Transfer Learning for Efficient and Accurate Image Forgery Detection

1st Dr.S.N.Tirumala Rao
Prof & Head, Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
nagatirumalarao@gmail.com

2ndPonnam Venkata sai teja
Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
saitejaponnam81@gmail.com

3rd kudari Abhiram
Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
kudariabhiram498@gmail.com

4th Shaik sharukh
Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
sharukhshaik761@gmail.com

5thM.Mounika Naga Bhavani
Asst.Prof, Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
medurimounika4@gmail.com

6th Dodda Venkatreddy
Asst.Prof, Dept of CSE,
Narasaraopeta Engineering College,
Narasaraopet-522601, Palnadu,
Andhra Pradesh, India
doddavenkatreddy@gmail.com

***Abstract*—Visuals are at the heart of information dissemination, especially on social platforms, but their credibility is not easy to ascertain because of their manipulability. Most of the forgery detection research done is mostly tailored to only a certain type of forgery and this limits its applicability in real life scenarios. The purpose of this study is to explore the use of transfer learning techniques of deep learning in improving the detection of forgeries. It is lso used for finding the differences in compression quality in pre-trained models by generating features from them. The method tests eight models for binary classification, and MobileNetV2 has the most accurate performance of 95% because of its lightweight nature and efficiency. Results of the experiment indicate that the accuracy and computational efficiency of the proposed method is satisfactory and surpasses the performance of existing state of the art approaches and can therefore be used in development for environments and scenarios where resources are limited.**

***Index Terms*—Intensive fake detection Error level analysis (ELA), transfer learning, through pretraining of models**

I. Introduction

At social media sites, and especially on such popular ones as Facebook and Twitter, altered pictures are used with the aid of deceiving and wrong information – in other words, image manipulation and photo fraud is a popular problem. The high number of uses of these graphics editing programs making forgeries difficult to the average person because they are undetectable through naked eye. Regarding this matter, this paper proposes a new technique called ELA-CNN that makes use of both ELA and CNN to accomplish the detection of digital image forgery. The intended technique should be able to deal with several forgery types – crack, splicing, and copy-move forgeries even when adversities like noise, scale and rotations are encountered[1]. This work is centered on establishing a dual mode multi-type forgery detector; improving accuracy and accelerated computation through models that have been trained prior and deployed, applying eight models that have been pre-trained where MobileNetV2 performed best. This method is extensively evaluated using the largest internal databases called CASIA2, showcasing its robustness and suitability for the operational environment.
The remaining parts of the paper will be structured in the following way: In section II, a detailed literature review about the previously developed digital forgery attack detection and prevention techniques will be provided. Section III describes the conceptual design of the research, which includes data collection, model development, and how the model is implemented. Section IV presents the obtained experimental results and their analysis by comparison with the recent developments in the field. In the last section, Section V, the authors draft the main conclusions of the paper and indicate the prospects of its further enhancement[1].

II. LITERATURE SURVEY

Gupta et.al [2] Through extensive research over time several methods have been developed for the detection of interstitial images. Often the traditional methods start go for artefacts and Na¨andotherclassification methods ıve Bayes and Support Vector Machine(SVM). Beyond Hand current developments use deep learning where.Convolutional and deep neural networks(CNNs).Often added to previously trained programs through transfer learning. A review of these developments that this section focuses on in terms of pre-trained web-based methods and deep learnin including convolutional and deep neural networks **(CNNs)**. Which are often combined with transfer learning and pre-trained models

Reviewing these developments in which this section focuses on pre-trained network-based methods and deep learning[2].

Jewelry neural network based methods

Deep Neural Networks (DNNs): Ribeiro et.al [3] are very adept at analyzing image networks because they are themselves very good at learning very complex objects.Several methods have been developed using deep learning to distinguish between fake and real fields in complex data mining models.Mallick et.al [4] DNN-based methods have been developed for splicing detection which show resistance to JPEG compression pixel of hybrid models along with other methods incorporating features such as conditional random fields (CRF) and spatial rich model (SRM) and CNN-combine multi- in the. resolution features of long-short-term memory (LSTM) networks for layered network detection and a minimum parameter CNN designed for real-time detection.
Deep learning methods based on lightweight CNN and super boundary-to-pixel direction (super-BPD) segmentation have been proposed to improve detection accuracy for copy-walk networks Furthermore. Some methods to handle copy-walk splicing fraud simultaneously by L2 regularization or twice -Use U-Net and other images with image compression techniques.

Pre-Trained Network-Based Techniques

Methods using pre-trained communication systems In particular transfer learning with pre-trained networks has gained popularity in image network research. Using the powerful subtraction methods such as Mask R-CNN with MobileNet-V1 and ResNet50v2 combined with YOLO CNN weights have been used for splicing detection[4].
Copy drive detection and splicing are two functions for multi-function networks such as FBI-Net which combines a Dilated Frequency Self-Attention Module (DFSAM) and a Discrete Cosine Transform (DCT) Some methods for correctly detecting a copy drive SmallerVGGNet and use use pre-trained models such as MobileNet-V2 while others mix generative anti-networks (GANs) and DenseNet models for better feature extraction and classification.

Summary and Objectives:

High accuracy of copy-walking and splicing networks remains elusive despite tremendous progress especially when both have been addressed. The main problem with deep learning models is their reliance on large datasets, whose relocation contributes to a significant reduction in learning. However there are still issues such as model complexity, heterogeneous performance evaluation, blurring, rotation, scaling and lack of attention to preprocessing methods etc. These problems drive the development of a more effective model that uses transfer learning to overcome these drawbacks [5]. A study focusing on the difference in compression between original and fake blocks showed the fake detection efficiency of CNNs.Even with 92.3% accuracy there is still an opportunity to evolve in simplifying the model for important performance measures such as recall, precision, F1 scores,and avoiding false positives and negatives. It will be mentioned these metrics are discussed in more detail in subsequent sections.

III. PROPOSED SYSTEM

The first step in the developed methodology is a complete set of data preprocessing steps that helps in the roper preparation of the dataset for training procedures. The image processing step generates processed images which are the primary inputs of the model that is used in the splicing or other copy-move operations. This step is also referred to as "error level analysis": one of the techniques used to highlight the regions that were more aggressively compressed than others . To meet the requirement of size, images were all artificially resized to 224x224 and the pixel values were all transformed between 0 and 1 range. The researchers also used these approaches to enlarge the variety of the data and encourage the capacity of the model even further. More specifically, a combination of random rotations, flips, zoom and brightness alterations, allow this model to be trained on several typical features associated with the real life domains' images and to reduce the chances of severe overfitting. Since the Model employs transfer learning, it has pre-trained CNN models such as MobileNet V2, ResNet50, and DenseNet. The top layers of these models would be customized and used in the setting of two tagged categorisation tasks while removing the original top layers completely and applying dropout in order to cut down any excessive fitting. Training is achieved using the adam optimizer; a binary cross-entropy loss function, and the first learning rate of 0.001. To avoid overfitting, we adopt an early stopping strategy where validation loss is observed. In this case, if the validation loss does not show any improvement over a period of 5 epochs, further training is stopped[6].
The training step is not taken lightly and there are graphical representations of training loss, validation loss, training accuracy and validation accuracy metrics over epochs in order to evaluate the performance of the model. These graphs are useful to show how the model improves with time and if there are any overfitting or underfitting instances. For example, an early stopping technique is applied to ensure best generalization of validation performance is achieved when any more training does not seem to be useful, as presented by the two diverging loss curves. Hereafter, the model post training is assessed using precision, recall, F1 score, and confusion matrices in order to test its performance in detecting forgeries[6].

PREPROCESSING

Before model training the data set is preprocessed to make the images ready for analysis. Application of the method of analysis (ELA) is an important step in identifying possible image changes. [7] ELA calculates the difference between the original and the amplified version to reveal differences.

Fig. 1. **Some of the images in dataset**

Areas with different compression levels are highlighted by this phenomenon which can indicate digital transformation. ELA is applied to images in both tampered ('Tp') and real ('Au') folders making it easier to edit and encode data to train the model to classify the images in the truth of the matter from fig 1 and fig 2

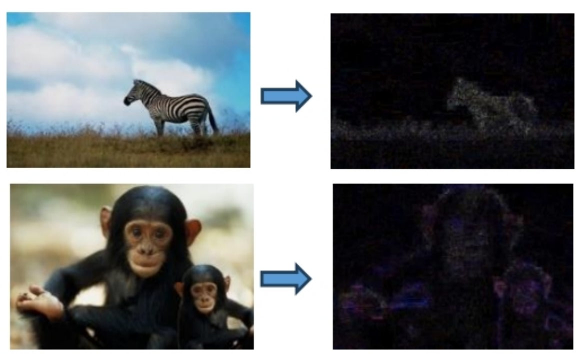

Fig. 2. Images Before And After ELA

MODEL BUILDING

The ELA-CNN model however has some drawbacks which need to be mentioned even as it outperformed most models in terms of image tampering detection. One of their drawbacks is its dependence on ELA; which is good in detecting various compression levels, but performs poorly when trying to detect re-compressed uniformly tampers. This renders the model ineffective against advanced forgery methods which apply Gaussian smoothing or adaptive compression during the post-processing phase. Also, though ELA-CNN has demonstrated better accuracy and execution speed than architectures such as VGG16 and ResNet, the reasons for this success are not far-fetched since its architecture was simple and designed for the binary classification task. The model employs pre-trained layers of MobileNetV2 which are specifically developed to detect such small scale contours with a small amount of parameters, leading to a shorter training time and better generalization for the CASIA2 dataset[7].

For the purpose of this work, all models have been compared in controlled experiments where the same datasets and settings of hyperparameters, such as learning rates and augmentation, have been used for training[8]. Nevertheless, these were still the cases when deeper models such as ResNet50 and ResNet101 appeared to have lesser performance due to overfitting and higher architectural complexity which might not suit the relatively small CASIA2 dataset. On the other hand, the relative performance pr the ELA-CNN model can be attributed to a more efficient use of resources, a simpler architecture and the combination of ELA that provides important features to improve the performance of forgery detection. It should be noted, though, that the scale of variations present in the dataset and the number of forged examples were limitations for the model in detecting cross domain attacks, suggesting that further development is required in terms of the ability of the model to withstand sophisticated forgery methods and harsh real-world scenarios from fig 3[9].

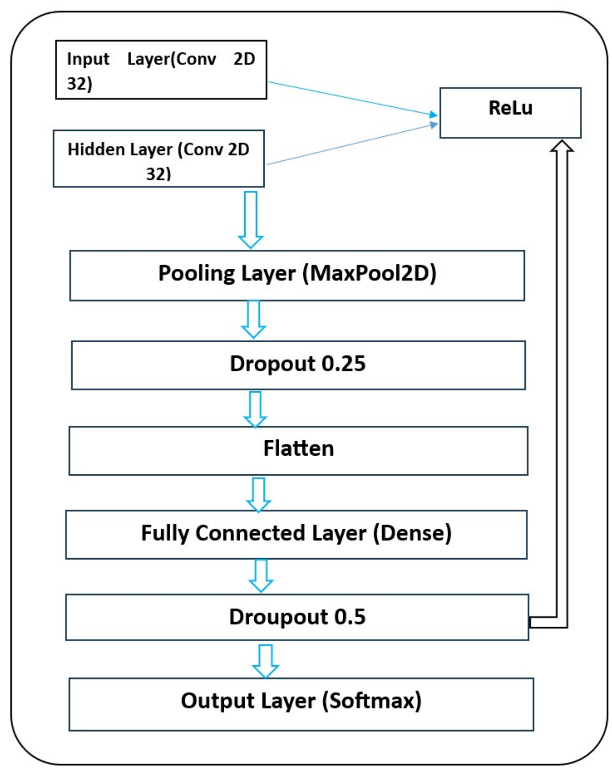

Fig. 3. Model Architecture

Overqualification is the performance of the independent test data is displayed on the validation loss curve. For image grids the dataset consists of 32 filters and 5x5 kernels each consisting of two convolutional layers. By extracting specific features from images this technique facilitates the identification of authentic and deceptive features from fig

4.[10]
Two convolutional layers with 32 filters and 5x5 kernels each are used to detect image grids. By extracting specific features from images this technique facilitates the identification of Authentic and deceptive features[11].

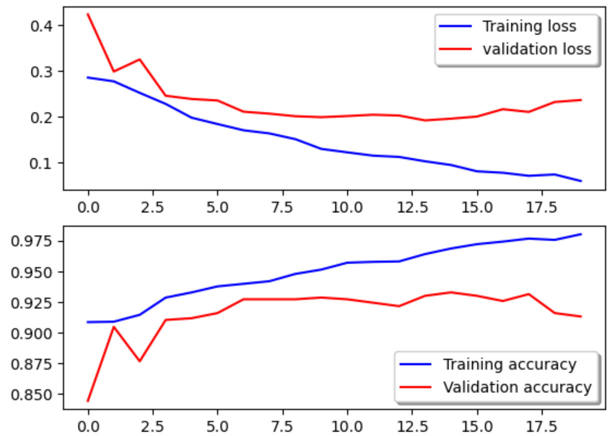

Fig. 4. ELA and CNN model

To prevent overfitting Early stopping technique used in the ELA-CNN model was trained over the course of 20 epochs using initial locations. The consistent decline in training loss and epoch 15 point to overfitting. In addition the X-axis depicts epochs and the Y-axis displays precision.This was the direction that both training and validation accuracy improved in plateauing about the same time as validation accuracy. With speed the model achieved a balance between performance and generalization, yielding training accuracy of 0.975 and validation accuracy of 0.92[12].

A. *Confusion matrix*

Confusion matrix is One of the most important analytical tools for image network recognition model is confusion matrix. Determine the percentage of correct and incorrect predictions for the final outcome by using below fig 5[13]. Positive True (TP): The model correctly predicted the image because (1,1) is in the matrix[14]. False positive (FP): The model incorrectly interpreted an image as false when it was true, even though it was represented by (0,1) in the matrix.True Negative (TN): The model defines the image as correct if it is in the matrix (0,0). Deep learning of the ELA-CNN model can provide a solid foundation for understanding and classifying which improves the accuracy of image mesh network detection using Convolutional Neural Networks (CNN) and Error Level Analysis (ELA)[15]. Integrating models to manipulate images properties and diverse datasets With an impressive accuracy of 93.13%, the ELA-CNN model outperforms methods such as VGG16 (86.26%)

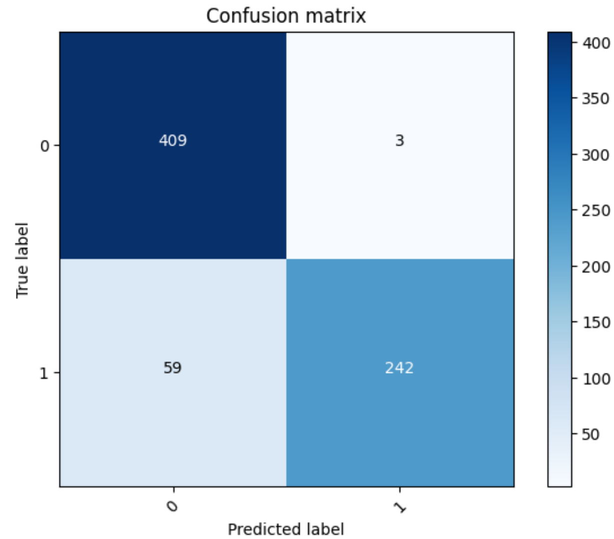

Fig. 5. Confusion Matrix

ResNet50 (20%)(42.22%), and ResNet101 (57.78%) resulting in improved accuracy and reliability. This proves that this is the best way to identify digital image interfaces. Perfthat ELA CNN achieved optimal balance between precision recall and resulting in a high F1 score from fig 6,7,8,9[16].

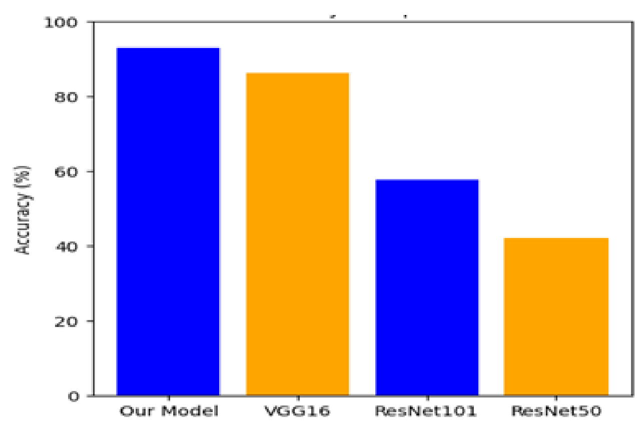

Fig. 6. Accuracy Comparision

Everything was extracted CNN and ELA together work very well to display image grids and are shown to be distinct from real grids. He noted how well the model performed in classification tests and cited the deep model design, large dataset training, flexibility in image analysis, and impressive overall efficiency of the methods Important features a we should note his recall, accuracy, and credit for F1 scores. [13] Improved classification accuracy is indicated by higher F1 scores with higher recall and accuracy. ResNet50 and ResNet101 have higher recall and accuracy [14]. But Figures 7, 8, and 9 show that the ELA-CNN model outperformed all

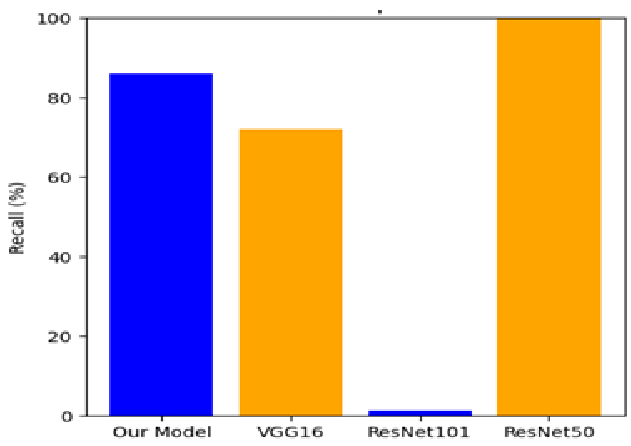

Fig. 7. Recall Comparision

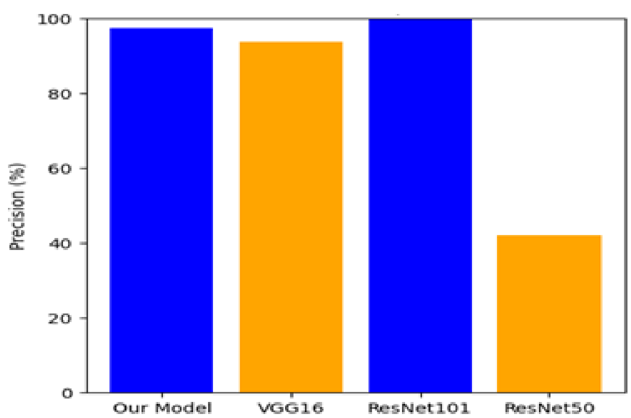

Fig. 8. Precision Comparision

three metrics[17]

Model	Class	Precision	Recall	F1-Score	Accuracy
CNN	Real	98.78%	80.4%	88.64%	99.85%
CNN	Fake	98.24%	80.1%	88.32%	99.62%

TABLE I
CLASSIFICATION REPORT

Total Trained Images	Correctly Predicted Images	Accuracy
2064	2059	99.76%
7437	6352	85.41%
9501	8411	88.53%

TABLE II
ACCURACY FOR DIFFERENT TRAINABLE IMAGES

In this project datasets and code were stored in Google Drive and models were trained and analyzed using Google

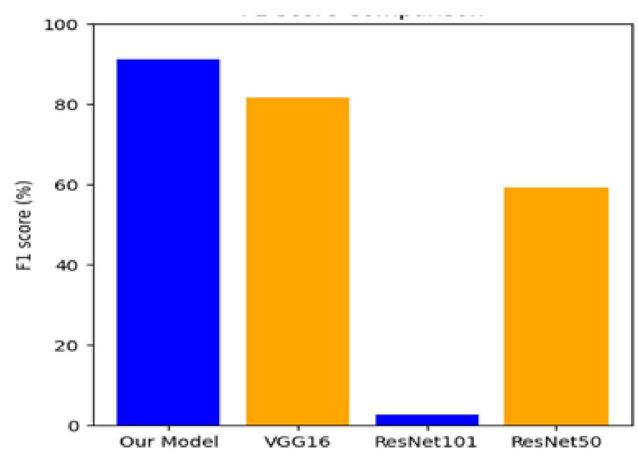

Fig. 9. F1-Score Comparision

Collab. At first we ran the code on the CPU. Which slowed down the execution time especially when training deeper neurons. We upgraded Colab premium to a T4 GPU to improve performance by using above table I and table II. Which significantly increased processing speed. These changes significantly shortened the training and evaluation time and made it easier to handle complex models and large data sets due to the speed of execution that allowed us to optimize and run the model repeatedly from fig 10[18].

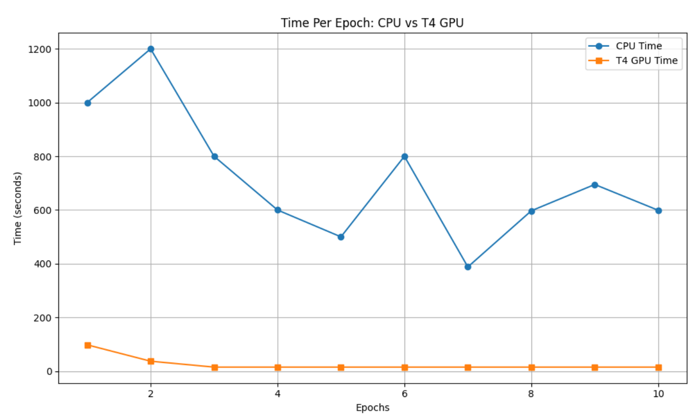

Fig. 10. Time For Epoch: cpu vs T4 Gpu

IV. CONCLUSION AND FUTURE SCOPE

The ELA-CNN model is a helpful tool for identifying image mesh networks due to its proven ability to distinguish between real and deceptive images. The performance of the model is clearly demonstrated by the confusion matrices and training parameters which also shows the accuracy of the model in image classification The CASIA2 dataset was used to train and test the model. With nearly 93% in search accuracy ELA had the highest ratings found by CNN. The implementation of the ELA-CNN method is simple and provides high accuracy with few training parameters making this model economical in terms of computation and training Besides in it . It reduces memory significant number of controls and helps to overcome system complexities especially when running concurrently on a run-by-run basis Run image splicing that is accurate for the current task when it comes to imaging operations and the ability to it maintains high accuracy with low parameters is more efficient and less expensive. Due to these advantages ELA-CNN is strongly recommended for image mesh network recognition tasks especially those requiring accurate and efficient knowledge. Future research should look at video and computer based lie detection methods.

V. REFERENCES

[1] Y. 1. Y. Rao, J. Ni, and H. Zhao, "Significant learning adjacent descriptor for picture joining area and localization," IEEE Get to, vol. 8, pp. 25611– 25625, 2020.

[2] Abhishek and N. Jindal, "Duplicate move and joining fraud location utilizing profound convolution neural arrange, and semantic division," Mixed media Instruments Appl., vol. 80, no. 3, pp. 3571–3599, Jan. 2021.

[3] S. Gupta, N. Mohan, and P. Kaushal, "Detached picture forensics utilizing all inclusive strategies: A audit," Artif. Intell. Rev., vol. 55, no. 3, pp.1629– 1679, Jul. 2021.

[4] W. H. Khoh, Y. H. Throb, A. B. J. Teoh, and S. Y. Ooi, "In-air hand motion signature utilizing exchange learning and its imitation assault," Appl. Delicate Comput., vol. 113, Dec. 2021, Craftsmanship. no. 108033.

[5]. K. B. Meena and V. Tyagi, "Picture Joining Fraud Location Methods: A Audit," Cham, Switzerland: Springer, 2021.

[6] K. Kadam, S. Ahirrao, K. Kotecha, and S. Sahu, "Discovery and localization of numerous picture grafting utilizing MobileNet v1," IEEE Get to, vol. 9, pp. 162499–162519, 2021.

[7] Singh, R., Agarwal, A., Khan, M. K. (2021). Picture impersonation revelation utilizing gathering of convolutional neural frameworks. Journal of Visual Communication and Picture Representation, 73, 102893.

[8] K. D. Kadam, S. Ahirrao, and K. Kotecha, "Productive approach towards discovery and distinguishing proof of duplicate move and picture grafting imitations utilizing veil R-CNN with MobileNet v1," Comp. Intell. Neurosci., vol. 2022, pp. 1–21, Jan. 2022.

[9] In 2020, Li, B., Li, X., and Huang, H. formulated a novel approach for picture fraud location, utilizing a lightweight convolutional neural arrange to upgrade effectiveness and precision in recognizing controlled images.

[10] Ribeiro, A., Oliveira, M., Pinto, A. (2020). Fighting Deepfake Picture Control Utilizing MultiClass Area Convolutional Neural Frameworks. In Methods of the all inclusive Joint Conference on Neural Frameworks (IJCNN) (pp. 1-8).

[11] S. Jabeen, U. G. Khan, R. Iqbal, M. Mukherjee, and J. Lloret, "A profound multimodal framework for provenance sifting with all inclusive imitation discovery and localization," Interactive media Apparatuses Appl., vol. 80, no. 11, pp. 17025– 17044, May 2021.

[12] D. Mallick, M. Shaikh, A. Gulhane, and T. Maktum presented a strategy for identifying copymove and grafting picture imitation utilizing CNN. Their work was displayed in Proc. ITM Web Conf., vol. 44, 2022, Craftsmanship. no. 03052.

[13] In another think about, M. N. Abbas, M. S. Ansari, M. N. Asghar, N. Kanwal, T. O'Neill, and B. Lee proposed a lightweight profound learning demonstrate for identifying copy-move picture fraud, especially centering on post-processed assaults. This inquire about was displayed at the IEEE 19th World Symp. Appl. Mach. Intell. Informat. (SAMI) in Jan. 2021, pp. 125–130.

[14] C. D. P. Kumar and S. S. Sundaram created a novel method for copy-move fraud location utilizing metaheuristics combined with ideal profound exchange learning. Their discoveries were distributed in Intell. Autom. Delicate Comput., vol. 35, no. 1, pp. 881–899, 2023.

[15] N. Krishnaraj, B. Sivakumar, R. Kuppusamy, Y. Teekaraman, and A. R. Thelkar planned an computerized profound learning-based combination show for recognizing copy-move picture imitation. Their work was distributed in Comput. Intell. Neurosci., vol. 2022, pp. 1–13, Jan. 2022.

[16] Kadam, K.D., Ahirrao, S., and Kotecha, K. (2021). Presenting the Different Picture Joining Dataset (MISD): A Comprehensive Asset for Different Grafting. Distributed in the diary Information, volume 6, issue 10, on page 102.

[17] Agarwal, R., Verma, O.P., Saini, A., Shaw, A., Patel, A.R. (2021). The approach of profound learning-based. In Imaginative Information Communication Innovations and Application. Singapore: Springer.

[18] Ashgan H. Khalil; Atef Z. Ghalwash; Hala Abdel-Galil Elsayed; Gouda I. Salama; Haitham A. Ghalwash: Approach of Enhancing Digital Image Forgery Detection Using Transfer Learning: IEEE 2023