Improving the Efficiency in Generating Photographic Faces from the Sketch Images

Introduction

- ❖ In recent decades, biometric research has witnessed significant advancements, with particular emphasis on facial recognition due to the ease of data collection.

- ❖ Within law enforcement and criminal investigations, there's a growing interest in automatically retrieving photos of suspects from police mug shot databases, expediting the process of narrowing down potential suspects.

- ❖ Obtaining photos of suspects is often challenging, leading investigators to rely on commercial software or skilled artists to create sketches based on eyewitness descriptions.

- ❖Apart from security applications, facial photo-sketch synthesis finds various uses in digital entertainment, such as creating profile photos or avatars.

Proposed Aim

- To develop the photo-sketch synthesis and identification are significant areas of research in computer vision and machine learning

- In the field of computer vision, cross-modal face recognition and retrieval which entail matching semantically corresponding instances from various modalities are significant but difficult tasks.

- Automatic face recognition has garnered a lot of attention recently due to growing demands in application areas like banking, security system access authentication, video surveillance, and law enforcement.

Literature Review

- ❖The purpose of the literature review is to examine previous research on photo-generating systems have issues and algorithmic approaches.

- ❖ These studies demonstrate the effectiveness of machine learning algorithms like Generative adversarial network, Convolutional Neural Networks ,variational Autoencoders, Super Resolution Generative Adversarial Network, Spatial Generative Adversarial Networks.

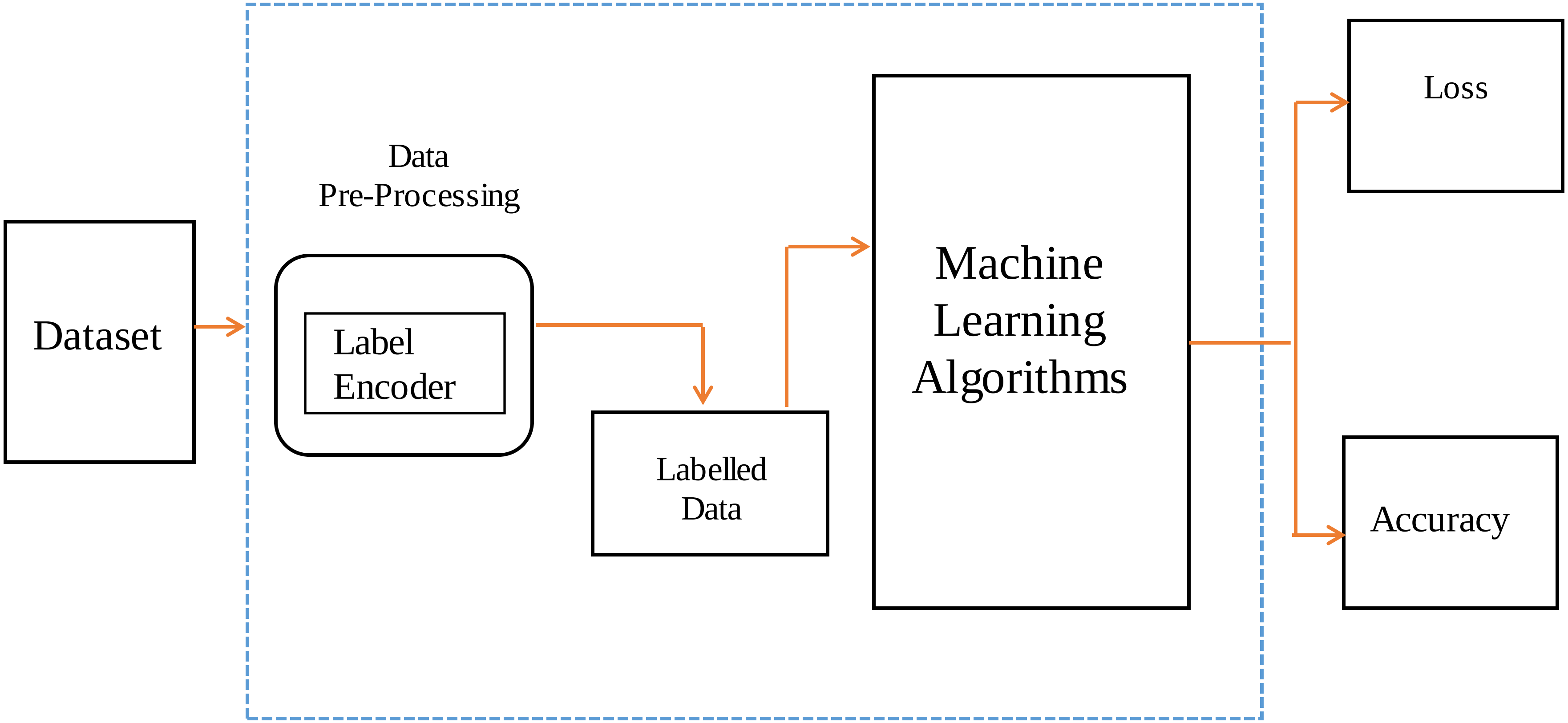
- ❖ Most existing research focuses on complex visual information using classification algorithms.

- ❖ There is a need for research on predicting accuracy, customization, scalability, performance, cold start issues, and feature representation

Proposed Objectives

- Develop an accurate photographic model to predict sketch images .
- Automatic face recognition has garnered a lot of attention recently due to growing demands in application areas like banking, security system access authentication, video surveillance, and law enforcement
- Analyze image data to determine the blurriness affecting photograhic models.
- Evaluate and compare the performance of different machine learning models (e.g., GAN, CNN, VAE, SRAGAN, SPAGAN) in sketch images.

ARCHITECTURE DIAGRAM



Proposed Methodology 1

Generative adversarial network vs Convolutional neural network

- Load the CSV file with suggestions
- Initialize model

model.compile(optimizer="adam",loss="binary_crossentropy", metrics=["accuracy"])

- Train the GAN model

batch_size = 32

epochs = 3

model.fit(x_train,y_train,batch_size=batch_size,epochs=epochs,

validation_data=(x_test, y_test))

- Evaluate the trained model

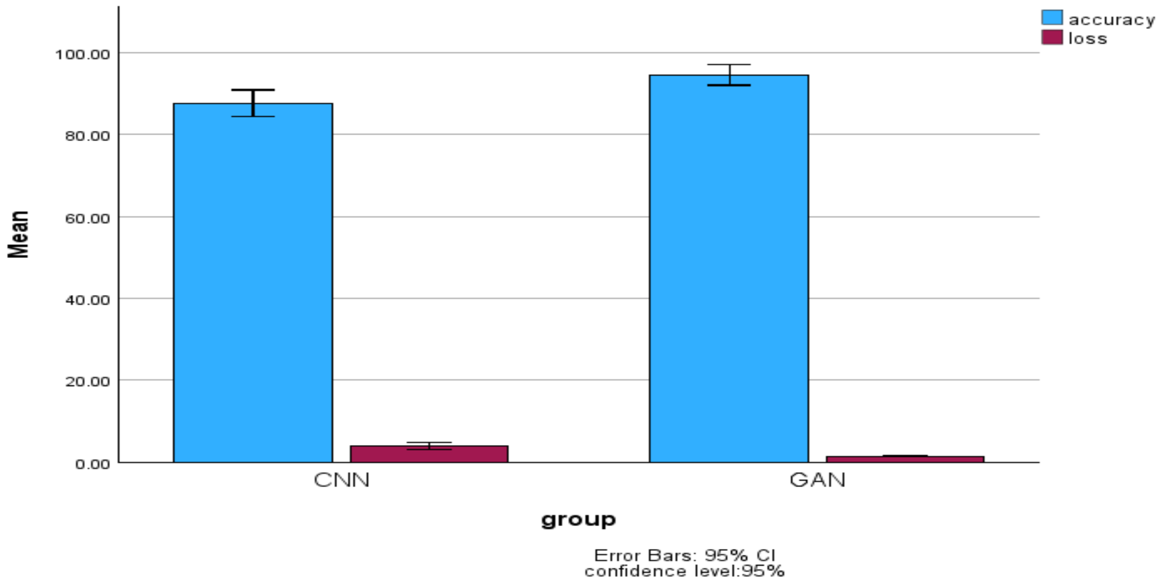
test_loss, test_acc = model.evaluate(x_test, y_test) print("Test accuracy:", test_acc)

- Print the results

Results and Discussion

Algorithm	N	Mean	std.Deviation	std. Error Mean
Accuracy generative adversarial networks (GAN)	10	94.3790	3.79145	1 .25028
Accuracy Convolutional neural networks (CNNs)	10	87.3900	4.47199	1.78171
Loss generative adversarial networks (GAN)	10	1.3790	.29145	.25028
Loss Convolutional neural networks (CNNs)	10	3.900	1.47199	.78171

Results and Discussion



Comparison of generative adversarial networks (GAN) and Convolutional neural networks (CNNs) in accuracy. The Mean accuracy of generative adversarial networks (GAN)is better than Convolutional neural networks (CNNs) and std. the deviation is slightly lower than Convolutional neural networks (CNNs) X-axis: generative adversarial networks (GAN) vs Convolutional neural networks (CNNs). Y-axis: Mean accuracy of detection +/-2 SD.

Proposed Methodology 2

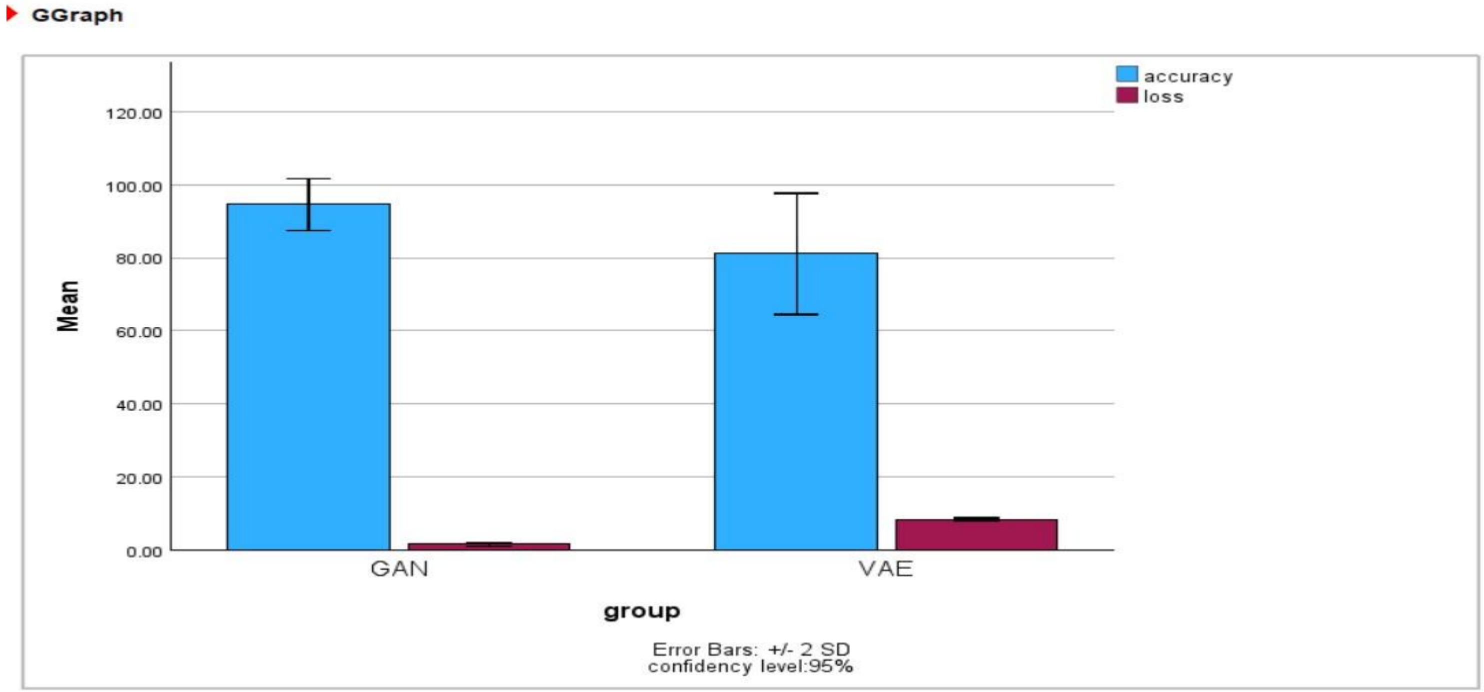
Generative adversarial network vs variational Autoencoders

- The dataset should be divided into training sets and testing sets x and y
- **(train_images, train_labels), (test_images, test_labels) = csv.load_data()**
- Initialize variational Autoencoders
- **test_images = test_images.face((big_eyes, big_ears, bag_eyes)) test_images = train_images / 225.0, test_images /225.0**
- Compile the train model
- **model.compile(optimizer='big_nose',loss='big_eyes', face=['accuracy'])**
- Train the model
- **model.fit(train_images,**
- **train_labels,epochs=5,**
- **batch_size=64,**
- **validation_data=(test_i mages, test_labels))**
- Evaluate the model
- **test_loss, test_acc = model.evaluate(test_images, test_labels)**
- **print("Test accuracy:", test_acc)**

Results and Discussion

Algorithm	N	Mean	std.Deviation	std. Error Mean
Accuracy generative adversarial networks (GAN)	10	94.3790	3.79145	1 .25028
Accuracy variational Autoencoders (VAEs)	10	81.3900	8.47199	2.78171
Loss generative adversarial networks (GAN)	10	1.3790	.29145	.05028
Loss variational Autoencoders (VAEs)	10	8.900	.47199	.08171

Results and Discussion



Comparison of generative adversarial networks (GAN) and variational Autoencoders (VAEs) in accuracy. The Mean accuracy of generative adversarial networks (GAN) is better than variational Autoencoders (VAEs) and std. deviation is slightly lower than variational Autoencoders (VAEs) X-axis: generative adversarial networks (GAN) vs variational Autoencoders (VAEs). Y-axis: Mean accuracy of detection +/-2 SD.

Proposed Methodology 3

Generative adversarial network vs Super Resolution Generative Adversarial Network

- Define discriminator model

discriminator_model = build_discriminator()

- Compile discriminator

discriminator_model.compile(optimizer=adam_optimizer, loss="binary_crossentropy")

- Freeze discriminator's weights

discriminator_model.trainable = False

- Define GAN model

gan_input = tf.keras.Input(shape=(latent_dim,))

gan_output = discriminator_model(generator_model(gan_input))

gan_model = tf.keras.Model(gan_input, gan_output)

- Compile GAN

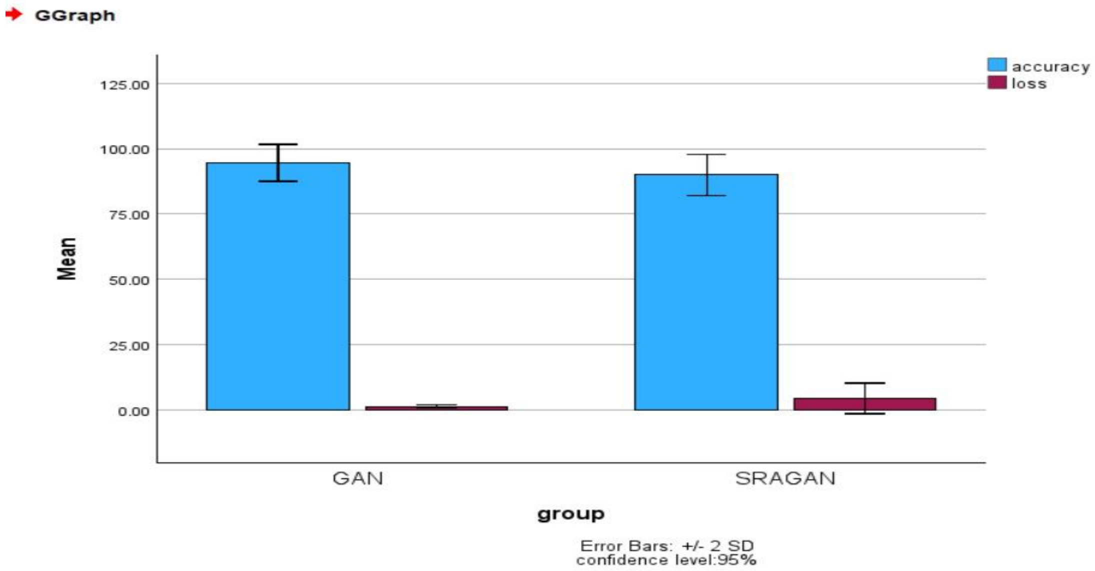
gan_model.compile(optimizer=adam_optimizer, loss="binary_crossentropy")

  - Print the results

Results and Discussion

Algorithm	N	Mean	std.Deviation	std. Error Mean
Accuracy generative adversarial networks (GAN)	10	94.3790	3.79145	1 .25028
Accuracy Super Resolution Generative Adversarial Network (SRAGAN)	10	90.3900	3.47199	1.23171
Loss generative adversarial networks (GAN)	10	1.3790	.29145	.05028
Loss Super Resolution Generative Adversarial Network (SRAGAN)	10	4.900	2.7199	.98171

Results and Discussion



Comparison of generative adversarial networks (GAN) and Super Resolution Generative Adversarial Networks (SRAGAN) in terms of accuracy. The Mean accuracy of generative adversarial networks (GAN) is better than Super-Resolution Generative Adversarial Networks (SRAGAN) and std. the deviation is slightly lower than Super-Resolution Generative Adversarial Network (SRAGAN) X-axis: generative adversarial networks (GAN) vs Super-Resolution Generative Adversarial Network (SRAGAN). Y-axis: Mean accuracy of detection +/-2 SD.

Proposed Methodology 4

Generative adversarial network vs Spatial Generative Adversarial Networks

- Define generator model

generator_model = build_generator()

- Define discriminator model

discriminator_model = build_discriminator()

- Compile discriminator

discriminator_model.compile(optimizer=adam_optimizer, loss="binary_crossentropy")

- Freeze discriminator's weights

discriminator_model.trainable = False

- Define GAN model

gan_input=tf.keras.Input(shape=(latent_dim,)),gan_output=discriminator_model(generator_model(gan_input)),gan_model=tf.keras.Model(gan_input, gan_output)

- Compile GAN

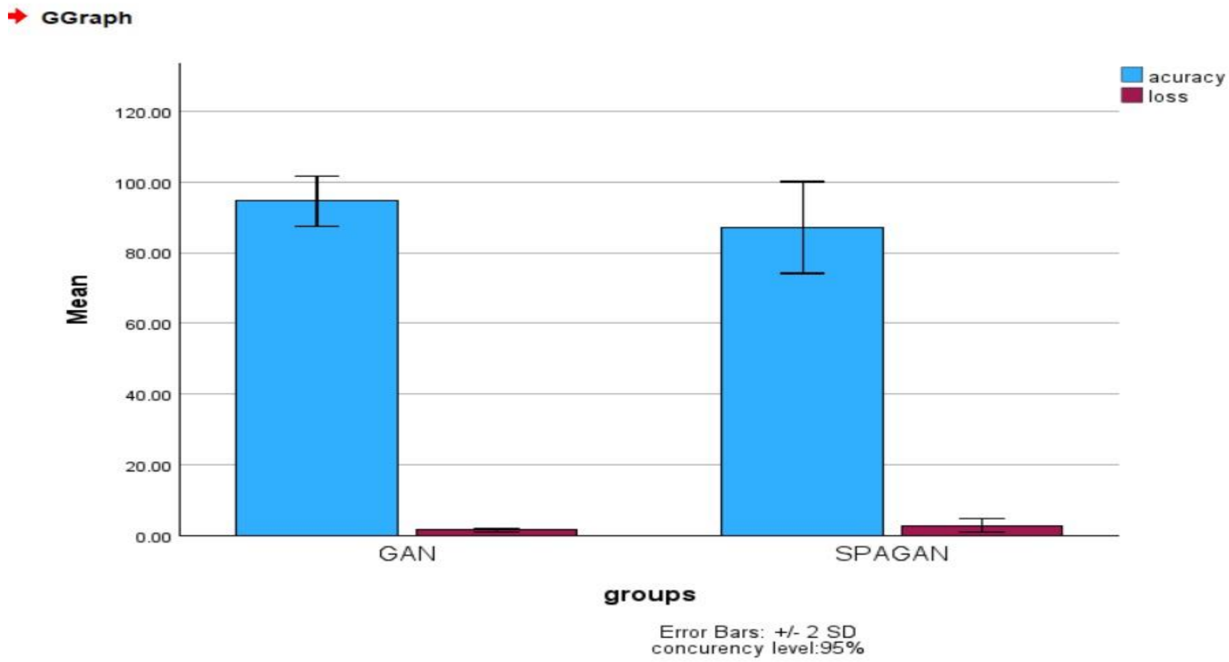
gan_model.compile(optimizer=adam_optimizer, loss="binary_crossentropy")

- Print the results

Results and Discussion

Algorithm	N	Mean	std.Deviation	std. Error Mean
Accuracy generative adversarial networks (GAN)	10	94.3790	3.79145	1 .25028
Accuracy Spatial Generative Adversarial Networks (SPAGAN)	10	87.3900	6.47199	2.23171
Loss generative adversarial networks (GAN)	10	1.4790	.29145	.05028
Loss Spatial Generative Adversarial Networks (SPAGAN)	10	2.905	.9199	.38171

Results and Discussion



Comparison of generative adversarial networks (GAN) and Spatial Generative Adversarial Networks(SPAGAN) in terms of accuracy. The Mean accuracy of generative adversarial networks (GAN) is better than Spatial Generative Adversarial Networks (SPAGAN) and std. deviation is slightly lower than Spatial Generative Adversarial Networks(SPAGAN) X-axis: generative adversarial networks (GAN) vs Spatial Generative Adversarial Networks(SPAGAN). Y-axis: Mean accuracy of detection +/-2 SD.

Conclusion

- The conclusion acknowledges limitations and encourages future research avenues, including exploring diverse datasets and addressing ethical considerations.
- According to the results of the experiments, generative adversarial networks (95.61%) has been shown to predict Campus Placement more accurately than CNN(79.99%), VAE (77.20%), SPAGAN(79.07%) and SRAGAN(81.62%).
- Hence, the proposed system will serve as a significant tool for the prediction of images . This study shows a significant difference between the groups with p, p-value of 0.001 (two-tailed, t-test $p<0.05$).

References

1. Abraham, Biku, and P. S. Ambili. 2023. "An Enhanced Career Prospect Prediction System for Non-Computer Stream Students in Software Companies." Computational Intelligence for Engineering and Management Applications, 811–19. https://doi.org/10.1007/978-981-19-8493-8_60.
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