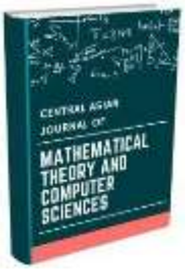

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Article

A Decision-Fusion Framework for Digital Image Forgery Detection Using Deep Feature Learning

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Abstract: Digital image manipulation has become increasingly sophisticated due to the rapid advancement of image editing software and the pervasive dissemination of visual content through online platforms. As a result, ensuring the authenticity and integrity of digital images has emerged as a critical challenge in digital forensics. In scenarios where active protection mechanisms such as watermarks or digital signatures are unavailable, passive (blind) image forgery detection techniques provide an effective alternative. This paper proposes a robust decision-level fusion framework for detecting digital image forgeries by integrating deep learning–based feature extraction with classical machine learning classifiers.

The proposed framework evaluates a diverse set of convolutional neural network (CNN) architectures, including spatial exploitation networks, lightweight models, and residual networks, to extract discriminative deep features from images. Experiments are conducted on three widely used benchmark datasets—MICC-F220, Columbia, and CoMoFoD. For each dataset, the top-performing CNN models are fine-tuned using different optimization strategies, including stochastic gradient descent with momentum (SGDM), Adam, and RMSprop. The extracted features are fused at the decision level and classified using a support vector machine (SVM).

Extensive experimental results demonstrate that the proposed fusion-based approach significantly improves detection accuracy and robustness while reducing false positive rates. The framework consistently outperforms individual deep learning models and existing state-of-the-art methods across all datasets, confirming its effectiveness for real-world image forgery detection applications.

Keywords: Digital image forensics; Image forgery detection; Passive image authentication; Decision-level fusion; Deep learning; Support vector machine; Convolutional neural networks

1. Introduction

Pictures play a vital part as important sources of data within the advanced domain. They serve as the fastest implies of passing on data and encouraging communication. Pictures are broadly utilized in a wide extend of areas, counting science, law, instruction, legislative issues, media, military operations, therapeutic imaging and conclusion, imaginative tries, computerized forensics, insights gathering, sports, logical distributions, news coverage, photography, social media, and trade. Over the final a few a long time, fake photos have had an affect on the application ranges portrayed over [1], [2]. The utilize of computerized pictures is significant over a few mechanical spaces and applications. Advanced cameras, individual computers, and progressed picture preparing computer program may be utilized to adjust and control photos. These instruments are able of being effectively balanced in measure and give different capacities for collaboration with the client. An picture may be promptly changed utilizing image-editing program to conceal or change pertinent or accommodating data inside the picture. Fraud location is to survey the judgment and legitimacy of a picture. Picture grafting, cloning, and tampering techniques are utilized to make fake pictures, coming about within the misfortune of image judgment. These carefully controlled photos are so mutilated that they are not identifiable, causing the misfortune of their genuineness[3]. Thus, analysts within the zone of picture preparing have centered their consideration on the confirmation of keenness and legitimacy of advanced pictures. Due to the advance in illustrations innovation and the accessibility of progressed equipment and computer program apparatuses, the creation of fake photos has developed much simpler. Advanced pictures can presently be easily adjusted . As of now, both specialists and unpracticed clients are able of proficiently controlling and altering with pictures [4], whereas the advancement of advances for distinguishing imitations is still in its early stages. Analysts have the issue of confirming the photos. The essential objective of altering or picture producing is to modify or create photographs in arrange to control certain information interior the image [5]. This modification of photographs may muddle the unmistakable markings and change the specifics of an picture in arrange to communicate wrong data [6]. The recreated portrayal, as seen in Figure 1, The user's content is. The picture shows four Iranian rockets, but upon closer examination, it gets to be apparent that as it were three of them are true. Also, a copy-move fraud procedure has changed two particular ranges of the picture by copying a few components and moving them somewhere else interior the picture.

Digital Images & Forgery

Advanced pictures are objects through which compelling communication can be carried out. It is simpler to communicate messages through pictures than through content. An picture may be characterized as a bi-dimensional work of the factors x and y. The work f(x, y) speaks to a picture, where x and y indicate the spatial arranges of the picture, and f speaks to the adequacy of the gray level or escalated at each x and y position. A advanced picture is characterized as an picture where the x and y facilitates has discrete or limited values. A pixel alludes to each person component that creates up a computer picture.

Figure 1. Concept of copy and paste using Gimp editor

A pixel is the fundamental building block of a computer picture. Pixels are sometimes referred to as picture elements, pels, and image elements. The value at a certain spot is finite, meaning it has a definite gray level or intensity. A digital picture may be defined as a finite matrix composed of rows and columns. The matrix values correspond to the pixel intensity values of the picture at each coordinate.

Types of Digital Images

Gray scale image: A gray scale image consists of different shades of gray between black and white. It is an 8-bit image where the intensity of each pixel ranges from 0 to 255. The value 255 represents complete white, while the value 0 stands for pure black. A binary image is one in which each pixel can only have one of two values, either 0 or 1. Usually, the pixel values for black and white are 0 and 255, but they can also be represented as 1 and 0. Binary images are commonly referred to as bi-level images because they are simple to process, making them very useful in various applications. An example of a color image is a digital photograph where each pixel contains information about the color of the image. This data is stored in RAM as raster maps. Each pixel holds information about three colors, known as RGB, which are used to determine the color's brightness and hue.

Image Features and Descriptors

Picture control or imitation location frameworks require particular highlights. An picture include alludes to any fundamental property or characteristic of an protest that makes a difference in recognizing it from other objects. Picture imitation location depends on a set of highlights, which can be extricated or created through a include extraction handle. The adequacy of location assignments is affected by the quality of these highlights, making this step basic. A highlight vector is utilized to store the whole set of extricated highlights. Each characteristic is characterized by one or more quantifiable factors. Nearby intrigued point coordinating is essentially based on picture highlights and their portrayals [7]. Characteristic highlights are those that are characteristic to the picture, such as brightness and surface. Manufactured highlights, on the other hand, are made through picture control. These incorporate components like recurrence spectra and adequacy histograms. A include ought to keep up its quality indeed when the picture experiences move operations, which is alluded to as move invariance. Rotational invariance implies that a highlight holds its unique shape notwithstanding of the point at which it is seen. Measure invariance suggests that a highlight remains steady in esteem in any case of its estimate. Invariance beneath reflecting, shear, and relative changes implies that highlights stay unaltered beneath these changes. These are called reflect invariants, shear invariants, and relative invariants, individually. Impediment invariance is the property of highlights that stay the same whether parts or all of an protest are covered up. Segregation requires that highlights are interesting and can recognize one question from another. The values of these highlights ought to be dependable, meaning comparable objects ought to have comparable highlight values. For highlights to be considered free, they ought to not have any critical measurable relationship with each other; changing one featureâ◎◎s esteem ought to not affect the values of others. A great highlight ought to be safe to clamor, artifacts, and other unsettling influences. Compactness is accomplished when the number of characteristics is negligible, permitting for proficient representation. Peculiarity implies the recovered features must contain sufficient data to form intrigued focuses clearly identifiable. Vigor guarantees that the highlight can withstand changes in lighting conditions, geometric varieties, concentrated, and picture twists.

Literature Review

Digital image forgery detection has attracted significant research attention over the past two decades due to the rapid growth of multimedia content and the ease with which digital images can be manipulated. Early research efforts primarily relied on traditional image processing techniques and handcrafted features to identify inconsistencies introduced during tampering operations. These methods typically focused on detecting copy–move forgeries, splicing artifacts, or resampling traces using block-based analysis, keypoint matching, and frequency-domain representations.

One of the earliest and most widely explored directions in image forgery detection is copy–move forgery detection (CMFD). Survey studies have highlighted the effectiveness of block-based and keypoint-based techniques for identifying duplicated regions within the same image. However, these approaches often suffer from high computational complexity and reduced robustness when images undergo post-processing operations such as compression, rotation, scaling, or blurring [8], [9]. To address these limitations, hybrid descriptors combining spatial and frequency-domain features were proposed, achieving improved robustness under geometric transformations [10], [11].

With the advancement of machine learning techniques, researchers began integrating statistical feature representations with classical classifiers. Mohammed et al. [12] demonstrated that combining copy–move detection with resampling analysis significantly improves forgery detection performance by reducing false positives. Similarly, Li and Zhou [13] introduced hierarchical feature point matching to enhance detection speed and accuracy in large images. Despite these improvements, handcrafted features remain sensitive to complex manipulations and often fail to generalize across diverse datasets.

The emergence of deep learning has fundamentally transformed image forgery detection research. Convolutional neural networks (CNNs) have shown remarkable capability in automatically learning hierarchical feature representations that capture subtle manipulation artifacts. Rao and Ni [14] proposed a CNN-based framework initialized with high-pass filters derived from spatial rich models to suppress image content and emphasize forensic traces. Their approach outperformed several state-of-the-art handcrafted methods on benchmark datasets. Kim and Lee [15] further demonstrated that CNNs can effectively detect image manipulation by focusing on high-frequency residual information rather than semantic content.

Subsequent studies extended deep learning approaches to address specific forgery operations such as median filtering and JPEG compression artifacts. Chen et al. [16] introduced a CNN-based forensic model for median filtering detection, achieving superior performance compared to traditional statistical methods, particularly on compressed images. Le-Tien et al. [17] proposed a low-complexity, data-driven deep learning model that leverages chrominance information for efficient forgery detection, significantly reducing computational cost without sacrificing accuracy.

Recent research trends emphasize hybrid and fusion-based strategies that combine deep features with classical machine learning classifiers. Ibrahim and Hasan [18] and Benmessahel [19] highlighted that deep feature descriptors extracted from pre-trained CNNs, when coupled with support vector machines (SVMs), yield enhanced detection performance and robustness. Transformer-based and attention-driven architectures, such as CMFDFormer, have also been proposed to capture long-range dependencies in forged regions, showing promising results on large-scale datasets [20].

Despite the progress achieved, several challenges remain unresolved. Many deep learning models are computationally expensive, require large labeled datasets, and exhibit limited generalization across different forgery types and datasets. Moreover, relying on a single model architecture may not sufficiently capture diverse manipulation artifacts. These limitations motivate the adoption of decision-level fusion strategies that integrate complementary deep representations to improve robustness and accuracy.

2. Materials and Methods

Image classification, object recognition, and segmentation based on language in images are just a few examples of the many Computer Vision applications that have extensively used CNNs over the past few years. When it comes to the design of CNNs, two main factors influence their effectiveness for vision tasks. First, CNNs make use of nearby pixels that are highly correlated, which supports the formation of clustered native connections. Second, feature sharing is a core aspect of CNN architecture, meaning a single filter is used to generate all output feature maps. These design ideas can also be beneficial for forgery detection [21].

In previous chapters, the results of forgery detection using spatial, lightweight, and residual models with the MICC-F220, Columbia, and CoMoFoD datasets were discussed. However, the image representations and geometrical transformations may affect the classification of forgeries using deep learning. In this chapter, a decision fusion model is proposed for image forgery detection on the MICC-F220, Columbia, and CoMoFoD datasets. The overall fusion approach proposed is illustrated in Figure 1. Initially, the deep learning models—AlexNet, GoogleNet, VGG16, VGG19, SqueezeNet, MobileNetV2, ShuffleNet, ResNet-18, ResNet-50, and ResNet-101—considered in the previous experiments are evaluated, and the top three models are selected for the fusion approach. These models are fine-tuned using optimizers such as SGDM, Adam, and RMSprop for the decision fusion approach. The machine learning algorithm SVM is used to make classification decisions using the fusion approach. The proposed algorithm, known as Algorithm 1, outlines the decision fusion approach applied to the MICC-F220, Columbia, and CoMoFoD datasets [22].

For each dataset, deep learning models are experimented with to identify the top three models—DL1, DL2, and DL3. These models are then combined to propose a decision fusion approach for image forgery detection using an SVM classifier. Predictions and accuracy are calculated for each decision fusion approach.

3. Results and Discussion

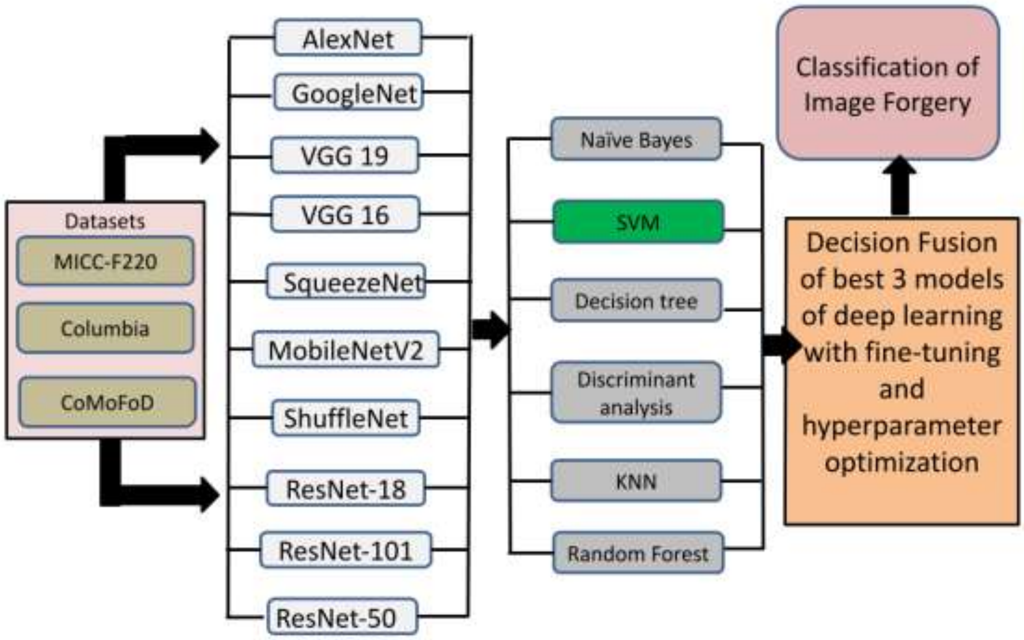

Figure 2. Decision Fusion approach

Decision Fusion of Dl Models for the Micc-F220 Dataset

Figure 2 illustrates the design of the deep learning-based fusion system proposed for the MICC-F220 dataset. Three deep learning models—SqueezeNet, MobileNetV2, and ShuffleNet—were chosen. These models were selected due to their high accuracy and precision. The system consists of three main components: data pre-processing, fusion model, and classification. During data pre-processing, the input image is prepared to meet the dimensional requirements of the fusion models. The classification stage uses a support vector machine (SVM) to determine whether the image is classified as forged or non-forged.

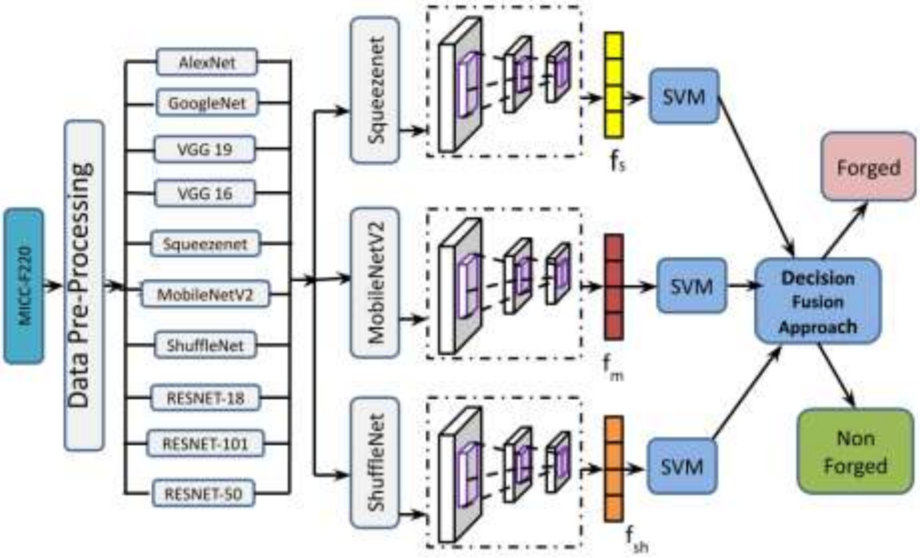

Figure 3. Decision Fusion Approach for the MICC-F220 Dataset

There are two stages to implementing the suggested system: pre-training and fine-tuning. The pre-trained implementation uses the pre-trained weights for classification instead of doing regularization. The categorization is subjected to regularization in the refined implementation. The feature maps from the SqueezeNet, MobileNetV2, and ShuffleNet are represented by the symbols fS, fM, and fS, H, respectively [23]. The fusion model makes use of the feature mapping fP that was pre-trained on the CNN output. As seen in Equation (1), this feature map fP is a composite of the feature maps acquired from the deep learning models.

$f_P = f_S + f_M + f_{SH}$------------(1)

As a local descriptor for the input patch, the fusion model employs feature map fP to extract picture features. Ysp fusion = f(x), where x is the patch in the input picture, represents the image for the fusion model. The local descriptor Yi is calculated using a sliding window of size w1 × w2 for a test picture size m × n, as shown in Equation (2). The input patches Xi are joined together to generate the new picture representation, which is provided by Equation (3), where s is the size of the stride used for converting the patches. The SVM classifies images as either forged or non-forged using this new image representation fsp fusion, as the feature map.

$Y_i = [\, Y_1 + Y_2 + Y_T] - - - - -(2)$

$f_{\text{spfusion}} = \frac{m-w_1}{s} + 1 * \frac{n-w_2}{s} + 1 - - - - -$--------(3)

Implementation and Results for the Micc-F220 Dataset with Decision Fusion Approach
Table 1 compared the accuracy of various implemented DL models with different ML algorithms for the MICC-F220 dataset and based on the best performance metrics, the outcomes of three DL models have been fused for the final results and decision. It is evident that the SVM ML algorithm with SqueezeNet, MobileNetV2 and ShuffleNet provides better results as compared to other DL models.

Table 1. Accuracy Result of various DL Models and ML Algorithms for the MICC-F220 Dataset

	ML Algorithms					
DL Models	Naïve Bayes	SVM	Decision Tree	Discriminant BAnalysis	kNN	Random Forest
AlexNet	72.27	92.72	88.18	83.63	87.27	91.81
GoogleNet	75.45	93.18	82.72	81.81	84.09	89.55
VGG16	71.81	92.72	85	82.27	86.81	87.72

VGG19	71.81	93.18	88.63	80.45	86.36	90.45
SqueezeNet	71.81	93.63	85.9	86.81	87.72	89.09
MobileNetV2	86.81	93.63	85.45	77.72	89.55	91.81
ShuffleNet	70.45	94.09	85.45	80.45	88.631	91.81
ResNet-18	72.73	92.27	87.73	83.18	84.55	90
ResNet-50	68.63	92.27	85	82.72	86.81	90.9
ResNet-101	74.54	91.81	82.27	82.27	89.54	89.09

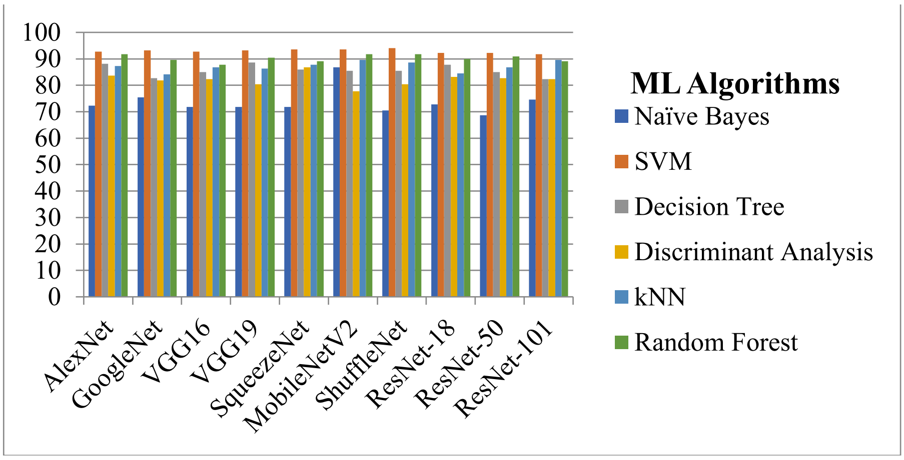

Figure 4. Accuracy Result of various DL Models and ML Algorithms

Hyperparameter Optimization for the Fine-Tuning Dl Models: Squeezenet, Mobilenetv2 and Shufflenet

As per the performance, best three models are considered for the optimization with various hyperparameters as shown in Table 2, Table 3 and Table 4.

Table 2. Hyperparameter Optimization with SGDM Optimizer

Parameter	**Value**
Momentum	0.9
Learn Rate Drop Period	20
L2 Regularization	1.0000e 04
Max Epochs	30
Mini Batch Size	22
Initial Learn Rate	1.0000e 03
Learn Rate Schedule	’piecewise’
Learn Rate Drop Factor	0.1
Gradient Threshold Method	’l2norm’
Gradient Threshold	inf
Reset Input Normalization	1

Table 3. Hyperparameter Optimization with Adam Optimizer

Parameter	Value
Initial Learn Rate	1.0000e 03
ϵ	1.0000e 08
Reset Input Normalization	1
Learn Rate Drop Period	20
L2 Regularization	1.0000e 04

Gradient Threshold Method	’l2norm’
Gradient Threshold	inf
Max Epochs	30
Mini Batch Size	22
Learn Rate Schedule	’piecewise’
Learn Rate Drop Factor	0.1
Gradient Decay Factor	0.9
Squared Gradient Decay Factor	0.999

Table 4. Hyperparameter Optimization with RMSprop Optimizer

Parameter	Value
Gradient Decay Factor	0.9
Squared Gradient Decay Factor	0.999
ϵ	1.0000e 08
Initial Learn Rate	1.0000e 03
Learn Rate Schedule	’piecewise’
Learn Rate Drop Factor	0.1
Learn Rate Drop Period	20
L2 Regularization	1.0000e 04
Gradient Threshold Method	’l2norm’
Gradient Threshold	inf
Max Epochs	30
Mini Batch Size	22
Reset Input Normalization	1

Datasets manage hyperparameters. It is conceivable for the SGD calculation to waver whereas taking after the ideal course of steepest plummet. To reduce this swaying, one approach is to incorporate a energy calculate within the parameter upgrade. Each parameter in an SGDM demonstrate is prepared utilizing the same rate of learning. A esteem of 0.9 is utilized for the slope rot figure to diminish swaying for the RMSprop and Adam optimizers. When preparing, the introductory learning rate is utilized. For Adam and the RMSprop optimizers, the esteem of epsilon is utilized to prevent division by zero within the organize parameter overhauls by including the balanced to the denominator. The total preparing set is navigated by the preparing calculation once amid an age, which is indicated as having a esteem of 30. The preparing set emphasess utilize a mini batch measure of 22, where 'value' could be a positive integer. It is possible to update the weights and survey the misfortune function's angle employing a mini-batch, which may be a parcel of the preparing set. For both the Adam and RMSprop optimizers, the rot rate of the squared angle moving normal could be a nonnegative scalar number littler than 1 [21]. To evacuate angle values that are as well tall, the slope edge approach is utilized. A nonnegative scalar esteem is the component for L2 regularization, which is additionally called weight rot. This command recalculates the normalization insights of the input layer amid preparing and resets the input layer's normalization.

Confusion Matrix of Fine-tuned DL Models with various Hyperparameter Optimizers for CoMoFoD Dataset

Table 5. Confusion Matrix of Fine-tuned DL Models with SVM ML Algorithm and various Hyperparameter Optimizers for CoMoFoD Dataset

	SGDM	Forged	0.3511	0.1489
		Non-forged	0.028	0.472
AlexNet	Adam	Forged	0.5	0

		Non-forged	0.5	0
	RMSprop	Forged	0.3353	0.1647
		Non-forged	0.3327	0.1673
	SGDM	Forged	0.4975	0.0025
		Non-forged	0	0.5
MobileNetV2	Adam	Forged	0.4682	0.0318
		Non-forged	0.0759	0.4241
	RMSprop	Forged	0.4975	0.0025
		Non-forged	0.2749	0.2251
	SGDM	Forged	0.4977	0.0023
		Non-forged	0.0003	0.4997
ShuffleNet	Adam	Forged	0.4943	0.0057
		Non-forged	0.0004	0.4946
	RMSprop	Forged	0.4923	0.0077
		Non-forged	0	0.5

The confusion matrix of SVM ML algorithm using the fine-tuned AlexNet, MobileNetV2 and ShuffleNet DL models for CoMoFoD dataset is summarized in Table 5. It is evident from Table 5 that the SGDM optimizer performance is much better as compared to other hyperparameter optimizers for the fine-tuned AlexNet, MobileNetV2 and ShuffleNet DL models.

Comparison of Performance Metrics of Fine-tuned DL Models and various Hyperparameter Optimizers for CoMoFoD Dataset

Table 6. Comparison of Metrics of Fine-tune Deep Learning Models for the CoMoFoD Dataset

DL Model & Optimizer	Precision(%)	Recall(%)	F1 score(%)	Accuracy(%)
AlexNet & SGDM	92.61	70.22	79.87	82.31
AlexNet & RMSprop	50.19	67.06	57.41	50.26
AlexNet & Adam	50	91.81	88.59	88.18
MobileNetV2 & SGDM	100	99.5	99.74	99.75
MobileNetV2 & RMSprop	64.4	99.5	78.19	72.26
MobileNetV2 & Adam	86.05	93.64	89.68	89.23
ShuffleNet & SGDM	99.93	99.54	99.73	99.74
ShuffleNet & RMSprop	100	98.46	99.22	99.23
ShuffleNet & Adam	99.91	98.86	99.38	99.39

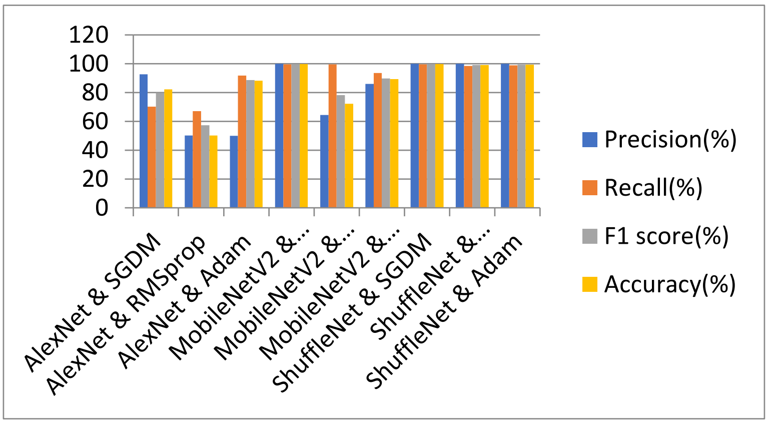

Figure 5. Comparison of Metrics of Fine-tune Deep Learning Models

Table 6 compares a number of fine-tuned DL models with respect to performance metrics such as accuracy, recall, F1 score, and precision. Using the SGDM hyperparameter optimizer with models like as AlexNet, MobileNetV2, and ShuffleNet yields clearly superior results when contrasted with other models and optimizers. The parameters of the fusion model may be fine-tuned by using the weight kernel initialization, as seen in Equation 4. The weights of the fusion model (Wf), the AlexNet model (Wa), the MobileNetV2 model (Wm), and the ShuffleNet model (Wsh) are represented in this equation. Equation (5) shows the initialization of the fusion model's weight, Wf. Instead of learning complicated picture representations, the fusion model may learn robust characteristics for detecting forgeries thanks to the initialization of the weights, which also serves as a regularization term.

$W_f = [\, W_{sj}\ W_{mj}\ W_{shj}] \ Where\ j = 1,2,3 - - - - - (4)$

$W_f = [\mathrm{W}_{\mathrm{s}}^{4\mathrm{k}-2}\mathrm{W}_{\mathrm{m}}^{4\mathrm{k}-2}\mathrm{W}_{\mathrm{sh}}^{4\mathrm{k}}] \ Where\ k = [j+1]mod11 + 1] - - - - (5)$

Possible Threats

When it comes to gadgets with restricted assets, creating and running profound and wide CNNs is no simple accomplishment. There are a plenty of hyper-parameters accessible for profound CNN, counting the enactment work, bit measure, layer organization, neuronal thickness, and more. Parameter tuning may be a challenging task due to the time required to assess a profound arrange and the choice of hyperparameters. Express detailing cannot mask the truth that hyper-parameter tuning is an instinctively propelled and time-consuming handle. CNN execution is altogether influenced by hyper-parameter choice. A convolutional neural network's (CNN) by and large performance is touchy to even small changes to the hyper-parameter values. That's why you would like an fitting optimization approach to bargain with the enormous plan challenge of hyper-parameter choice. Fast graphics preparing units (GPUs) are fundamental for effective convolutional neural arrange (CNN) preparing. Shockingly, CNN regularly falls flat to pinpoint the precise area of the altered locale within the picture. It is still exceptionally troublesome and resource-intensive to prepare profound and high-capacity plans. To speed up CNN inquire about, there's still a require for a few progressions in equipment innovation. Concerns approximately CNNs for the most part rotate on their run-time pertinence. Also, since of its tall computational fetched, CNN isn't well-suited for usage on compact equipment, especially in portable gadgets. To cut down on execution time and control utilization, a few equipment quickening agents are required for this. As profound convolutional neural systems (CNNs) are frequently misty, they might be troublesome to get it and clarify. Hence, in some cases it isn't simple to confirm them. Profound CNN based models are more computationally costly than other conventional calculations. They require much more information to perform well. CNN models are dark boxes in nature, so it is difficult to decipher the show. CNNs are computationally costly. CNN needs a tall sum of information to perform well, and it takes more time in preparing.

4. Conclusion

At last, the proposal proposed the choice combination based approach for the datasets MICC-F220, Columbia and CoMoFoD independently. The combination based approaches were based on the past evidential comes about of spatial misuse, light-weight and leftover models. For the MICC-F220 dataset, the Spatial Abuse based DL Models chosen are SqueezeNet, MobileNetV2 and ShuffleNet. These models were considered for the combination approach as they give way better exactness and precision compared to the others. The proposed choice based combination approach performed superior with the exactness of 100% as compared to the pre-trained DL models considered. Additionally, for the Columbia dataset, the lightweight based DL models chosen for the combination are VGG19, MobileNetV2 and ResNet50. The proposed combination approach performed way better with the exactness of 100% as compared to the pre-trained DL models considered. The leftover based DL models chosen for the choice based combination approach for the CoMoFoD dataset are AlexNet, MobileNetV2 and ShuffleNet. The proposed choice combination approach performed superior with the precision of 99.73% as compared to the pre-trained DL models considered.

Future scope

The proposed research of the fusion with multi-task oriented can be implemented further. In the future, image forgery can be extended with anomalies in video as well for the benefit of society in the form of a digital world. Hybrid algorithms can be developed to improve the execution time with minimum levels as deep learning makes use of huge numbers of resources and lots of time is taken in execution. The implementation of meta-heuristics can be done with the integration of deep learning models. The integration of Generative Adversarial Networks (GANs) and Emerging Capsule Network can be explored in the emerging forensics challenge and can be done to elevate the performance of the projected approach on various emerging and large images forgery and forensics datasets.

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