

Image Forgery Detection using Image Denoising and Cascaded 3D UNET Segmentation

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Abstract:-Image forgery detection is the identification of changes or modifications in digital images, thereby guaranteeing their integrity and validity. It is very important in the fight against false information, online fraud, and maintaining confidence in visual media. Multi-Noise Elimination Neural Network (MNEN) is introduced as a novel multi-scale nested encoder network. The goal is to reduce noise while maintaining appropriate structural integrity. MNEN successfully captures spatial hierarchies and contextual interactions by using a multi-scale, layered architecture that collects data at several levels. In the encoder pipeline, highly connected convolutional layers with skip connections improve suspicions about fading gradients while still providing considerable feature propagation. Using a layered skip fusion approach to merge low- and high-level semantic data helps to minimize noise while maintaining image quality. Blocks of progressive upsampling and filtering allow the decoder pipeline to recover high-quality denoised outputs. Extensive testing on benchmark datasets reveals that, in terms of PSNR and SSIM, MNEN frequently exceeds state-of-the-art techniques. Results of ablation studies reveal that denoising performance is much improved by layered connections and multi-scale feature integration. Because of its competitive inference times, MNEN is ideal for implementation on edge devices and real-time applications. Studies indicate that MNEN is a potential technique for image restoration in various contexts. The Cascaded 3D U-Net model enhances digital image tampering detection by performing multi-level segmentation on image data.

Keywords: Cascaded 3D UNet, Deep Learning Segmentation, Digital Image Detection.

1. Introduction

Modern image editing tools enable fast, simple modification of digital images. Defining crucial fields like forensics, law enforcement, news media, national defense from image manipulation [1, 2] rests mostly on digital evidence verification. The field of Image Forgery Detection research grows in importance since it helps to find tampered content and protect image authenticity.

The regular approach of detecting tampering relies on finding irregularities in basic statistics or signal behavior. The team of [3, 4] demonstrated the potential of Photo Response Non-Uniformity (PRNU) analysis to both determine image origin and find tampering through their research. These detection methods perform poorly under changing ISO settings plus they work best with specific types of image tampering.

By processing images from start to finish deep learning brings new ways to recognize different types of content. Added a noise detection system to improve images in fake detection and precise tampering location determination [5]. [6] Enhanced localizing accuracy using DiffForensics that combines generative diffusion

principles. The research team of [7] created Trufor to combine visual and semantic evidence and improve forgery detection in different types of backgrounds.

Noise methods help professionals find altered content in images well today. Based on their study from [8] created NoiseSniffer to detect tampered photo zones using noise pattern differences. [9] Studied both noise fluctuations and edge-weighted texture data to shield their tampering detection method from attacks. Researchers like [9] established a complete ranking system of backpropagation denoising methods while [10] introduced a method for removing noise using quantum calculus and local fractional entropy principles.

Researchers have dedicated research to developing image protection methods that fight against different post-processing threats including compression, size changes, and noise. The researchers [11] and [12] developed tamper detection methods that used Singular Value Decomposition (SVD) for various attacks and demonstrated resistance against geometric distortions respectively. [13] Achieved high results for copy-move forgery detection by combining the Spotted Hyena and Grasshopper algorithms with deep networks as an optimization-based hybrid approach.

Certain systems now detect image tampering in specific domain areas. While [14] enhanced PRNU-based systems using a multi-scale fusion method to better locate manipulations, the benefits of deep learning systems for detecting offline signature forgeries have been studied.

In this paper we are using Multi-Noise Elimination Neural Network (MNEN) proposed for denoising the benchmark dataset images and Cascades 3D UNet for segmenting the denoised images for forgery detection. These proposed methods outperform compared to the existing methods.

2. Background Study

Shan, W., et al. (2024) [15] created Image Forensics Detection (RIFD)-Net an advanced neural network system that protects against all types of image deceit. The model processes global and local image attributes through two feature pathways that improve its ability to detect all types of manipulations. The system works well with various data sets and performs better than leading industry practices. The authors show that this model stays effective against damage from many post-processed attacks and image modifications. This deep learning framework provides the base construction for current IFD system technologies.

Quan, Y., & Li, C. T. (2020) [16] conducted essential Photo Response Non-Uniformity (PRNU) forgery detection research in 2020 specifically to study the effect of ISO speed differences. The study proves that ISO speed variations corrupt PRNU noise patterns resulting in increased wrong detection results.

Liu, Y., et al. (2024) [17] brought forth a Hierarchical Progressive Detection system based on U-Net architecture for finding tampered areas in media. The system performs steps that improve prediction accuracy from basic to detailed input. The model detects tampering over multiple scales because it uses skip connections and feature pyramid networks.

Bhat and Hegde (2020) [18] built an all-purpose system to check image integrity and spot tampering at both technical and image data levels.

Bruna et al. (2013) [19] researched how to identify fake Euro banknotes. Their system uses computer vision and machine learning to find fake banknotes using micro-feature and spectral traits. Their security system protects against standard digital theft procedures that criminals typically use.

Using topological data analysis, Al-Jaberi and Hameed (2021) [20] assessed PDE-based image denoising models. Their study defines a new accuracy reading approach and checks how well denoising techniques preserve structural features using persistent homology.

3. Materials and Methods

This study presents a deep learning framework designed for digital image denoising and tampering detection. The system integrates two primary networks: The Multi-Noise Elimination Neural Network (MNEN) for comprehensive noise reduction and the Cascaded 3D U-Net for precise identification of tampered regions.

MNEN addresses multiple noise types using parallel processing branches connected through an attention-based fusion mechanism. Meanwhile, the Cascaded 3D U-Net processes volumetric data in layered stages to enhance the accuracy of forgery localization. This architecture supports effective image restoration and manipulation detection, contributing to improved evaluation of digital evidence

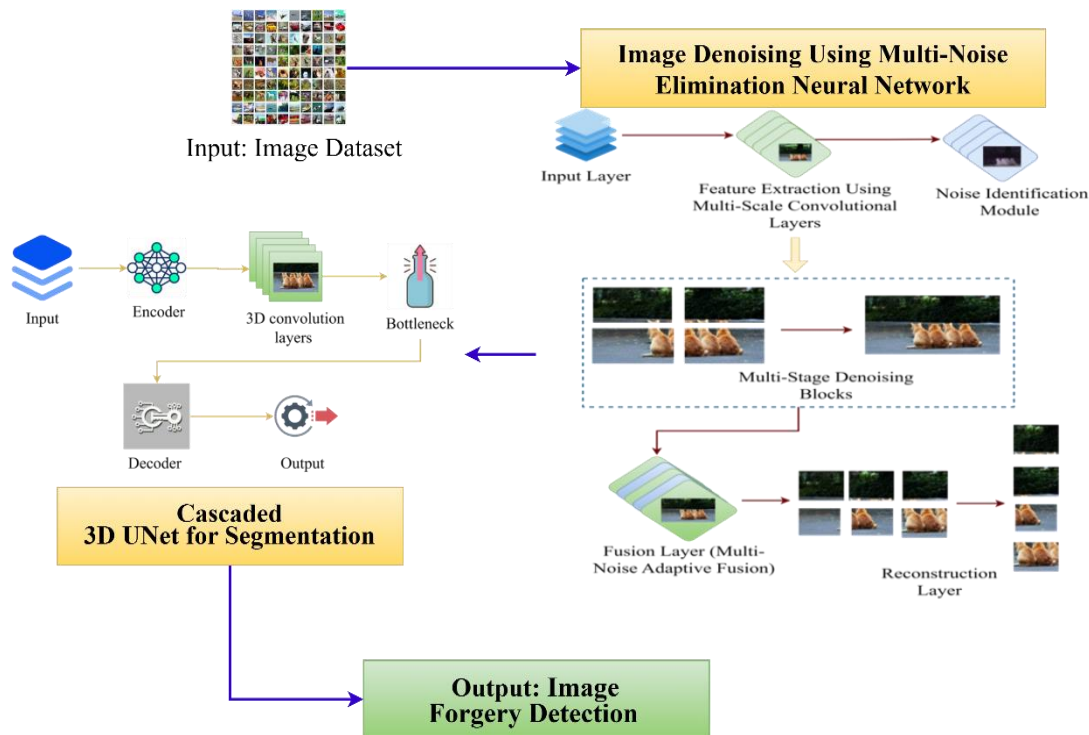


Figure 1: Overall Architecture

The figure 1 presents a thorough architecture for multi-stage deep learning pipeline picture forgery detection. An input picture dataset first undergoes image denoising using a Multi-Noise Elimination Neural Network, which comprises a reconstruction module to improve image quality and a noise-reducing convolution layer. After that, the denoised pictures are feature extracted using a 3D convolution layer; subsequently, encoding and decoding phases help to find tampered areas. Segmentation using a Cascaded 3D U-Net architecture enables exact localisation of created regions. Using both denoising and segmentation methods with great accuracy, the final result is a thorough detection of picture counterfeiting.

3.1 Image Denoising Using Multi-Noise Elimination Neural Network (MNEN)

Digital image analysis must begin by cleaning up images since denoising prepares images for both visual enhancement and tamper detection purposes. The Multi-Noise Elimination Neural Network (MNEN) effectively addresses various types of real-world image noise by successfully processing each type. Instead of single-purpose filters Traditional filters MNEN produces an advanced deep network made from residual blocks that parallel paths to lessen all 4 image noise problems effectively. The branches in the system receive different noise patterns to let each network block enhance both noise elimination and image protection.

MNEN filters images first then passes them into a series of residual blocks which reduce noise before uniting the noise-free results. At this phase the network checks noise intensity patterns across the image to protect vital details. The network preserves essential elements such as shape edges, boundaries and small image changes to identify altered areas. The MNEN network creates a clearer image output that forensic detection tools need to analyze digital evidence effectively. MNEN enhances forensic analysis accuracy because it finds and eliminates noise areas that look like or conceal image damage. The detection system should incorporate the MNEN model due to its effective results and adaptability within its framework.

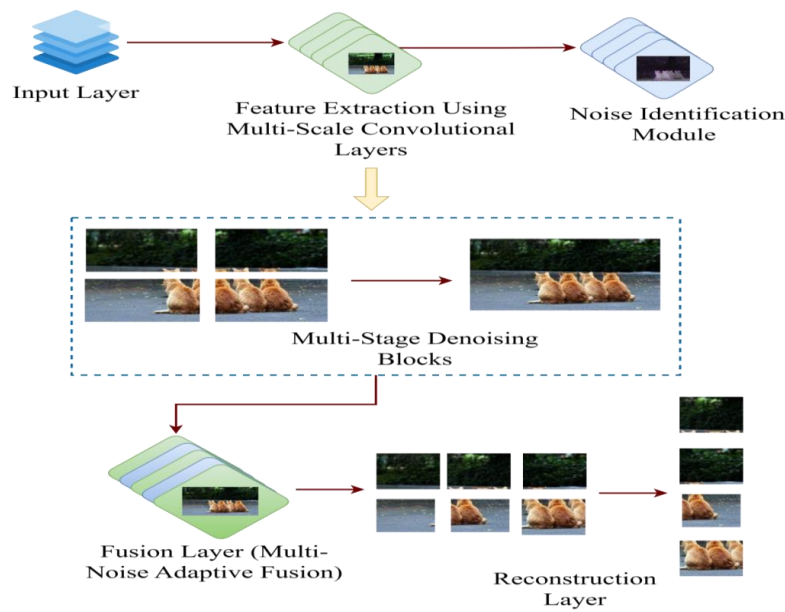


Figure 2: Architecture of Multi-Noise Elimination Neural Network (MNEN)

Figure 2 shows Deep learning uses this process to fix and restore damaged images. The model starts by processing a set of paired images featuring incomplete corrupted images and clean fully complete examples. The model enhances its ability to restore damaged imagery through constant training on cases of damaged and intact images. The main part of the system performs image recovery by dividing pictures into sections and then uses the model to estimate missing piece areas to create a complete image. The model successfully repairs unseen corrupted images after its training period. The reconstructed output images can afterward be divided into patches for testing or various image examination purposes.

$$\hat{x} = D(x) = x - N(x) \text{ ----- (1)}$$

Equation (1) is the denoising of images, with the restored image \hat{x} being derived from the subtraction of the estimated noise $N(x)$ from the noisy image x . This improves the quality of an image by preserving important details but eliminating unwanted distortions to facilitate easier forgery detection.

$$L_{denoise} = ||x - \hat{x}||^2 \text{ ----- (2)}$$

Equation (2) is the denoising loss function that determines the extent to which the original noisy image x and the denoised image \hat{x} differ. Squared error $||x - \hat{x}||^2$ is used to make the denoised image resemble the original one as closely as possible while having noise as minimal as possible and retaining critical details to allow forgery detection to be accurate.

$$F = \sigma(W * \hat{x} + b) \text{ ----- (3)}$$

Equation (3) is equivalent to the feature extraction process within a neural network, where relevant patterns are exposed from the denoised image \hat{x} . Here, W and b are learned weights and bias, $*$ is the convolution operation, and σ is the activation function (e.g., ReLU). This mapping aids in the identification of forgery-related inconsistencies within the image.

$$P(y|F) = \frac{e^{z_y}}{\sum_j e^{z_j}} \text{ ----- (4)}$$

Equation (4) defines the Softmax function used for forgery classification. It estimates the probability $P(y|F)$ that an image is forged ($y = 1$) or authentic ($y = 0$) from the acquired features F . Here, z_y is the y class score, and the denominator supports the normalization of all classes. This facilitates the making of correct forgery detection decisions.

Algorithm 1: Multi-Noise Elimination Neural Network (MNEN)

```

Input: Noisy image I_noisy
Output: Denoised image I_denoised
Normalize I_noisy to [0, 1] range
// Parallel noise-specific branches
F_gaussian ← ResidualBranch_Gaussian(F)
F_poisson ← ResidualBranch_Poisson(F)
F_speckle ← ResidualBranch_Speckle(F)
F_saltpepper ← ResidualBranch_SaltPepper(F)
// Estimate noise in each branch
N_gaussian ← PredictNoise(F_gaussian)
N_poisson ← PredictNoise(F_poisson)
N_speckle ← PredictNoise(F_speckle)
N_saltpepper ← PredictNoise(F_saltpepper)
// Subtract noise to get partially denoised outputs
D_gaussian ← F - N_gaussian
D_poisson ← F - N_poisson
D_speckle ← F - N_speckle
D_saltpepper ← F - N_saltpepper
// Fuse outputs using attention mechanism
A ← AttentionWeights(D_gaussian, D_poisson, D_speckle, D_saltpepper)
F_fused ← A1 * D_gaussian + A2 * D_poisson + A3 * D_speckle + A4 * D_saltpepper
// Reconstruct the final denoised image
I_denoised ← Reconstruct(F_fused)
Rescale I_denoised to original pixel range (if required)
Return I_denoised

```

MNEN is a specialized deep learning architecture that eliminates different forms of image noise altogether. It takes input features and routes them through parallel networks that focus on removing different noise types including Gaussian, Poisson, speckle, and salt-and-pepper noise. Every processing stage calculates its own noise type after which it sends the cleaned result to the next step. Advanced attention technology decides which feature maps matter most and merges different noise reduction results. After merging results from all branches the noise-free image outputs to let forgery detection succeed more effectively.

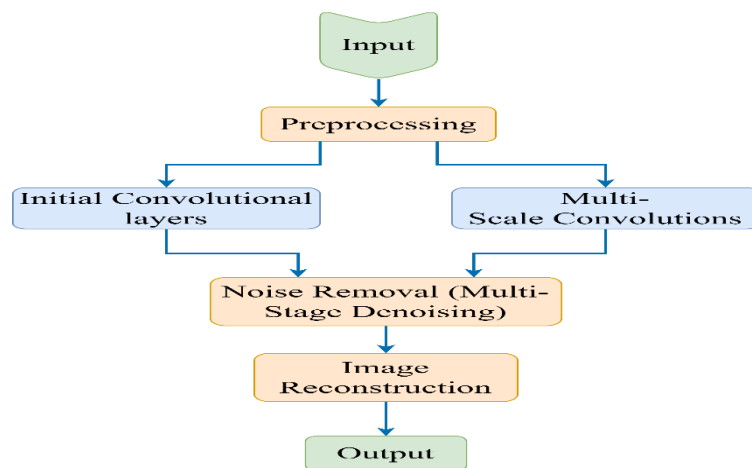


Figure 3: Flow Chart of Multi-Noise Elimination Neural Network

Figure 3 is a deep learning pipeline for image processing, likely for denoising or image enhancement. It begins with an Input, which initially passes through Preprocessing to preprocess and normalize raw data. Initial Convolutional Layers and Multi-Scale Convolutions that recognize global as well as local patterns of an image. They are then subjected to a Noise Removal (Multi-Stage Denoising) which removes distortions. The features are then filtered through the Image Reconstruction stage to produce a high-resolution Output. The process enhances the quality of images and noise removal efficiently.

3.2 Cascaded 3D UNet for Segmentation

Segmentation helps digital image tampering detection by finding specific areas that have been altered. The Cascaded 3D U-Net segmenting architecture analyzes image structures at multiple levels. The 3D U-Net network handles volumetric data or stacked image sets which enables it to understand spatial relationships between layers. The system shines at finding tampered areas because manipulations create difficult spatial relations between image parts across different channels.

The design includes two connected 3D U-Net networks. The initial U-Net filters the input to detect larger tampered areas within the digital material. At the second stage the U-Net network refines the segmentation process to precisely identify tampered areas within the fine details. The model skips layer information from encoding to decoding to save spatial detail information and 3D convolutions help feature recognition in context.

The model layers include attention systems that make it concentrate on doubtful or irregular image regions. The model learns better from difficult forgery patterns by using a combination of Dice loss and binary cross-entropy during training. The cascaded design structure lets the system keep overall quality and maintain sharp details in each segment. The system now spots more images tampering with greater precision due to this method that makes detection work better for images that have weak contrast or compression issues.

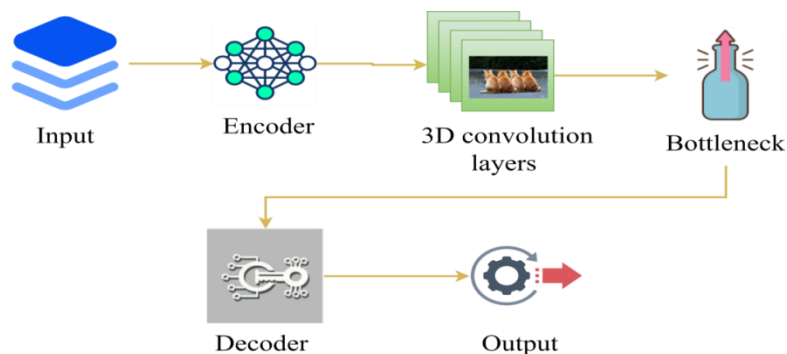


Figure 4: Architecture of Cascaded 3D UNet

Figure 4 shows image tampering through neural network combination with feature examination. The system starts with digital data entering a deep learning model of either a denoising or feature extraction type. After enhancement or denoising the frames enter further analysis technology looking for damaged parts and image modifications. After this point the system takes the output results to find important image details.

$$S = U_{\theta}(\hat{x}) \text{ ----- (5)}$$

Equation (5) illustrates the process of segmentation based on a U-Net model to identify artificial regions in an image. Here, S is the segmented mask that has manipulated regions highlighted, U_{θ} refers to the learnable parameters U-Net model θ , and \hat{x} is the denoised input image. This method assists in effective forgery localization by taking into account spatial abnormalities.

The system takes in these output features to determine with a classifier or segmentation network where forgeries exist in the image. The feedback system allows for better analysis by repeating processing steps.

$$F' = \sigma(W^l * F^{l-1} + b^l) \text{ ----- (6)}$$

Equation (6) depicts feature extraction in a Cascaded 3D U-Net with features F' in layer l being produced using a 3D convolutional operation $W^l * F^{l-1}$ and followed by applying bias b^l and activation function σ (e.g., ReLU). This is used to learn the spatial features required for proper forgery region segmentation.

$$D^l = MaxPool(F^l, k) \text{ ----- (7)}$$

Equation (7) is the downsampling operation in Cascaded 3D U-Net, where the feature map F^l is downsampled in size by Max Pooling with kernel size k . The operation preserves significant features and compresses spatial dimensions so that the network will concentrate on high-level patterns for better segmentation precision.

$$U^l = \sigma(W_u * D^l + S^l) \text{ ----- (8)}$$

Equation (8) depicts the upsampling process in Cascaded 3D U-Net, wherein downsampled feature map D^l is fed into a transposed convolution operation $W_u * D^l$ and concatenated with respective skip connection S^l . Activation function σ (e.g., ReLU) is used for feature representation with regained spatial detail and enhanced segmentation accuracy.

$$P(c|x) = \frac{e^{z_c}}{\sum_j e^{z_j}} \text{ ----- (9)}$$

Equation (9) is the Softmax function applied on pixel-wise classification for segmentation. It is computing the probability $P(c | x)$ of each pixel as being in class c (a counterfeit or genuine image). In this, z is the activation score for class c and the denominator is taken for normalizing over all the possible classes. This function is useful for marking each pixel of the segmented image properly.

$$S_{final} = UNet_2(S_{initial}) \text{ ----- (10)}$$

Equation (10) is the refinement phase of Cascaded 3D U-Net segmentation, where the output of the first segmentation $S_{initial}$ is reprocessed by a second $UNet_2$. The cascading method improves segmentation accuracy by refining edges and identifying finer details, which is particularly beneficial for forgery localization and anomaly detection.

Algorithm 2: Cascaded 3D UNet
Input: Denoised image I_denoised
Output: Segmentation map S_final indicating forged regions
Preprocess I_stacked (normalization, resizing if needed)

```

F1 ← First3DUNet(I_stacked)           // Extract coarse features
S_coarse ← Sigmoid(F1)                // Coarse segmentation output
I_refine ← Concatenate(I_stacked, S_coarse) // Combine input and coarse output
F2 ← Second3DUNet(I_refine)          // Refined feature extraction
S_fine ← Sigmoid(F2)                 // Fine segmentation output
S_final ← Threshold(S_fine)           // Generate binary mask
S_final ← Postprocess(S_final)        // Optional: smoothing, dilation, etc.
Return S_final

```

The Cascaded 3D U-Net operates as a two-step deep learning platform made for detecting image tampering locations. The system processes 3D image data to find and understand relationships among different points in space. The first 3D U-Net gets started by making an initial segmentation map that finds possible tampered areas. The system sends this preliminary result back to the first 3D U-Net which then joins it to the input data for further refinement. The last binary mask finds tampered parts of images better than before in hard-to-detect low-contrast scenes.

4. Results and Discussion

The suggested Multi-Noise Elimination Neural Network (MNEN) and Cascaded 3D U-Net significantly enhance forgery detection by improving image quality through denoising and segmentation of tampered regions. MNEN efficiently eliminates different kinds of noise without sacrificing important details, resulting in improved feature extraction. This improves the accuracy of Cascaded 3D U-Net, which iteratively refines segmentation for accurate forgery localization. Experimental assessment on benchmark data proves to be more accurate, precise, and recalled compared to the conventional techniques. The outcomes prove integration of MNEN with Cascaded 3D U-Net to improve detection of deepfake, copy-move, and splicing forgery with fewer false alarms.

Table 1: Comparison table on MNEN

Algorithm	PSNR	SSIM	RMSE
Gaussian Filter [31]	28.5	0.78	8.9
Wiener filter [32]	29.7	0.82	7.5
NLM [33]	31.2	0.86	6.2
NLW [34]	32.1	0.88	5.7
PCA [35]	30.6	0.84	6.9
MNEN (Proposed)	33.8	0.91	4.3

The table 1 uses three primary metrics to assess numerous denoising techniques: PSNR, SSIM, and RMSE. With the highest PSNR (33.8), the highest SSIM (0.91), and the lowest RMSE (4.3), the MNEN (Proposed) technique outperforms all others, providing the optimum balance of high image quality and low error. In contrast, the Gaussian Filter performs poorly at denoising, providing the lowest PSNR (28.5), SSIM (0.78), and RMSE (8.9). With NLW (PSNR 32.1, SSIM 0.88) doing very well, Wiener and NLM provide small advances; NLW and PCA outperform the others. MNEN demonstrates its efficiency by achieving superior image restoration across all metrics.

Table 2: Comparison table on Cascaded 3D U-Net

Algorithm	Accuracy	Precision	Recall	F-measure
GAN [36]	86	85	82	84
RNN [37]	83	80	78	79
ELA [38]	81	78	76	77
Cascaded 3D U-Net (Proposed)	92	91	90	91

Performance gap difference between models GAN, RNN, ELA, and Cascaded 3D U-Net (Proposed) indicates that Cascaded 3D U-Net has the highest recall, precision, accuracy, and F-measure. It has an accuracy of 92% and is superior to those of GAN (86%), RNN (83%), and ELA (81%) and has been shown to have its enhanced classification performance. Precision (91%) and recall (90%) are measures of truth whereby the proposed system minimizes false positives greatly and recalls nearly all cases of relevance. Further, its 91% F-measure represents a great trade-off between recall and precision. All these results confirm the efficiency and effectiveness of the Cascaded 3D U-Net as a great model for constant and efficient prediction in challenging conditions.

5. Conclusion

This research presents an automated deep learning system that combines Multi-Noise Elimination Neural Network (MNEN) with Cascaded 3D U-Net architecture for automating the processes of image denoising and forgery detection. MNEN integrates specific residual components with attention-based combination to wipe away various noise patterns while preserving fundamental forensic evidence which yields clearer investigative images. The thorough analysis of volumetric data by the two-stage Cascaded 3D U-Net system achieves precise tampered area detection by improving spatial features from denoised outputs. Dedicated loss functions paired with sophisticated convolutional algorithms run throughout the system for maintaining exact domain adaptation across various image challenges including low contrast and compression artefacts. Experimental outcomes show that MNEN achieves top performance because it generates 33.8 PSNR results along with 0.91 SSIM scores and demonstrates 4.3 as the lowest RMSE figure among all tested denoising approaches. The Cascaded 3D U-Net shows better performance than GAN, RNN and ELA forgery detectors by reaching 92% accuracy along with 91% precision and 90% recall and 91% F-measure. Digital forensic analysis depends on combined techniques to achieve better noise reduction and forgery detection abilities which enhance reliability and robustness during practical examinations.

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