DMorphNet: Face Morphing Detection Using Generative Adversarial Networks and EfficientNet-B6

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Abstract. In today's world, face recognition is widely used in biometric security systems like border control, passports, identity verification, and so on. These systems are vulnerable to face-morphing attacks, where two or more face images are blended together to make a real image that can fool a whole verification system. So considering this situation, our model will help to prevent such types of attacks. Existing methods fail to effectively detect such morphs' images, especially under real-world conditions like compression, noise, or ageing effects. Therefore, there is a need for an efficient and accurate model to detect morphed faces using deep learning techniques and adversarial features. Python is used as the programming language, along with frameworks such as TensorFlow, Keras, and scikit-learn. The model we use is EfficientNet-B6. It is a deep convolutional neural network, which is designed for high accuracy and computational efficiency. It also balances the network depth, width & image resolution; it also provides strong representation of features for complex image patterns. For this network, the main tasks are face analysis or image classification. And the classifier we use, which is SVM, means "support vector machine. " It is a supervised machine learning classifier that can separate the data into different classes. It focuses on improving generalization and reduces overfitting. SVM is more robust, stable, and effective for high-dimensional features. It enhances the classification accuracy and consistency.

Keywords: Face Morphing Attack Detection, GAN-based Morphing, EfficientNet-B6, Support Vector Machine, Deep Feature Extraction, Biometric Security, Deep Learning.

1 Introduction

Face recognition technology has become widely used in recent years. It provides a convenient and contactless method of identity verification. The face morphing attack is one of the most dangerous and one of the growing threats. In this attack, the facial images of two or more people are digitally combined to make a single image that looks like all

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of the people who contributed to it. These altered photos are frequently mistaken for authentic ones by face recognition software, which can result in identity theft and security lapses. According to recent research, it is worth noting that the issue of facial morphing attacks has grown more hazardous and difficult as a result of the increasingly rapid advancements in image generation and manipulation techniques. In particular, the use of Generative Adversarial Networks (GAN) has significantly improved the visual realism of fake, morphed facial images, making them challenging to detect using traditional methods [6][7]. As an outcome, face morphing attack detection (MAD) has received notable attention from the research community.

The baseline work by [1] proposed a GAN-based deep learning framework for detecting face morphing attacks. Morphing-related patterns could be captured using deep learning models that were trained using GAN-generated morphed images, it was found in a study. The experiments showed that this approach achieved improved detection results compared to conventional techniques. Using GAN-generated morphs during training plays an important role, which was analyzed through research. Another important point is that deep learning classifiers like this one often struggle to maintain performance when encountering novel morphing methods or datasets they haven't seen during training. In 2025, [2] introduced MADation, in which foundation models are applied to solve the problem of face morphing attack detection. The results showed better accuracy on different datasets by using pretrained vision models to develop the detection system. In our observation, the technique was also able to perform more consistently when tested across diverse data. Despite these improvements, there are certain practical limitations [3–5]. Because the models are large, they require more computation and memory, which makes them difficult to use in real-time applications or on devices with limited hardware support. In the same year, several IEEE studies [3–5] investigated deep learning–based detection methods, mainly aiming to improve resistance against increasingly advanced morphing attacks. Although these approaches produce promising results, they still struggle with generalization across various morphing techniques and datasets.

In 2024 the focus of research moved towards addressing the shortcomings of existing detection techniques and the growing realism of morphing attacks. [6] investigated the use of multispectral imaging for the detection of differential face morphing attacks. Their findings indicate that non-visible facial information can offer additional cues for differentiating between genuine and manipulated images. However, the practical use of these methods is constrained by their dependence on specialized imaging hardware. In the same year, [7] proposed MLSD-GAN. This is a GAN-based architecture that can create very realistic morphing attacks by using latent semantic disentanglement. Their study highlighted how challenging it is for many existing detection methods to cope with high-quality morphs. Several IEEE studies published in 2024 [8–12] evaluated CNN-based and hybrid detection frameworks and reported strong performance under controlled conditions. However, the effectiveness of these methods declined noticeably when they were applied to compressed or noisy images or to morphing techniques that were unfamiliar to them.

Earlier studies conducted in 2023 explored alternative feature representations to improve the robustness of face morphing attack detection. [13] proposed a detection method that combines high-frequency feature extraction with progressive enhancement learning. The results suggest that morphing operations frequently produce subtle changes in high-frequency image components that are detectable. Other studies [14–16] demonstrated the effectiveness of frequency-based and multi-feature approaches, particularly in challenging scenarios involving low-quality or altered images. Multiple review and survey articles have provided significant insights into the progression of face-morphing attacks and detection methodologies. [17] presented a detailed review of face morph generation and detection methodologies, classifying morphing techniques and emphasizing the shortcomings of conventional handcrafted feature-based methods. [18] examined diverse morphing attack generation techniques and their associated detection strategies, observing that numerous early deep learning-based methods encounter difficulties in generalizing across datasets. [19] analyzed a wide range of studies related to face morphing attack generation and detection and also discussed the datasets and evaluation methods commonly used in this field. Their findings indicate several ongoing challenges in this area, such as the absence of well-established benchmark datasets and the reduced performance when applied across different datasets. Motivated by these limitations and extending the work in [1], this paper introduces D-MorphNet, a hybrid face morphing attack detection approach. The suggested method uses a Support Vector Machine (SVM) for classification and EfficientNet for deep feature extraction. The approach aims to detect realistic GAN-generated morphing attacks while keeping computational complexity low, minimizing overfitting, and improving generalization from the classification process

2 Literature Review

Face recognition systems are widely used in many applications such as identity verification, access control, and security systems. However, these systems can be exploited through face morphing attacks, in which facial images from multiple individuals are combined into a single image. Such morphed images often look natural and can confuse automated recognition systems. Because of this problem, many researchers have worked on methods to detect whether a face image is real or morphed. The work reported by [1] is considered the base study for this research. In their work, a GAN-based deep learning approach was proposed for face morphing attack detection. The authors trained deep learning models using GAN-generated morphed images and showed that the system could learn useful features related to morphing artefacts. The experimental results showed improved detection performance. However, since the model was trained as an end-to-end classifier, its performance may decrease when new morphing techniques or different datasets are used. Some recent works have focused on improving the detection capability by using large pretrained models. [2] proposed a morphing attack detection method based on foundation models. Their approach showed better performance when tested on different datasets, indicating improved generalization. At the same time, the use of large models increases computational complexity. Other IEEE works [3–5] also explored deep learning-based morphing detection methods. Although these methods achieved good accuracy, their performance was affected when tested on images generated using unfamiliar morphing techniques. Several studies have attempted to deal with more realistic morphing attacks. [6] studied morphing attack detection using multispectral images. Their study found that features outside the visible spectrum provided additional cues for separating genuine and morphed faces. At the same time, this approach depends on specialized imaging equipment, making it less suitable for practical deployment. [7] proposed MLSD-GAN, a technique designed to produce highly realistic morphed facial images. Their work demonstrated that many existing detection methods fail when faced with such realistic morphs. In addition, a number of IEEE studies [8–12] analyzed CNN-based and hybrid detection approaches. These studies reported reasonable performance under controlled conditions but observed reduced accuracy when images were affected by noise, compression, or unknown morphing processes. Some researchers investigated whether morphing artefacts could be detected using different types of features. [13] proposed a method based on high-frequency feature extraction combined with progressive enhancement learning. Their study showed that morphing operations can introduce changes in high-frequency components of images. This approach showed improved performance when evaluated using visually realistic morphed images. Comparable observations were reported in other IEEE studies [14], where frequency-based and combined feature representations contributed to more stable detection under difficult conditions.

Survey studies have helped in summarizing and organizing existing research on face morphing attacks. Kumar and Singh [15] presented a detailed review of face morph generation and detection techniques. Their analysis covered different methods and pointed out the limitations associated with traditional handcrafted feature-based approaches. [16] examined various techniques used for generating morphing attacks as well as the corresponding detection strategies. In their work, many early deep learning-based methods were found to perform poorly when tested on different datasets. [17] presented an extensive survey on face morphing attack generation and detection, in which commonly used datasets, detection techniques, and evaluation protocols were examined. They also discussed major challenges such as the lack of standard datasets and poor cross-dataset performance, which are still open issues in this research area.

3 Methodology

3.1 Dataset Construction and Morph Image Generation

We took real face images from the FaceMorph_EClub_Task set on Kaggle. This dataset has 202,599 actual images, including all different lights, poses, and looks. Morph images were created by using an AI-based tool called AI FaceSwap. It blends features from two different images into a single image. It works well for real-world situations. We focused on making these images look realistic, not artificial or unrealistic. We use real images to generate 21000 morphed images. We review and label images. The final dataset contains 45000 images. Out of which 24000 are real images and 21000 are morphed images. The dataset was divided into training, validation, and testing sets. The training set contained 30,000 images, including 16,000 real and 14,000 morphed images. The validation set contained 13,000 images, including 7,000 real and 6,000 morphed images. To monitor performance of the model during training, we used a training set that included 2000 images balanced with 1000 real images and 1000 morphed images. We make sure the model doesn't see the same identities in both training and testing, so the results are fair and realistic.

3.2 Image Standardization and Preprocessing

EfficientNet-B6 required a fixed-size image, so we resized each image in the dataset to 528x528 pixels. Before feature extraction, to keep things consistent, we keep all the images in a consistent manner. CLAHE is used to improve the contrast of the image without adding noise, and because of this, small facial features become clear. To add variety in the dataset, we added blurry and noisy images saved with different compression, like JPEG; adjusted the contrast and brightness; and flipped images. Because of these changes, training images work better with real-life scenarios. And these data augmentation techniques help to model and deal with different types of images. First we resize the image, then compress and normalize the image for testing. We keep the same steps for both real and morph images.

3.3 System Design and Model Selection Rationale

We cannot use one large model for the complete system. We divided the work into two parts. Firstly, we take features from the images, and then we do classification because our dataset is very small. First, we use a deep learning model, but the results are not good on new images. It was just learning the training data, so that's why we changed it. We use different CNN models for feature extraction. The EfficientNet model gives better output, and it is not more difficult, so we selected the EfficientNet-B6 model for our project. It can see small details in the face, which helps to find morphing images. We also tried MobileNet and ResNet, but they cannot give better results. We decided to use SVM for the classification because it is simple and works well when the data is small. SVM helps to distinguish the images, that is, which facial images are real and which are morphs.

3.4 Deep Feature Representation Using EfficientNet-B6

In the updated D-MorphNet framework, EfficientNet-B6 is employed as the deep feature extraction backbone instead of EfficientNet-B5. The model is used in a transfer learning setting, where the pretrained EfficientNet-B6 (trained on ImageNet) is utilized to extract high-level and discriminative facial representations from both genuine and morphed images. The final classification layer of EfficientNet-B6 is removed so that the network functions purely as a feature extractor rather than performing end-to-end classification.

Let the input facial image be represented as I∈R^(H×W×C). The deep feature extraction process using EfficientNet-B6 can be expressed as

$$F = f_{B6}(I; \theta)$$

where f_B6 (·) denotes the EfficientNet-B6 feature extraction function, θ represents the pretrained network parameters, and F∈R^d is the resulting deep feature vector. Each convolutional block inside EfficientNet-B6 performs a transformation of the form:

$$X_l = \sigma(W_l * X_{l-1} + b_l)$$

where X_{l-1} and X_l denote the input and output feature maps of layer l, W_l and b_l are the convolutional weights and bias, $*$ represents the convolution operation, and $\sigma(\cdot)$ is the nonlinear activation function (Swish activation used in EfficientNet).

After the final convolutional stage, Global Average Pooling (GAP) is applied to convert spatial feature maps into a fixed-length feature vector:

$$F = \frac{1}{N}\sum_{i=1}^{N} X_L^{(i)}$$

where X_L represents the final convolutional feature maps and **N** denotes the total number of spatial locations.

From our perspective, we use the EfficientNet-B6 model with pre-trained weights and delete the final classification layers. After that, we apply a global average pooling layer, and the output is converted into a feature vector. These features help to capture the important facial details like structure, texture, and morphing artefacts. Firstly, the model is used with fixed layers to extract the features without making more changes. After that we fine-tune the model by making the top layers trainable while keeping the earlier layers fixed. This helps the model focus on detecting the morphing patterns without losing the general facial features, which are already learned. Because EfficientNet-B6 is deeper and more advanced, it can capture more details in images more effectively. The extracted features are sent to the SVM classifier, which decides the final decision on whether the face image is real or morphed.

3.5 Hybrid Classification Using Support Vector Machine

After extracting detailed features from the images using EfficientNet b6, we pass those features to the SVM for further classification. EfficientNet-B6 learns all the important features in the images, and SVM classifies them as "morph" or "real". We keep classification and feature extraction totally separate. And this combination works well with the new images and gives better generalization.
Extracted feature vectors are as follows:

$$F_i \in \mathbb{R}^d$$

with the corresponding class label $\boldsymbol{y_i} \in \{\mathbf{-1}, \mathbf{+1}\}$

where
$y_i = -1$ represents a genuine face and
$y_i = +1$ represents a morphed face.

SVM identifies a hyperplane that separates the real and morphing images from the feature space. It is denoted as$w^T F + b = 0$ where w is the weight vector and b is the bias term.
In order to minimize classification errors and maximize the margin between the two classes, these parameters are learnt.
The optimization problem solved by the SVM is:

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{N} \xi_i$$

subject to:

$$y_i(w^T F_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

with the corresponding class label:$y_i \in \{-1, +1\}$

where
$y_i = -1$ represents a genuine face and
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Where $\xi_i$are slack variables allowing limited misclassification, C is the regularization parameter controlling the trade-off between margin maximization and classification error, and the total number of training samples.As the SVM uses high-level features extracted from EfficientNet-B6 instead of raw pixel values, it is able to distinguish genuine and morphed faces more effectively within the learned feature space. The deep features obtained from EfficientNet-B6 capture meaningful and distinctive characteristics of the images, which supports improved class separation.

In the testing stage, the final prediction is made based on the output of the SVM decision function:

$$\hat{y} = \text{sign}(w^T F + b)$$

In this work, EfficientNet-B6 is used to extract deep features, which are then classified using an SVM to detect morph attacks. Treating feature extraction and classification as two distinct stages allows the model to generalize more effectively and helps prevent overfitting compared to conventional end-to-end deep learning models below in fig. 1.

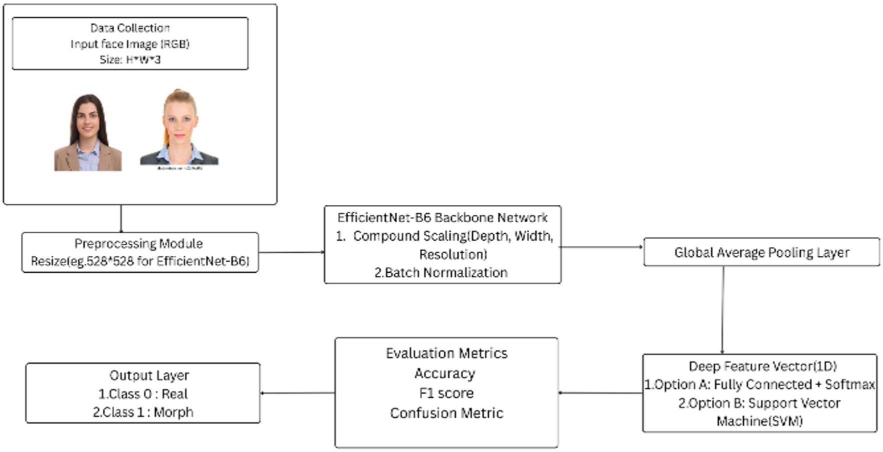

Fig. 1 Architecture Diagram

4 Result and Analysis

This section presents the experimental evaluation of the DMorphNet system for detecting face morphing attacks. It uses the EfficientNet-B6 as a deep feature extractor, and a Support Vector Machine (SVM) is used for the final classification of facial images. The performance of the system was evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, and ROC–AUC curves. In order to test the effectiveness of our system, we tested it against other Efficient-Net versions too. By comparing different EfficientNet models, we were able to examine how the proposed architecture performs in morph detection tasks.

4.1 Quantitative Performance Evaluation

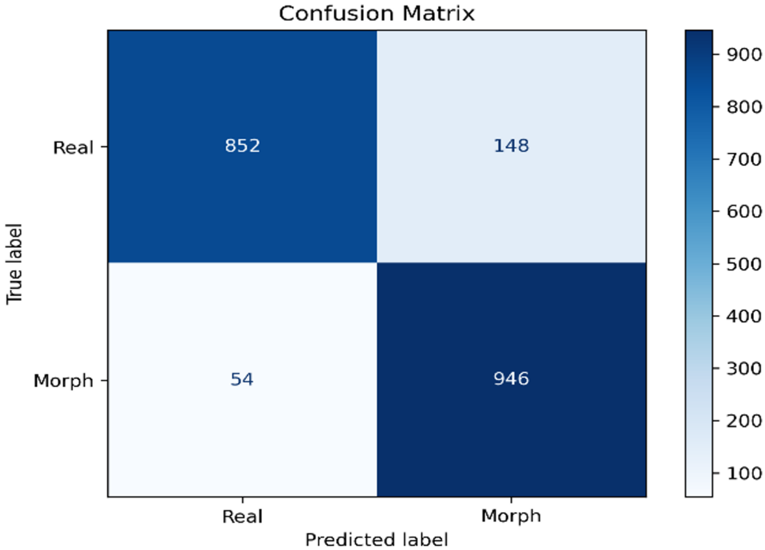

Fig. 2 Confusion Matrix

The combination of the EfficientNet-B6 + SVM framework was evaluated using a separate test dataset that contains real and morphed images all evaluation in fig. 3. The model classification result shows in the confusion matrix below. It illustrates how many images were correctly and incorrectly classified by the model.

Table 1. Confusion Matrix Results

Actual Class	Predicted Real	Predicted Morph
Real Images	852	148
Morph Images	54	946

From the confusion matrix, the following values can be observed:
True Positives (TP): 946 morph images correctly classified as morphs
True Negatives (TN): 852 real images correctly classified as real
False Positives (FP): 148 real images incorrectly classified as morphs
False Negatives (FN): 54 morph images incorrectly classified as real

These results indicate that our system is able to detect morph attacks with a high level of accuracy. 54 false negatives are detected, which are important in biometric systems because undetected morph images could potentially allow identity fraud. The number of **false positives (148)** is slightly higher; this is generally considered acceptable in security-sensitive applications. Images that are detected as suspicious can always be checked manually, reducing the risk of fraudulent images being approved.

Overall, our Dmorphnet system achieved an 89.9% accuracy, indicating that it performs well in distinguishing between real and morphed facial images.

4.2 Comparative Analysis of Efficient-Net Architectures

To better understand the effectiveness of the D-morphnet system, a comparative analysis of three EfficientNet variants was conducted: EfficientNet-B0, EfficientNet-B5, and EfficientNet-B6. The result is shown in Table 2, in that EfficientNet-B6 + SVM performs better than the other models. The baseline EfficientNet-B0 model achieved lower accuracy; this is mainly because of its shallower architecture and limited ability to capture subtle facial patterns present in morphed images. It performs well on basic facial recognition tasks. It struggles to detect the small visual artefacts in morph images. When EfficientNet-B5 was used with an SVM classifier as a feature extractor, the performance improved compared to the baseline model. EfficientNet-B5 is able to capture more detailed facial features and helps the classifier to differentiate between real and morphed images. EfficientNet-B6 has a deeper architecture and a large number of parameters, which helps to capture detailed features in the face image. The combination of EfficientNet-B6 and an SVM classifier gives more effective results as compared to other models. It correctly identifies real and morphed images and improves the model accuracy.

Table 2. Comparative Analysis of Efficient-Net Architectures

Model	**Feature Extraction**	**Classifier**	**Feature Dimension**	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
EfficientNet-B0	CNN baseline	Softmax	1280	62.4	0.63	0.61	0.62
EfficientNet-B5	Deep features	SVM (Linear)	2048	66.13	0.66	0.66	0.66
EfficientNet-B6 (Proposed)	Deep features	SVM (RBF)	2304	89.9	0.90	0.90	0.90

To measure the performance of our system, a Receiver Operating Characteristic (ROC) curve was generated. It shows the True Positive Rate (TPR) and the False Positive Rate (FPR) at different threshold values. The ROC curve obtained for our model is shown in Fig. 3. The area under the curve (AUC) value for our model is 0.965. A value close to 1.0 indicates that the model performs well in differentiating between genuine and morphed facial images. The curve also rises sharply near the starting point, which means that the system can detect most morph images while keeping the number of false positives relatively low.

4.3 ROC Curve and AUC Analysis

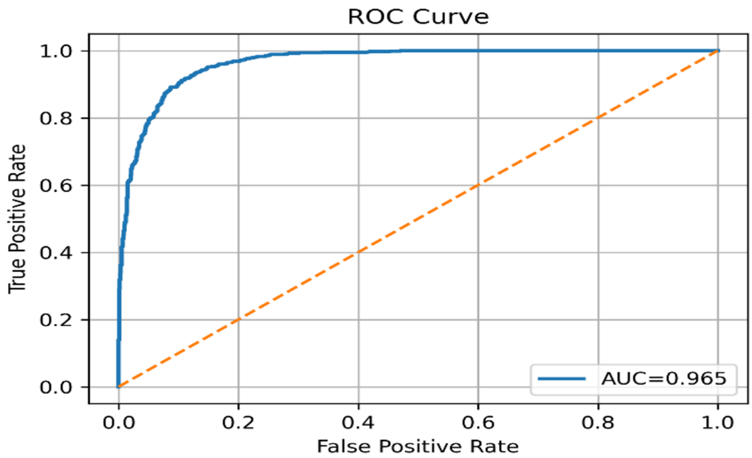

Fig. 3 ROC Curve

4.4 Effect of Threshold Optimization

To improve the performance of the morph detection system, selecting a proper classification threshold is important. Otherwise, the model may wrongly classify real images as morph and also miss some morph images. So, choosing the right threshold is very important. We tested different threshold values, and we observed how the model prediction changed for real and morphed images. After testing different values, we selected the value that gives good balance to detect morph images and avoid incorrect real images. For this, we worked on a validation dataset. The model achieved 89.9% accuracy on the test dataset using the selected threshold value. To improve the reliability of the system, we should use the proper threshold value.

4.5 Real-Time Prediction Capability

The main goal of our system is to check whether the model quickly identifies a real or morphed image. We just not only checked on testing data but also uploaded new images to check how well they perform on real-time data. Our proposed system follows a simple process. Preprocessed and normalized images are uploaded on the system. And then the feature is extracted from the image using EfficientNet b6. SVM is used for classification, and those extracted features are passed to the SVM. After that, it detects whether the image is a morph or real based on feature extraction and classification. After the feature extraction, our system gives the prediction very quickly. Our proposed system works on both single-face images and multiple-face images. Real-time detection of images is shown in Fig. 4 and Fig. 5. These results show that our system accurately detects morph and real faces

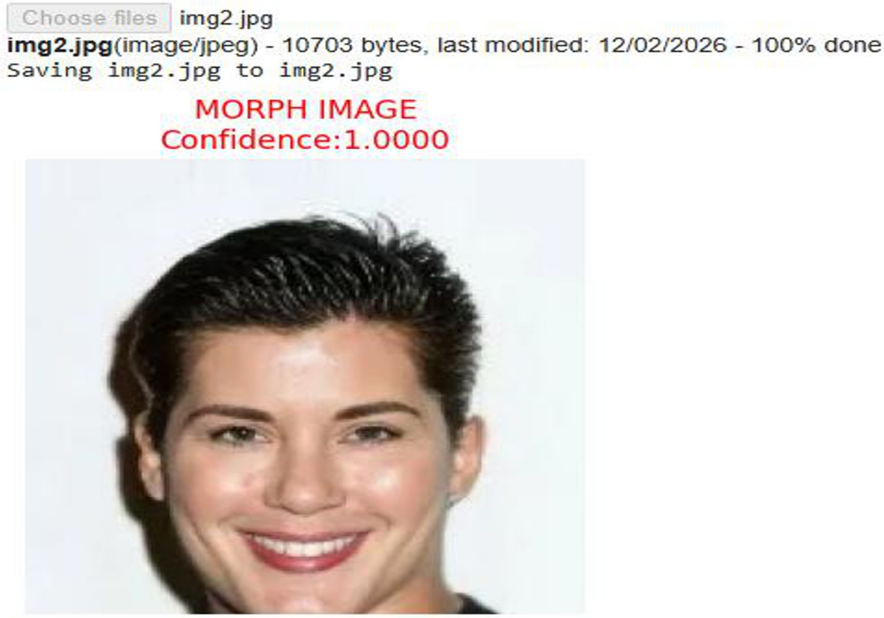

Fig. 4 Real-Time Detection of Morph Image

Fig. 5 Real-Time Detection of Real Image

4.6 Discussion

To extract very small facial features from the morph images, we used EfficientNet. We used SVM as a classifier and passed the extracted features to it. It helps to detect real and morph images and improves the model performance. The ROC-AUC curve indicates that our model is correctly distinguished between two classes. Morphed images were correctly identified by our model. Only a small number of images were missed by the model. Our model performs well on testing data. Based on overall observation, our model performs well on applications where quick detection is required. Our system was able to process images in a small amount of time. We were not recording the exact runtime values. After performing many experiments, the result shows that our proposed system is useful for detecting the morphing attacks. And it can be used in security systems like identity verification, border control, and passports.

5 Conclusion

This study presented D-MorphNet, a framework that helps prevent face morphing attacks on face recognition systems. Face morphing attacks are a growing concern as image editing techniques and GAN-based morph generation get better. These attacks make it hard to identify faces, especially in real-life situations. The goal of this work was to create a detection method that works well without using much computer power. It also had to be able to work with unseen data. To achieve this, we created a dataset using realistic morphs from the FaceMorph_EClub_Task dataset. The dataset had both fake images. We split it into training, validation, and testing sets to ensure an evaluation. Instead of using a single deep learning model, our framework separates feature learning from decision-making. We chose EfficientNet-B6 for feature extraction because it is good at representing images and does not use much computer power. For classification, we used a support vector machine (SVM). Experimental results showed that EfficientNet-B6 with an SVM classifier can effectively separate fake facial images. Fine-tuning and adding data to the dataset improved the framework's performance. It worked better when trained on data and carefully adapted to the task. Compared to deep learning approaches, our method achieved similar robustness with lower computer requirements. This is important for use. Overall, this study shows that using features with classical machine learning classifiers is effective in detecting face morphing attacks. The D-MorphNet framework offers a balance between robustness and efficiency, making it suitable for practical biometric systems. D-MorphNet can help prevent face morphing attacks in face recognition systems. The use of D-MorphNet can provide an efficient way to detect face morphing attacks. DMorphNet is a framework that can be used in practical biometric systems.

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