge effects; demonstrate stability and consistency across different scales [13].
- Key Point Positioning: The scale and position of feature points are determined using least squares fitting applied to the second-order expansion of the scale function, as detailed in (5) [12].

$$D(X) = D + \frac{\partial D^T}{\partial X^2} X + \frac{1}{2} X^T \frac{\partial^T D}{\partial X^2} X \quad \text{…………………(5)}$$

With the first derivative being 0, the point of the feature is:

$$\hat{X} = -\frac{\partial^2 D^{-1}}{\partial X^2} \frac{\partial D}{\partial X} \text{………………………………(6)}$$

Finally, the equation for obtaining the feature point is:

$$D\left(\hat{X}\right) = D + \frac{1}{2}\frac{\partial D^T}{\partial X}\hat{X} \quad \text{......................(7)}$$

Principal point of the feature point. For a feature point is necessary to sample its neighborhood pixels and specify the direction parameters with (8).

$$m(x,y) = \sqrt{(L(x+1,y) - L(x-1,y))^2 + (L(x,y+1)L(x,y-1))^2} \text{..................(8)}$$

$$\theta(x,y) = tan^{-1}(\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)}) \quad \text{.........................(9)}$$

The equation (8) represent the gradient pattern at *(x,y)* and in (9) the range is 0-360 degrees, when is divided in to "*n*" columns it represents the direction [12].

2.2. KNN algorithm

K-nearest neighbors' algorithm (KNN) is a simple, effective an efficient algorithm where the letter K, is used to note the number of nearest neighbors in order to predict some test sample. Using the Euclidean distance *d(x,y)* defined as [14]:

$$d(x_i, x_j) = \sqrt{\Sigma(a_r(x_i) - a_r(x_j))^2} \quad \text{...........................(10)}$$

KNN algorithm is used to estimate the class of the test, instead of the test set, as shown in (11).

$$c(x) = \arg\max \textstyle\sum_{i=1\ to\ k} \delta(c, c(y_i) \text{ ....(11)}$$

where $y_i - y_k$ are the nearest neighbors for a particular test, c is the set of class label.

2.3. Probabilistic Neural Network

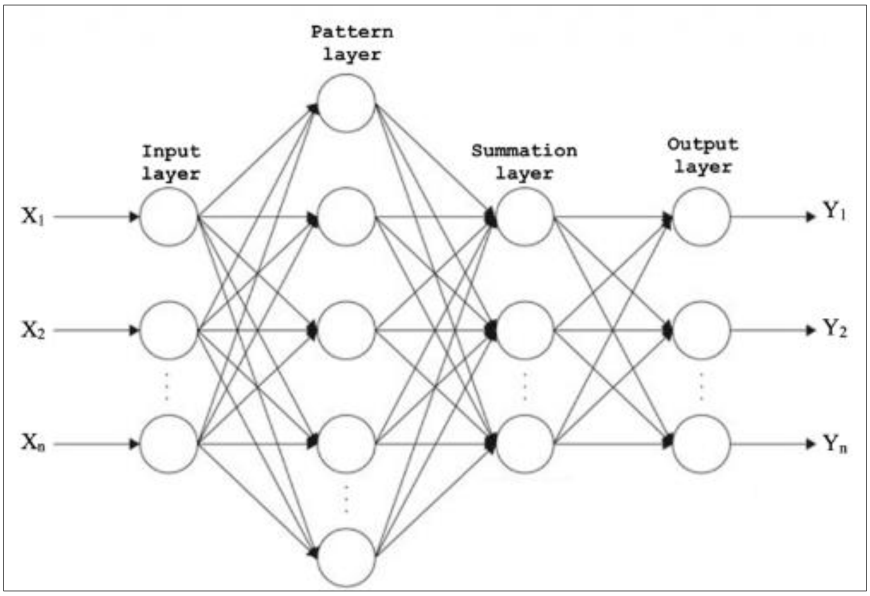

Figure 1 Architecture of Probabilistic Neural Network

Neural networks are extensively employed for pattern classification through learning from examples. Various neural network paradigms utilize different learning strategies; however, all of them generate pattern statistics based on a training dataset, which are then used to classify new patterns.

A frequently utilized neural network model for classification is the PNN. This algorithm addresses certain limitations inherent in Back-Propagation models [15] and does not require an extensive dataset. The PNN algorithm comprises four components: the input layer, the pattern layer, the sum layer, and the output layer. PNNs are valued for their ability to map each input pattern to multiple classifications more efficiently than other neural network models, making them highly effective for data categorization. Furthermore, PNNs provide superior classification performance compared to artificial neural network-based logistic regression models [16].

3. Description of the algorithm

10 photographs were captured that we handle as the original photographs, from each one the person/animal was extracted and 30 different backgrounds were placed, creating a database of 300 modified images. All photographs and images used in this project are free of copyright and obtained by the participating researchers.

For the training of the neural network, the feature vectors of 24 out of 30 images modified with respect to the original were used, with 240 images used for training. Regarding the test data set, the feature vectors of the other 60 remaining images were used for the test set. It is then concluded from the database that 80% will be training and 20% testing.

The photographs vary in pixel dimensions; however, due to the scale-invariant nature of the SIFT algorithm, this variability does not impede the comparison process. The Python environment was chosen for implementing the proposed algorithm because of its flexibility, substantial support within the scientific and technological community, and its extensive array of tools.

The algorithm, as illustrated in Figure 2, incorporates the extraction of SIFT characteristic points, the KNN algorithm, and the PNN.

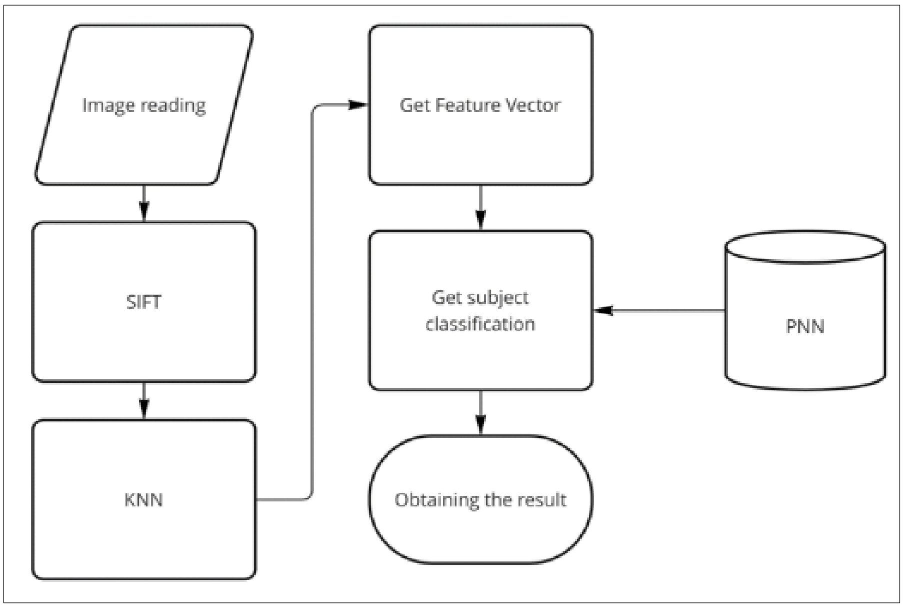

Figure 2 Modified image analysis algorithm

The steps of the algorithm are detailed as follows:

- Image Reading: The images are read into the Python environment and stored as arrays. This process is applied to both the original image and the modified image to be compared, with the goal of determining if a person/animal from the original image appears in the modified version. The images do not need to be of the same size. For further processing, both images are converted to grayscale.
- SIFT Algorithm: Both images are processed using the SIFT algorithm, which utilizes the following parameters to identify key points and descriptors: number of octaves = 4, number of scale levels = 5, initial $\sigma = 1.6$, and $k = \sqrt{2}$. If the intensity at an extreme point fall below a threshold of 0.03. Figure 3 illustrates an original image with the key points and descriptors extracted.

Figure 3 Key points and descriptors

- Apply the KNN: The descriptor of a feature in the first set is taken and compared to all other features in the second set calculating the distance. And the closest one is returned. The algorithm returns the best matches k, they are classified in ascending order of their distances so that the best matches (with low distance) are at the front, searching in the case of our approach the 8 best ones. The best 8 matches of two images are shown in Figure 4.

Figure 4 Counterfeit image analysis algorithm.

- Get Feature vector: After obtaining the 8 key points where the algorithm makes the match in the modified image, a sweep is made from the upper left part of the matrix to the lower right part until finding the first of those points, from this point the distance to the other 7 points in the order that they appear in the sweep. After carrying out this process, the vector of characteristics is obtained, this being 7 elements, each of the elements of the vector is divided by the sum of the 7 values so that the sum of the final vector is 1 to later be used in the PNN.
- Get subject classification: Once the vector of characteristics of the modified image is obtained, it is introduced to the previously trained neural network, which will result in a "classification" that represents one of the 10 original images with which it was trained.
- Depending on the result of the classification: it is observed that if it was of the expected class (original image) or if it chose another class, this information for the test set will help to build the confusion matrix to perform the statistical analysis of the results.

4. Results

10 photographs were captured that we handle as the original photographs, from each one the person/animal was extracted and 30 different backgrounds were placed, creating a database of 300 modified images. All photographs and images used in this project are free of copyright and obtained by the participating researchers.

As in any classification process, the results improve depending on the quantity and quality of the data used in the classifier. It was mentioned earlier in the explanation of the algorithm that vectors of 7 representative elements of distances created from the best matches between two variables are used.

Figure 5 Scale-independent matching

The SIFT algorithm by its nature is not affected by scale changes, which in the case of our experiments greatly facilitated the correct comparisons to obtain good feature vectors, a case of a scale-independent comparison to obtain the 7 values is shown in Figure 5.

In the validation set of 60 images, the PNN exhibited notable performance. With a relative error of 6.666% and an accuracy of 93.333%, the PNN successfully classified 56 out of the 60 images correctly. This indicates that the classifier effectively determined whether the person/animal from the original photograph was accurately placed into the modified images. Specifically, 56 images were correctly identified, reflecting the model's effectiveness in achieving its intended goal. Conversely, 4 images were misclassified, highlighting some areas for potential improvement. These misclassifications suggest opportunities for refining the PNN to enhance its accuracy further. Overall, the results demonstrate the PNN's strong performance in image classification tasks and its capability to handle image modifications effectively, reinforcing its practical utility in verification and modification detection applications

5. Conclusion

The results of this study affirm that the proposed method, which combines the Scale-Invariant Feature Transform (SIFT) algorithm with a probabilistic neural network, effectively addresses the challenge of digital image manipulation and counterfeit detection. The algorithm performed as anticipated, achieving a notable relative error rate of 0.666%, which underscores its capability to accurately classify manipulated images. Despite its higher computational cost compared to other methods, SIFT consistently provided reliable feature points that effectively represented the person or object across different images.

However, the study also highlights the need for a larger dataset to enhance both training and testing phases, which could lead to improved classification accuracy and more robust performance. While SIFT excels in performance, future work should explore additional algorithms that handle image rotations and noise efficiently while maintaining the high-performance levels of SIFT. Incorporating preprocessing techniques to address SIFT's limitations could further refine the model, making it more adaptable to a wider range of image variations and conditions. Future research will focus on expanding the dataset and integrating advanced algorithms to bolster the robustness and versatility of the image classification system.

Compliance with ethical standards

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Disclosure of conflict of interest

The Authors confirm that the content of this manuscript has no conflict of interest.

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