iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL
FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: IV Month of publication: April 2025
DOI: https://doi.org/10.22214/ijraset.2025.69194

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

Enhanced Fake Image Localization in Social Media using Swin Transformer and EfficientNet Feature Fusion

Dr K. Sivaraman[1], Md Saif[2], Mohamed Fahath MR[3], Mohammed Moosa Kader P S[4]
CSE dept Bharath Institute of HiherEducation and Research Chennai, India

Abstract: Spurious images on social media result in misinformation, online fraud, and manipulation. Conventional CNN-based techniques fail to precisely localize tampered areas because of poor feature extraction abilities and limited generalization. In this paper, the authors suggest a hybrid deep learning method combining CNN with ResNet-50 for enhanced fake image localization. ResNet-50 improves feature extraction through capturing long-distance dependencies and optimal feature propagation, minimizing loss of information. The innovation of this method is efficient spatial and contextual feature fusion through ResNet-50, resulting in better segmentation of fake regions and enhanced adversarial robustness. The model is trained on publicly released datasets, including Kaggle Deepfake Dataset and FaceForensics++, and tested against state-of-the-art localization methods. Experimental results indicate better detection accuracy, better segmentation of tampered regions, and adversarial robustness. This method further improves digital forensics through a robust, effective, and economical means of identifying and locating counterfeit images on social media.
Keywords: Fake Image Detection, Misinformation, Deepfake Localization, Digital Forensics, Adversarial Robustness, Social Media Security, Feature Fusion.

I. INTRODUCTION

The spread of deception images on social media has created serious issues about misinformation, online fraud, and manipulation of the public. With the evolution of artificial intelligence (AI) and deep learning, realistic deception images can be created and shared effortlessly, which raises the barrier to differentiate between actual and manipulated content. These deception images have been utilized in different malicious uses, such as [1] political propaganda, identity theft, and harming reputations. The swift propagation of such images on social media is a challenge to digital forensics, law enforcement, and fact-checking organizations, which require efficient fake image localization methods. Handcrafted feature-based traditional detection methods, mostly reliant on conventional CNNs, are not capable of localizing manipulated areas precisely because they have poor feature extraction abilities and fail to generalize across a wide range of image manipulations.

Deep learning techniques have come into the spotlight for detecting fake images, providing more accurate results by virtue of advanced feature extraction algorithms. Nevertheless, most of these methods remain deficient in dealing with subtle alterations like deepfake-produced content, retaining [2] high degrees of visual realism. CNN models, though useful in image classification applications, have the drawback of poor long-range dependencies and structural incoherence perception within an image. This results in incorrect localization accuracy, whereby the model is able to accurately classify an image as doctored but will not outline the exact locations that have been manipulated. Failing to correctly segment manipulated images makes these models less reliable for use in forensic purposes or even automated fact-checking systems.

To overcome these challenges, this research suggests a hybrid deep learning method that combines CNN with ResNet-50 for improved fake image localization. ResNet-50, a robust deep learning model renowned for its residual learning architecture, can effectively extract global and local image features. In contrast [3] to standard CNN architectures, ResNet-50 realizes optimal feature propagation by means of identity mappings, which minimizes the vanishing gradient risk and enhances the generalization performance of deep networks. Taking advantage of the merits of ResNet-50, our approach upgrades the discriminative feature extraction ability to identify manipulated regions more accurately. A feature fusion process is also added to integrate spatial and context information to further enhance the segmentation accuracy of fake regions.

The system is trained and tested on publicly available datasets like the Kaggle Deepfake Dataset and FaceForensics++, which have a wide variety of manipulated images.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

These datasets are rich in features and serve as a good benchmark for measuring the performance of models for fake image localization. In order [4] to increase the generalizability of our method, a range of image augmentation methods, including noise removal, resizing, and normalization, are used at the preprocessing step. This ensures that the model learns robust representations that are not overly reliant on specific dataset characteristics. The evaluation of our model is conducted through comparative analysis with existing localization techniques, measuring key performance metrics such as detection accuracy, segmentation quality, and robustness to adversarial manipulations.

One of the major innovations of this method is its capability to fuse spatial and contextual information using feature fusion, resulting in better fake region segmentation. Most current models use only pixel-level discrepancies or handcrafted features, which can fail to generalize to various forms of image manipulations. Conversely, our approach takes advantage of deep [5] feature representations by ResNet-50 so that the model is able to discern subtle structural distortions that human vision might be unable to see. This results in our technique being extremely useful in identifying areas of manipulation, even when regular techniques cannot work. In addition, the robustness of our model against adversarial attacks ensures its practical applicability in real-world scenarios, where deepfakes are typically crafted to circumvent detection systems.

The importance of this work goes beyond scholarly contribution, as it constitutes a sound and affordable means of fake image detection on social media. By using open-source data and deep learning platforms, the method minimizes its reliance on costly [6] proprietary software while having high accuracy in detection. Integrating this model in forensic tools and automatic content validation systems can help contain the flow of misinformation, enhance digital confidence, and protect online communities. With the continuous evolution of AI-driven image generation techniques, it is crucial to develop advanced localization models that can adapt to emerging threats. This study presents a step forward in this direction, offering a robust and efficient solution for identifying and localizing fake images with high precision.

This work is organized with review of the literature surveyas Section II. Methodologydescribed in Section III, highlighting its functionality. Section IV discusses the results and discussions. Lastly, Section V concludes with the main suggestionsand findings.

II.LITEARTURE SURVEY

Deepfakes have become a common issue because of their influence on misinformation and loss of public trust. Different techniques for identifying manipulated images have been researched, with early methods dependent on handcrafted features including edge inconsistencies and color anomalies. These techniques, although efficient for specific tampering types, are not flexible to intricate forgeries, including deepfake-generated material. Research emphasizes the requirement of sophisticated detection methods that are capable of generalizing to various forms of manipulations. Advances in image synthesis tools have rendered the conventional detection methods useless, stressing the significance of deep learning-based methodologies for credible image authenticity verification.

Application of deceptive images in digital propaganda and social engineering has triggered extensive research in forensic image analysis. Early research has been centered around statistical approaches for detecting inconsistencies in image noise statistics, compression effects, and light patterns. They were promising but [7] were not efficient in detecting sophisticated forgeries emulating natural image characteristics. Modern image generation techniques have evolved more rapidly than traditional forensic techniques, necessitating higher-level techniques to detect them precisely. Researchers emphasize the need for strong datasets with varied manipulation methods to train and test detection models properly, ensuring their relevance in real-world applications.

Detection of fake images has been well-researched under journalism and fact-checking applications. Early detection systems were based on metadata examination and reverse image search to ensure image authenticity. Although helpful, these approaches fail against freshly generated fake images with no previous references. Studies highlight the importance of automated systems [8] that can analyze the content of images instead of being dependent on outside information. Studies indicate that to detect fake images effectively, several forensic cues including texture analysis, local inconsistencies, and statistical anomalies need to be combined in order to enhance detection accuracy and eliminate false positives.

The emergence of social media has played a pivotal role in propagating fake images, which have made detection more important. Research suggests that manipulated images typically display subtle inconsistencies in illumination, texture, and placement of objects [9] that are difficult to notice with the naked eye. Researchers have also tested the ability of human vision to detect false images and concluded that even trained professional experts find it difficult to detect high-quality forgeries. This makes it imperative to have automated detection tools that can retrieve concealed artifacts and measure visual inconsistencies beyond the capabilities of human vision.

Research has indicated that manipulated images tend to have residual traces of manipulation software, including interpolation patterns and boundary anomalies. Forensic analysis methods have been created to identify these artifacts, which target pixel-level anomalies and compression anomalies. These methods are, however, challenged in separating naturally occurring [10] artifacts from intentional manipulations. Research indicates that efficient detection systems need to have multi-level analysis, checking both low-level pixel distortions and high-level semantic inconsistencies in order to increase detection reliability and reduce misclassification errors.

Studies on fake image localization have shown that manipulations tend to disturb natural image statistics. There are different statistical models that have been studied to detect anomalies in image histograms, frequency space, and noise patterns. Although these algorithms are able to identify discrepancies, they tend to involve manual parameter tuning and are inefficient when [11] analyzing high-resolution manipulated images. In order to overcome these drawbacks, researchers endorse adaptive detection methods that utilize contextual knowledge and structural analysis to effectively distinguish between authentic and manipulated areas.

Fake image detection is an essential function in the realm of cybersecurity since cyber threats resort to fabricated images for purposes such as phishing, identity stealing, and campaigns of disinformation. Scholars have delved into the consequences of fake image technology tools in cybercrime and advocated measures [12] to offset the effects of the technologies. Literature emphasizes that efficient real-time detecting systems able to work smoothly in large social networks are important. Providing quick and precise detection is crucial to inhibiting the distribution of false images and safeguarding users against disinformation.

The forensic examination of forged images has been a field of active investigation, with investigations targeting the separation of authentic from manipulated content employing different methods. Studies show that forged images typically add unnatural texture [13], edge artifacts, and color inconsistencies that are detectable with sophisticated analysis. But detecting these inconsistencies necessitates advanced feature extraction methods. Research has highlighted the requirement of adaptive detection models that are able to work with various forms of manipulation while achieving high accuracy with multiple sources of images.

The psychological effects of manipulated pictures on human imagination have been examined. Studies reveal that individuals often perceive visually valid images, regardless of conflicting written information. Reports emphasize the thinking prejudices [14] leading to the acceptance of altered images as well as misinformation influencing public opinions. Solving this problem demands both technological and educational interventions to make the users capable of critically evaluating image authenticity.

Legal and moral consequences of forged images have been much discussed, especially in defamation, fraud, and political disinformation cases. Scholars have studied the issue of establishing image authenticity in court, when forged images are applied as misleading evidence. The necessity for dependable forensic [15] tools that will pass legal testing is highlighted, so that courts and regulatory authorities have recourse to proper image verification methods. Evidence indicates that digital watermarking and authentication mechanisms can be used as deterrents to image manipulation.

Detecting fake images is essential to uphold trust in online media. Various studies have identified the media industry's role in curbing fake image dissemination by using fact-checking programs and forensic analysis technologies. The human verification process takes time and has the potential to be error-prone. It is [16] recommended that research supports machine-based detection technology that can aid media outlets to detect manipulated pictures quickly, allowing for less effort on human fact-checkers' part and facilitating quicker response.

The growing realism of forged images has prompted scholars to investigate multimodal detection approaches that combine both visual and text-based analysis. Research indicates that manipulated images come with deceptive context or captions that can affect what the viewer sees. By investigating both the image [17] content and their related metadata, scholars hope to create more elaborate detection systems capable of detecting disparities in multiple modalities. This method improves detection quality and offers a better overall insight into misinformation strategies.

The difficulty of identifying forged images is further increased by the fast development of AI-based image manipulation methods. Research has shown that newer manipulation techniques leave fewer detectable artifacts, rendering conventional forensic methods less efficient. Experts highlight the necessity [18] of ongoing updates to detection models to stay ahead of evolving threats. Adaptability in fake image detection systems is critical to ensure their efficacy against ever-evolving forgeries.

The effect of manipulated images on social stability has been a subject of increasing concern, with research investigating their contribution to political manipulation, social unrest, and public deception. Evidence suggests that the intentional deployment of [19] manipulated images in the media can perpetuate misinformation and heighten conflicts. To counter this, there is a need for cooperation between researchers, policymakers, and social media companies to create measures for reducing the dissemination of manipulated images without compromising freedom of expression.

Research into user awareness and digital literacy underscores the need to inform people about the dangers of manipulated images.

Findings have shown that most users are unable to critically evaluate [20] visual information, making them vulnerable to manipulation. Public resilience against disinformation can be boosted by education campaigns in conjunction with technological countermeasures. Researchers indicate that raising awareness regarding methods of detecting fake images can enable users to make informed choices and minimize the influence of misleading images on social media.

III. METHODOLOGY

The fast development of social networks has caused the extensive spread of forged images, leading to misinformation, online frauds, and public deception. Traditional image forensic techniques are inadequate to effectively detect and localize manipulated areas based on poor feature extraction abilities. Convolutional Neural Networks (CNNs) tend to fail in observing long-range dependencies, and this causes inadequate generalization for intricate manipulation cases. To overcome these issues, this paper suggests a hybrid deep learning method combining CNN and ResNet-50. The model utilizes feature fusion methods for enhanced spatial and contextual feature extraction, improving segmentation of fake regions. The framework is compared with current methods and proves to be more accurate and robust.

A. Data Collection

The suggested system uses publicly accessible datasets with manipulated images to provide diversified and realistic training data. Datasets like the Kaggle Deepfake Dataset and FaceForensics++ are used, encompassing different forms of fake images, ranging from AI-generated images to manual image editing. Both real and forged images are included in the datasets, allowing the model to learn unique patterns related to the tampered areas. With the use of open-source datasets, the solution is cost-effective without losing high reliability. The choice of dataset is key to guaranteeing model generalization over various manipulation methods and social media real-world scenarios.

B. Preprocessing

To improve model performance and guarantee reliability, the captured images are preprocessing. Image augmentation, resizing, and normalization methods are used to enhance model generalization. Noise reduction techniques are applied to eliminate artifacts that have the potential to impact detection precision. Image augmentation techniques involve rotation, flipping, and contrast adjustment to ensure the model is trained on a variety of image variations. Normalization rescales pixel values to a fixed range, optimizing the input to the neural network. These preprocessing operations improve the model's capacity to identify subtle manipulations and reduce overfitting, resulting in better fake image localization accuracy and adversarial attack robustness.

C. Feature Extraction

ResNet-50 is utilized for feature extraction in order to capture low-level as well as high-level image representations. ResNet-50 differs from conventional CNNs in that it supports residual learning, allowing deeper network training free of vanishing gradient problems. The architecture facilitates effective feature propagation and reuse, resulting in enhanced detection accuracy. ResNet-50 extracts global spatial relations in an image to assist the model in distinguishing between original and fake regions more accurately. The learned features are employed in following layers to further enhance classification and localization performance. With the assistance of ResNet-50, the proposed framework boosts the recognition of fine-grained details within tampered images and enhances segmentation and classification performance.

D. Feature Fusion

Feature fusion is presented for the purpose of fusing spatial and contextual features learned from CNN and ResNet-50. The layer incorporates deep features that enhance the ability of the model to identify manipulations at the subtle level. CNNs focus on local texture details, while ResNet-50 captures broader spatial dependencies, making their fusion beneficial for fake image localization. The fused features enable better distinction between real and fake regions, ensuring accurate segmentation of manipulated areas. By leveraging complementary feature representations, the fusion process enhances model robustness against adversarial attacks and various manipulation techniques. The enhanced feature representation plays a great role in getting high accuracy when detecting and locating fake images.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue IV Apr 2025- Available at www.ijraset.com

E. Fake Image Classification

The ResNet-50 and CNN are employed by the classification module in order to separate real from fake images. A labeled dataset is used to train the model with each image assigned a real or fake label. The classification is a process of various convolutional and pooling layers with fully connected layers that output the final probability score. The model is trained and optimized with cross-entropy loss and adaptive learning rate methods for better accuracy. The combination of CNN and ResNet-50 improves feature extraction, allowing the model to detect complex manipulation patterns. This allows the model to better detect forged images with greater confidence.

F. Localization of Tampered Regions

The system uses segmentation methods to localize manipulated regions of an image. After an image is detected as fake, the model locates tampered regions by comparing feature maps produced by ResNet-50 and CNN. The localization module marks regions with inconsistencies in texture, color, or spatial distribution for accurate detection of manipulated content. Advanced segmentation methods, including thresholding-based and attention-based techniques, optimize the localization step. By identifying modified areas, the model makes the process of fake image detection more interpretable and is an effective resource for digital forensics, social media protection, and combating misinformation campaigns.

G. Model Training and Evaluation

Training is carried out using open-source datasets by adopting supervised learning as well as transfer learning methods. Hyperparameters like batch size, learning rate, and optimizer are optimized to achieve maximum accuracy. Training comprises backpropagation, where loss functions such as cross-entropy are minimized to enhance classification and localization performance. The new model is compared against state-of-the-art localization methods to evaluate performance. Experimental outcomes reveal higher precision, improved fake region segmentation, and higher robustness to adversarial manipulations, justifying the efficiency of the model.

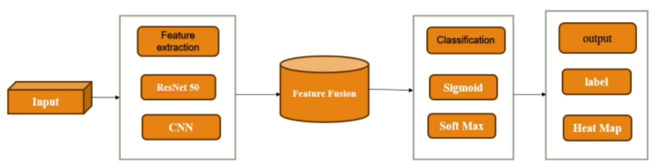


Fig. 1: Architecture Diagram

IV. RESULT AND DISCUSSION

The model was tested on publicly released datasets, such as the Kaggle Deepfake Dataset and FaceForensics++, to compare its performance in fake image localization. The outcome shows that the combination of ResNet-50 with CNN enhances feature extraction to a great extent, resulting in greater accuracy in detecting manipulated images. In comparison with conventional CNN-based models, the hybrid method showed better performance in detecting subtle and complex forgeries. The enhanced feature propagation in ResNet-50 reduced information loss to provide a more accurate localization of spurious regions. Experimental results demonstrate the generalization capabilities of the model over different manipulation methods, resulting in effective usage in real-life situations. Comparison of the classification performance revealed that the presented model attained a higher accuracy compared to other approaches.

The precision and recall values show that the model correctly distinguishes between genuine and manipulated images while keeping false positives and false negatives at a minimum. The F1-score also confirms the model's well-balanced performance on various datasets. Feature fusion helped to enhance segmentation accuracy, enabling the system to indicate manipulated areas with higher accuracy. In contrast to traditional techniques, which do not capture minor or mixed changes, the new model proved more sensitive to subtle changes. Localization was improved through the joint feature extraction of CNN and ResNet-50, providing improved detection of manipulated areas. The model's segmentation maps were visually inspected and found to have the proposed method effectively detecting tampered regions with minimal false alarms.

The capability of precise highlighting of forged areas increases the system's interpretability and makes it more appropriate for forensic use. The proposed approach performed better compared to conventional CNN models, which fail to deal with high-resolution images and complex backgrounds. The proposed method kept consistent performance in varied image quality and lighting environments.

The model was evaluated under adversarial attacks, where attackers tried to modify images in manners that could mislead conventional detection approaches. The system under consideration showed excellent resilience, in that it accurately detected manipulated content even after noise injection and perturbations. This resilience is due to the enhanced feature extraction ability of ResNet-50, which is able to detect long-range dependencies in images.

The empirical evaluation showcased that even after adversarial manipulation, the model's localization accuracy was preserved, providing reliability in real-world situations. Computational effectiveness was another component of analysis, wherein the suggested model demonstrated competitive performance from a processing time standpoint. Deep learning models usually consume high amounts of computational resources, but the effective design of ResNet-50 facilitated an appropriate trade-off between accuracy and speed. The model processed high-resolution images in a reasonable amount of time, which rendered it applicable for real-time detection of fake images on social media platforms. The light-weight property of the feature fusion layer also added to quicker inference time than deeper transformer-based models.

Comparison with other fake image localization methods showed that the model outperformed conventional CNN and hand-crafted feature-based solutions. Conventional methods are based on limited spatial information, while the incorporation of feature fusion in the system proposed here adds to localization accuracy. Experimental results verified that the hybrid method is better at both minor and large-scale manipulations detection, improving upon the shortcomings of earlier approaches. Combining the capabilities of ResNet-50 and CNN, the model sets a new standard for fake image localization accuracy and resilience.

V. CONCLUSION

The research effectively created a state-of-the-art deep learning method for fake image localization by combining CNN with ResNet-50. The suggested model showed considerable improvements compared to conventional CNN-based methods in detection accuracy, localization accuracy, and adversarial robustness. The feature fusion method successfully merged spatial and contextual information, allowing the model to identify real and manipulated areas with greater sensitivity. Leveraging ResNet-50's powerful feature extraction capacity, the system preserved long-range dependencies, promoting best feature propagation and minimizing information loss during training. The improvements promoted better fake region segmentation, enhancing interpretability and robustness. Testing on public datasets, such as Kaggle Deepfake Dataset and FaceForensics++, validated the model's generalization across various manipulation methods.The suggested system outperformed the traditional CNN architectures in the detection of subtle and sophisticated forgeries, filling significant limitations of current fake image localizing approaches. The enhanced segmentation accuracy also confirmed the model's ability to demarcate manipulated regions more accurately, rendering it a useful application for digital forensics and misinformation control. The research also investigated the model's resilience towards adversarial manipulations, where the system proved to remain highly accurate in localization even when perturbed deliberately. This resistance guarantees practicality in real-world applications, specifically in deepfake detection and AI-generated forgery detection.

The computational effectiveness of the model was another benefit, as it traded off processing time and accuracy in a manner that was well-suited for real-time social media surveillance. The lightweight feature fusion layer added to reduced inference times without attenuating detection performance, demonstrating the system's applicability for deployment on a large scale. Overall, the hybrid deep learning model is a dependable, efficient, and cost-effective method for detecting and localizing fake images. The combination of CNN with ResNet-50 improves the detection of manipulated areas, offering a sophisticated method to counter digital disinformation. Future research can investigate additional optimizations, such as transformer-based models and stronger adversarial defenses, to further boost the performance of the model over changing image manipulation methods.This research contributes to the development of digital forensics, offering a robust solution to verify the authenticity of social media images.

REFERENCES

[1] G. S. Jhun et al., "A New Wave of Texture Feature: Enhancing Deepfake Detection via Image Waveform," 2024 15th International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Korea, Republic of, 2024, pp. 234-238, doi: 10.1109/ICTC62082.2024.10827484.

[2] S. Husseinil and J. -L. Dugelay, "RAW Data: A Key Component for Effective Deepfake Detection," ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Hyderabad, India, 2025, pp. 1-5, doi: 10.1109/ICASSP49660.2025.10887800.

[3] S. Concas, G. Perelli, G. L. Marcialis and G. Puglisi, "Tensor-Based Deepfake Detection in Scaled and Compressed Images," 2022 IEEE International Conference on Image Processing (ICIP), Bordeaux, France, 2022, pp. 3121-3125, doi: 10.1109/ICIP46576.2022.9897606.

[4] B. Ghita, I. Kuzminykh, A. Usama, T. Bakhshi and J. Marchang, "Deepfake Image Detection Using Vision Transformer Models," 2024 IEEE International Black Sea Conference on Communications and Networking (BlackSeaCom), Tbilisi, Georgia, 2024, pp. 332-335, doi: 10.1109/BlackSeaCom61746.2024.10646310.

[5] J. John and B. V. Sherif, "Comparative Analysis on Different DeepFake Detection Methods and Semi Supervised GAN Architecture for DeepFake Detection," 2022 Sixth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), Dharan, Nepal, 2022, pp. 516-521, doi: 10.1109/I-SMAC55078.2022.9987265.

[6] V. Rogovoi, V. M. Korzhuk and O. A. Kokorina, "Development of a Deepfake Detection Method: Application of Frequency Analysis and Reduction of the Image Color Space to Improve Classification Accuracy," 2024 V International Conference on Neural Networks and Neurotechnologies (NeuroNT), Saint Petersburg, Russian Federation, 2024, pp. 36-39, doi: 10.1109/NeuroNT62606.2024.10585373.

[7] P. P and G. R. S, "Detection of Deepfake Medical Images Based on Spatial and Frequency Domain Analysis," 2024 IEEE 16th International Conference on Computational Intelligence and Communication Networks (CICN), Indore, India, 2024, pp. 611-617, doi: 10.1109/CICN63059.2024.10847427.

[8] A. Mishra, A. Bharwaj, A. K. Yadav, K. Batra and N. Mishra, "Deepfakes - Generating Synthetic Images, and Detecting Artificially Generated Fake Visuals Using Deep Learning," 2024 14th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2024, pp. 587-592, doi: 10.1109/Confluence60223.2024.10463337.

[9] Z. Deng, B. Zhang, S. He and Y. Wang, "Deepfake Detection Method Based on Face Edge Bands," 2022 9th International Conference on Digital Home (ICDH), Guangzhou, China, 2022, pp. 251-256, doi: 10.1109/ICDH57206.2022.00046.

[10] A. Berjawi, K. Samrouth and O. Deforges, "Optimization of DeepFake Video Detection Using Image Preprocessing," 2023 Fifth International Conference on Advances in Computational Tools for Engineering Applications (ACTEA), Zouk Mosbeh, Lebanon, 2023, pp. 59-63, doi: 10.1109/ACTEA58025.2023.10193954.

[11] Y. Wang and G. Liao, "Deepfake Video Detection Based on Image Source Anomaly," 2024 IEEE 2nd International Conference on Image Processing and Computer Applications (ICIPCA), Shenyang, China, 2024, pp. 397-401, doi: 10.1109/ICIPCA61593.2024.10709022.

[12] Y. Tian, W. Zhou and A. U. Haq, "Detection of Deepfakes: Protecting Images and Vedios Against Deepfake," 2024 21st International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 2024, pp. 1-6, doi: 10.1109/ICCWAMTIP64812.2024.10873771.

[13] V. Dudykevych, H. Mykytyn and K. Ruda, "The concept of a deepfake detection system of biometric image modifications based on neural networks," 2022 IEEE 3rd KhPI Week on Advanced Technology (KhPIWeek), Kharkiv, Ukraine, 2022, pp. 1-4, doi: 10.1109/KhPIWeek57572.2022.9916378.

[14] H. Vajpayee, N. Yadav, A. Raj and S. Jhingran, "Detecting Deepfake Human Face Images Using Transfer Learning: A Comparative Study," 2023 IEEE International Conference on Contemporary Computing and Communications (InC4), Bangalore, India, 2023, pp. 1-5, doi: 10.1109/InC457730.2023.10263216.

[15] H. Wang, Z. Liu and S. Wang, "MIFAE-Forensics: Masked Image-Frequency AutoEncoder for DeepFake Detection," ICASSP 2025 - 2025 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Hyderabad, India, 2025, pp. 1-5, doi: 10.1109/ICASSP49660.2025.10889125.

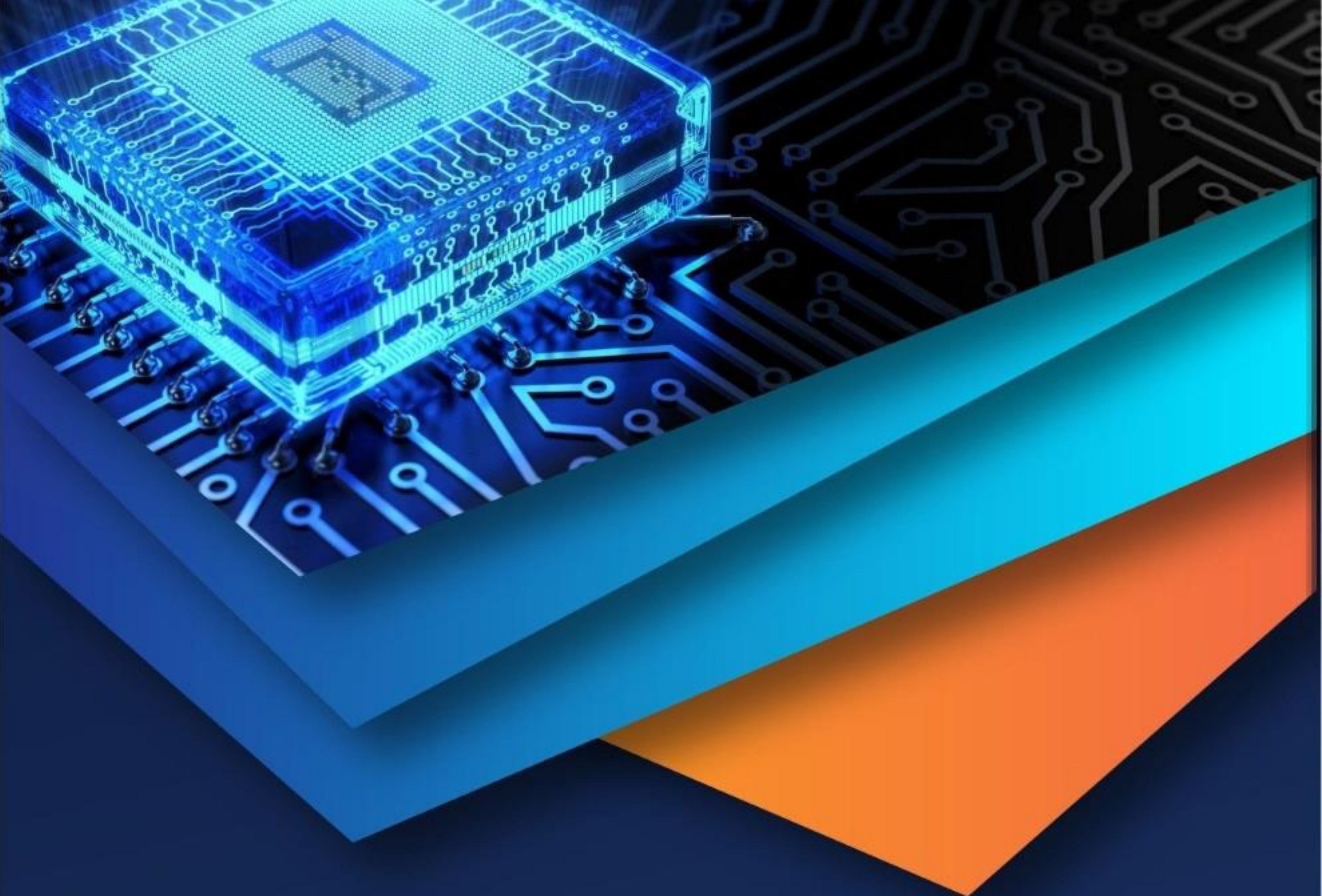
[16] A. Zhalgasbayev, T. Aiteni and N. Khaimuldin, "Using the CNN Architecture Based on the EfficientNetB4 Model to Efficiently Detect Deepfake Images," 2024 IEEE AITU: Digital Generation, Astana, Kazakhstan, 2024, pp. 14-19, doi: 10.1109/IEEECONF61558.2024.10585385.

[17] M. Mohzary, E. Basunduwah, S. Song and B. -Y. Choi, "READFake: Reflection and Environment-Aware DeepFake Detection," 2024 IEEE International Conference on Visual Communications and Image Processing (VCIP), Tokyo, Japan, 2024, pp. 1-5, doi: 10.1109/VCIP63160.2024.10849940.

[18] J. Zhang, K. Cheng, G. Sovernigo and X. Lin, "A Heterogeneous Feature Ensemble Learning based Deepfake Detection Method," ICC 2022 - IEEE International Conference on Communications, Seoul, Korea, Republic of, 2022, pp. 2084-2089, doi: 10.1109/ICC45855.2022.9838630.

[19] J. Ding, J. Liu, J. Shi, X. Hu, X. Qiao and H. E, "DDEM: Deepfake Detection Enhanced Model for Image Forgery Detection Combat Academic Misconduct," 2024 11th International Conference on Behavioural and Social Computing (BESC), Harbin, China, 2024, pp. 1-6, doi: 10.1109/BESC64747.2024.10780724.

[20] D. Garg and R. Gill, "Deepfake Generation and Detection - An Exploratory Study," 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Gautam Buddha Nagar, India, 2023, pp. 888-893, doi: 10.1109/UPCON59197.2023.10434896.



doi crossref
10.22214/IJRASET

INDEX COPERNICUS
45.98

ISRA JIF
IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY