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AI Powered Fake Image Detection System using ResNet and U-Net

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Abstract: Nowadays, it is very easy to edit images and create fake photos using advanced tools and deepfake technology. This creates problems like spreading false information and security risks. In this project, we developed an AI-based system to detect fake images, mainly for use on social media. The system uses ResNet to understand important features of an image and U-Net to find exactly which part of the image is edited. It not only detects whether an image is fake but also shows the modified area clearly. The model is designed to run on a Raspberry Pi, making it lightweight and suitable for real-time use. This system can be useful in areas like social media monitoring, document verification, and cybercrime investigation
Keywords: Image Forgery Detection, Deep Learning, ResNet, U-Net, Deepfake Detection, Raspberry Pi.

I. INTRODUCTION

Digital images are widely used today, especially on social media, but it has become very easy to edit or manipulate them using advanced tools and deepfake technologies. This creates serious problems like spreading false information and reducing trust in digital content. Traditional methods are not strong enough to detect these modern image forgeries. To solve this problem, this work uses artificial intelligence and deep learning techniques. The system uses ResNet to extract important features from images and U-Net to find and highlight the exact tampered areas. It can accurately detect whether an image is real or fake. The model is also designed to run on a Raspberry Pi for real-time and low-power usage. This helps in applications like social media monitoring, digital verification, and security systems.

II. LITERATURE REVIEW

[1] "Advancements in Image Splicing and Copy-move Forgery Detection Techniques (2021)". This paper presents a survey of passive image forgery detection techniques, mainly focusing on copy-move and image splicing forgeries. The authors discussed traditional methods, machine learning approaches, and deep learning-based techniques used in forgery detection. Various datasets such as CASIA and Columbia datasets were analyzed for evaluating detection models. The study concluded that deep learning methods provide better accuracy and robustness compared to traditional approaches. However, challenges still exist in detecting sophisticated manipulations and improving generalization across datasets.

[2] "Image Forgery Detection Using Deep Learning Techniques (2021)". This paper proposed the use of CNN-based architectures such as ResNet and VGG for image forgery detection. The models were trained using forged and authentic image datasets to classify manipulated images. Experimental results showed high detection accuracy for forged images. However, the approach required high computational power and struggled with real-time implementation and highly compressed images.

[3] "Efficient Deep Neural Network for Real-Time Image Forgery Detection (2021)". The authors developed a lightweight deep neural network optimized for edge devices such as Jetson Nano. Model compression and pruning techniques were used to reduce computational complexity while maintaining accuracy. The system achieved faster real-time detection but performance dropped under image compression and heavy manipulations.

[4] "U2-Net for Image Forgery Detection and Localization (2021)". This paper modified the U2-Net architecture for image forgery detection and localization tasks. The model was compared with ManTra-Net for detecting tampered image regions. Experimental results demonstrated that U2-Net effectively localized manipulated regions and achieved better localization accuracy in some cases. However, performance decreased for highly compressed and heavily post-processed images.

[5] "Deep Learning for Image Forgery Detection (2022)". This paper explored CNN-based deep learning models such as ResNet50 for image forgery detection. Data augmentation techniques were applied to improve model performance. The study achieved high accuracy in detecting forged images but required large labeled datasets and high computational resources for training.

[6] “Edge-Based CNN for Real-Time Tamper Detection (2022)”. The authors proposed an edge-based CNN architecture optimized for edge devices like Raspberry Pi. The model focused on lightweight computation and faster processing for tamper detection. Although the system achieved real-time performance, it lacked robustness against complex image manipulations and advanced forgery attacks.

[7] “An Active Image Forgery Detection Approach Based on Edge Detection (2023)”. This paper proposed an active image forgery detection method using edge-based watermarking techniques. The method embedded watermark information into image edge regions and compared extracted edge information for tamper detection. The approach achieved accurate tamper localization and robustness against JPEG compression, but geometric transformations affected the detection accuracy.

[8] “Toward Deep-Learning-Based Methods in Image Forgery Detection: A Survey (2023)”. This survey paper reviewed various deep learning approaches used in image forgery detection, including CNN, RCNN, and LSTM architectures. The study discussed copy-move and splicing forgery detection methods along with available benchmark datasets. The survey concluded that deep learning methods outperform traditional handcrafted feature-based methods, but advanced forgeries still remain difficult to detect.

[9] “Image Forgery Detection Techniques: Latest Trends and Key Challenges (2024)”. This paper reviewed recent advancements in active and passive image forgery detection methods. It analyzed machine learning and deep learning techniques used for tamper detection and localization. The authors concluded that passive deep learning methods provide higher accuracy and flexibility. However, multi-forgery detection and dataset limitations remain significant challenges.

[10] “Advanced Techniques in Forgery Image Detection Using Deep Learning and AI Algorithm (2024)”. This study proposed the use of CNNs, GANs, and hybrid AI models for image forgery detection. Data preprocessing, augmentation, and feature extraction techniques were applied to improve detection performance. The hybrid CNN-GAN model achieved higher accuracy and robustness. However, the model required large datasets and high computational power for effective training.

[11] “Image Forgery Detection Using Convolutional Neural Networks (2024)”. This paper evaluated different CNN architectures such as VGG and ResNet for image forgery detection. The models were trained and tested on forged and authentic image datasets. Among all models, ResNet-101 achieved the best performance in terms of accuracy, precision, recall, and F1-score. However, the approach focused mainly on image classification rather than forgery localization.

[12] “UCM-Net: A U-Net-Like Tampered-Region-Related Framework for Copy-Move Forgery Detection (2024)”. The authors proposed UCM-Net, a U-Net-based framework designed for copy-move forgery detection and localization. The architecture used ASPP modules, self-correlation calculations, and residual U-blocks to capture multi-scale tampered features. Experimental results showed that the model outperformed state-of-the-art methods in tampered-region localization. However, the architecture required high computational resources and complex training procedures.

[13] “A Deep Learning Framework for Detecting Digital Image Forgery Using a Hybrid U-Net (2024)”. This paper introduced a hybrid U-Net architecture combining VGG16 feature extraction, modified U-Net semantic segmentation, and binary classification for forgery detection. The model was evaluated using the CASIA2 dataset with 5-fold cross-validation. Results showed improved robustness and accuracy compared to existing methods. However, the system required large labeled datasets and computationally expensive training.

[14] “Automated Detection of Fake Images for Social Media Integrity Using Deep Learning (2025)”. This paper proposed a CNN-based fake image detection system with GUI support for social media integrity applications. The model supported single and batch image analysis with confidence visualization. The system achieved good detection accuracy but struggled with ambiguous images and lacked tampered-region localization features.

[15] “Detecting AI-Generated Images Using a Hybrid ResNet-SE Attention Model (2025)”.

The study proposed a hybrid SE-ResNet50 model integrating squeeze-and-excitation attention mechanisms with ResNet architecture. The model was trained using the CIFAKE dataset for AI-generated image detection. The proposed model achieved strong accuracy and generalization performance. However, it required high computational power and remained vulnerable to adversarial attacks.

[16] “Deep Vision Against Deception Using CNN Strategies for Fake Social Media Profile Detection (2025)”. This paper compared machine learning and deep learning models such as KNN, SVM, DNN, LSTM, and ResNet for fake social media profile detection. The ResNet-based architecture achieved the best performance. However, the dataset diversity was limited, affecting the model’s generalization ability.

[17] “A Comprehensive System for Detecting and Verifying Counterfeit Images using Deep Neural Networks (2025)”. The authors proposed a comprehensive counterfeit image verification framework using EfficientNet, DenseNet, ResNet, metadata analysis, and

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anomaly detection techniques. The system effectively detected manipulated and morphed images. However, the study highlighted challenges related to dataset standardization and detection of advanced manipulations.

[18] "Hybrid Approach for Robust Deep Fake Image Detection (2025)". This paper proposed a hybrid deepfake detection framework combining CNN spatial analysis, DFT/DWT frequency analysis, transformer attention mechanisms, and ensemble learning. The model achieved high detection accuracy and good generalization across datasets. However, the architecture involved high computational complexity and required larger diverse datasets.

[19] "Multi-Scale Edge-Guided Image Forgery Detection (2025)". The authors proposed a multi-scale edge-guided CNN framework for tampered-region localization. Edge detection and multi-scale feature extraction techniques were used to improve forgery localization accuracy. Although the method improved detection performance, computational cost increased significantly for large images.

[20] "Exploring the Role of Artificial Intelligence in Image Forgery Detection and Prevention: A Focus on MD5 and OpenCV (2025)". This paper combined MD5 hashing, OpenCV analysis, and AI-based models such as CNNs, RNNs, and Vision Transformers for forgery detection and prevention. The hybrid approach improved detection robustness and adaptability compared to traditional methods. However, the approach required significant computational resources and depended heavily on dataset quality.

III. METHODOLOGY

A. System Architecture

The proposed system is designed to detect and localize manipulated regions in digital images using deep learning techniques implemented on a Raspberry Pi platform. The system architecture consists of five major stages: input acquisition, image preprocessing, feature extraction using ResNet, localization using U-Net, and output generation. Initially, the system receives an image either from a camera module or from a cloud-based dataset. The input image is preprocessed to improve image quality and prepare it for deep learning analysis. The processed image is then passed to the ResNet model, which extracts deep visual features and determines whether the image is real or manipulated. After classification, the image is forwarded to the U-Net model, which performs pixel-level segmentation to identify and highlight the tampered regions. Finally, the system displays the detection result and localized manipulated area through a monitor or HDMI output connected to the Raspberry Pi. The complete workflow of the proposed system is illustrated in Fig. 1.

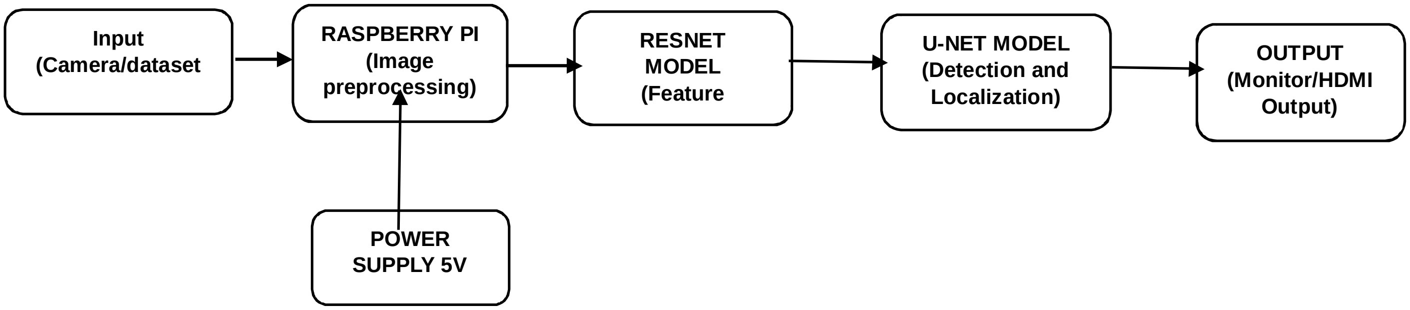

Fig. 1. Block Diagram of the Proposed Fake Image Detection System

B. Image Preprocessing

Image preprocessing is an important step in the proposed system, as it improves the quality and consistency of the input images before they are processed by the deep learning models. The input images obtained from the camera or dataset may contain variations in size, brightness, noise, and color distribution, which can affect the detection accuracy. Therefore, preprocessing operations such as image resizing, normalization, noise reduction, and format conversion are performed using the OpenCV library in Python. The images are resized to a fixed resolution suitable for the deep learning models, and pixel values are normalized to improve training efficiency and convergence. Noise reduction techniques are applied to remove unnecessary distortions and enhance important visual features. These preprocessing operations ensure that the input data is standardized and optimized for accurate feature extraction and localization. B. Image Processing and Deep Learning Analysis. The image processing and analysis stage forms the core of the proposed fake image detection system. Initially, the input images obtained from the camera or cloud-based dataset undergo preprocessing operations such as image resizing, normalization, noise reduction, and format conversion using the OpenCV library in Python. These preprocessing techniques standardize the input data, improve image quality, and ensure compatibility with the deep learning models.

After preprocessing, the images are passed to the ResNet model for feature extraction and classification. ResNet uses convolutional layers and residual learning with skip connections to identify important visual features such as edges, textures, illumination inconsistencies, and manipulation artifacts commonly found in forged images. By analyzing these extracted features, the model determines whether the input image is authentic or manipulated with high accuracy.

Following classification, the image is processed by the U-Net model for forgery localization. U-Net employs an encoder–decoder architecture with skip connections to perform pixel-level segmentation and accurately identify tampered regions within the image. The encoder captures contextual information, while the decoder reconstructs spatial details to generate a segmentation mask highlighting the manipulated areas. This combined approach of ResNet-based classification and U-Net-based localization enhances both detection accuracy and interpretability of the system.

C. Output Generation

The final stage of the proposed system is output generation. After the image has been analyzed by the ResNet and U-Net models, the system displays the classification result along with the localized manipulated regions. The output indicates whether the image is real or fake and visually highlights the tampered portions detected by the segmentation model. The results are displayed through a monitor or HDMI interface connected to the Raspberry Pi. The proposed system is designed to operate in real time with low computational complexity, making it suitable for applications such as social media monitoring, document verification, cybercrime investigation, and digital image authentication.

IV. PROBLEM STATEMENT

With the rapid rise of advanced image editing and deepfake technologies, detecting manipulated images has become increasingly difficult, leading to misinformation and security risks. Most existing image forgery detection systems are computationally intensive and not suitable for real-time deployment on low-power devices like Raspberry Pi. Additionally, many methods only detect forgery at the image level without accurately localizing the tampered regions. Therefore, there is a need for a lightweight, efficient system that can both detect and precisely identify manipulated areas in real time.

V. CONCLUSION

In our project, we developed a system to detect fake images using AI technology. The system uses ResNet to understand image features and U-Net to find edited parts. It can not only tell whether an image is fake but also highlight the manipulated area. Compared to older methods, this approach gives better accuracy and results. The model is designed to be lightweight and efficient. It can run on a Raspberry Pi, making it suitable for real-time use. This makes it useful for social media monitoring and security purposes. It can also help in detecting cybercrimes and verifying digital images. Overall, the system is simple, effective, and practical for real-world applications. In the future, it can be improved to detect more complex deepfake images.

VI. ACKNOWLEDGMENT

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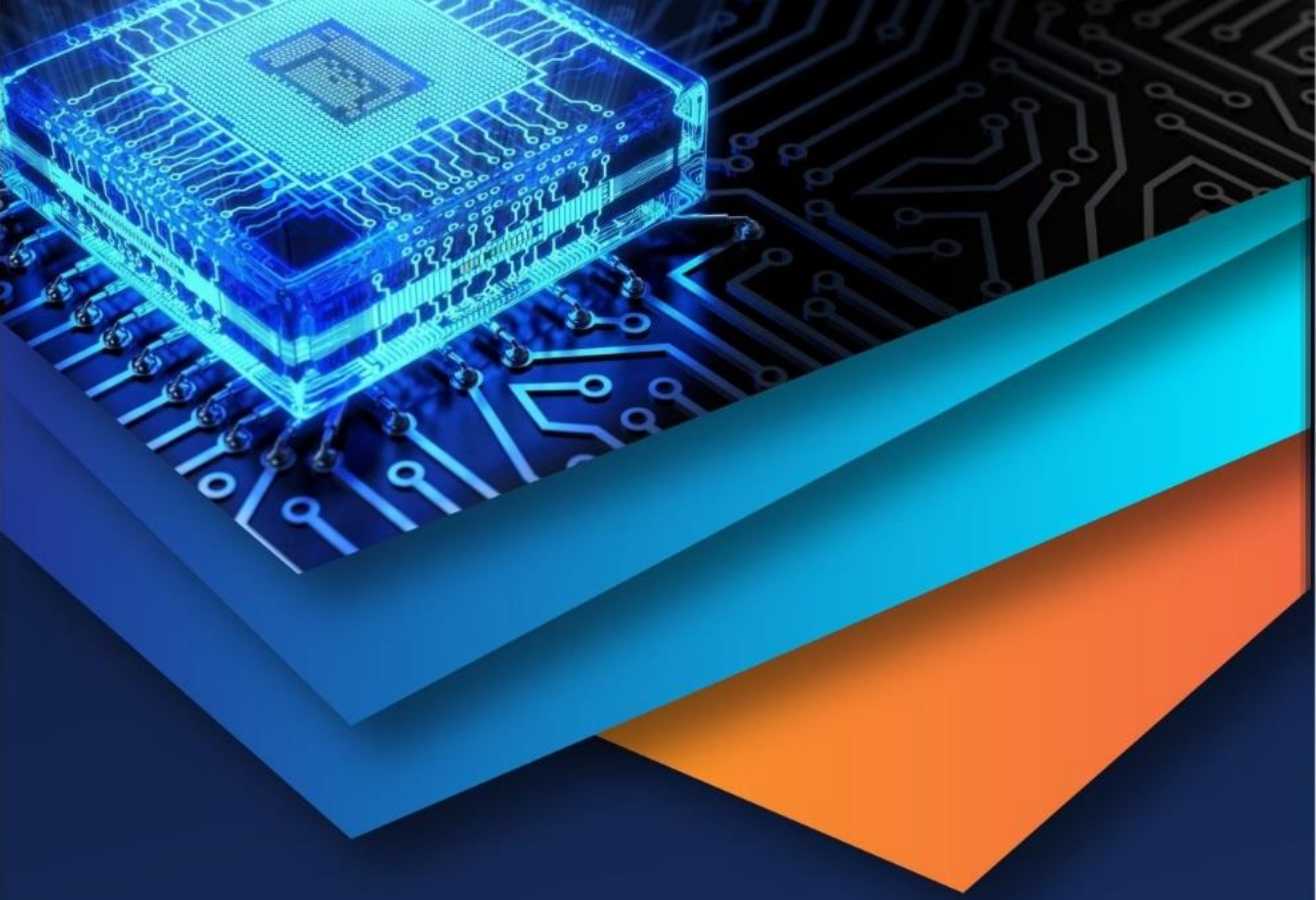

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