A NOVEL FORGERY DETECTION IN FACE IMAGES USING ENHANCED CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT. Passive multimedia forensics turned into an active subject in current times. Nevertheless, less attention was paid on Forgery Detection (FD). Recent, research on forensic detection has obtained less accuracy. This paper proposed a FD technique in image frames of the videos using enhanced CNN to trounce such downsides. In the initial stage, the input video is taken as of the dataset and then converts the videos into image frames. Next, perform pre-sampling intended for reducing the useless frames. In the subsequent stage, perform preprocessing for ameliorating the image frames. Then, face detection is done as of the image utilizing the Violas-Jones (V-J) algorithm. The SURF, LBP are extorted from the image and select the necessary features from the extorted features using Improved Crows Search Algorithms (ICSA). Finally, the chosen features are inputted to the Enhanced Convolutionals Neural Network (ECNN) classifier for detecting the forged image frames. The investigational outcome indicates that the ECNN classifier, which is proposed identifies the forged or original image frames of videos more precisely than other existing methods.

1. INTRODUCTION

The rapid augmentation of images processing software and the progression in cameras (digital) has brought about a big quantity of doctored images with no

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noticeable traces, creating a great demand aimed at automatic FD algorithms for ascertaining the honesty of a applicant image [1]. Nowadays it produces a huge difficulty for validating images [2]. Image forgery implies the manipulation of the image (digital) to cover some significant or helpful information as of it. Many research works focused upon image forgery detection (IFD). The disclosure of the forgery algorithm will depend on the image source [3]. The FD could well be developed as, i) active or ii) passive. Active approaches were utilized conventionally via engaging data hiding (watermarking) or else digital signatures [4]. Normally, the image Watermarking (WM) is either embedded at the interval of time of the image acquisition or advanced after further processing of the real image. Contrary to active approaches, passive approaches do not count on pre-registration or pre-embedded information and no meticulous research have been done on them. Passive methods for image forensic work on the dearth of any signature or water-mark [5]. In the field of Machine Learning we are having different application like Plant Disease Prediction [6], Cancer prediction [7], Security [8] and so on.

In this paper Section 2 comprises of the related work where several related articles are referred and work related to the reference are expressed in detail. In Section 3, the detailed methodology including feature extraction, face identification, feature selection and algorithms are deployed. In Section 4, the results are discussed and concluded in Section 5.

2. Related Work

Wu-Chih Hu et al. [9] suggested an IFD system aimed at efficiently identifying a tampered back- or fore-ground image utilizing image WM along with alphas mattes. This approach had '2' parts: i) WM embedding and ii) identification of tempered images. The component-hue-difference-centered spectral matting was utilized for attaining the alphas matte. Subsequently, DWT-DCT-SVD-centered image WM was utilized for including the WM. Lastly, the difference betwixt the attained singular values was utilized for detecting the tempered background and foreground images.

Gunjan Bhartiya and Anand Singh Jalal [10] presented a technique to detect sham on JPEG image. An algorithm was modeled to categorize the image blocks as i) non-forged or ii) forged centered upon an exacting traits existed in

multiple-compressed images. This approach modeled the characters presented on the histograms of double compressed images for FD utilizing feature-centered clustering. The method performed was superior to the prior works that used the probability centered system for detecting a forgery on JPEG images. This approach showed the accuracy centered on quantitatively and qualitatively analysis only.

3. METHODOLOGY

Data Collection

As of YouTube, the data is collected. The presented videos having a resolution bigger than 480p which was tagged with "face", "newscaster" or "newsprogram" in the youtube8m data-set was taken.

3.1. **Convert videos into frames.** The inputted video is originally converted into frames which are mathematically written as in Eq. 3.1.

$$(3.1) \qquad I = \{f_1, f_2, f_3, ..., f_n\}.$$

3.2. **Preprocessing.** The presampled frames are preprocessed. The preprocessing involves choosing the standard image size, removal of noise and 'RGB' to 'LAB' color spaces conversion which is explained as follows.

3.2.1. *Standard image size.* Here, the image is set with a fixed size. If the system gets a disparate size of images for doing the task, then it may produce unwanted or error result. To avoid such drawbacks, the input images are initially fixed at standard size.

3.2.2. *Removal of noise.* In this stage, the salts and pepper noise has been eliminated using Modified Weiner Filter (MWF) which produces a better result than the normal Weiner Filters (WF). It is also more effective in preserving the edges. It is a Pixelwise linear filter formed by evaluating the local mean as well as variance about each pixel. The image I_p value at a point (u, v) is in Eq. 3.2.

$$(3.2) \qquad I_E = I_p(u, v) = \eta + \frac{\sigma^2 - r^2}{\sigma^2}(I_i(u, v) - \eta),$$

wherein, η is the area's mean that is under consideration, σ^2 implies the variance, r^2 is the noise variance, I_i signifies the image under consideration for noise

removal and I_E denotes the enhanced image that is utilized intended for further steps.

3.3. **Detect Objects (Face) using Viola Jones Algorithm.** The pre-processed image achieved from LAB color image goes through object identification. V-J offer speed as well as effectual ways of identifying a face in the rendered image. This encompasses the below phases.

3.3.1. *Haar like features.* This resembles the Haar-wave-lets that are how it achieved its name and it is a rectangular digital image elements. The '2'-rectangle element value imply the disparity betwixt the sum of the pixels amongst '2' rectangular areas. The total is gauged via the traits of a '3' rectangle amid the '2' external rectangles lessened as of the sum on the central rectangle. Eventually, a '4'-rectangle constituent gauges the variance betwixt diagonal pairs of the rectangles. Rectangular Features value illustrated in Eq. 3.3.

$$(3.3) \qquad V_{RF} = |\sum P_{A(black)} - \sum P_{A(white)}|,$$

where, V_{RF} implies the rectangular feature's value, $P_{A(black)}$ implies the black area's pixels, $P_{A(white)}$ is the pixels of white area.

3.4. **Feature Extraction.**

3.4.1. *Speeded Up Robust Feature (SURF) feature.* This employs a Hessian matrix grounded BLOB (Binary Large Objects) detector for fixing the points. Aimed at feature description in addition to orientation assignment, it employs wave-let responses in horizontal along with vertical directions via using appropriate Gaussian weights. A neighbor about the keys point is designated as well as partitioned into sub-regions, and after that, for every sub-region, the wave-let responses are regarded and also signified to get SURF. The descriptor vector '$d(y)$' aimed at each sub-region is illustrated in Eq. 3.4.

$$(3.4) \qquad SURF = d(y) = \left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right).$$

3.4.2. *Local binary pattern.* The LBP is basically a texture centered feature that has extensive applications in image classification. The LBP feature is provided in Eq. 3.5.

$$(3.5) \qquad LBP = \sum_{s=1}^{n} 2^s \times S_f(I_N - I_C),$$

where, I_N signifies the neighboring pixel on a square window, I_C implies the central pixel in the square window, 's' signifies the number of neighboring pixels around a center pixel. 'S_f' signifies specific function and $(I_N - I_C)$ is marked as the thresholds value and it is estimated in Eq. 3.6.

$$(3.6) \qquad S_f = \left\{ \begin{array}{l} 1; \; if(I_N - I_C) \geq 0 \\ 0; \; if(I_N - I_C) < 0 \end{array} \right. .$$

3.5. **Feature Selection.** The Crows search algorithms (CSA) is enthused on the intelligence activities of crows. The CSA has established its potential to attain the optimal solution intended for particular search spaces configurations. Nevertheless, its convergence is not certain on account of the unproductive exploration of its search strategy. Under this situation, its search strategy offers great challenges when it confronts higher multimodal formulations. To overcome these difficulties this proposed method uses the ICSA. The improvement is carried out by adding Levy fight for performing the random movement. In Lévy flights, the step size is managed by means of a heavy-tailed probabilities distribution termed as Lévy distribution. These are effectual discovering the search space comparing to the uniform arbitrary distribution.

3.6. **Classification.** Specifically, each neuron of an FM is connected to a region of neighboring neurons on the prior layer. Such kind of neighborhood is labeled as the neuron's receptive area on the former layer. The FM can well be obtained via initially convolving the inputted with a learned kernel and afterward executing an element-wise nonlinear activations function on the convolved outcomes. Perceive that, to produce each FM, the kernel is shared via the total spatial input location. The total FM is attained via employing numerous disparate kernels. The feature value at a location (a, b) in the k_{th} FM of l_{th} layer, $q_{a,b,k}^l$, is computed in Eq. 3.7.

$$(3.7) \qquad q_{a,b,k}^l = w_k^l x_{a,b}^l + b_k^l,$$

where w_k^l and b_k^l imply the weight factor as well as bias terms of the k_{th} filter of the l_{th} layer, and $x_{a,b}^l$ signifies the inputted patch grounded location (a, b) of the l_{th} layer. Note that the kernel w_k^l that creates the feature map $q_{a,b,k}^l$ is shared. Such mechanism have numerous pros, say, it could lessen the design intricacy and make the network simple to train. The activations function commences non-linearities to CNN that are enviable aimed at multiple-layer networks for
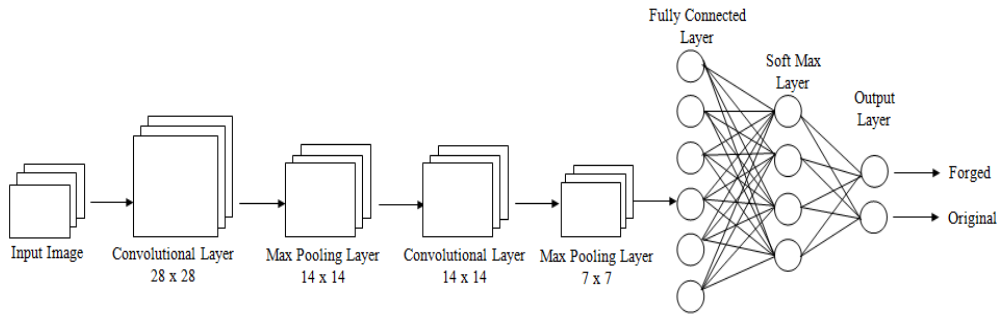
FIGURE 1. Architecture diagram of ECNN

detecting non-linear features. Let $n(.)$ implies the nonlinear activations function. The activation value $n_{a,b,k}^l$ of the convolutions feature $q_{a,b,k}^l$ could well be calculated in Eq. 3.8.

$$(3.8) \qquad n_{a,b,k}^l = n(q_{a,b,k}^l).$$

4. RESULTS AND DISCUSSIONS

The proposed system using FD-ECNN's performance analysis value with that of existing techniques, for instance, SVM and K-Nearest Neighbor (KNN), Fruit-fly optimization algorithm-support vector-NN (FOA-SVNN) together with Neural Network (NN) for different metrics comparison is evinced in Table 1. Table 1

TABLE 1. Demonstrate the performance of the proposed ECNN with the existing FOA-SVNN, SVM, KNN and NN

Performance Metrics	Proposed ECNN	Existing FOA-SVNN	Existing SVM	Existing KNN	Existing NN
Accuracy	0.9721	0.94	0.8704	0.7979	0.8784
Specificity	0.9856	0.9583	0.94	0.9467	0.94
Sensitivity	0.9567	0.94	0.6701	0.5588	0.6897

displays the ECNN-FD with the existent techniques' comparison in respects of accuracy, specificity, sensitivity. As of Table 1, it is apparent that the existing NN has provided the bad performance than the existent methods. Next, existing KNN is a lot superior to the NN in the FD system. From overall observation centered on the table value, it proves that the ECNN-FD system provides better
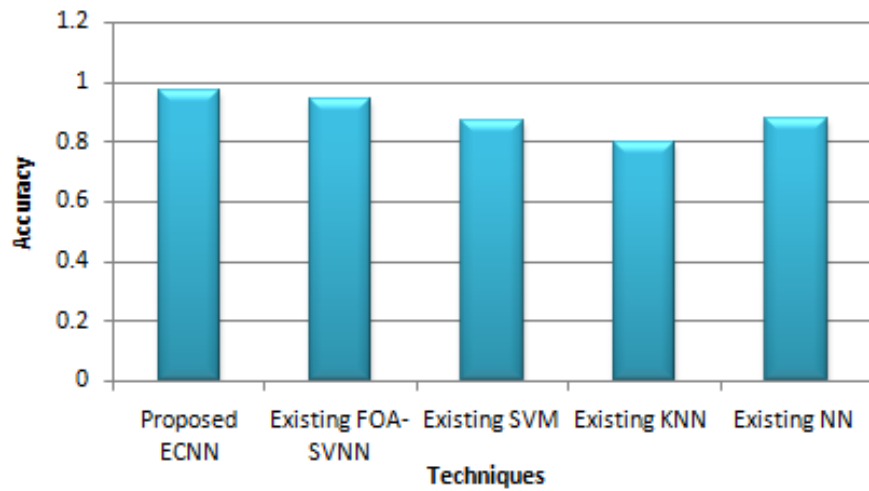
FIGURE 2. Accuracy performance comparison for proposed ECNN with existing methods
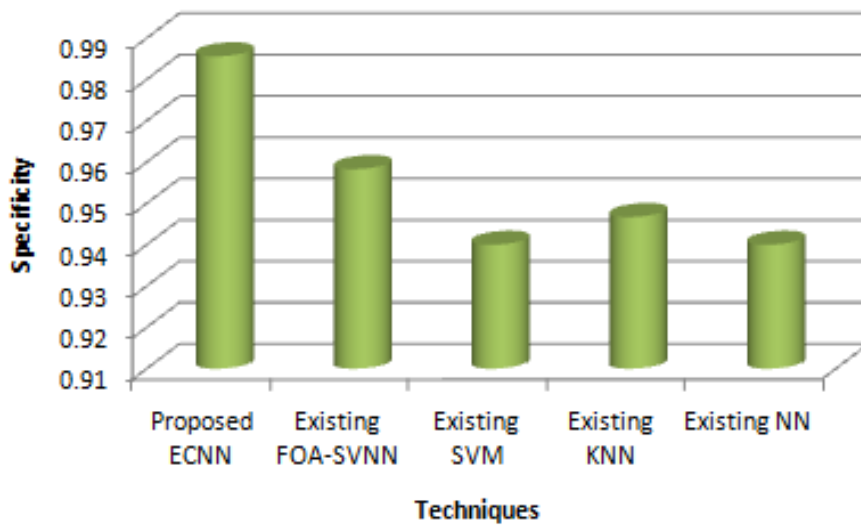

FIGURE 3. Demonstrate the performance of the proposed ECNN with existing detection methods in term of specificity

performance compared to the other existing methods.

Fig. 2 and Fig. 3 evinces the comparison graph intended for the ECNN with the existing techniques based on specificity measure. The proposed method's specificity is (0.9856). The existing systems FOA-SVNN, SVM, KNN, and NN

have 0.9583, 0.94, 0.9467, and 0.94 respectively. Hence, it establishes that the specificity value is high for the proposed work than the prevailing systems.

5. CONCLUSION

In multimedia, many forgeries are present nowadays. Video editor together with Adobe Photoshop is a few multi-media software as well as tools which are utilized to edit or temper medial files. This work selects the necessary features as of the extorted features using ICSA algorithm, in the final stage, the image is classified grounded on the preferred features using ECNN. The proposed classification technique's performance is weighted against that of the existent techniques. The proposed ECNN performance is contrasted with the prevailing FOA-SVNN, SVM, KNN, as well as NN concerning sensitivity, accuracy, along with specificity. Experimental outcomes exhibited that the ECNN classifies the objects more accurately compared to the existent techniques. In the future, this proposed work can extend via using advanced classifiers.

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