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IMAGE FORGERY DETECTIONBASED ON FUSION OF LIGHTWEIGHT DEEP LEARNING APPROACH

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Abstract: The popularity of capturing images has increased in recent years, as images contain a wealth of information that is essential to our daily lives. Although various tools are available to improve image quality, they are often used to falsify images, leading to the spread of misinformation. This has resulted in a significant increase in image forgeries, which is now a major concern.

Toaddressthis,adecisionfusionmethodisproposedinthisproject,whichuseslightweightdeeplearning-basedmodels for detecting image forgery. The proposed approach involves two phases that utilize pretrained and fine-tuned models, including SqueezeNet, MobileNetV2, and ShuffleNet, to extract features from images and detect image forgery. In the firstphase,lightweightmodelsareusedtoextractfeaturesfromimageswithoutregularization,while inthesecondphase, fine-tuned models with fusion and regularization are employed to detect image forgery.

Keywords: ImageForgery,DeepLearning,Lightweightmodels,ConvolutionalNeuralNetworks(CNN)

I. INTRODUCTION

Images and videos are widely used as evidence in various contexts, including trials, insurance fraud, and social media. However,theeasyaccessibilityofdigitaleditingtoolshasgivenrisetoquestionsabouttheauthenticityofimages. [1]Imageforensicsauthoritiesaimtodeveloptechnologicalinnovationstodetectimageforgeries,whichcanbeclassified into copy-move and splicing categories. [2]Various image forgery detection techniques have been proposed over the years,includingthosethatexploit theartifactsleftbymultipleJPEGcompressionandcamera-basedmethods.Detecting forged images is essential as they can mislead peopleand threaten individuals'lives. Previous studies haveattempted to identifycopy-pasteorsplicingofforgedareasinimagesbyextractingvariouspropertiessuchaslighting,shadows,sensor noise,andcamerareflections[3].Severalresearchers[4-9]haveassessedthecredibilityofimagesbydeterminingwhether they are authentic or forged. There are currently numerous techniques [7-15] available for identifying forged regions in images that rely on detecting artifacts left by multiple JPEG compressions and other image manipulation techniques. Camera-basedmethods[16]havealsobeenexplored,wheredetectionisbasedondemosaicingregularityorsensorpattern noise. The irregularities in the sensor pattern are extracted and compared for anomalies [17].

Using lightweight models is motivated by the need to prevent overfitting of convolutional neural network (CNN) architectures, as well as their ability to be easily deployed on resource-constrained hardware and learn enriched representations.[19-23] ShuffleNet [24] is particularly efficient as it generates more feature map channels for a given computationcomplexity budget, which encodesmoreinformation and iscrucialfor theeffectivenessof smallnetworks. MobileNet [21] utilizes deep-separable convolutions and has achieved state-of-the-art results, demonstrating its effectivenessacross a wide range of tasks. SqueezeNet, [25] on the other hand, isoptimized forfast processing speed in CNNsystemswithsignificantlyfewerparametersthanAlexNet,whilemaintainingstandardaccuracy.Theutilizationof lightweight models not only enables effective deployment on resource-restricted hardware but also helps in learning enriched representations.

This paper proposes a decision fusion method that uses lightweight deep learning models for detecting image forgery. The method consists of two phases: feature extraction from images using SqueezeNet, [25] MobileNetV2, [22] and ShuffleNet [24] without regularization in the first phase, and detection of image forgery using fine-tuned models with fusionandregularizationinthesecondphase.Themaincontributionsofthispaperincludetheproposeddecisionfusion- based system using lightweight models for imageforgery detection, the two-phase implementation of the fusion system usingpretrainedandfine-tunedweights,andthereductionoffalsematches,falsepositiverate,andultimatelyincreasing the accuracy of the approach due to the utilization of lightweight models.

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II. LITERATURESURVEY

Amerini et al. made progress in identifying and pinpointing single or double JPEG compression through the use of convolutional neural networks (CNNs). They tested different types of input for the CNN and conducted experiments to uncover any potential problems that require further study.

Xiao et al. developed a method for detecting splicing forgery using two components: a coarse-to-refined convolutional neuralnetwork(C2RNet) anddiluted adaptiveclustering.C2RNetinvolvestwo convolutionalneuralnetworks(C-CNN andR-CNN)thatanalyzeimagepatchesofdifferentscalestoidentifydifferencesinimagepropertiesbetweentampered and un-tampered regions. To reduce computational complexity, an image-level CNN replaces patch-level CNN in C2RNet, enabling the method to learn differences in various image properties for stable detection performance while reducing computational time.

Zhangetal.conductedastudyontwostages.Inthefirststage,theyusedaStackedAutoencodermodeltolearncomplex features for each patch. In the second stage, they integrated contextual information for each patch to improve detection accuracy.

Goh et al. proposed a hybrid evolutionary framework for performing a quantitative study to assess all features involved in image tampering in order to identify the best feature set. Following the evaluation and selection of features, the classificationmechanismisoptimizedforimprovedperformance.Thehybridframeworkcanalsodeterminetheoptimal multipleclassifierensemblesforthebestclassificationperformanceintermsofaccuracyandlowcomplexityfordetecting image tampering.

Changeetal.proposedanewalgorithmtodetecttamperedinpaintingimages,consistingoftwostages:suspiciousregion detection and forged region identification. The method searches for similar blocks in the image and uses a similarity vector field to eliminate false positives. It identifies forged regions using the multi-region relation (MRR) method and canidentifytamperedareaseveninimageswithuniformbackgrounds.Thealgorithm'scomputationalspeedisimproved by a two-stage searching algorithm based on weight transformation.

Lamba et al. developed a method for identifying duplicated regions in an image using discrete fractional wavelet transform. The approach involves dividing the image into fixed-sized overlapping blocks and applying the transform to each block to extract features. The feature vectors are then arranged in a lexicographical order and subjected to block matching and filtering to identify any replicated blocks. The method is capable of detecting both single and multiple duplicated regions in an image.

Linetal.developedamethodtodetecttamperedimagesbyanalyzingthedoublequantizationeffectinthediscretecosine transform (DCT) coefficients. This approach has several advantages, including the ability to locate the tampered region automatically, fine-grained detection, insensitivity to different types of forgery methods, ability to work without fully decompressing JPEG images, and fast speed. The experimental results on JPEG images are promising.

III. PROPOSEDSYSTEM

The proposed decision fusion architecture utilizes lightweight deep learning models, including SqueezeNet, MobileNetV2, and ShuffleNet, implemented in two phases: pre-trained and fine-tuned. In the pre-trained model implementation, pre-trained weights are used without regularization, whereas regularization is applied in the fine-tuned implementation to detect image forgery.

Thesystemconsistsofthreestages:datapre-processing,classificationusingSVM,andfusion.Theimageinthequeryis pre-processed based on the required dimensions of the deep learning models. The paragraph explains the use of deep learning models and the implementation strategy for regularization to identify image forgery.

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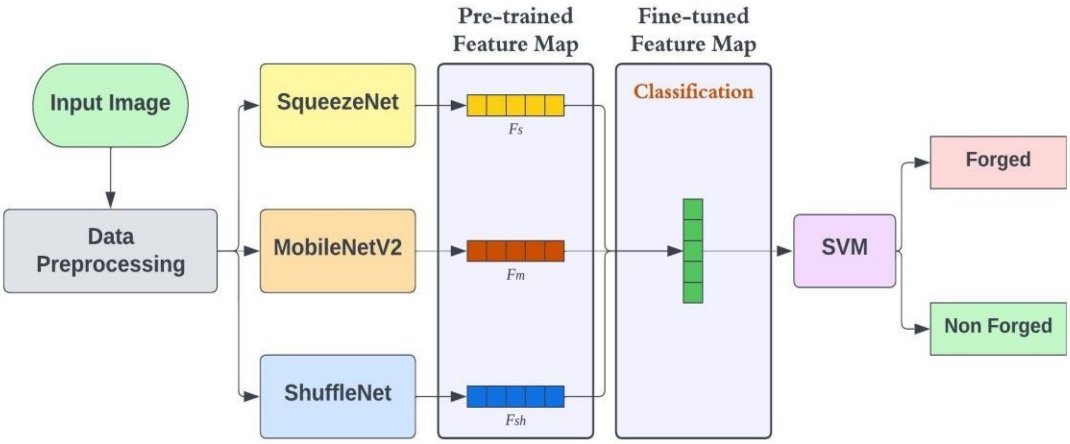

Fig.1FusionbaseddecisionmodelforForgeryDetection

DataPreprocessing:

The first stage of the forgerydetection process involves pre-processing thequery imageto determineif it isauthenticor fake.Thedimensionsoftheinputimageareadjustedtomeettherequirementsofthespecificmodelbeingused(227x227 for SqueezeNet, 224x224 for MobileNetV2 and ShuffleNet). The image is then pre-processed based on the required dimensions before being passed to each model, which generates a feature vector in subsequent stages.

LightweightDeepLearningModels:

TheSeverallightweightdeeplearningmodels,includingSqueezeNet[25],MobileNetV2[21],andShuffleNet[24],have been evaluated for imageclassification fusion.Thesemodelshavebeen widelyusedforimageclassification,andin this section,theyarebrieflydiscussed.Asummaryofthemodels,includingtheirdepth,parameters,andrequiredimageinput size, is presented in Table 1.

TABLEIPARAMETERSOFLIGHTWEIGHTDEEPLEARNINGMODELS

Models	**Depth**	**Parameters(millions)**	**Imageinput size**
SqueezeNet	18	1.24	227x227
MobileNetV2	53	3.5	224x224
ShuffleNet	50	1.4	224x224

Classifier:

TheproposedapproachusesSVMasaclassifier,whichisknownforitspopularityandefficiencyinbinaryclassification. The performance of the approach is evaluated at the image level using various performance metrics, such as precision, recall (TPR), false positive rate (FPR), F-score, and accuracy.

FusionandRegularization:

The proposed system uses lightweight deep learning models with pretrained weights for image forgery detection. The system is implemented as a fusion of the decision of these models. The input image is first passed to the lightweight models to obtain their respective feature maps. The feature maps from SqueezeNet, MobileNetV2, and ShuffleNet are denoted as f_s, f_m, and f_{sh}, respectively. The output feature map from the pretrained lightweight deep learning model is usedforthefusionmodel,whichisacombinationofthefeaturemapsobtainedfromthelightweightmodels.Thisfeature map, denoted as f_p, is obtained using Equation (1).

$$f_p=f_s+f_m+f_{sh} \tag{1}$$

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DesignFlow:

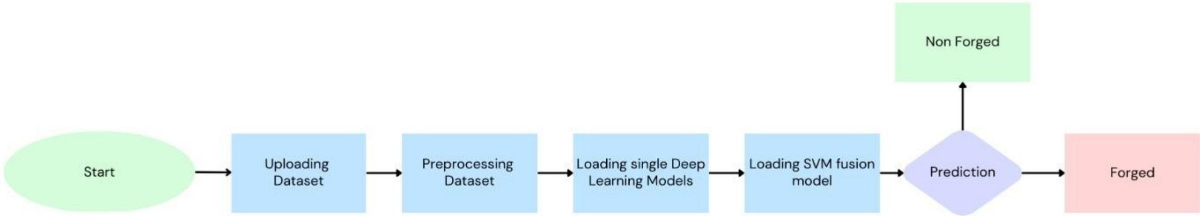

Fig.2Designflow

IV. IMPLEMENTATION

BaselineModules:

Thissystemcomprisesseveralmodulesaimedatoptimizingtheperformanceofimageclassificationalgorithms.Thefirst module enables the upload of the MICC-F220 dataset to the application. The dataset is pre-processed in the second module,whichinvolvesreadingalltheimages,normalizingtheirpixelvalues,andresizingthemtoaconsistentsize.The third module involves training three algorithms - SqueezeNet, MobileNetV2, and ShuffleNet - and extracting features fromthemtotrainthefusionmodel.Thepredictionaccuracyofallthreealgorithmsisevaluatedontestdata.Inthefourth module, features are extracted from all three algorithms to create a fusion model, which is then trained with SVM to improve accuracy. The fifth module involves extracting SIFT features from the images using the existing technique, training them with SVM, and evaluating prediction accuracy. The sixth module plots the accuracy graph for all the algorithms,whiletheseventhmoduledisplaystheperformancetableforallthe algorithms.Overall,thesemoduleswork together to enhance the accuracy of image classification algorithms and make them more effective for practical applications.

Dataset:

ThestudyemployedthepubliclyavailableMICC-F220dataset,whichconsistsof110nonforgedand110forgedimages in color format with 3 channels and dimensions ranging from 722 × 480 to 800 × 600 pixels. Figure 7.1 displays the images, with Figures 2a-2j representing forged images manipulated using 10 different combinations of geometrical and transformational attacks, and Figure 2k representing a nonforged image. The researchers randomly selected 154 images from the dataset for training and reserved the remaining images for testing.

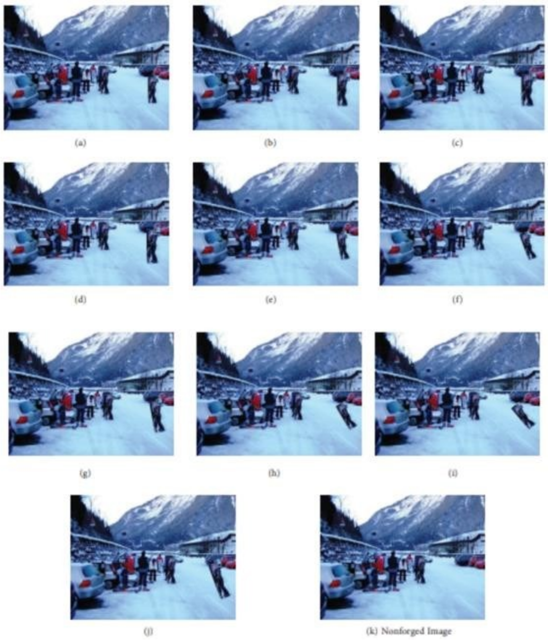

Fig.3Datasetwith10different combinationsofgeometricalandtransformationattacks;(a–j),forged;(k),nonforged images.

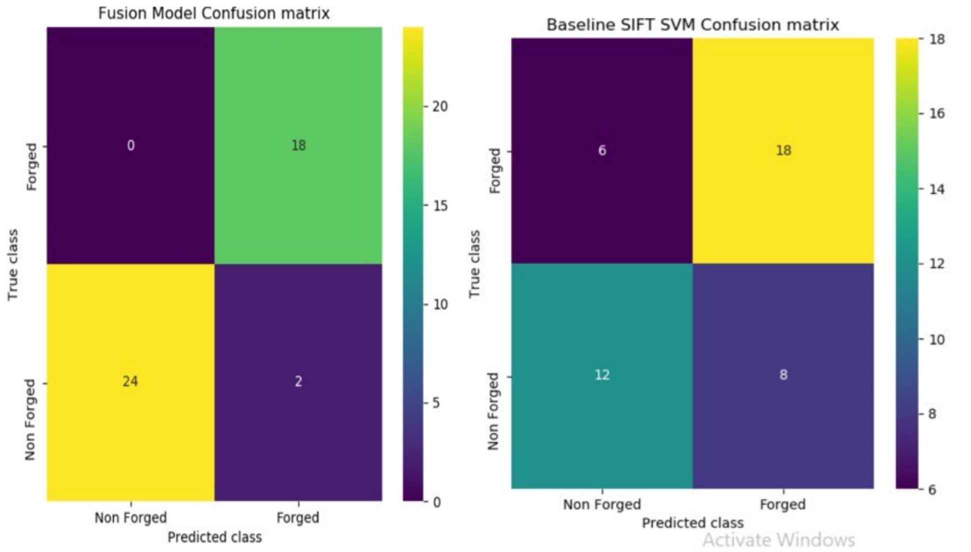

Fig.4ConfusionmatrixesoffusionmodelandbaselineSIFTSVM. TABLE

2PERFORMANCE COMPARISION

Method	**Accuracy**	**Precision**	**Recall**	**FScore**
ExistingSFITSVM	68.1	67.9	67.5	67.5
Only SqueezeNet	79.5	81.1	79.5	79.2
Only ShuffleNet	56.8	62.7	56.8	51.1
Only MobileNetV2	81.8	82.9	81.8	81.6
ProposedFusionModelSVM	95.4	95	96.1	95.3

V. CONCLUSION

Image forgery detection helps to differentiate between the original and the manipulated or fake images. In this paper, a decision fusion of lightweight deep learning based models is implemented for image forgery detection. The idea was to usethelightweightdeeplearningmodelsnamelySqueezeNet,MobileNetV2,andShuffleNetandthencombineallthese modelstoobtainthedecisionontheforgeryoftheimage.Regularizationoftheweightsofthepretrainedmodelsis implemented to arrive at a decision of the forgery. The experiments carried out indicate that the fusion based approach gives more accuracy than the state-of-the-art approaches. In the future, the fusion decision can be improved with other weight initialization strategies for image forgery detection.

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