

Web Framework For Improving Deepfake Images

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Abstract

Improving the quality of deepfake images is an important condition for their effective detection, since artifacts, noise, and blur can hide key signs of forgery. Optimizing visual quality allows you to preserve critical textural and structural features, which increases the accuracy of detection algorithms. OpenForensics was chosen as the dataset. The training sample was divided into training, testing, and validation samples. The sample size is 500 images. In this paper, a web framework is proposed to improve the quality of images of human faces with the ability to generate dataset parameters, which allows for a universal approach to forming training parameters. Improving image quality will help to better detect deepfake images. The accuracy of improving image quality using neural networks is 91%.

Keywords

Deepfake, image, quality improvement, CNN

1. Introduction

Over the past decade, artificial intelligence-based image generation technologies, including deepfakes, have undergone rapid development. Deep neural networks are at the heart of such systems, which are capable of synthesizing highly realistic facial images, changing expressions, facial expressions, and even a person's identity in audiovisual materials. Despite significant progress in this area, one of the current problems remains the insufficient quality of the generated images, including artifacts, blurring, loss of textures and structural details.

These shortcomings significantly reduce the plausibility of deepfakes and limit their use in scientific, creative, or applied tasks. In response to these challenges, this paper proposes a specialized framework and architecture of a convolutional neural network, developed taking into account the specifics of improving deepfakes. The proposed solution is based on a combination of modern approaches to super-resolution, detail enhancement and artifact suppression, using deep multi-level features and feedback mechanisms. The created architecture allows not only to improve the visual quality of deepfakes, but also provides flexibility in tuning for different types of generators and source data.

The importance of improving image quality for deepfakes detection is due to the fact that methods for detecting fake images are mostly based on the analysis of low-level textural and spatial features, which can be distorted due to poor image quality or generation artifacts. The presence of blur, noise or structural defects complicates the work of recognition algorithms, reducing the accuracy of detecting fake features. Moreover, modern methods for deepfakes detection often use convolutional neural networks, which are sensitive to details that can be lost in low-quality images.

Therefore, improving the quality of deepfake images before processing allows you to preserve critical diagnostic features, improve the informativeness of the data and, as a result, ensure more reliable and accurate detection of fake content.

Information Technology and Implementation (IT&I-2025), November 20-21, 2025, Kyiv, Ukraine

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The aim of the research is to develop, implement and evaluate the effectiveness of a framework that allows you to improve the quality of deepfake images through adaptive reconstruction of structural and textural characteristics using convolutional neural networks.

2. Problem statements

To develop a comprehensive system, the following tasks must be implemented:

- develop the main framework modules for generating dataset parameters and improving image quality;
- develop and implement a convolutional network architecture with recurrent connections to improve the quality of deepfake images;
- conduct research and analyze the results by metrics.

3. Literature review

The influence of scientists on the development and analysis of image quality enhancement technologies using neural networks is fundamental and multifaceted. Thanks to scientific research, this field has rapidly evolved from simple filtering methods to complex deep architectures capable of restoring images with extreme accuracy. In work [1], to achieve the goal of the study, a dataset of 1063 ultrasound images was created by artificially degrading the quality of the original high-quality images. The images were evaluated by doctors, and the obtained scores were averaged to form labels. After data cleaning, 478 images were selected for training and testing models. To build a quality assessment system, a deep convolutional neural network and a residual network were used, and a transfer learning strategy was also applied, which allowed to improve learning under conditions of limited data volume. The test results demonstrated that the proposed CNN approach is effective and suitable for quantitative assessment of the quality of ultrasound images.

In [2], a new algorithm for assessing the quality of screen images is proposed, which, instead of using all patches, selects only those that are closest to subjective assessments, which increases the accuracy of the model compared to traditional CNN approaches at the patch level. In [3], a new architecture Distortion-Aware CNN (DACNN) is proposed for blind image quality assessment, which effectively predicts the quality of both synthetically and authentically distorted images, thanks to the distortion type recognition module, adaptive fusion of their features and an accurate quality prediction module, which is confirmed by experiments on eight different databases. In [4], the PW-360IQA model is proposed - a multi-channel convolutional neural network with perceptual weighting for assessing the quality of 360-degree images, which takes into account the properties of human vision, viewing trajectories and the probability of distortions, providing high accuracy with reduced computational complexity compared to current approaches. In [5], the Image Quality Transformer (IQT) model is presented, which combines a CNN backbone with a transformer architecture for full-reference image quality assessment, providing high accuracy on standard and generative datasets, and showing the best results at the NTIRE 2021 competition. In [6], the TRIQ architecture is proposed, which combines a convolutional neural network with a lightweight transformer encoder and adaptive position coding for image quality assessment, demonstrating high results on public datasets. In [7], an improved deep convolutional neural network (D-CNN) architecture for deepfake detection is presented, which effectively processes inter-frame differences, demonstrates high accuracy (up to 99.33%) on seven different datasets, and provides good generalization by training on images from different sources.

The study [8] presents an overview of modern deepfake detection methods based on deep learning, with a focus on video, image, audio and multi-format recognition, where the most common approach remains the use of convolutional neural networks, and the main focus of most works is on increasing accuracy.

The paper [9] proposes an efficient CNN model for detecting deepfake videos, which combines manual feature distillation, target region extraction, augmentation and frame ensemble, which provides high accuracy with reduced model complexity and demonstrates competitive results on the DFDC and Celeb-DF v2 datasets. The paper [10] reviews modern technologies for creating and detecting deepfake videos, in particular with facial manipulation in videos, and proposes a generalized approach to their detection using machine learning and computer vision, using current tools and large datasets such as DFDC. The performance of using GPUs is considered in the paper [11].

4. Dataset

The datasets selected are OpenForensics [12] <https://zenodo.org/records/5528418#.Ypd1S2hBzDd>. This dataset contains real and fake images with a high level of processing complexity. This dataset is designed with multi-face annotations specifically for face forgery detection. The dataset size is more than 5000 images of 256 x 256 pixels. An example of the dataset is shown in Figure 1.



Figure 1: Examples of real and fake images

The training sample was divided into training, testing, and validation samples. The sample size is 500 images.

5. Formation of dataset parameters

One of the key aspects is the process of generating a dataset, so our task was to develop an approach for generating this dataset, for example images.

We use the JSON format as a way to store parameters and transfer data over the Internet via a separate API. JSON is a common format for transferring data over the network between individual servers.

The main page consists of a block displaying all studies (i.e. datasets) and a button for creating a new dataset (Figure 2).

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Universal dataset's configuration system

Create New Item

Item deleted successfully

| No | Name | Details | Action |
|----|------------|----------------------|------------------|
| 1 | deepfake_1 | deepfake_1 | Show Edit Delete |
| 2 | IHC-2000 | immunohistochemistry | Show Edit Delete |

Figure 2: Main web page

The main elements are:

- Path to the folder with images;
- Image height;
- Image width;
- Image type;
- Crop;
- Single image selection;

The path to the image provides the ability to enter the URL to the folder with files or to the archive with files

The height and width of the images is an important aspect, which is one of the key when choosing the architecture of the neural network, so bringing all the images in the sample to the same format allows classification without errors and exceptions.

The "Crop" operation is often used when it is necessary to divide a large image into smaller portions according to the requirements of the neural network architecture and the capabilities of the execution environment (computer, cloud storage).

Path to folder:

Height:

Width:

Width:

File Type:

Width:

Crop

No

64 x 64

128 x 128

256 x 256

512 x 512

Custom

Choose an Image:

Figure 3: Settings web page

The software module is implemented using the PHP programming language and the Laravel framework/

The module is based on the use of the MVC pattern, which allows you to clearly separate the controller, model and view of the project.

A feature of this project is the presence of the FaceDetector class, which is responsible for processing and highlighting faces in the image, for example, for the task of searching for deepfakes

The config.get method has been developed, which allows you to get specific parameter values. This approach also simplifies the process of training a neural network and retraining by different scientists, since in this case the training sample will be of the same type, which simplifies the setup process.

6. Framework

Web-based frameworks are structured software platforms that provide a set of tools, libraries, and templates to facilitate the development of web applications. They define a standard approach to building applications, reduce the amount of routine code, and facilitate rapid and unified creation of

functionality. The structure of the modules of a web-based deepfake detection framework is shown in Figure 4.

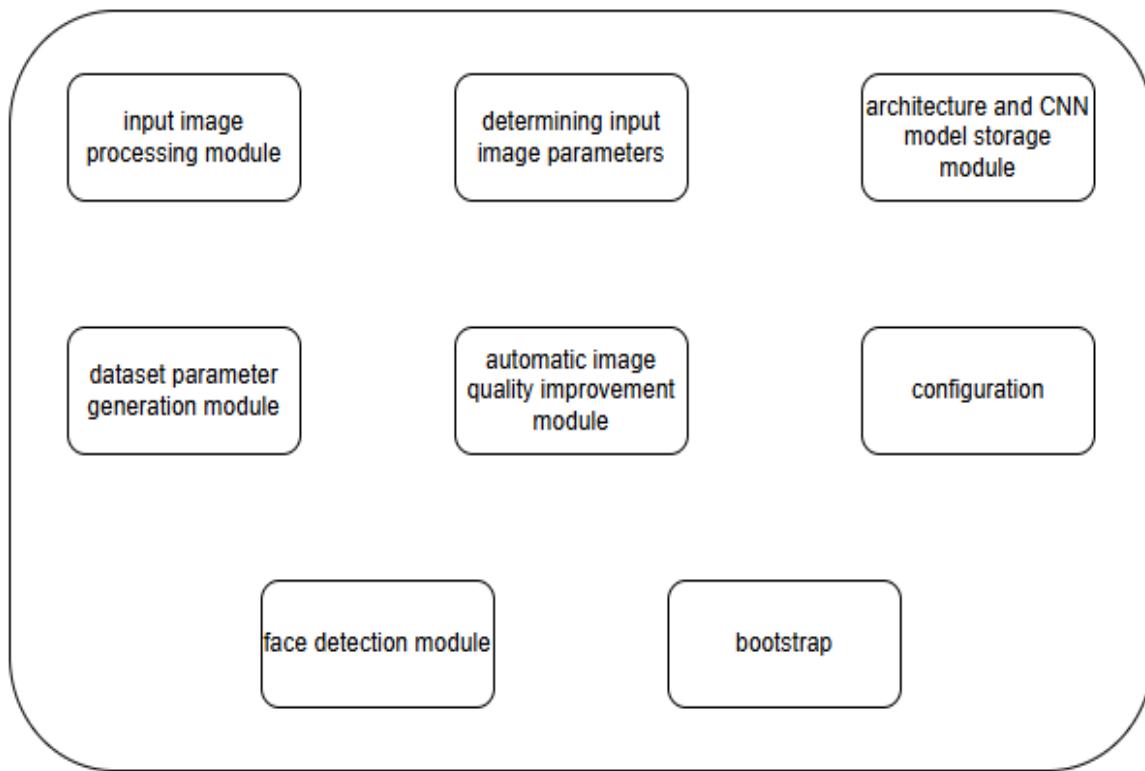


Figure 4: Structure of framework modules for web-based deepfake detection

Input image processing module is responsible for processing the input image, including specifying the path to the image folder and other parameters.

Determining input image parameters is intended for determining and storing the input image parameters in the database.

Architecture and CNN model storage module is intended for storing the convolutional neural network architecture configuration files and the models themselves in the form of files. Then you can use ready-made models for a specific type of task.

Dataset parameter generation module is implemented as a web page with fields for specifying dataset parameters, implemented using the Laravel framework.

Automatic image quality improvement module is responsible for directly improving the quality of images using convolutional neural networks.

Face detection module is intended for highlighting faces in images, which allows you to select only the necessary area in the image and reduce the number of calculations.

Thanks to frameworks, web development becomes more productive, safer and organized, which makes them an integral part of modern software engineering.

7. Formation of poor-quality images

To generate possible poor-quality images, blurring, shadow correction, and salt-and-pepper noise algorithms were used. An example of a noisy image is shown in Figure 5.



Figure 5: Example of a noisy image

Noise is a key tool in improving the robustness of computer vision models. Different types of noise affect different aspects of an image—geometry, color, brightness, or texture. Noise analysis and modeling allow us to assess the robustness of algorithms, improve the quality of preprocessing, and build more adaptive systems.

8. Convolutional neural network architecture

Image enhancement is one of the key tasks in computer vision, covering detail restoration, noise removal, resolution enhancement, and artifact correction.

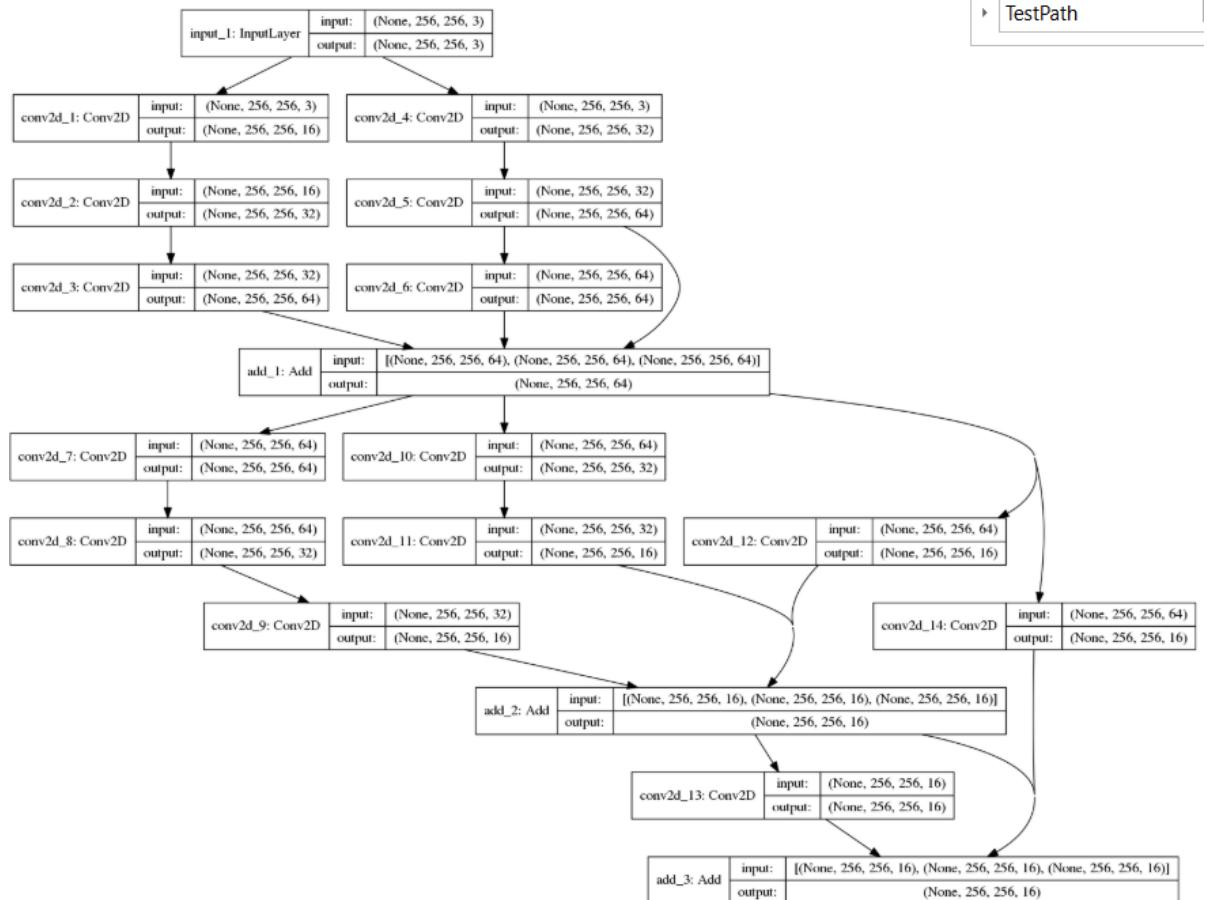


Figure 6: Proposed convolutional neural network architecture for image quality improvement

Convolutional neural networks (CNNs) have proven to be a powerful tool for solving these tasks due to their ability to automatically extract and generalize relevant spatial features. Over the past decade, a number of architectures have been proposed that are specifically adapted to processing low-quality or corrupted images, including autoencoders, U-Nets, Residual Networks, GAN-based solutions, etc. Convolutional neural networks fundamentally differ from traditional (classical) image processing algorithms in terms of their approach to data analysis, flexibility, learning ability, and adaptation to complex tasks. Traditional algorithms require manual tuning of filters and features (e.g., edge detectors, gradient histograms, color histograms, etc.), while CNNs learn to extract relevant features from data by training on a large number of images.

The proposed architecture of the convolutional neural network is shown in Figure 6.

Total params: 134,067

Trainable params: 134,067

Non-trainable params: 0

The image sample is divided into two parts: test and training. A feature of Unet networks and convolutional networks in general is the presence of repeated blocks. Therefore, we will present them as a set of operations:

$$O_{cnn} = \{\langle C \rangle; \langle B \rangle; \langle A \rangle; \langle Add \rangle\} \quad (1)$$

where $\langle C \rangle$ -set of convolution functions

$\langle B \rangle$ -batch normalization operation;

$\langle A \rangle$ -set of activation functions

$\langle Add \rangle$ -set of layers of the recurrent block

Let us consider in more detail the key blocks separately:

Convolution block

Formally, the convolution process can be represented as follows:

$$I_{y,x} \times h = \sum_{i=-n_2}^{n_2} \sum_{j=-m_2}^{m_2} I(y-i, x-j) \cdot h(i, j) \quad (2)$$

where n_2 is half the filter height, m_2 is half the filter length, x is the pixel column position, y is the pixel row position, $I_{y,x}$ is the input image, h is the convolution kernel.

GELU Activation Function

Formula for finding the activation function;

$$f(x) = 0.5x \left(1 + \tanh \left(\sqrt{\frac{2}{\pi}} (x + 0.044715x^3) \right) \right) \quad (3)$$

GELU allows small negative values when the input is less than zero, providing a richer gradient for backpropagation.

9. Experiments

The performance assessment of convolutional neural networks (CNN), particularly in classification tasks, is based on quantitative metrics that reflect the accuracy of the model's decision-making.

Training parameters:

Number of epochs: 45

steps_per_epoch=3

Accuracy

The Accuracy metric is the basic metric for balanced classes.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (4)$$

where TP is true positive, TN is true negative, FP is false positive, FN is false negative.

Figure 7 shows the results of the accuracy of the neural network.

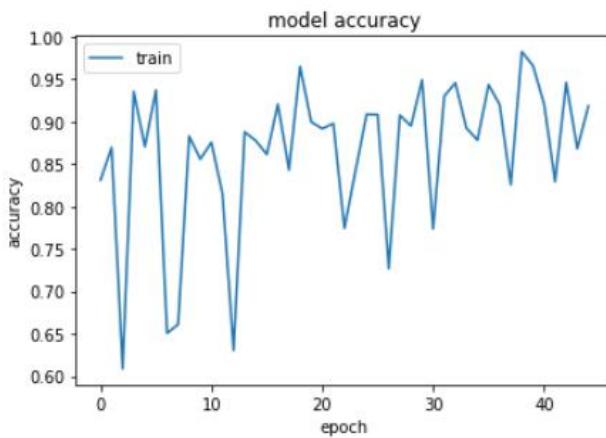


Figure 7: Neural network accuracy results

Accuracy is one of the simplest and most commonly used metrics for evaluating the quality of a classification model. It shows what proportion of predictions the model made were correct. The value of Accuracy ranges from 0 to 1 (or from 0% to 100%). The network performance estimates based on the loss criterion are shown in Figure 8.

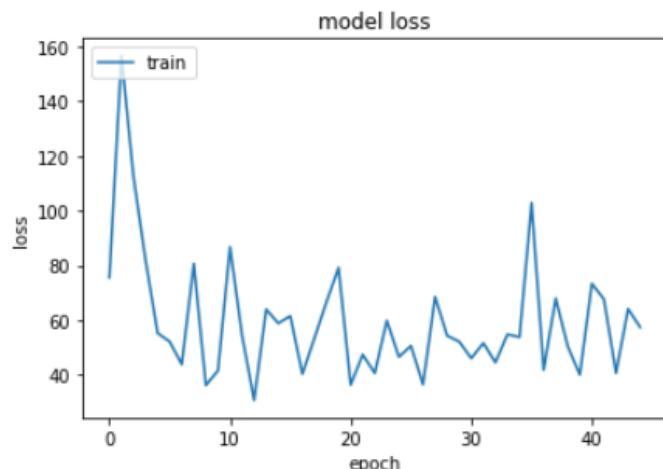


Figure 8: Neural network accuracy results

An important element for integrating deep learning methods into cloud services is the use of MLops [13] practices, an example of the structure of a Terraform configuration file is shown in Figure 9.

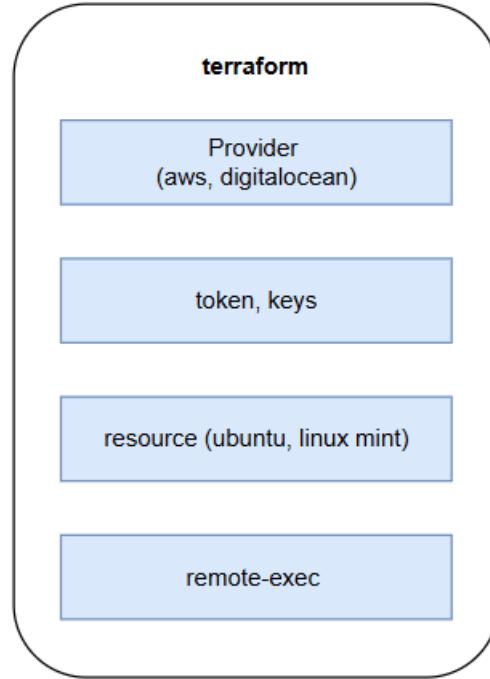


Figure 9: Terraform structure

Loss is a key metric in the training process of neural networks, measuring how much the model's predictions differ from the true labels (correct answers). Unlike metrics such as accuracy or precision, which are used to evaluate the finished model, loss is used during training to update the network's weights.

Conclusions

Based on the analytical approach and principles of developing software modules based on web systems, the main framework modules have been developed to generate dataset parameters and improve image quality.

Artificially noisy images have been generated for experiments. A convolutional network architecture with recurrent connections has been implemented to improve the quality of deepfake images.

The accuracy of improving image quality using a neural network is 91%.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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