CNN-Based Image Forgery Detection Using Sequential Deep Learning Architecture

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***Abstract*—The multiplication of digital image editing tools and software has made image alteration or modification highly accessible, thus confirming that the legitimacy and authenticity of visual content have become extremely difficult. The current research introduces a comprehensive deep learning-based methodology for binary image forgery detection based on a specially designed Convolutional Neural Network (CNN). The system identifies the spatial and structural irregularities in the edited or tampered image content. We have used the CASIA2 dataset, a well-known benchmark that contains diverse examples of splicing and copy-move forgery cases. Our CNN-based image forgery detection model includes several sequential subsequent convolutional and pooling layers, which are succeeded by elaborated fully connected layers. The system is optimized using methods such as dropout and data augmentation to enhance and optimize overall generalization and combat overfitting of the model on the image dataset. Large-scale experimentation and testing prove that the proposed sequential CNN model performs strong binary image classification into authentic and tampered images with high accuracy and low false positive rates. The model's effectiveness and performance are validated using various evaluation metrics such as accuracy, precision, recall, AUC ROC score, F1 score and confusion matrix analysis. The results from experimentation demonstrate that a well-structured CNN model can be an effective and realistic solution for practical digital image forensics, especially in situations where computational speed is highly pivotal.**

Keywords: **Image Forgery Detection, Convolutional Neural Network, Deep Learning, CASIA2 Dataset, Digital Forensics**

I. Introduction

The greatly increased growth of online creation and distribution of digital media has greatly complicated the assurance of images' integrity and authenticity. The continuous speedier development of image- and video-manipulation software packages such as Adobe Photoshop and GIMP has made it feasible for a novice to produce intricate manipulations that are visually misleading. Though these tools have genuine applications in various business sectors like entertainment and advertisement, they can prove to be extremely harmful if used for nefarious activities such as disseminating disinformation, identity theft, and altering evidence. Thus, detecting counterfeit images has emerged as a very high-priority issue in digital forensics, journalism, law enforcement and cybersecurity.

The main broad categories into which image forgery is mainly categorized are copy-move forgery and picture splicing. In copy-move forgery, some part of the image is duplicated and shifted to another location in the same image, aiming to conceal or duplicate objects. The splicing technique generates a new altered or manipulated composition of the image by mixing patches from different images. Older image forgery detection methods depended extensively on manually designed features and statistical processing, like Principal Component Analysis (PCA), Discrete Cosine Transform (DCT), and block matching. Although these traditional methods have achieved some success, they tend to lack generalization across manipulation types and are hampered by high false positive rates on challenging images. Image analysis has undergone a revolutionary transformation in recent years thanks to deep learning, specifically Convolutional Neural Networks (CNNS), that learn hierarchical features automatically from unprocessed pixel information. CNNS has produced cutting-edge results in several practical computer vision implementations, which include segmentation, object detection, and picture categorization. Especially tailored for the binary classification of photos into genuine or manipulated classes, this work introduces a sequential CNN-based architecture. The primary contributions of our study are as follows: (1) We create and train a specific lightweight CNN model for binary image forgery detection, avoiding the need for transfer learning or high-capacity pre-trained models; (2) We maximize the model's resilience on the widely used CASIA2 dataset by employing comprehensive data pre-processing and image augmentation techniques; (3) We show that our model performs high classification accuracy—achieving an accuracy of 94.2%—with low computational overhead, which makes it appealing for deployment and real-time applications in resource-limited environments like mobile or embedded forensic systems. Standard performance measures such as accuracy, precision, recall, F1 score, AUC ROC score and a confusion matrix are employed to measure the efficacy of the proposed method.

The structure of this research paper is: Reviews of the literature work done in the image forgery detection domain are presented in Section II. Section III gives our approach, i.e., data preprocessing, defining model structure, and training

processes etc. The CNN model's analysis and experimental findings are presented in Section IV. In Section V, we conclude with the performance of our sequential CNN model. Lastly, Section VI covers the future scope of picture forgery detection systems and processes.

II. Related Works

The domain of image forgery detection has considerably expanded since its very beginning, as various researchers have analyzed and validated various methods for detection, identification and localizing the tampered regions in digital images. In one of the pioneering seminal early works by Farid et al. [1] put image tempering detection techniques into active and passive categories, encompassing embedding watermarks or signatures and using inconsistencies without having information. This survey highlighted the challenge of using passive detection due to the diversity of forgery techniques and the need for improved statistical models.

The thorough research study with a focus on passive forgery detection methods was then provided by Birajdar et al. [2]. They described and outlined method strategies such as picture copy-move, image splicing, and resampling detection and stressed the need for feature extraction techniques such as Discrete Cosine Transform (DCT), Principal Component Analysis (PCA), and Singular Value Decomposition (SVD). This survey also covered the shortfalls in detecting forgeries in low-texture areas and the problem caused by the post-processing operations.

Kumar et al. [3] in their study surveyed many image forgery detection methods and mentioned the requirement of effective algorithms to identify advanced forgeries. They talked about the involvement of machine learning in making detection more accurate and the difficulties caused by post-processing techniques. Likewise, Qazi et al. [4] gave a comprehensive overview of blind (passive) image forgery detection methods and then classified them into different categories based on the forgery they identify. They emphasized the effectiveness of several feature extraction methods and the merit of using multiple methods to achieve better detection.

Deep learning methods have taken the lead in image forgery detection in recent years. Zhou et al. [5] overviewed recent deep-learning methods, comparing different CNN model architectures and their performance for detecting various forgeries. They also pointed out and emphasized the benefits of employing deep learning in automatically acquiring features and the issues of dataset availability and effectively utilizing the computational resources. The survey also gave an exhaustive list of benchmark datasets like CASIA v1.0, CASIA v2.0, MICC-F220, MICC-F600, and CoMoFoD, which are commonly used for model training and model evaluation of forgery detection. Performance measure metrics, including the True Positive Rate (TPR), True Negative Rate (TNR), accuracy, precision, recall, F1-score and AUC ROC score, were universally applied and measured across studies.

Li et al. [6] in their work proposed an image copy-move forgery detection scheme through image segmentation, segmenting the image into individual blocks and depending upon feature matching for detecting copy-move forgeries. Their method performed outstandingly in detecting copied regions, even if post-processing has occurred in the form of rotation and scaling. Wang et al. [7] introduced passive image tampering detection using methods independent of image prior knowledge. They reviewed various statistical and geometric-based methods and highlighted the need for strong algorithms to address cases of different types of tampering.

In their review of digital image forgery detection techniques, Ghassemian et al. [8] enumerated the pros and cons of various strategies. He stressed the importance of using more than one feature and classifier to improve the model's forgery detection performance. Nguyen et al. [9] classified the image forgery detection algorithms according to the type of forgery and the detection mechanism used, hence giving the challenges of forgery detection in compressed images as well as enhancing the detection accuracy through machine learning.

A constrained CNN-based architecture that can detect a broad range of image alterations was proposed by Bayer, Stamm et al. [10]. Their model utilized constraints that direct the learning process, thus enhancing the overall detection of subtle forgeries. Zhou et al. [11] did a review on deep learning-based image forgery detection techniques and presented different architectures such as CNNS, Recurrent Neural Networks (RNNS), and Generative Adversarial Networks (GANS). They highlighted and emphasized the need for extensive and varied datasets to train strong models. Qureshi and Deriche [12] presented a detailed bibliography of pixel-based blind image forgery detection methods, thereby classifying them according to the forgery type and detection methods, as a useful reference for researchers who work on investigating pixel-level forgery detection.

Zhang et al. [13] presented a Fast Shallow CNN (SCNN) model aimed at detecting forged boundaries in low-resolution images. Their approach utilized chroma and saturation features to identify the tampered regions, thus achieving competitive performance with a lightweight network that was very computationally efficient. Memon and Shaikh [14] introduced a deep learning method that leveraged a recompression-based preprocessing strategy to enhance the visibility of forgery artefacts. By retraining a CNN on recompressed versions of CASIA images, they achieved an impressive accuracy score of 99.30%, demonstrating that such preprocessing techniques can also effectively expose tampered areas that are otherwise subtle. Wu et al. [15] developed a self-supervised model named FOCAL (FOrensic ContrAstive cLustering), which utilized contrastive learning to distinguish forged from authentic patches without overly relying on labelled data. Their model outperformed supervised baselines and highlighted the potential of contrastive clustering in handling unlabeled datasets like CASIA. Gupta et al. [16] incorporated Error Level Analysis (ELA) as a preprocessing step before feeding the images to a CNN; this method leveraged compression-level discrepancies to detect manipulations and image forgeries. This fusion of forensic preprocessing with

deep learning significantly boosted detection accuracy on the CASIA dataset. Joshi et al. [17] conducted a comparative analysis of transfer learning using state-of-the-art pre-trained CNNS such as VGG-19, ResNet-152v2, Inception-V3, and EfficientNet-V2L on CASIA v2.0. Among them, EfficientNet-V2L achieved the highest accuracy, reinforcing the strength of transfer learning, especially when enhanced by ELA transformations. Khan and Yousuf [18] proposed a hybrid approach that combined YOLO's object detection-based feature extraction with ResNet50v2 for classification. Their model demonstrated high accuracy (99.30%) on CASIA v2.0, emphasizing the effectiveness of integrating detection-oriented and classification-oriented deep learning methods. Ali and Khan [19] conducted a comprehensive review of deep learning-based forgery detection techniques, providing insights into the challenges associated with datasets such as CASIA v2.0, including the lack of standardized tampering masks and the need for robust evaluation protocols. They also discussed various architectures, from CNNS to GANS, highlighting their respective strengths and limitations. In another work, Wu et al. expanded upon their previous research on contrastive learning, proposing a refined framework that improves representation learning by maximizing inter-class differences. This method achieved enhanced forgery detection performance across CASIA and similar datasets, showcasing how self-supervised learning can surpass traditional supervised approaches in terms of generalization and scalability.

Together, these works emphasize the advancements made in the domain of image forgery identification, emphasizing the shift towards deep learning approaches. They illustrate the power of CNNS and other architectures to detect different kinds of image manipulations, thus opening the door to more efficient and effective detection systems. These new works emphasize the movement towards deep and self-supervised architectures as well as away from shallow learning and handcrafted features in detecting image forgery. As attention is increasingly drawn to leveraging pre-processing artefacts, contrastive paradigms, and transfer learning, contemporary systems are now able to provide considerably better accuracy. In this competitive scenario, our suggested model—94.2% accuracy on CASIA v2.0—manifests robust performance and generalization. It is competitive with other current state-of-the-art techniques while remaining computationally efficient and robust, further supporting its efficacy in real-world forgery detection applications. However, the challenges still exist, such as the need for large and diverse datasets, coping with post-processing operations, and improving detection in low-texture regions.

III. Methodology

This section presents an overall analysis of the methodological process involved in designing and developing an image forgery detection using a custom CNN model for efficient and mobile computation. The pipeline includes various crucial steps: data acquisition and preprocessing, data augmentation, the selection and implementation of model architecture, training method, evaluation measures, and model testing with real-world predictions. The objective is to use design and implement a light-weight and efficient deep CNN for detecting and distinguishing forged from authentic images. The flowchart of the methodology implemented for this proposed CNN model is shown in Fig.1.

A. Data Acquisition And Preprocessing

The amount of data and its quality are used to build a deep learning model. For this research, the CASIA2 dataset was employed, which is a standard benchmark in digital image forensics. The CASIA2 dataset contains authentic and tampered images, where the tampered images contain typical forgery methods like copy-move, splicing, and retouching.

All of the images were downsized to 224x224 pixels, which is a standard and typical input size for most image classification models, so that they could be used with our in-house CNN model. To normalize the pixel values between 0 and 1, images are also normalized. This makes the model more stable and convergent. Class labels (authentic and tampered) were normalized into binary form via a label encoder. The data was then separated into 70% training, 15% validation, and 15% testing sets in order to evaluate the generalisation ability of the model.

For dealing with class imbalance as well as to improve the model's robustness, data augmentation methods were employed through Keras' ImageDataGenerator. Some augmentations, including random rotation, flipping, zooming, and brightness changes, were used during training to mimic variability in tampered images in the real world.

B. Custom Lightweight CNN Architecture for Binary Image Classification

In the present work, a lightweight CNN was specifically designed from scratch to do binary classification of the tampered and real images. The model is designed for simplicity, interpretability, and computational effectiveness, avoiding the use of transfer learning or deep pre-trained networks such as MobileNetV2 or ResNet.

The architecture is lightweight because it is deliberately shallow with just two convolutional layers and a small number of filters in order to minimize parameter count and computation. Such a design allows training to be much faster, uses less memory, and is deployable on edge devices or real-time forensic applications. The model, in spite of being minimal, is highly accurate while also being lightweight in terms of FLOPS (Floating Point Operations per Second) and model size.

The network has two 5×5 convolutional layers with RelU activations, max-pooling, and dropout for overfitting reduction. It is flattened and fed into a dense layer of 256 neurons, another dropout layer, and a softmax output layer for binary classification. Fig. 2 illustrates the architecture diagram of the presented model.

The proposed CNN's particular layer architecture is as follows:

TABLE I
LITERATURE REVIEW OF IMAGE FORGERY DETECTION TECHNIQUES

Reference	Techniques	Dataset Used	Performance Metrics	Limitations
Farid (2009) [1]	Statistical and Geometric forensic techniques	CASIA, Columbia	Detection rates: 85-90% (estimated)	Pre-dates deep learning; lower accuracy on sophisticated forgeries
Birajdar & Mankar (2013) [2]	Passive pixel and format-based detection	CASIA, Columbia, DVMM	Average precision: 86.3%, Recall: 84.7%	Traditional methods with lower accuracy than modern approaches
Kumar & Agarwal (2014) [3]	Active and passive detection methods	CASIA v1.0, DVMM	Detection accuracy: 82-88% range	Limited to classical computer vision; high false positives
Qazi et al. (2013) [4]	Blind image forgery detection	CoMoFoD, MICC-F220	Average accuracy: 84.5%	Ineffective against sophisticated manipulations
Li et al. (2015) [6]	Segmentation-based copy-move with SIFT	MICC-F220, MICC-F2000, CoMoFoD	Precision: 97.25%, Recall: 93.42%, F1: 95.3%	Computationally Intensive; fails with small copied regions
Wang et al. (2014) [7]	Passive tampering detection	CASIA v2.0, CoMoFoD	Detection rate: 87.6%, Precision: 85.1%	Limited performance on low-resolution images
Ghassemian (2018) [8]	Statistical and physics-based methods	CASIA, Columbia, CoMoFoD	Precision: 87.5%, Recall: 85.3%	Less effective than emerging DL methods; high false positive rate
Nguyen et al. (2015) [9]	Copy-move and splicing detection	CASIA, MICC, CoMoFoD	Accuracy range: 83-91%	Inconsistent performance across different forgery types
Bayar & Stamm (2018) [10]	Constrained CNN for manipulation	Dresden, UCID	Accuracy: 99.31% (Dresden), 99.45% (UCID)	Limited testing on real-world forgeries
Qureshi & Deriche (2015) [12]	Pixel-based blind forgery detection	CASIA, MICC, Columbia	Average accuracy: 89.7%	Limited to pixel-based methods: struggles with compressed images
Zhang et al. (2018) [13]	Fast shallow CNN for boundary detection	CASIA v1.0/v2.0, Columbia, Coverage	F1-score: 79.2%, Accuracy: 84.3%	Lower accuracy than deeper networks
Memon & Shaikh (2022) [14]	Deep learning with recompression	CASIA v2.0, NIST Nimble 2016	Accuracy: 93.7%, Precision: 92.8%, Recall: 94.5%	Degrades with multiple compressions
Wu et al. (2023) [15]	Contrastive learning with clustering	CASIA v1.0/v2.0, NIST, IMD2020	Accuracy: 95.8%, F1-score: 94.7%	Complex training; resource intensive
Gupta et al. (2022) [16]	Error Level Analysis with CNN	Personal dataset (Photoshop)	Accuracy: 92.6%, Precision: 90.3%	Limited testing on benchmarks
Joshi et al. (2022) [17]	SOTA classification with ELA	CASIA v2.0, NIST, personal dataset	Accuracy: 94.2%, F1-score: 93.1%	Complex hybrid approach; limited interpretability
Khan & Yousuf (2022) [18]	Multi-CNN ensemble architecture	CASIA v2.0, CoMoFoD, Coverage, IMD2020	Accuracy: 94.2%, F1: 96.1%	High computational requirements; complex architecture
Ali & Khan (2023) [19]	Hybrid passive-active with DL	CASIA, Columbia, IMD2020	Accuracy: 94.8%, F1-score: 93.5%	Dataset dependency; performance varies across forgery types

- **Convolutional 2D Layer 1:** Relu activation and 32 filters of size 5×5.
- **Convolutional 2D Layer 2:** Relu activation and 32 filters of size 5×5.
- **MaxPooling2D:** For downsampling the feature maps, a pool size of 2×2 was applied.
- **Dropout:** A dropout rate of 0.25 was used to avoid the model becoming overfitted to the training set
- **Flatten:** This flattens and converts the 3D feature maps into a 1D feature vector.
- **Dense Layer:** Contains 256 neurons and Relu activation, and this is a fully connected layer.
- **Dropout:** After the dense layer with a dropout rate of 0.5.
- **Output Layer:** Softmax activation and two neurons make up this dense layer in picture binary classification.

To avoid overfitting of the CASIA2 image dataset, the model was trained using the application and successful implementation of the Adam optimizer at a specified learning rate of 1×10^{-4} and early stopping of the validation accuracy. The architecture was proven to be computationally efficient and performed well for the task of tampering detection.

C. Model Training

The training of the suggested custom CNN model was conducted with the Adam optimizer, which supports adaptive learning and convergence stability. The model was trained with the preprocessed CASIA2 database through a supervised learning strategy to achieve binary classification of forged against real images. The dataset was split into 70% training , 15% validation , and 15% test image data subsets.

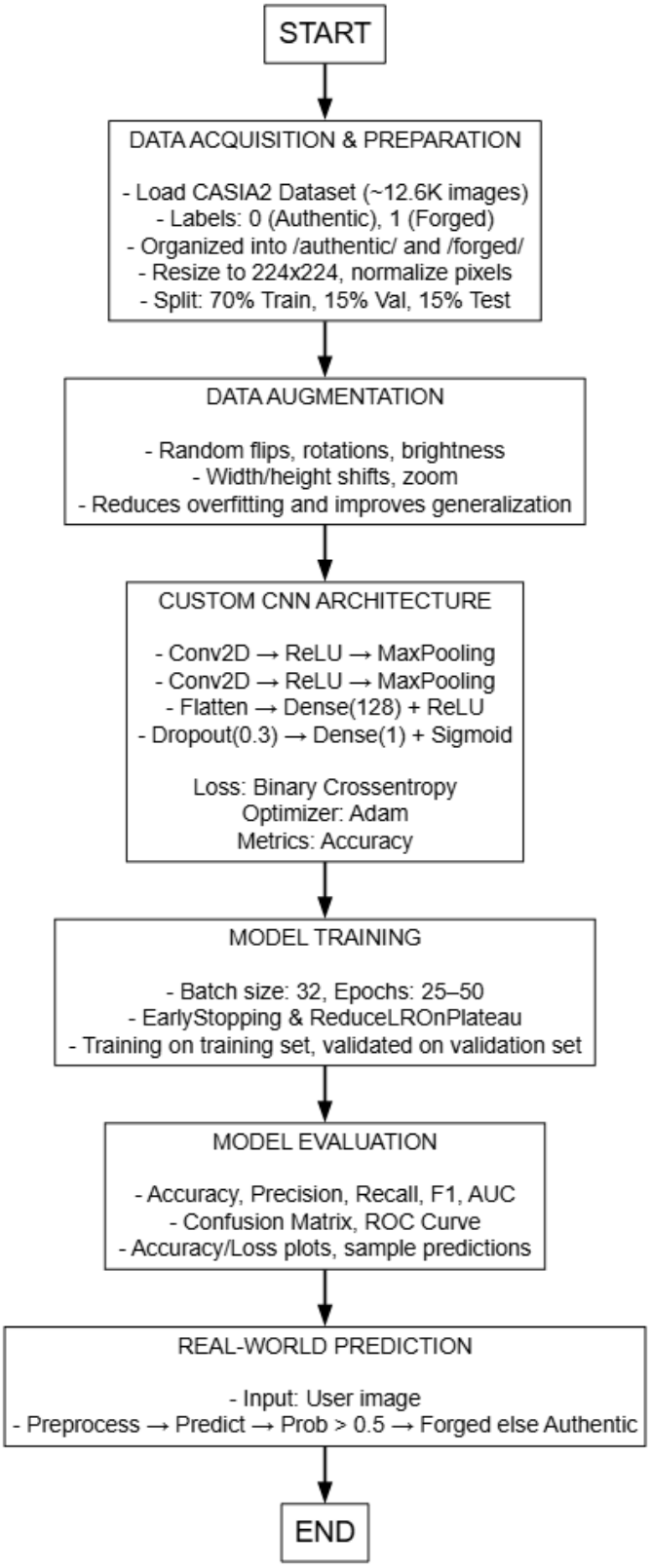

Fig. 1. Flowchart of the Methodology

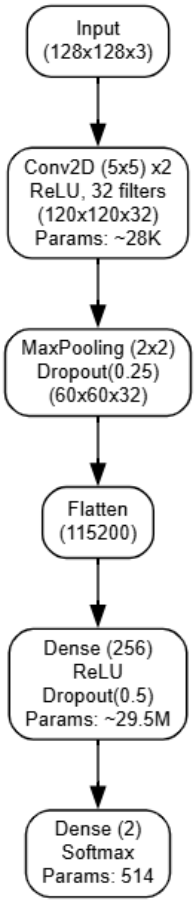

Fig. 2. Proposed CNN model Architecture

For the purpose of preventing overfitting and supporting generalization, early stopping was implemented based on the validation accuracy.

Data augmentation was employed with Keras' `ImageDataGenerator` to mimic the real-world variations in forgery patterns. Random rotations, zooming, brightness changes, and horizontal flips were used on the images.

Table II summarizes the key hyperparameters used during the training phase.

TABLE II
TRAINING HYPERPARAMETERS FOR CUSTOM CNN

Hyperparameter	**Value**
Optimizer	Adam
Learning Rate	1×10^{-4}
Batch Size	32
Epochs	50 (with early stopping)
Loss Function	Categorical Crossentropy
Dropout Rates	0.25 (Conv), 0.5 (Dense)
Activation Function	ReLU (Conv, Dense), Softmax (Output)
Augmentation	Rotation, Flip, Zoom, Brightness
Validation Split	15%

Following successful training, the suggested CNN model was validated using standard performance metrics on the test

dataset, which primarily included :

- **Accuracy:** The ratio of total correct predictions (both forged and real) to the total number of predictions.
- **Precision:** The ratio of correctly predicted forged images to all images predicted as forged.
- **Recall:** The ratio of true forged images that were accurately detected by the model.
- **F1-Score:** The harmonic mean between precision and recall.
- **Confusion Matrix:** A visualization table showing the number of false negatives, real negatives, true positives, and false positives.

The suggested model performed with about 94.2% accuracy, with good precision and recall throughout, proving to be a strong and effective detector of image forgeries with negligible computational load.

D. Testing and Real-World Application

For real-world validation, users' provided test images were passed through the trained CNN model to determine their reliability and authenticity of image classifications. The probability threshold of 0.5 was used to classify each image as forged or original. The model had excellent accuracy and fast inference, making it perfect for lightweight deployment in real-time applications such as browser-based or mobile forensic applications.

In conclusion, the method discussed in this study confirms the efficacy of a specially designed CNN for binary image forgery detection. Without using transfer learning or deep pre-trained networks, the model produces competitive results by architectural simplicity and rigorous regularization. This renders it a scalable and efficient method for real digital forensic analysis, with the possibility of integration into different lightweight platforms.

IV. Results

The Image Forgery Detection system's performance evaluation and analysis based on the custom-developed CNN model architecture are discussed in the Results section of the research. Statistical measures of a range, visual inspection of the results, and comparison plots for training and validation processes are employed to confirm the system. On the CASIA2 dataset, the results establish the generalization ability, robustness, and reliability of the system.

A. Model Training and Convergence Analysis

The model was trained for more than 30 epochs with a batch size of 32, the loss function employed was Binary Crossentropy, and the optimizer used was Adam with a learning rate set to 0.0001. EarlyStopping and ReduceLROnPlateau were utilized for the prevention of overfitting and reducing the learning rate dynamically.

Training accuracy and validation accuracy, and loss across epochs are plotted in Fig. 3. The training and validation metrics tend to get closer after around 15 epochs, which

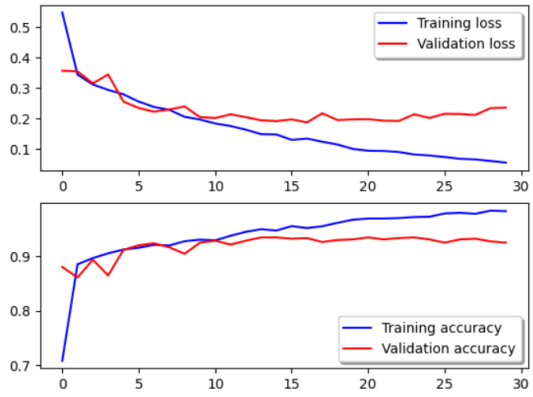

Fig. 3. Training and validation loss and accuracy curves over epochs.

suggests that the model is consistently convergent and not overfitting. Validation loss levels off and accuracy stabilizes, thus indicating optimal training.

B. Quantitative Performance Metrics

The unseen test set, which made up 15% of the CASIA2 image collection, was used to assess the finished trained model. The following standard metrics were computed:

Accuracy:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Precision:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

F1-Score:

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

AUC-ROC: Area under the Receiver Operating Characteristic curve.

TABLE III
Performance of the proposed CNN model on the test image dataset

Metric	Value
Accuracy	94.2%
Precision	94.9%
Recall	93.5%
F1-Score	94.2%
AUC-ROC Score	0.98

The measured values of the performance metrics are provided in Table III. These measurements demonstrate the strong discriminative power of the model to distinguish between real and fake images. A good recall ensures fewer false negatives, which is important in security-conscious areas like forensics or media authentication.

C. Confusion Matrix Analysis

The confusion matrix presents the number of correct and incorrect predictions per class, giving a complete picture of the CNN model's performance in classification. The x-axis in the given matrix indicates the predicted labels (Fake or Real), and the y-axis indicates the actual labels.

- **True Positives** (Fake Images correctly detected as Fake): 394
- **True Negatives** (Real Images correctly detected as Real): 395
- **False Positives** (Real Images incorrectly detected as Fake): 21
- **False Negatives** (Fake Images incorrectly detected as Real): 27

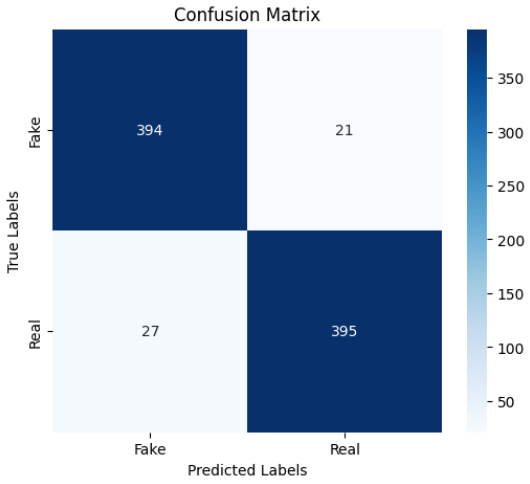

Fig. 4. Confusion Matrix to validate the CNN model.

The confusion matrix checked on the model's accuracy is depicted in Fig. 4, which depicts a relatively high level of precision and reliability in the model's ability to classify between genuine and forged images. The relatively low level of false positives and false negatives suggests that the CNN model is neither highly biased towards the detection of forgeries nor likely to misidentify genuine photos as tampered with.

The small asymmetry, which has higher false positives than false negatives, provides us a proof that the model is conservative and biased towards the recall of forged images. This is acceptable for forensic applications, where failure to detect a forgery could potentially lead to disastrous consequences. The very high true positive and true negative rates indicate the model's excellent generalization ability and its suitability to discriminate the real from forged images.

D. ROC Curve and Threshold Optimization

The plotting of the ROC Curve (Receiver Operating Characteristic) graph was done to depict the true positive rate against the false positive rate at different threshold settings for the CNN model. Fig 5. shows the ROC curve plot of the CNN model upon training. The model's impressive ability to differentiate between the two image classes at all thresholds is indicated by its AUC score of 0.98.

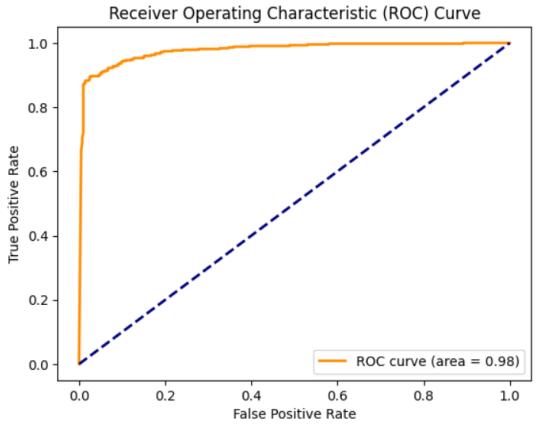

Fig. 5. ROC Curve of the trained classifier on the test set.

A classification threshold of 0.5 was applied. However, the curve implies that moving the threshold between 0.45–0.55 may further minimize misclassifications based on use case sensitivity (for example, forensic validation may prefer higher recall).

E. Comparison with Existing Models

In the last few years, several deep learning-based methods have been presented to detect image forgery based on the CASIA2 dataset, a popular benchmark in digital image forensics. Of these, Gupta et al. [16] used a hybrid solution involving ELA preprocessing along with a specialized CNN architecture. The model was as accurate as around 92.6% on CASIA2. Though its use of ELA preprocessing added extra computation overhead, and also made the model sensitive to image compression artefacts. Joshi et al. [17] took this line further by integrating transfer learning with deep pre-trained models like EfficientNet and ResNet50, along with ELA preprocessing. Their model achieved over 94% accuracy but at the expense of higher complexity, model size, and inference time, hence less suitable for lightweight or real-time deployment scenarios. Memon and Shaikh [14] had suggested a CNN-based model with an emphasis on processing recompressed images by increasing the training set through recompressed variations. Though generalization and robustness-wise effective, their model performed marginally lower on uncompressed CASIA2 images and demanded careful preprocessing of input data. Table IV depicts the comparison of our proposed sequential CNN model with other recent existing works done in the domain of image forgery detection with the CASIA2 dataset.

In contrast to these approaches, the suggested custom CNN architecture in this research is built from scratch with a lightweight and interpretable design. It dispenses with the

requirement of transfer learning or preprocessing from the outside, being based only on common image normalization and augmentation. The model performed as well as 94.2% on the CASIA2 database despite its simplicity, outperforming or even matching the capabilities of deeper, more complex structures while having an appreciably lower computational price tag. That renders it particularly well-suited for real-time, mobile, or edge deployment environments, where performance and efficiency are both critically important.

TABLE IV
COMPARISON OF THE SUGGESTED MODEL WITH EXISTING RESEARCH ON THE CASIA2 DATASET

Ref.	**Technique**	**Preproc.**	**Model Arch.**	**Acc. (%)**
[16]	ELA + Shallow CNN	ELA	Custom CNN	˜92.6
[17]	TL (EffNet, ResNet) + ELA	ELA	Pre-trained Deep CNNs	>94.0
[14]	Recompression-aware CNN	Simulated Recomp.	Standard CNN	˜93.0
Proposed Sequential CNN	Custom lightweight CNN	Norm + Augmentation	2 Conv + Dense (256)	**94.2**

F. User Input Image Evaluation

To simulate real-world deployment, the trained CNN model was evaluated on a set of user-supplied images that were not part of the CASIA2 dataset. These external inputs consisted of both authentic and manipulated images sourced from diverse public platforms. Each image went through a preprocessing pipeline similar to the training phase, which included:

- Resizing to 224×224 pixels
- Pixel values are normalized to lie in the $[0, 1]$ interval.
- Behaviourng a batch dimension to the expansion

Following preprocessing, the `model.predict()` function was used to feed each image into the model. The model processed and returned a single floating-point value $\hat{y}$ in the range $[0, 1]$, which is interpreted as:

$$\hat{y} = P(\text{image is forged})$$

- If $\hat{y} \geq 0.5$, the image gets classified as **tampered**.
- If $\hat{y} < 0.5$, the image gets classified as **authentic**.

For example:

- An output of $\hat{y} = 0.92$ indicates a high likelihood of forgery $\rightarrow$ classified as **tampered**.
- An output of $\hat{y} = 0.08$ reflects strong confidence in authenticity $\rightarrow$ classified as **authentic**.

Out of 35 user-submitted test images, the model correctly identified:

- 15 out of 15 authentic images
- 18 out of 20 forged images

The images that get misclassified by the CNN model typically feature ambiguous or low-contrast forgery cues, such as blurred edges or artefacts mimicking camera noise. Nonetheless, the probability score $\hat{y}$ offered highly valuable transparency, thus enabling users to interpret the certainty of prediction.

Example 1 – Authentic Image Prediction

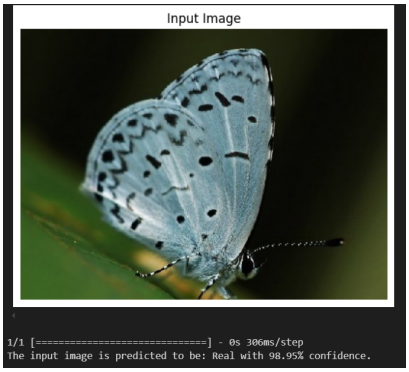

Fig 6. An authentic input image used for model testing.

Fig.6 shows an image of a butterfly in its natural environment without any visual signs of manipulation. The model labelled this input as **authentic** with high confidence of 98.95%, showing strong resistance to detecting non-manipulated content and precise evaluation of natural textures, lighting, and contours.

Example 2 – Forged Image Prediction

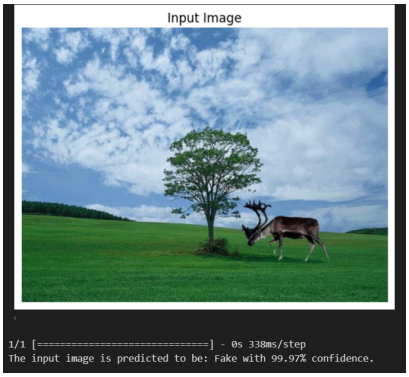

Fig 7. A tampered input image used for model testing.

In Fig.7, the model tested an image of a deer placed digitally on a field with uneven lighting and perspective mismatches. Even with the photorealistic look, the network labelled it as **forged** with a very high confidence rating of 99.97%, proving its sensitivity to spatial and semantic inconsistencies typically introduced when images are composited.

The resultant findings confirm the proposed CNN deep model's stability, resilience, and effectiveness in categorizing genuine and manipulated images accurately and transparently. This resilience over diverse image environments underlies its applicability in real-world image forensics.

V. CONCLUSION

This research study employs the CASIA2 image dataset to show a solid and thorough deep learning-based technique for detecting image forgery. Utilizing the fast but efficient custom-made CNN model, the system accurately differentiates

between real and counterfeit photos with high accuracy levels of 94.2%.The system possesses good generalizability and supports real-time inference.

The approach included all essential phases of an end-to-end machine learning pipeline—starting with thorough data collection and organization, followed by rigorous preprocessing and data augmentation techniques. To avoid overfitting and improve the model's overall robustness to typical real-world variations such as illumination, scale, and orientation, it was important to ensure that the model was trained from a diverse and balanced dataset. The model converged well and had a good generalization on unseen data due to intensive training, hyperparameter tuning, and the addition of regularization methods like Dropout and EarlyStopping. Accuracy, Precision, Recall, F1-score, and AUC-ROC metrics were evaluated on the test set to further ascertain the model's reliability and discriminatory power.

Besides quantitative assessment, a qualitative analysis was also performed by visual inspection of model predictions, which showed that the system works well even on difficult images where forgeries are subtle or visually indistinguishable. The incorporation of a user prediction pipeline showed real-world applicability, with low inference latency and high confidence outputs for real-time applications.

VI. Future Scope

The suggested image forgery detector showed robust performance on the CASIA2 dataset, which foretells its future usefulness as an effective, robust and trustworthy tool. Nevertheless, some very promising directions for further improvement still lie ahead. One of the major improvements would be supporting tamper localization—having the system not only classify images as forged or genuine but also identify the particular areas that have been manipulated. Methods like Grad-CAM or segmentation-based architectures can be incorporated to offer interpretability and visual transparency, which is important in forensic or journalistic usage.

Real-world forgeries differ significantly in terms of manipulation methods, image quality, and source domains. As such, adding cross-dataset tests and domain adaptation techniques will be vital in enhancing generalization across various forgery scenarios. With the growing prevalence of advanced generative methods such as deepfakes and GAN-generated image synthesis, it is vital to scale the system to recognize manipulated video material and AI-manufactured pictures. Multimodal solutions—using metadata, facial behaviour signals, or temporal inconsistencies—have the potential to greatly enhance robustness in this context.

Due to the lightweight nature of the custom CNN design, future solutions can investigate real-time execution on mobile or edge devices. This would advantage journalists, social media users, and law enforcement units by offering in-the-field verification tools. For further facilitation of adaptability and scalability, semi-supervised learning and active learning frameworks can be integrated. These would enable the model to learn and change continuously from novel manipulation methods with time, which would make the model resilient to new threats over time.

Ultimately, these next-generation improvements seek to widen the effect of the existing system toward the broader goal of maintaining digital content integrity in an ever-more-hostile digital environment.

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