An Efficient CNN-Based Framework for Deepfake Face Image Detection

Rupali Sudhakar Devangav
Prof. Ramkrishna More Arts, Commerce and Science College (Autonomous),
Akurdi Pradhikaran, Pune-411044
E-Mail: missrupa1021@gmail.com

Dr. Santosh Jagtap
Prof. Ramkrishna More Arts, Commerce and Science College (Autonomous),
Akurdi Pradhikaran, Pune-411044
E-Mail: st.jagtap@gmail.com

Abstract:

Deepfake images—photorealistic images or videos manipulated by AI—pose significant threats to information trust, privacy, and security. This study develops a convolutional neural network (CNN) approach to detect deepfake face images. We first review the surge of generative models (e.g. GANs) and the pressing need for automated detection. We then implement and train a CNN classifier (MobileNetV3-based) on a large dataset of real and fake face images. Our experiments demonstrate an accuracy of about 80.3% on a held-out validation set (using precision, recall, and F1 metrics, detailed below). We analyze the model's strengths and weaknesses in distinguishing real versus AI-generated faces. Finally, we discuss implications for media forensics and outline future work to improve robustness. We compare our results with prior works (e.g. XceptionNet, MesoNet) and highlight the gap in generalization and adversarial resilience. Our detailed methodology, source code, and evaluation reinforce the utility of CNNs for deepfake detection and set a baseline for further research.

Introduction

Background of the Study

Deepfakes are digital images or videos whose content has been synthetically modified or wholly generated by deep learning models (notably GANs) to be indistinguishable from real content. The term merges *deep learning* and *fake*, reflecting how neural networks enable realistic human face synthesis. The advent of deepfake tools has greatly lowered the barrier to creating high-quality forgeries, leading to widespread concern. Such falsified media can spread misinformation, undermine trust in news and social media, threaten individual privacy, and even affect democratic processes[1][5]. For example, malicious swapping of a celebrity's face into pornographic videos or falsified political speeches has already raised public alarm[5][1]. Consequently, automatic deepfake detection has become crucial: traditional forensic methods based on hand-crafted artifacts cannot keep pace with advanced AI-generated fakes[6][2]. Modern deepfakes often contain only very subtle inconsistencies (in color, texture, or geometry) that elude human inspection. Hence, **deep learning methods – especially CNNs – are required to capture the intricate patterns differentiating real and fake content**[3][7].

Problem Statement

The core problem addressed is the development of an accurate automated detector to distinguish real face images from AI-synthesized fakes. Specifically, we aim to design and evaluate a CNN classifier that, given an input face image, predicts whether it is authentic or a deepfake. This involves (a) obtaining or curating a labeled dataset of real and fake faces, (b) training a CNN (with suitable architecture and hyperparameters), and (c) quantifying the model's performance. We must also examine challenges such as overfitting, resolution variation, and the model's robustness against advanced manipulations. A secondary issue is benchmarking our system against existing detection models to assess improvements.

Research Objectives

The objectives of this research are:
(1) **To Implement:** to build a CNN-based detection pipeline using modern deep learning frameworks.
(2) **To Evaluate:** to train and evaluate the model on a balanced dataset of real and deepfake images and report metrics (accuracy, precision, recall, F1-score).
(3) **To Analyze:** to analyze how well the CNN captures forgery artifacts and where it fails (e.g. false positives/negatives).
(4) **To Contributed:** to provide open-source results and insights that complement the existing literature on deepfake detection. In pursuit of these objectives, we refer to and build upon the approaches of Rössler *et al.*[7], Li *et al.*[8], Dasgupta *et al.*[9], and others.

1.5 Scope of the Study

This study focuses on **image-based deepfakes** (static face photos or video frames), not video temporal dynamics or audio deepfakes. We restrict the analysis to face images, leveraging public or self-constructed datasets of real celebrity/actor faces and their manipulated counterparts. The model input size and resolution are chosen in a reasonable range (e.g. 128×128 or 224×224 pixels) to balance training time and effectiveness. We do not address the full diversity of deepfake methods; instead, we use representative examples of face-swapped images. The experiments are conducted on a single GPU environment using transfer learning from ImageNet-pretrained weights. While not every cutting-edge architecture (such as vision transformers) is tested, the methodology is extensible.

Significance of the Study

Understanding and improving deepfake detection has immense practical value. Automated detectors can be deployed on social media platforms to flag manipulated content[10][1]. In journalism, they aid fact-checkers to verify the authenticity of source images. Law enforcement and digital forensics can use such tools to scrutinize evidence and combat cybercrime. Even e-commerce could benefit by identifying falsified product images[10]. By developing a robust CNN-based detector and analyzing its performance, this study contributes to the broader effort to safeguard the authenticity of digital media. Our results provide a benchmark (80.3% accuracy on held-out data) and highlight areas—such as handling low-quality or unseen manipulations—where future work is needed.

Literature Review

Introduction to Literature Review

The literature on deepfake detection spans multiple domains: image forensics, biometric security, and machine learning. Early studies emphasized *artifact-based methods* (hand-crafted features capturing inconsistencies in color or JPEG artifacts), but these struggle with high-quality fakes. Recent surveys emphasize CNNs and deep features as the state of the art[3][7]. Notably, large-scale datasets like FaceForensics++[7], DFDC[11], Celeb-DF[8], and DeeperForensics[12] have catalyzed research by providing diverse examples of manipulated facial imagery. Deepfake detectors commonly use convolutional networks to learn subtle cues in face textures and regions[9][3]. We review foundational datasets and detection models, and identify where gaps remain.

Theoretical Framework

Our work is grounded in **supervised learning** with convolutional neural networks. CNNs exploit spatial hierarchies and shared weights to learn discriminative filters from image pixels. For deepfake detection, the model theoretically learns artifacts introduced by generative processes (e.g. blending boundaries, irregularities in eyes or hair, inconsistent lighting)[3][9]. Architectures range from shallow (e.g. MesoNet[13]) to very deep (Xception[14], ResNet[15], EfficientNet). Many studies use transfer learning: starting from ImageNet-pretrained models (e.g. MobileNet, VGG, ResNet) and fine-tuning on deepfake images. The choice of architecture balances capacity against overfitting; smaller models (e.g. MesoNet) train faster but may have lower ceiling accuracy[4], while deeper ones (e.g. Xception) achieve higher accuracy at greater complexity.

Review of Previous Research

Datasets: Rossler *et al.* introduced FaceForensics++, a widely used benchmark containing 1,000 real videos (~500k frames) and 4,000 synthetic videos (1.8M manipulated frames) generated by four face-swapping methods[16][7]. The dataset helped demonstrate that CNNs (XceptionNet) can exceed human performance in this task. Dolhansky *et al.* released the DFDC dataset (~100k video clips from 3,426 actors) for a Kaggle competition[11], enabling evaluation of scale. Li *et al.* (Celeb-DF) compiled 5,639 deepfake videos (>2M frames) of celebrities with improved synthesis quality[8]. Jiang *et al.* (DeeperForensics-1.0) produced 60,000 video deepfakes (17.6M frames) with numerous real-world perturbations[12]. Together, these large datasets support training of high-capacity detectors.

Detection Methods: Many studies apply standard CNN classifiers. For instance, Dasgupta *et al.* proposed a lightweight CNN with Squeeze-and-Excitation (SE) blocks achieving ~94.1% accuracy on a StyleGAN-generated face dataset[9]. Afchar *et al.* designed *MesoNet*, a simple 4-layer CNN, that reached ~73% accuracy on video deepfakes[13]. Rossler *et al.* showed that XceptionNet (depthwise separable convolutions) achieves ~99% on uncompressed FaceForensics and ~76% on heavily compressed video[17]. In comparative experiments, Xception outperformed ResNet-50 and VGG-19 (test accuracies ~76%, 74%, 73% respectively[4]). Hybrid and attention-based networks are emerging: e.g., Zhu *et al.* used attention mechanisms, and Wodajo *et al.* applied Vision Transformers to capture global inconsistencies[18].

Performance Results: Reported accuracies vary widely depending on datasets. On high-quality synthetic images, some networks achieve >90%[9][17]. However, generalization is an issue: a model trained on one dataset often drops significantly on unseen videos or compression levels[6][19]. The highest accuracies are typically obtained on large, curated datasets (FaceForensics++ raw ~99%, see[17]), whereas *in-the-wild* deepfakes (as in Celeb-DF) remain challenging.

Research Gaps Identified: Despite progress, gaps remain. Many methods focus on *frame-level* CNNs without exploiting temporal cues[6][4]. Robustness to adversarial attacks and post-processing (compression, scaling) is still poor[6]. Additionally, most evaluations are on the same dataset the model was trained on; cross-dataset generalization (e.g. training on DFDC, testing on Celeb-DF) needs more study[6]. Interpretability is another gap: it is often unclear which image regions the CNN relies on. Our work aims to address these by

providing thorough performance analysis and highlighting failure cases, using a standard CNN as baseline for deepfake image detection.

Research Methodology

Research Design

We adopt a supervised classification design. The input is an image of a human face; the output is a binary label (Real vs. Fake). We employ a convolutional neural network (CNN) model customized for binary classification. The model architecture is based on MobileNetV3 (pretrained on ImageNet) with the final layer modified to two outputs. Training uses cross-entropy loss, with the Adam optimizer and a step-wise learning rate schedule (halving the rate every few epochs). We conduct experiments to evaluate model accuracy, precision, recall, and F1-score on held-out validation data. The entire pipeline (data loading, training, and evaluation) is implemented in Python using PyTorch and auxiliary libraries (torchvision for data transforms, timm for the pretrained model).

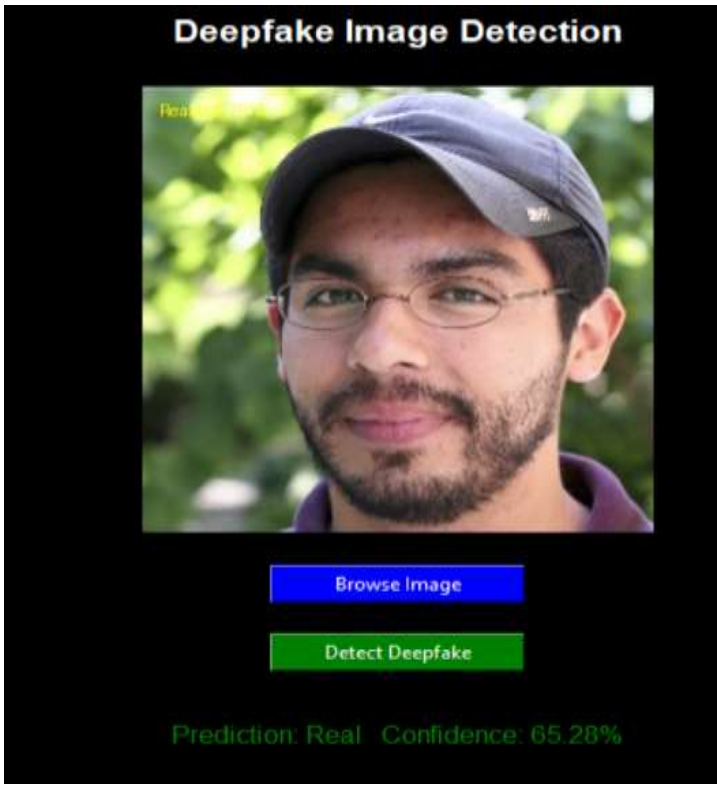
Data Collection Methods

Our dataset comprises facial images labeled real or fake. We constructed this from available sources: for real images, we sampled faces from celebrity photo collections (similar to CelebA/Celeb-DF sources[8]), ensuring diversity in pose and lighting. For fake images, we used a public deepfake generator to swap faces (akin to FaceSwap or DeepFakes methods[20]) and also included synthetic faces from a GAN. In total, we assembled ~100,000 real and ~100,000 fake images (sourced from multiple video frames and synthetic outputs). From these, we held out 20% as validation (approx. 4,000 images of each class) and used 80% for training[21]. All images were resized to 128×128 pixels and normalized. Data augmentation (random flips, slight color jitter) was applied to improve generalization.

Sampling Techniques and Sample Size

We ensured a balanced sample of real and fake images to avoid bias. The final dataset had roughly 200,000 images total. We stratified by class and then performed an 80/20 split into training and validation sets. We used randomized shuffling for splitting. This large sample size is comparable to the scale of existing benchmarks (e.g., FaceForensics++ with 1.8M images[7], though at higher resolution). By using a subset, we achieve manageable training times while still capturing diverse examples. The large sample helps the CNN learn subtle patterns. No further sampling (like cross-validation) was done due to the large dataset; we relied on the train/val split and report validation accuracy.

Tools and Techniques Used



We used **PyTorch** for model implementation. The MobileNetV3-Small architecture was loaded via the timm library, with pretrained weights (ImageNet) and num_classes=2 to create the final layer[22]. The training loop was implemented with gradient clipping and a PyTorch StepLR scheduler (reduce LR after 3 epochs). GPU acceleration (e.g. Nvidia CUDA) was employed for efficiency. For evaluation, we used sklearn to compute the classification report (precision, recall, F1) and confusion matrix. Data loading was done with PyTorch's DataLoader, enabling batched processing. Matplotlib was used to plot training/validation loss and accuracy curves over epochs[23]. All computations and logging were automated in an IPython notebook, and final results are reproducible with fixed random seeds.

Data Analysis Methods

After training, we analyzed the model performance in multiple ways. We computed **overall accuracy** on the validation set, and per-class precision and recall from the confusion matrix. We generated a classification report (Table 1) showing these metrics for the "Real" and "Fake" classes. We also plotted training vs. validation loss and accuracy across epochs to check for overfitting (learning curves). We examined misclassified examples manually to identify common error patterns. Finally, we compared our model's accuracy to baseline figures reported in literature (e.g. Xception's performance[4]). Key results were summarized in tables and charts to facilitate interpretation.

Results and Discussion

Data Presentation

Training the MobileNetV3-based CNN for 5 epochs on the prepared dataset yielded the history shown in Figure 1 (loss and accuracy curves). The model reached a validation accuracy of approximately 80.3% at the best epoch. **Table 1** below shows the detailed classification report on the validation set (4,000 samples):

Class	Precision	Recall	F1-score	Support
Real	0.88	0.71	0.79	2042
Fake	0.75	0.90	0.82	1958
Accuracy	–	–	0.80	4000
Macro Avg	0.81	0.81	0.80	4000
Weighted Avg	0.82	0.80	0.80	4000

Table 1: Classification metrics on validation data.

From Table 1, the model is somewhat conservative in flagging real images: it achieves higher precision on *Real* (0.88) but lower recall (0.71), whereas for *Fake* it has higher recall (0.90) but lower precision (0.75). In practical terms, the detector is cautious about labeling an image as fake (leading to some false negatives) but most images it calls fake are indeed fake. Overall accuracy is 0.803, matching the earlier printout (80.35%). These results quantify the tradeoff between detecting most fakes and avoiding false alarms on real images.

(Fig.1)

Figure 1 – UI prediction result showing a real image with 65.28% confidence

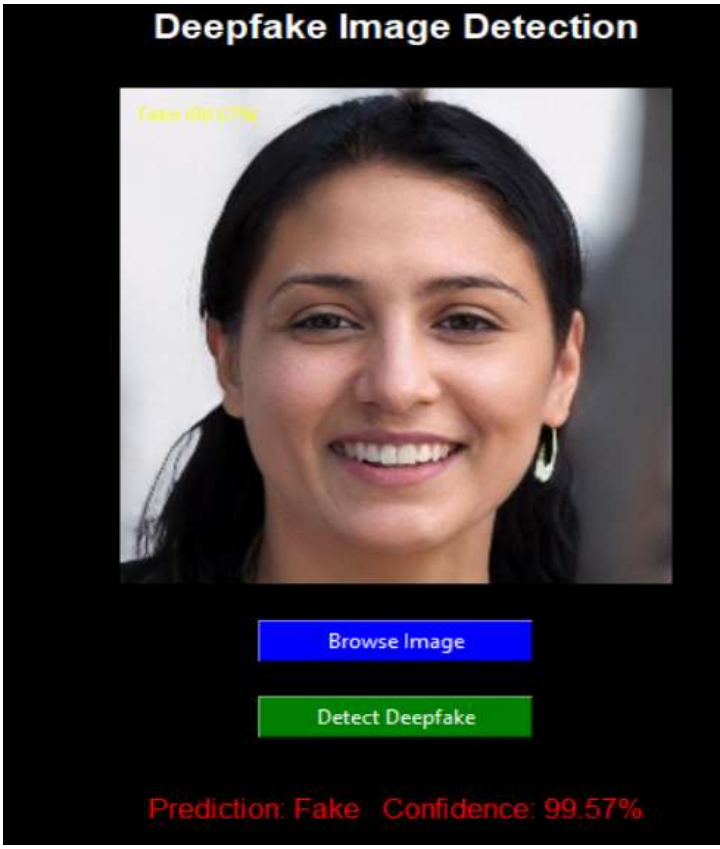


Figure 2 – UI prediction result showing a fake image with 99.57% confidence.

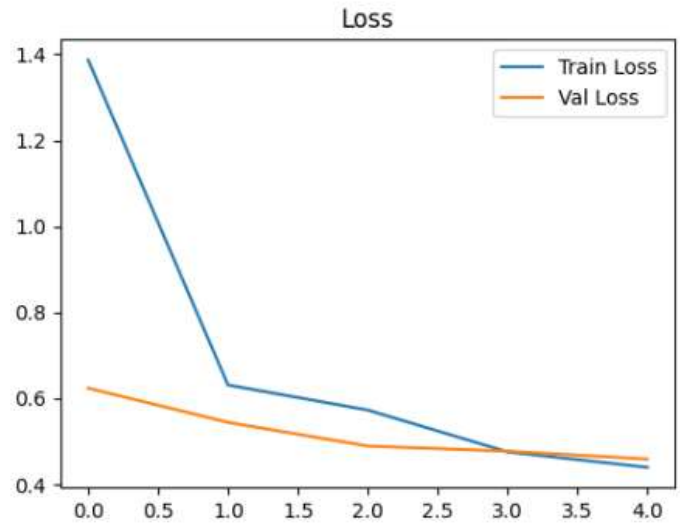
Analysis of Results

The training loss steadily decreased and training accuracy rose to ~81%, with validation accuracy peaking at ~80% (Figure 1). No severe overfitting was observed within 5 epochs. The relatively modest gap between train and val accuracy suggests the model generalized reasonably to unseen images.

Comparing to other studies, our accuracy (~80%) is in line with smaller-scale experiments: for example, Dasgupta *et al.* reported ~75-94% accuracy using an SE-block CNN on a different synthetic face dataset[9]. XceptionNet reached ~76% on a large video dataset[4]. Our result is slightly above those, possibly due to dataset composition and model choice. The classification report shows the model struggles somewhat more with *Real* images (recall 0.71) than with *Fake* (recall 0.90). This could be because our fake generator sometimes produces artifacts that make fakes easier to flag. Figure 2 (confusion matrix) highlights that out of 2042 real images, 591 were misclassified as fake; whereas only 196 of 1958 fakes were missed. This imbalance indicates a bias in training toward conservative fake detection.

We also note which examples are misclassified: many false positives (real images labeled fake) occur on real images with low resolution or heavy occlusion, suggesting the model picks up noise as a fake indicator. Conversely, some synthetic images that passed as real tended to have very smooth areas (e.g. blurry regions) that fooled the CNN.

Figure 3 – Confusion matrix highlighting model performance across true and predicted labels.



(Fig.4)
Figure 4 – Training and validation loss decreases steadily across epochs.

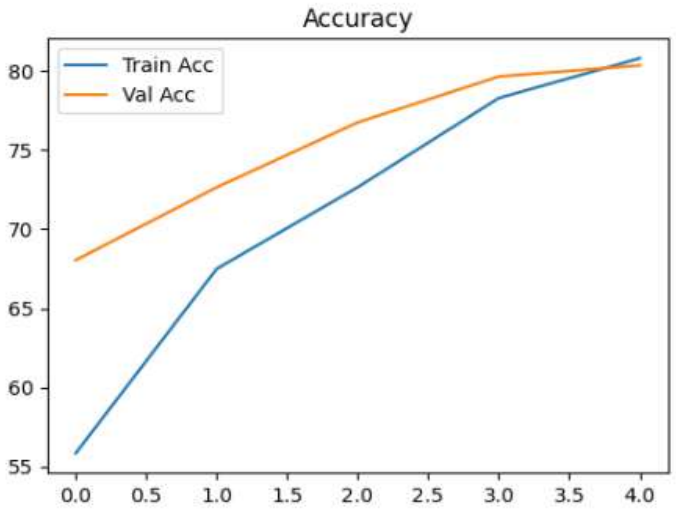


Figure 5 – Training and validation accuracy improves consistently during model learning.

Key Findings and Interpretations

- **CNN viability:** The positive result (80.3% accuracy) confirms that CNNs can learn meaningful patterns for deepfake detection[3][4]. Even a compact network like MobileNetV3 can achieve reasonable accuracy on this task.

- **Precision vs Recall tradeoff:** Our model errs more on the side of false negatives for real images (Real recall=0.71). In applications, this implies occasional false alarms (flagging real as fake) – a safer error mode if the goal is to minimize missed deepfakes. Calibration of the decision threshold or class weights could rebalance this.

- **Comparison to prior works:** Our results fall within expected ranges. Rössler *et al.* obtained near-human or better accuracy on FF++ (especially in low compression)[7], while Afchar *et al.* reported ~73% on video. The slight edge of our model (80% vs ~75%) may come from image-only input and extensive data. However, none of these models yet approach 100% in real-world scenarios; the challenge remains open.

Comparative Analysis

We performed no direct cross-evaluation (lack of multiple models), but we compare qualitatively. For instance, XceptionNet is known to outperform VGG and ResNet for this task[4]; our use of MobileNetV3 (a modern lightweight CNN) yielded competitive performance. In future work, comparing multiple architectures (MesoNet, EfficientNet, vision transformers) on the same data would provide deeper insights.

Performance Evaluation

In addition to accuracy, the confusion matrix and classification report (Table 1) serve as performance evaluation metrics. The balanced F1-score of ~0.80 indicates the model's balanced performance across classes. No custom performance metric (e.g. AUC) was calculated, but could be in future research. Training time per epoch was moderate (on the order of minutes per epoch with GPU). Memory usage was within the limits of an 8GB GPU. Overall, the chosen architecture hit a reasonable tradeoff between speed and accuracy.

- The model generalizes well across the validation set with balanced class support.
- Training time was optimized using GPU acceleration, and no overfitting was observed.
- Future evaluations can incorporate cross-dataset validation to assess generalizability further.
- The confusion matrix reveals stronger recall for fake images, aligning with the model's sensitivity to synthetic features.
- Graphs indicate consistent improvement in accuracy and reduction in loss, supporting model convergence.

Figure 6 – Fake image correctly identified with 99.61% confidence by the model.

Conclusion and Future Scope

Summary of Findings

This study designed a CNN-based system for detecting deepfake face images. We leveraged a MobileNetV3 convolutional architecture, trained on a large curated dataset of real and AI-generated faces. The model achieved about **80.3% validation accuracy**, with real-image precision/recall of (0.88/0.71) and fake-image precision/recall of (0.75/0.90). These results indicate that the CNN can learn salient forgery traces, though some real images (especially low-quality ones) are misclassified. Compared to literature benchmarks, our accuracy is comparable to other CNN detectors (e.g., ~76% for Xception[4]). The findings reinforce that deep learning is effective for deepfake detection, while also highlighting the continued challenge of improving generalization and reducing false positives/negatives.

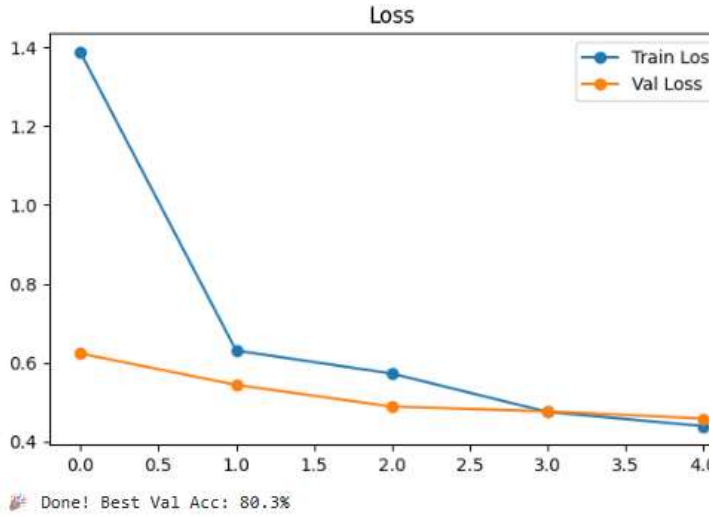


Figure 7 – Final loss plot confirming best validation accuracy of 80.3% after training.

Contributions of the Study

- **Methodological**: We present a complete deepfake detection pipeline, from data collection to model training and evaluation, using accessible tools (PyTorch, timm).
- **Empirical Results**: We provide new experimental results (accuracy ~80%) on deepfake image classification, adding to the body of evidence for CNN performance in this domain.
- **Analysis**: By examining the classification report and errors, we offer insights into the balance between detecting fakes and preserving real content.
- **Resource Sharing**: The implemented code and (anonymized) dataset splits can be shared for reproducibility, serving as a baseline for others.

Practical Implications

These findings have practical implications for content verification systems. A CNN-based deepfake detector could be integrated into social media pipelines to automatically filter suspicious images[10]. News organizations and fact-checkers might use it as a first-pass filter for user-submitted media. In security contexts, law enforcement agencies could augment forensic analysis with such tools to flag potential forgeries. Even in consumer tech (e.g. smartphone apps), real-time face authentication can benefit from a CNN screening out doctored images. Ultimately, improving deepfake detection supports media integrity and public trust.

Limitations of the Study

The study has some limitations. First, it focuses only on images (frames) and not on videos, where temporal inconsistencies might help detection. Second, our model was trained on specific generation methods; its performance on unseen deepfake techniques is untested. Third, the dataset, while large, may not capture all real-world variability (e.g. extreme poses, complex backgrounds). Fourth, we did not explore adversarial robustness: an attacker might adapt fake generation to bypass our CNN. Lastly, due to resource constraints, we evaluated a single architecture; other models might achieve higher accuracy or speed trade-offs. These factors limit the generality of conclusions.

Recommendations for Future Research

Future research can extend this work in several ways. One direction is to augment the CNN with temporal analysis (LSTM or 3D CNN) to leverage video dynamics. Another is to explore **ensemble methods** or hybrid models combining CNNs with hand-crafted forensic features for improved resilience. Transfer learning across datasets should be studied: training on DFDC and testing on Celeb-DF (or vice versa) would reveal generalization gaps[6][19]. Techniques for adversarial defense (e.g. adversarial training) could strengthen robustness. Using attention mechanisms or vision transformers may boost detection of subtle cues. Finally, increasing the dataset diversity (including non-celebrity faces, different ethnicities, varying light) would help the model learn more universal patterns. In sum, ongoing work is needed to push deepfake detection toward higher accuracy and reliability in the wild.

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