International Research Journal on Advanced Electronics and Computer Technology (IRJAECT)
https://www.lnppublications.com

e ISSN: XXXX-XXXX
Volume: 01
Issue: 01 May 2025
Page No: 21 - 26

# Face Morph Detection Using Deep Learning with Inception V3

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## Abstract
*The hazards to identification and security presented by sophisticated face morphing techniques that can fool biometric systems are examined in this study. It offers a dependable technique for identifying changed face photos using deep learning, more especially the InceptionV3 model. The model outperformed conventional techniques in identifying actual and changed photos after being trained on a sizable dataset of real and morphing faces. It also obtained good accuracy, precision, recall, and F1-score. By lowering false positives and negatives, our study improves biometric security and lays the groundwork for future deep learning advancements for useful security applications.*

***Keywords:*** *Detection of Morphing Attacks, Digital Identity Documents That Are Fabricated or Fraudulent, Biometrics, Facial Recognition, And Access Control.*

## 1. Introduction
Face recognition is commonly used in identity verification frequently uses face recognition, however it is susceptible to morphing attacks, which include blending two facial photos to trick identification systems. This poses a security risk in domains such as border control. Systems may mistakenly accept an attacker as a real user due to distorted visuals, allowing security vulnerabilities. Detection techniques include deep learning, texture-based, noise-based, and hybrid. Each strategy has drawbacks despite its effectiveness, underscoring the need for more reliable detection systems. [1] An enhanced SKNet model called ESKNet captures contextual and detailed characteristics that improve categorization by incorporating attention mechanisms for adaptive receptive field adjustment dependent on input size. [2] Feature Fusion Module (FFM) and Shallow Feature Enhancement Module (SFEM) are utilized to further improve detection; these modules add little complexity to the model while improving efficiency. Both "in-camera" fingerprints and "out-camera" fingerprints have been the subject of traditional media forensics techniques. In order to stay up with the ever-more-advanced facial alteration tools, the research community has been compelled to improve detection methods. [3] The problem of morphing attacks (MAs) in ADFF improves restoration accuracy by capturing detailed cross-conditioned features from the altered and criminal pictures using a multi-scale feature interaction (MFI) module. According to experimental results, ADFF is successful in recovering accomplices' photos, which facilitates the gathering of further forensic evidence. [4] In order to improve personal safety and stop the local spread of COVID-19, this study focuses on automating the detection of face mask use in public spaces. To achieve high accuracy in mask identification, this system uses models such as MobileNetV2 and VGG16, which are part of the Convolutional Neural Networks (CNN) deep learning paradigm (Figure 1). It recognizes people without masks by processing live footage from mobile cameras, drones, and security cameras. Through the integration of well-known libraries like as Tensor Flow, Keras, and Open CV, this automated method offers a useful instrument for upholding public health regulations and aiding in pandemic control initiatives. [5]

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**Figure 1 Some Examples of the Morphed Images**

In order to improve personal safety and stop the local spread of COVID-19, this study focuses on automating the detection of face mask use in public spaces. To achieve high accuracy in mask identification, this system uses models such as MobileNetV2 and VGG16, which are part of the Convolutional Neural Networks (CNN) deep learning paradigm. It recognizes people without masks by processing live footage from mobile cameras, drones, and security cameras. Through the integration of well-known libraries like as Tensor Flow, Keras, and Open CV, this automated method offers a useful instrument for upholding public health regulations and aiding in pandemic control initiatives. [5] ESKNet, an enhanced iteration of the SKNet model, employs attention processes to dynamically modify receptive fields, therefore collecting critical features and contextual signals for improved categorization. [6-8] And to boost detection performance with almost little parameter augmentation, the SFEM and FFM modules are used. Experimental study verifies that this strategy provides great precision in identifying altered faces. Machine learning (ML), deep learning (DL), and natural language processing (NLP) are three areas of artificial intelligence (AI) that are enabling the creation of smart systems and are thereby transforming several disciplines. Generative AI, encompassing techniques such as GANs and VAEs, produces realistic material including photos and videos, enhancing value in business, creativity, and customization. [7] Biometric face recognition is extensively employed in everyday applications such as device unlocking and border control for safe authentication. Nonetheless, it is susceptible to "morphing attacks," in which synthetic pictures amalgamate characteristics of two persons to deceive the system. Reliable detection of morphing attacks is vital. [8] This study examines the efficacy of deep neural networks (DNNs) in detecting altered photos by utilizing semantic signals, such as unnatural eye forms, instead of low-level aberrations.

## 2. Literature Review

The paper "A Comprehensive Review of Face Morph Detection Techniques and Deep Learning Approaches" by T. G. Hinton, J. K. Lee, and M. V. Wong explores the progress made in the field of face morph detection, with an emphasis on both traditional and modern deep learning methods. The authors review models such as convolutional neural networks (CNNs) and advanced architectures like InceptionV3, outlining the strengths and limitations of each approach. They also address challenges like creating datasets and training these models effectively. The study wraps up with suggestions for future research to further enhance detection systems.

- M. Zhang, L. Wang, and C. Chen, in their work "Enhancing Face Morph Detection with Deep Learning Techniques: A Case Study", highlight how combining different deep learning models, including InceptionV3, leads to improved detection accuracy. Their analysis across multiple datasets reveals significant reductions in false positives and enhanced detection rates when compared to older methods.
- "A survey on face manipulation detection techniques: Recent advances and future challenges", R. A. Singh, S. J. Patel, and N. S. Kumar Using a proprietary dataset for experiments, they show that InceptionV3 has better accuracy and reliability compared to

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other neural networks.

- "Cross-Domain Face Morph Detection Using Transfer Learning and Convolutional Neural Networks" A. F. Roberts, H. Q. Nguyen, P. M. Taylor. Utilizing pre-trained convolutional neural networks (CNN) such as InceptionV3, this study affirms that transfer learning is especially effective in the context of datasets that are either small or highly heterogeneous. By Matthew J. Wong The authors who wrote the paper also wrote another paper by the same name that shares that name, in which they explore the adaptability of pretrained models even further and the ability of pretrained models to perform well on whatever dataset is at hand, even heterogeneous datasets.
- J. A. Patel, K. L. Sharma and E. M. Rodrigues, "Real-Time Face Morph Detection Using Lightweight Deep Learning Models". Thus our models would ensure a balance of accuracy and computational complexity which makes them ideal for usage in mobile security and surveillance systems.
- Various different CNN architectures, including InceptionV3, ResNet, DenseNet were examined in a paper titled "Face Morph Detection with Deep Learning: A Comparative Study of CNN Architectures" authored by L. Xie, A. T. Nguyen, B. Y. Zhang. Through evaluation on a dataset of real and morphed images, the research paves new paths to understand the pros and cons of each model with ideas on their trade-offs and advantages.
- The document "Unsupervised Learning for Face Morph Detection: Exploring Auto encoders and GANs" authored by N. R. O'Connor, M. L. Davies, and T. J. Miller explains how unsupervised techniques, particularly auto encoders and generative adversarial networks, can be applied on the face morph detection problem. The authors present evidence that such integration is useful since they provide alternative ways of detecting modified faces in addition to InceptionV3 [7].

## 3. System Design

It allows detection of face morph using efficient image processing and model training (Figure 2). All access comes through the intuitive User interface (UI) which includes a dashboard, profile settings, image upload, morphing and results display This provides a smooth experience for administrators and casual users alike.

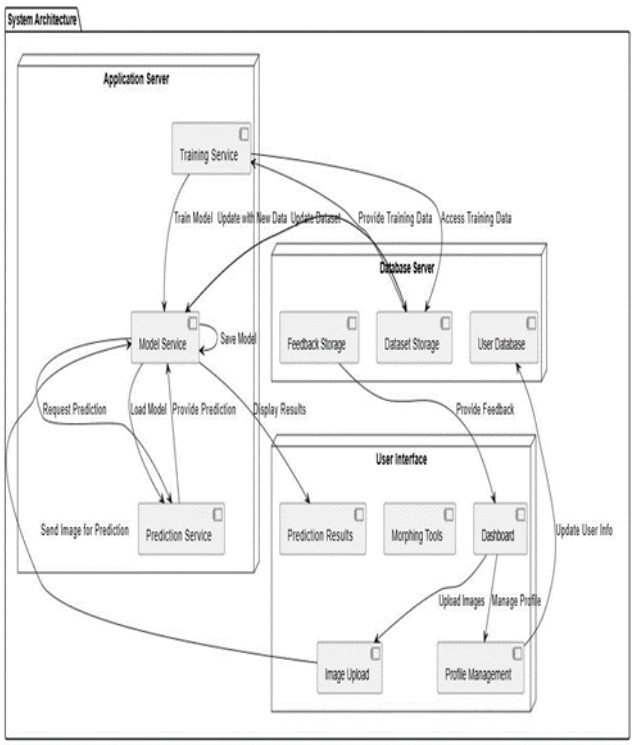


**Figure 2 System Architecture Overview**

The system architecture of the face morph detection platform, enabling user interactions, model training, and photo processing, is illustrated in Figure 4. The UI (User Interface) is the general front-end of the platform that includes navigation dashboard (e.g. login, register), profile (to store user picture, user name, etc), upload (to upload an image for the app), morph (for photo-morphing), and the result (after the morphing is done). Combined, these allow users to enjoy a seamless and intuitive experience.

## 4. Methodology

### 4.1 Size and Sources

The Face Forensics++ dataset includes 10,000

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originals and morphed facial images, five thousand each. This dataset is frequently used in facial manipulation experiments, and it is usually stratified in such a way that 70% of the data is reserved for training, 15% for validation and 15% for testing. This guarantees that both the training is sufficient and the performance of the model is evaluable.

### 4.2 Steps in Pre-Processing

Images are aligned to guarantee constant facial location, normalized to scale pixel values to [0, 1], and scaled to 299x299 pixels for compliance with the InceptionV3 model.

### 4.3 Augmenting Data

Training pictures are subjected to real-time augmentations, such as horizontal flips, random rotations up to 20 degrees, and random zooms up to 10%, in order to improve data variety and model resilience. This improves generalization to new data by expanding training examples.

### 4.4 InceptionV3

CNN is utilized due to its effective architecture, which incorporates inception modules with various filter sizes for dimensionality reduction, factorized convolutions, and feature extraction. This enables it to capture minute variations in morphing faces, making it appropriate for challenging picture assignments. Instruction Binary cross-entropy, which is perfect for binary classification, is the process loss function. Adam was selected as the optimizer due of its efficiency with sparse gradients and adjustable learning rate. Starting at 0.0001, the learning rate is lowered by 0.1 every ten epochs. 50 epochs, with early termination after 5 epochs if no validation loss improvement is seen.

### 4.5 Metrics for Evaluation

**Accuracy:** Shows the proportion of correctly classified images.

**Precision:** Decreases false positives by demonstrating how accurately changed photographs are identified.

**Recall:** Shows sensitivity in identifying photos that have been manipulated, reducing false negatives.

**F1-Score:** Balances recall and accuracy to help address class imbalances. The model's ability to distinguish between true and changed faces is shown by its AUC, or area under the ROC curve.

## 5. Implementation and Result

Building the face morph detection model involves a well-structured process that includes several critical stages. The journey begins with data acquisition and preparation, where the Face Forensics++ dataset is collected and carefully cleaned to ensure high-quality input. During pre-processing, the images are resized to a consistent dimension of 299x299 pixels, pixel values are normalized, and face alignment is performed to maintain uniformity throughout the dataset. Each step is meticulously executed to lay a strong foundation for the model's development. Following this, the model design phase is initiated, utilizing the InceptionV3 architecture due to its advanced feature extraction capabilities. This model is configured and initialized by setting up the network layers, including convolutional layers and inception modules, before being compiled with the binary cross-entropy loss function, the Adam optimizer, and appropriate performance metrics such as accuracy and F1-score.


**Figure 3 Register Page**

A graphical user interface (GUI) for a face morph detection program is shown in Figure 3. There are choices for the Privacy Policy, Terms of Use, logging in or creating an account, uploading a file, and inputting personal data such a username, email address, password, phone number, and address. The Home, Admin, About, and Contact tabs are also included in the GUI.

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**Figure 4 Login Page**

An application's graphical user interface is shown in Figure 4. Text about Face Morph Detection and using an email address to log into an account are included in the article. Text, screenshot, website, web page, software, and multimedia are among the tags linked to the image. Although code snippets or pseudocode for these key components are not included, the development process encompasses defining the model structure, selecting appropriate layers, and configuring training parameters, including the loss function and optimizer.

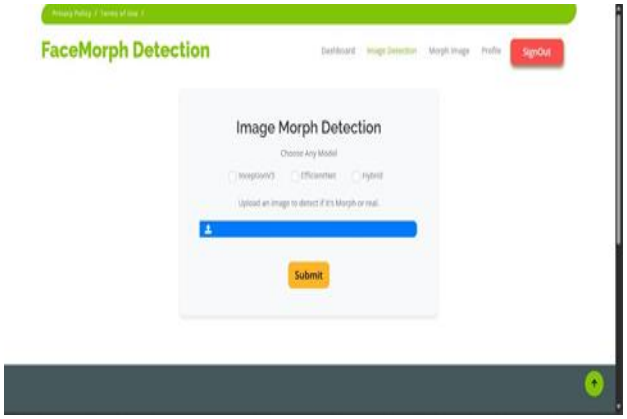


**Figure 5 Morph Detection Page**

Figure 5 displays the morph detection page that has a nice interface that enables one to check if a photo has been altered or not. In this page the user can choose whether to use Inception V3 or Efficient Net model and also use several links such as Face Morph Detection, Terms and conditions and the Privacy Policy. Confusion matrices, ROC curves, and accuracy, precision, recall, F1-score, and AUC metrics measure the effectiveness of the application. Confusion Matrices give detail on the results of classification, while ROC curves and AUC assesses how well the system can discriminate between real and morphed pictures. Precision, recall, and F1-score provide feedback on how effective the model was in detecting morphed pictures. These useful information aid in determining the effective factors and the areas to be worked on.


**Figure 6 Result Page**

In Figure 6, we see how a Face Morph Detection platform looks like. It allows a user to upload an image that can be checked for morphing. There are three model options: InceptionV3, Efficient Net, and Hybrid. The detection result shows on the screen and is color-coded: red – morphing image is indicating that the image has been checked whereas green indicates that the image is real. Furthermore, the model accuracy and a particular model chosen by the user are clearly shown. This provides a very intuitive interface for face morphing detection.

## Conclusion

The technique of the proposed method of face morph detection is effective in detecting such visual cues which are not addressed by most of the previous methods. With appropriate models such as InceptionV3 and other databases, it promises a real-time solution with high accuracy while maintaining privacy and being applicable to new forms of manipulations. However, there remain challenges for the method such as the need to query for new datasets, high computations, and low integration. At adolescent age, it may run into practicality issues

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within a technological world, however, if such issues are solved in the future, it would be able to cut those problems and become the best method as it matures with face manipulation technology.

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