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# **Image Morphing Detection: A Fusion Approach with Deep Learning Models**

**Mrs. Swathi Turai<sup>1</sup>, Vaishnavi Deva<sup>2</sup>, Neha Kandikonda<sup>3</sup>, Pradeep Saranga<sup>4</sup>, Subramaniam Jekkula<sup>5</sup>**

Assistant Professor, Dept. of CSE-Data Science, ACE Engineering College, Hyderabad, Telangana, India<sup>1</sup>

IV B. Tech Students, Department of CSE (Data Science), ACE Engineering College, Hyderabad, India<sup>2,3,4,5</sup>

**ABSTRACT:** As digital technology has grown quickly, it has become easier to change and misuse images, which raises serious questions about the accuracy of visual data. So, figuring out if a picture is real or fake has become a big deal in the field of digital forensics.

This paper introduces a deep learning-based approach that integrates the ResNet50v2 architecture with YOLO convolutional neural network (CNN) weights to precisely identify forged images. The proposed system works on groups of images and learns from the MICC-F220 dataset, which has both real and fake images. The system's goal is to make forgery detection more accurate, reliable, and faster by using powerful deep learning models and a well-organized dataset.

The new method is a strong and effective way to find altered images, which helps make digital security better. It is very helpful for media forensics, checking the accuracy of social media posts, and police investigations because it helps make sure that digital visual content is credible and trustworthy.

**KEYWORDS:** Image Forgery Detection, ResNet50v2, YOLO, Deep Learning, MICC-F220 Dataset, Image Splicing, Copy-Move Forgery.

## **I. INTRODUCTION**

Digital imaging technologies and AI-powered editing software are always getting better, making it easier and more accessible than ever to change pictures. Because of this, the chances of digital images being changed or faked have gone up a lot. Most traditional ways to find fake images rely on manually created features, statistical methods, or metadata analysis. These methods worked well in the past, but they often have trouble finding advanced manipulations like copy-move forgery and image splicing, especially when the changes are small and don't leave many visible traces. This shows how badly we need an automated, reliable, and computationally efficient solution that can tell the difference between real and fake images in real life.

This study presents a framework based on deep learning for detecting image forgery in order to solve this problem. The suggested system uses the ResNet50v2 architecture and pre-trained YOLO convolutional neural network (CNN) weights through transfer learning. This combination makes the model better at finding useful features in images, improves classification accuracy, and keeps computation efficient. The model is trained and tested with MICC-F220 dataset which includes both real and forged images. Its performance is measured through commonly accepted parameters like accuracy, precision, recall and F1-score to provide dependable and consistent results.

The proposed framework responds to the growing abuse of manipulated digital images in the spread of false information, as well as in the fabrication of evidence and alteration of media content. By using modern methods of deep learning and computer vision, the system successfully detects typical types of picture forgery such as copy-move and splicing attacks. Furthermore, the architecture is designed to be scalable and flexible, making it appropriate for practical uses in areas of interest such as digital forensics, social media analysis, journalism, and cybersecurity. Given its modular structure it is also possible for future expansion to real-time detection and cloud-based verification platforms, which together would see the final development of enhanced digital trust and authenticity in visual information.

## II. LITERATURE SURVEY

### └ **Digital Image Forgery Detection Using Passive Techniques – Hany Farid, 2009**

This is a foundational survey of passive image forgery detection techniques which are based on pixel-level statistical analysis, compression artifacts and lighting inconsistencies. These techniques need not refer to any previously embedded information and work by studying natural traces left in digital images. Although these methods laid the way for digital image forensics, they are less effective against modern manipulations that are of high resolution or have been generated using artificial intelligence and closely mimic the properties of natural images.

### └ **CNN for Image Forgery Classification – Yao Rao & Ni, 2016**

This study introduced convolutional neural network (CNN) models for classifying images as either authentic or forged. By automatically learning deep features from image data, the model aimed to identify subtle artifacts introduced during tampering. While the approach showed promising results on limited datasets, it faced challenges in handling large-scale data, managing dataset imbalance, and maintaining robustness across various forgery techniques and post-processing operations.

### └ **Copy-Move Forgery Detection Using Deep Convolutional Features – Jahandar Bappy et al., 2021**

The model utilizes both local and global features of the image in order to detect the duplicated regions using a fully convolutional structure. It was able to show good performance on benchmark datasets like MICC-F220 and CoMoFoD. However, its effectiveness was reduced when images contained geometric transformations such as rotation, scaling, and/or complex distortions.

### └ **Hybrid Deep Learning Model for Image Splicing Detection – Peng Zhou et al., 2021**

This particular research was a hybrid approach of features that were handcrafted (noise patterns, texture descriptors), features that were extracted deep through ResNet architectures. The combination of traditional and deep learning methods improved the accuracy of the detection, especially on the CASIA v2 dataset. Despite its better performance, the model's reliance on handcrafted preprocessing steps makes it difficult to adapt the model to new datasets and previously unseen forgery techniques.

### └ **Forgery Detection Using ResNet50 Transfer Learning – Li Wei et al., 2023**

In this work, the ResNet50 transfer learning technique was used to improve the detection of image forgery. The model was fine-tuned on datasets such as MICC-F220 and CASIA resulting in improvement in the convergence speed and detection accuracy. While the results were encouraging, the study pointed to declining performance as it was tested on underlying datasets it hasn't encountered before, denoting the limitations on generalization ability.

### └ **Lightweight CNN Models for Real-Time Forgery Detection – Amit Patel & Rina Mehta, 2023**

This work studied lightweight architectures MobileNet and EfficientNet for forgery detection on mobile and embedded platforms. The models did a good job of accuracy competitiveness while having significantly lower computational cost and model size. However, they had problems with identifying very realistic or professionally edited forgeries.

### └ **Comprehensive Review of Image Forgery Detection Using Deep Learning – S. Natarajan et al., 2025**

This recent review paper analysed advancements for deep learning-based forgery detection methods. It benchmarked different architectures such as CNN, ResNet, DenseNet, and YOLO on different datasets such as CASIA, CoMoFoD, and MICC-F220. The authors concluded that hybrid and fusion-based models are a better balance between detection accuracy and computational efficiency, suggesting a promising direction of future research.

## III. EXISTING SYSTEM

Existing image forgery detection uses the methods which classifies into three different categories: traditional image processing techniques, machine learning-based methods and deep learning models.

Traditional approaches are based on investigating the low-level image features of pixel intensity variations, edge information and color inconsistencies. Methods such as edge detection, histogram analysis and statistical comparisons are commonly used to detect basic manipulations. While these methods can identify some simple changes like direct

copying and pasting, they are not strong enough to identify advanced changes or AI-generated forgeries, detecting changes that are small and well done.

These models depend on the manual extraction of features of faces, such as description of textures or color histograms or noise patterns, to make the distinction between the original and false photo. Although they tend to be more accurate than purely traditional methods, the accuracy of these methods is strongly dependent on effective feature engineering. This reliance creates a lack of flexibility and it is hard to generalize over diverse types of forgery or over types of forgery which have not been seen before.

More recently, approaches based on deep learning (specifically, Convolutional Neural Networks, CNNs) have been extensively used for image forgery detection. Unlike previous techniques, CNNs are able to automatically learn hierarchical feature representations directly from the image data, therefore increasing the detection accuracy. Advanced architectures like ResNet50v2 use residual learning to add depth and stability to the model while transfer learning helps to achieve better results even in cases where training data is scarce. However, these deep models can be computationally intensive and demand large-scale annotated data sets to realize their full potential check, and their practical application can become an issue in resource-limited environments.

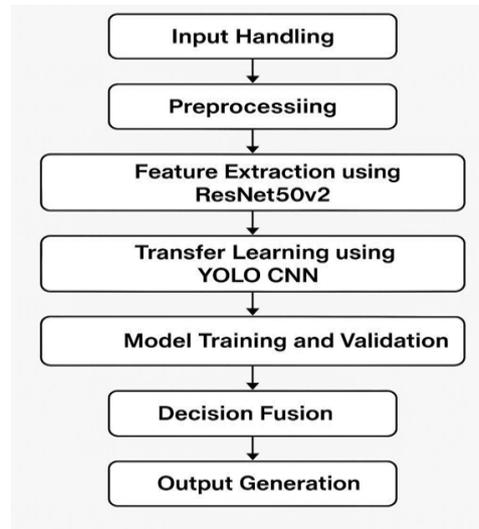
#### **IV. PROPOSED SYSTEM**

The proposed Decision Fusion Model is developed based on a deep learning model, where ResNet50v2 is the base feature extraction network and YOLO convolutional neural network (CNN) pre-trained weights are used via transfer learning. By combining these two architectures the model enjoys the knowledge learned on large scale data, which improves feature representation ability and overall detection performance while maintaining computational requirements at reasonable levels.

ResNet50v2 makes use of residual connections that allow it to train deeper neural networks because it solves the vanishing gradient problem. This design enables the model to learn complex visual patterns and subtle details in an image that are very important to be able to identify manipulated regions. Through a series of convolutional layers, batch normalization and pooling operations, the network learns both low-level features, such as edges, textures, and color variations, as well as higher-level, semantic information, such as the shape of objects and their context in the image.

Incorporating YOLO pre-trained weights further strengthens the system by improving its ability to identify and localize suspicious regions. This enables the framework not only to classify an image as authentic or forged but also to detect areas that may have been tampered with. During the processing stage, the input image is initially analyzed using YOLO-based feature representations, after which ResNet50v2 refines these features to identify inconsistencies like boundary distortions, texture irregularities, and color mismatches. The combined architecture provides a balanced trade-off between detection accuracy, processing speed, and computational efficiency, making it well-suited for real-time and practical image forgery detection scenarios.

## V. METHODOLOGY

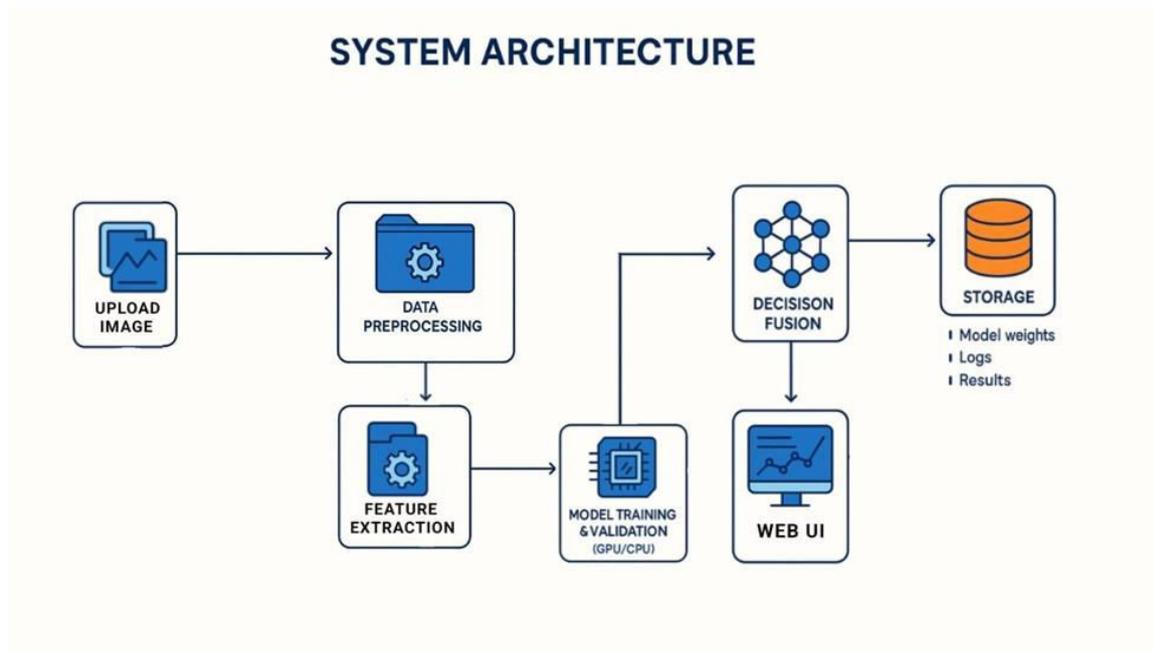


The proposed image morphing detection system is organized as a multi-stage processing pipeline in order to achieve accurate and efficient analysis. In the first stage, images are either collected from users or from some standard benchmark data-sets such as MICC-F220. Each image is checked to be in the correct format and resolution then proceeds further. Preprocessing is then done which includes resizing images into a fixed dimension, normalizing pixel values, and normalizing input data to keep high uniformity. Several enhancement operations, e.g., noise filtering and color adjustment, are performed to mitigate variations that are not useful and enhance the quality of the feature extraction.

Feature extraction is done with the ResNet50v2 architecture. By making use of residual learning, this deep network can efficiently manage vanish gradients problems and also train deeper layers efficiently. The model produces of hierarchical representation of features, containing not only low-level features such as edges, textures, color transitions, but also high-level semantic information which are relevant to forgery detection. These representations facilitate detecting slight traces of manipulation like irregular boundaries, unnatural mixing of blend, structural inconsistencies etc.

To enhance the process of localization capabilities, pre-trained CNN weights of YOLO model is added in the form of transfer learning. YOLO helps the system to detect and zoom in on possible areas of manipulation in the image. This integration allows the framework to not only identify the images as genuine or counterfeit but it can also be used to delineate suspicious areas. Transfer learning saves overall training time and enhances performance and can be useful when you have limited data.

The integrated ResNet50v2--YOLO model is trained and valuation by supervise learning using MICC-F220 data set. Model performance is evaluated with broadly-accepted evaluation metrics, such as accuracy, precision, recall, and F1-score, to get consistent and reliable results. A decision fusion mechanism is used to combine outputs of both the feature extraction and localization components in order to generate the final decision regarding the authenticity of an item. The strength of this system is that the results are interpretable, such as authenticity confidence scores and visual interpretations such as the bounding box or heatmap, so the system could be used for digital forensics, media authentication, and to work in the real world.

**VI. SYSTEM ARCHITECTURE**

The proposed architecture of the system is designed as a modular and scalable framework in order to provide reliable, secure, and efficient image forgery detection. The workflow starts with the image acquisition module where the users or automated batch systems upload images in common formats like a jpg or png file format. Each file uploaded is checked to meet the format and size requirements before it is secured and stored in the temporary or cloud-based storage. Relevant metadata—including file name, resolution, upload time, and user identification—is recorded to maintain traceability and support auditing. In addition, benchmark images from datasets such as MICC-F220 can be incorporated for training and evaluation purposes.

During the preprocessing phase, images are adjusted to suit the input specifications of the deep learning model in order to increase the robustness of the model and reduce overfitting, data augmentation techniques such as rotation, horizontal and vertical flipping, and random cropping are used during training. The processed dataset is then split into training, validation, and testing datasets so that there are consistency and no bias in the evaluation of performance. This involves resizing to a fixed resolution, normalizing pixel values, and converting color spaces where necessary. Image enhancement operations, such as noise removal, contrast balancing, and color correction, are applied to improve overall feature clarity.

Feature extraction is carried out using the ResNet50v2 deep encoder, which produces multi-level feature maps capturing texture patterns, structural characteristics, and potential manipulation traces. These extracted features are passed to the detection module, where transfer learning integrates pre-trained YOLO CNN weights to enhance localization capability. The combined ResNet50v2-Yolo architecture learns to classify in the training process both if an image is genuine or forged and what are suspicious parts in it.

A decision fusion part combines the results of the classification performed by ResNet50v2 and localization outputs of YOLO to give their final conclusion on authenticity together with a confidence score. Forged areas detected are visually represented by means of bounding boxes or heatmaps to better interpret them. The system also includes a web-based user interface that enables authorized users to upload images, review detection outcomes, download analytical reports, and access historical records securely. All uploaded data, trained models, logs, and detection reports are systematically stored to facilitate auditing, future retraining, and performance monitoring. This structured design ensures long-term scalability, maintainability, and practical deployment capability.

**VII. RESULTS**

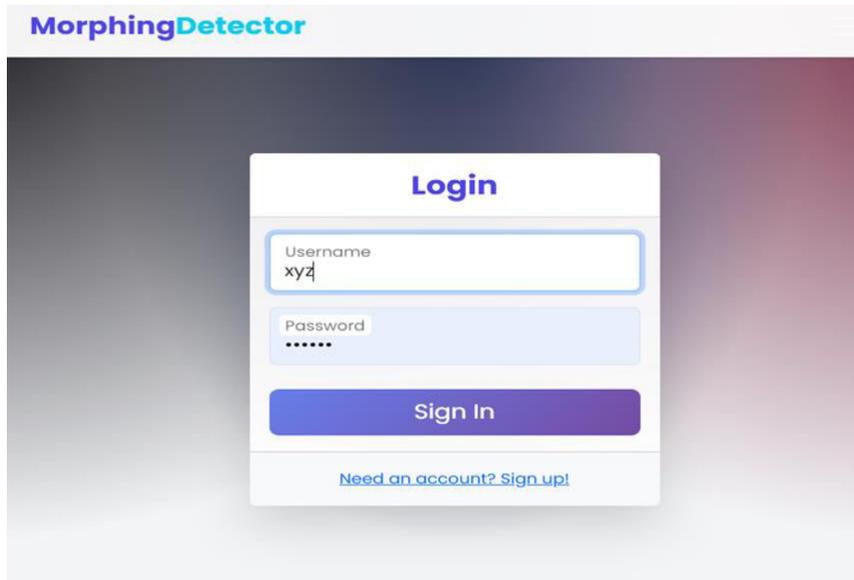


Fig. 8.1

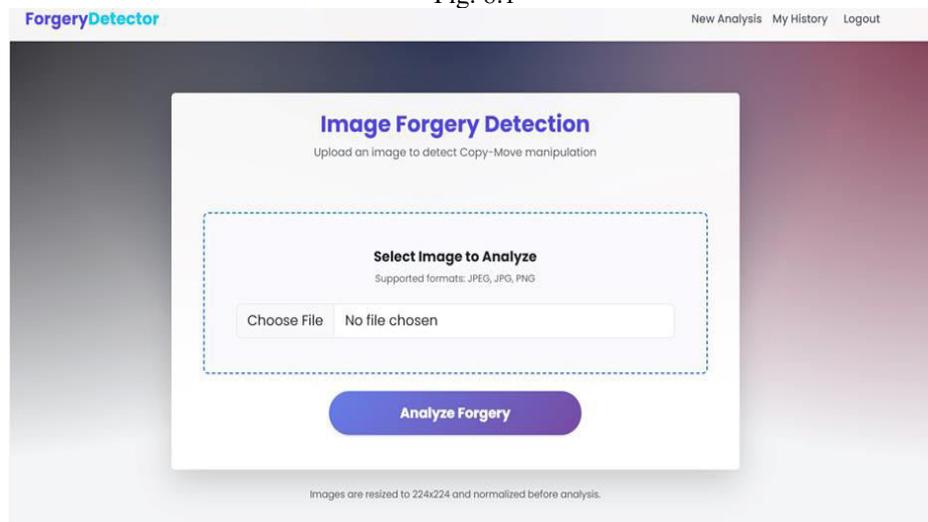


Fig. 8.2

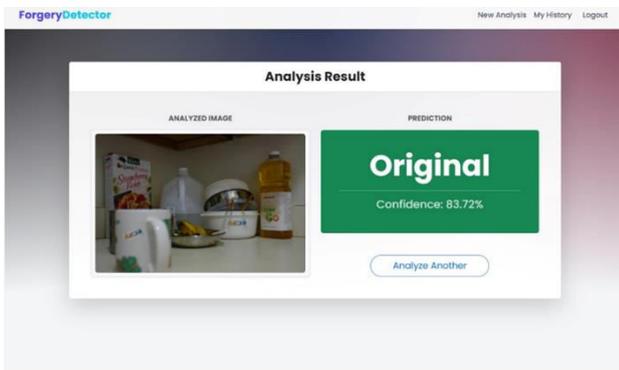


Fig. 8.3

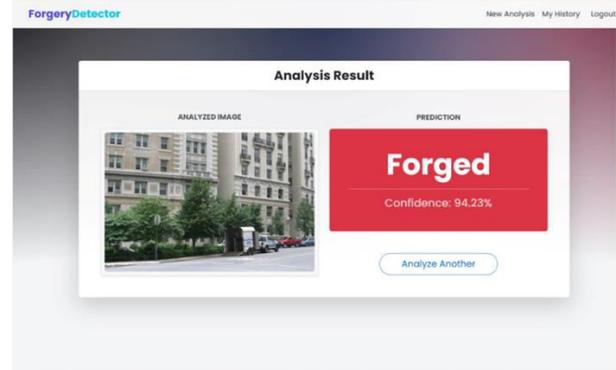
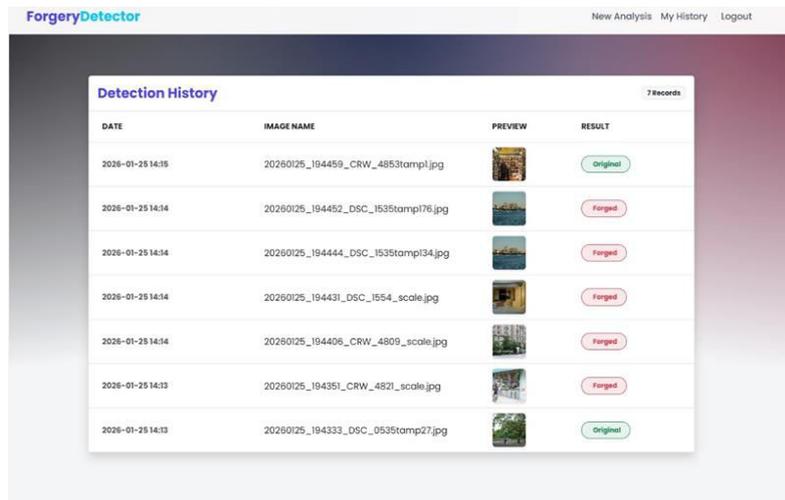


Fig. 8.4



DATE	IMAGE NAME	PREVIEW	RESULT
2026-01-25 14:15	20260125_194459_CRW_4853stamp1.jpg		Original
2026-01-25 14:14	20260125_194452_DSC_1535stamp176.jpg		Forged
2026-01-25 14:14	20260125_194444_DSC_1535stamp134.jpg		Forged
2026-01-25 14:14	20260125_194431_DSC_1954_scale.jpg		Forged
2026-01-25 14:14	20260125_194406_CRW_4809_scale.jpg		Forged
2026-01-25 14:13	20260125_194351_CRW_4821_scale.jpg		Forged
2026-01-25 14:13	20260125_194333_DSC_0535stamp27.jpg		Original

Fig. 8.5

## VIII. CONCLUSION

The project titled "Image Morphing Detection: A Fusion Approach with Deep Learning Models" is a great example of how advanced deep learning techniques can be used to detect manipulated and forged images. By incorporating ResNet50v2 and YOLO CNN pre-trained weights, the proposed system can achieve good performance in terms of accuracy, adaptability and robustness. The fusion-based framework helps improve the feature extraction and region localization, and can be used for detecting common types of forgery such as image splicing and copy-move manipulation. Utilizing the MICC-F220 dataset and transfer learning techniques the model successfully differentiates between genuine and tampered images with preserved optimal computational efficiency.

This work is a meaningful contribution to the field of digital forensics and information security by providing a reliable solution to the problem of verifying the authenticity of an image. The framework can be extended to practical application such as social media monitoring, law enforcement analysis, misinformation detection and validation of digital media content.

In summary, the proposed system enhances the robustness of digital image verification in real-world applications like media verification, forensics, and cybersecurity near future applications. Its automated preprocessing, analysis, and classification features make it scalable, efficient, and user-friendly. As image editing technologies are continually advancing, the fusion-based approach presented here creates a strong foundation for further research and development

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in artificial intelligence-based image forgery detection, where transparency, credence, and trust in digital information in the visual spectrum can be instilled.

**IX. FUTURE SCOPE**

Future improvements to the proposed system can address the need to increase data integration and model intelligence. One direction can be adding multi-modal sources of data such as metadata, contextual information, device-level attributes and environmental factors associated with image capture. Leveraging different types of data would enable the model to build a more thoughtful picture of patterns of image authenticity, enhancing the performance and dependability of image detection across complex real-world scenarios.

Advanced methods of deep learning can also be studied to further enhance performance. Techniques like autoencoders, self-supervised feature learning and generative models, can be applied to automatically learn more discriminative and compact feature representations from-large scale datasets.

From a viewpoint of detecting forged evidence, the research can be expanded in future to accommodate multiple types of manipulations in a unified architecture. Beyond copy-move and splicing, the system is capable of improving on retouching, image morphing and other advanced editing schemes in a single integrated system pipeline. Expanding the range of detection capacities in different categories of forgery will further its use in digital forensics and media and cybersecurity backgrounds. Moreover, the framework can be adapted for addressing novel challenges like video forgery and deepfake detection, which is becoming more and more popular in social media and cybercrime activities. Optimizing to work with deep learning models in real-time would enable their use in surveillance systems and online content verification systems. Incorporating Explainable AI (XAI) mechanisms to emphasize manipulated regions and offer clear visual justifications for decisions would further enhance transparency and interpretability, as well as user confidence in their decisions. Overall, these improvements will enhance the adaptive nature, scalability, and pragmatic usability of AI-based systems for finding forgeries in future digital ecosystems.

**REFERENCES**

- [1] Barni, M., et al. "A Survey on Image Forgery Detection Techniques." IEEE Access, 2021.
- [2] Chen, S., and Gupta, R. "Deep Learning-based Image Tamper Detection." Pattern Recognition Letters, 2022.
- [3] Hussain, M. et al. "Copy-Move Forgery Detection Using CNN." Elsevier Journal of Visual Communication, 2023.
- [4] Zhang, Y. "Transfer Learning for Image Forensics." Springer Forensic Vision Journal, 2023.
- [5] He, K. et al. "Deep Residual Learning for Image Recognition (ResNet)." CVPR, 2016.
- [6] Redmon, J. et al. "You Only Look Once: Unified, Real-Time Object Detection (YOLO)." CVPR, 2016.



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