Real vs. Fake Faces Image Classification

Statistical Deep Learning

2023 Fall

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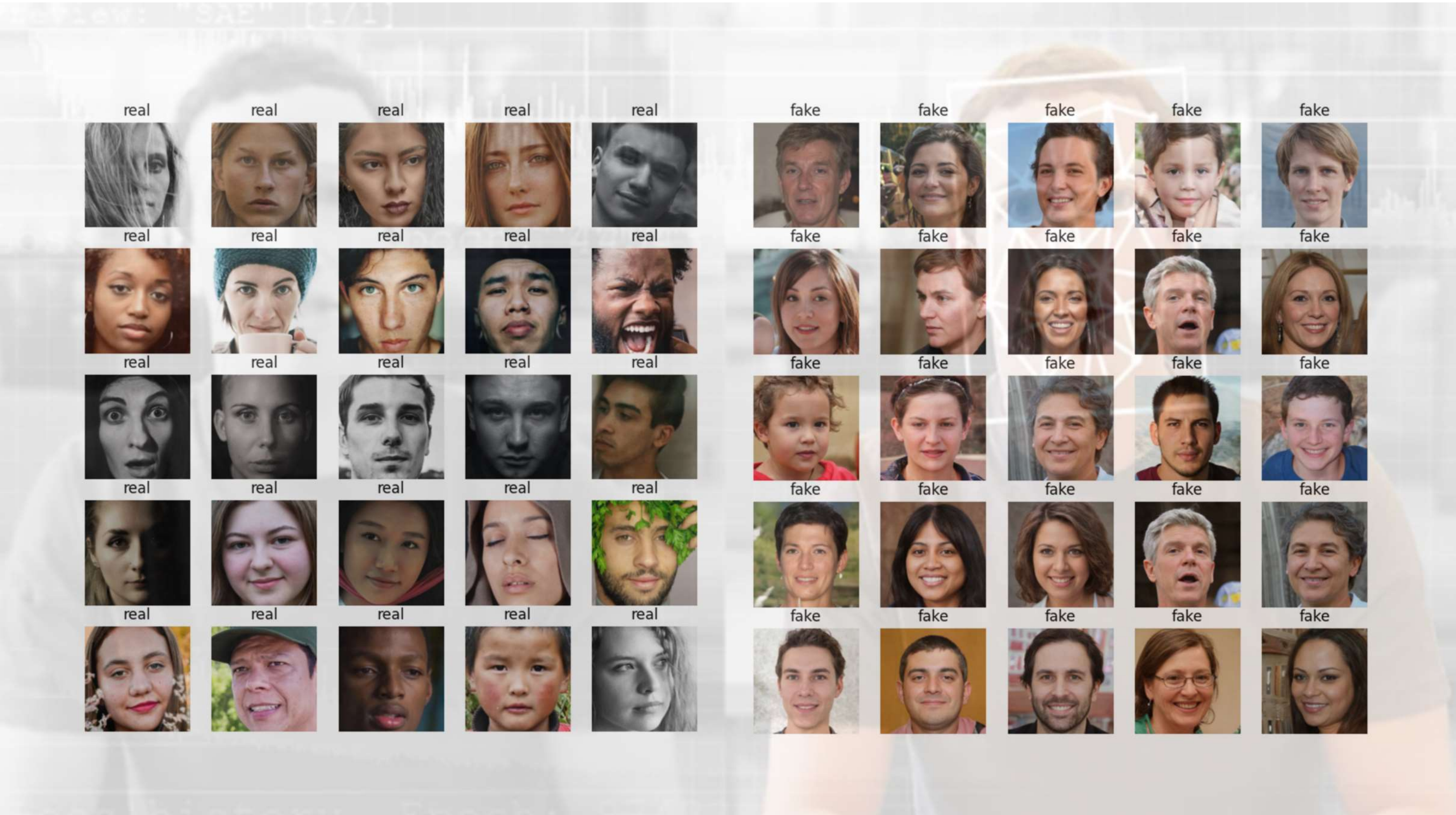
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Exploring & Preprocessing the Dataset

1. Data Source

- Data Sourced from Kaggle
- Dataset link: https://www.kaggle.com/datasets/hamzaboulahia/hardfakevsrealfaces/data

2. Data Description

- Number of real face images : 589
- Number of fake face images : 700
- A total of 1289 images used for the classification

3. Data Loading and Preprocessing

- Real and face face images loaded separately
- Assigned Labels: ‘0’ for fake face images, ‘1’ for real face images
- Datasets are combined and shuffled for randomness

4. Split the Dataset

- Split ratio: 80% for training and 20% for testing

5. Image Preprocessing

- Preprocessed to be consistent in size 300x300 pixels
- Normalized pixel values to the range [0,1]

```python
# Load fake and real data
fake_images = [os.path.join(train_fake_dir, filename) for filename in fake_image_files]
real_images = [os.path.join(train_real_dir, filename) for filename in real_image_files]

fake_labels = [0] * len(fake_images)
real_labels = [1] * len(real_images)


# Combine / Suffle the datasets
combined_images = fake_images + real_images
combined_labels = fake_labels + real_labels

combined_data = list(zip(combined_images, combined_labels))
random.shuffle(combined_data)

# Split into train and test sets / Separate images and labels of train and test sets
split_ratio = 0.8
split_index = int(split_ratio * len(combined_data))
train_data = combined_data[:split_index]
test_data = combined_data[split_index:]

train_images, train_labels = zip(*train_data)
test_images, test_labels = zip(*test_data)
```

```python
def preprocess_image(image_path):
    image = load_img(image_path, target_size=(300,300))
    image = img_to_array(image)
    image /= 255  # Normalize pixel values to the range [0, 1]
    return image

train_images = [preprocess_image(image_path) for image_path in train_images]
train_images = np.array(train_images)
train_labels = np.array(train_labels)

test_images = [preprocess_image(image_path) for image_path in test_images]
test_images = np.array(test_images)
test_labels = np.array(test_labels)

X_train = train_images
y_train = train_labels
X_test = test_images
y_test = test_labels
```

Convolutional Neural Network Model Generation

```python
num_classes = 2  # fake and real

model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same', input_shape=X_train.shape[1:]))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(128))  # Reduced to 128 neurons
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes))
model.add(Activation('softmax'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 300, 300, 32)      896

 activation (Activation)     (None, 300, 300, 32)      0

 max_pooling2d (MaxPooling2  (None, 150, 150, 32)      0
 D)

 dropout (Dropout)           (None, 150, 150, 32)      0

 conv2d_1 (Conv2D)           (None, 150, 150, 64)      18496

 activation_1 (Activation)   (None, 150, 150, 64)      0

 max_pooling2d_1 (MaxPoolin  (None, 75, 75, 64)        0
 g2D)

 dropout_1 (Dropout)         (None, 75, 75, 64)        0

 flatten (Flatten)           (None, 360000)            0

 dense (Dense)               (None, 128)               46080128

 activation_2 (Activation)   (None, 128)               0

 dropout_2 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 2)                 258

 activation_3 (Activation)   (None, 2)                 0

=================================================================
Total params: 46099778 (175.86 MB)
Trainable params: 46099778 (175.86 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Architecture

- Two convolutional layers with ReLU activation
- Max-pooling layers for feature extraction
- Dropout layers for regularization
- Fully connected layers for classification
- Softmax activation for binary classification

CNN Model Training and Evaluation

```python
y_train = to_categorical(y_train, num_classes=num_classes)
y_test = to_categorical(y_test, num_classes=num_classes)

# Compile the model
opt = Adam(learning_rate=0.0001)
model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])

# Data augmentation
datagen = ImageDataGenerator(rotation_range=40, width_shift_range=0.2,
                             height_shift_range=0.2, shear_range=0.2, zoom_range=0.2,
                             horizontal_flip=True, fill_mode='nearest')

# Fit the model
batch_size = 32
epochs = 10
history = model.fit(X_train, y_train, batch_size=batch_size, epochs=epochs,
                    validation_data=(X_test, y_test), verbose=1)
```

```
Epoch 1/10
33/33 [==============================] - 210s 6s/step - loss: 0.6539 - accuracy: 0.8070 - val_loss: 0.2441 - val_accuracy: 0.9845
Epoch 2/10
33/33 [==============================] - 203s 6s/step - loss: 0.1378 - accuracy: 0.9564 - val_loss: 0.2083 - val_accuracy: 0.9457
Epoch 3/10
33/33 [==============================] - 196s 6s/step - loss: 0.1042 - accuracy: 0.9622 - val_loss: 0.1715 - val_accuracy: 0.9767
Epoch 4/10
33/33 [==============================] - 210s 6s/step - loss: 0.1105 - accuracy: 0.9612 - val_loss: 0.1186 - val_accuracy: 0.9922
Epoch 5/10
33/33 [==============================] - 205s 6s/step - loss: 0.1007 - accuracy: 0.9593 - val_loss: 0.1432 - val_accuracy: 0.9922
Epoch 6/10
33/33 [==============================] - 195s 6s/step - loss: 0.0702 - accuracy: 0.9777 - val_loss: 0.0871 - val_accuracy: 0.9922
Epoch 7/10
33/33 [==============================] - 211s 6s/step - loss: 0.0316 - accuracy: 0.9913 - val_loss: 0.0591 - val_accuracy: 0.9922
Epoch 8/10
33/33 [==============================] - 195s 6s/step - loss: 0.0275 - accuracy: 0.9913 - val_loss: 0.0530 - val_accuracy: 0.9961
Epoch 9/10
33/33 [==============================] - 205s 6s/step - loss: 0.0216 - accuracy: 0.9942 - val_loss: 0.0554 - val_accuracy: 0.9961
Epoch 10/10
33/33 [==============================] - 205s 6s/step - loss: 0.0200 - accuracy: 0.9971 - val_loss: 0.0364 - val_accuracy: 0.9961
```

Overview of Steps

1. Label Encoding
- Converted labels into one-hot encoding

2. Model Compilation
- Configured the model with Adam optimizer and categorical cross-entropy loss

3. Data Augmentation:
- Utilize ImageDataGenerator for augmenting training data

4. Batch Size & Number of Epochs
- Set batch size to 32, controlling the number of samples per gradient update
- Defined the number of training epochs as 10

5. Model Training
- Trained the model using the fit() function with training and validation data
- Monitored training and validation accuracy

Accuracy & F1 Score of Convolutional Neural Network

```
y_pred = model.predict(X_test)
y_pred = (y_pred > 0.5).astype(int)

y_test = y_test.flatten()
y_pred = y_pred.flatten()

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.4f}')

# F1 score
f1 = f1_score(y_test, y_pred, average='binary')
print(f'F1 Score: {f1:.4f}')
```

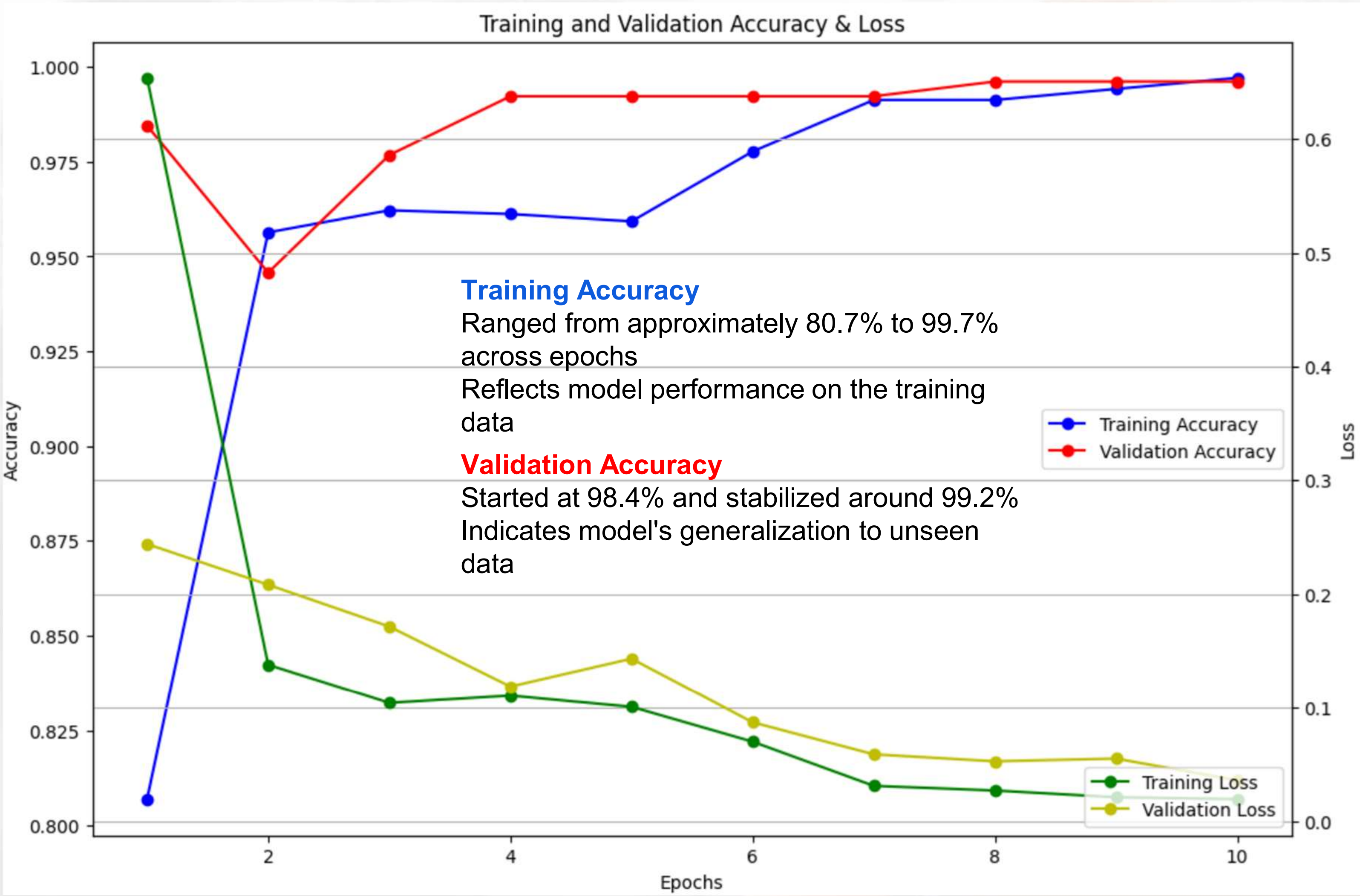
```
9/9 [==============================] - 11s 1s/step
Accuracy: 0.9961
F1 Score: 0.9961
```

1. Accuracy: 0.9961
- Reflects the CNN model's correctness in classification

2. F1 Score: 0.9961
- Represents the balance of precision and recall in binary classification

Visualizing Model Performance

```
training_acc = history.history['accuracy']
validation_acc = history.history['val_accuracy']
training_loss = history.history['loss']
validation_loss = history.history['val_loss']

epochs = range(1, len(training_acc) + 1)

plt.figure(figsize=(12, 8))

# Plot accuracies
plt.plot(epochs, training_acc, 'bo-', label='Training Accuracy')
plt.plot(epochs, validation_acc, 'ro-', label='Validation Accuracy')
plt.title('Training and Validation Accuracy & Loss')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend(loc='center right')

# Plot losses
plt.twinx()  # Create a twin y-axis
plt.plot(epochs, training_loss, 'go-', label='Training Loss')
plt.plot(epochs, validation_loss, 'yo-', label='Validation Loss')
plt.ylabel('Loss')
plt.legend(loc='lower right')

plt.grid()
plt.show()
```



Training Accuracy

Ranged from approximately 80.7% to 99.7% across epochs

Reflects model performance on the training data

Validation Accuracy

Started at 98.4% and stabilized around 99.2%

Indicates model's generalization to unseen data

Conclusion

1. Training Accuracy

- Started around 80.7% in the first epoch and steadily improved to nearly 99.7% in the last epoch.
- Indicates effective learning from the training data.

2. Validation Accuracy

- Began at 98.4% in the first epoch and stabilized at around 99.2% in later epochs.
- Showed robust generalization to unseen data.

3. Overall Model Performance

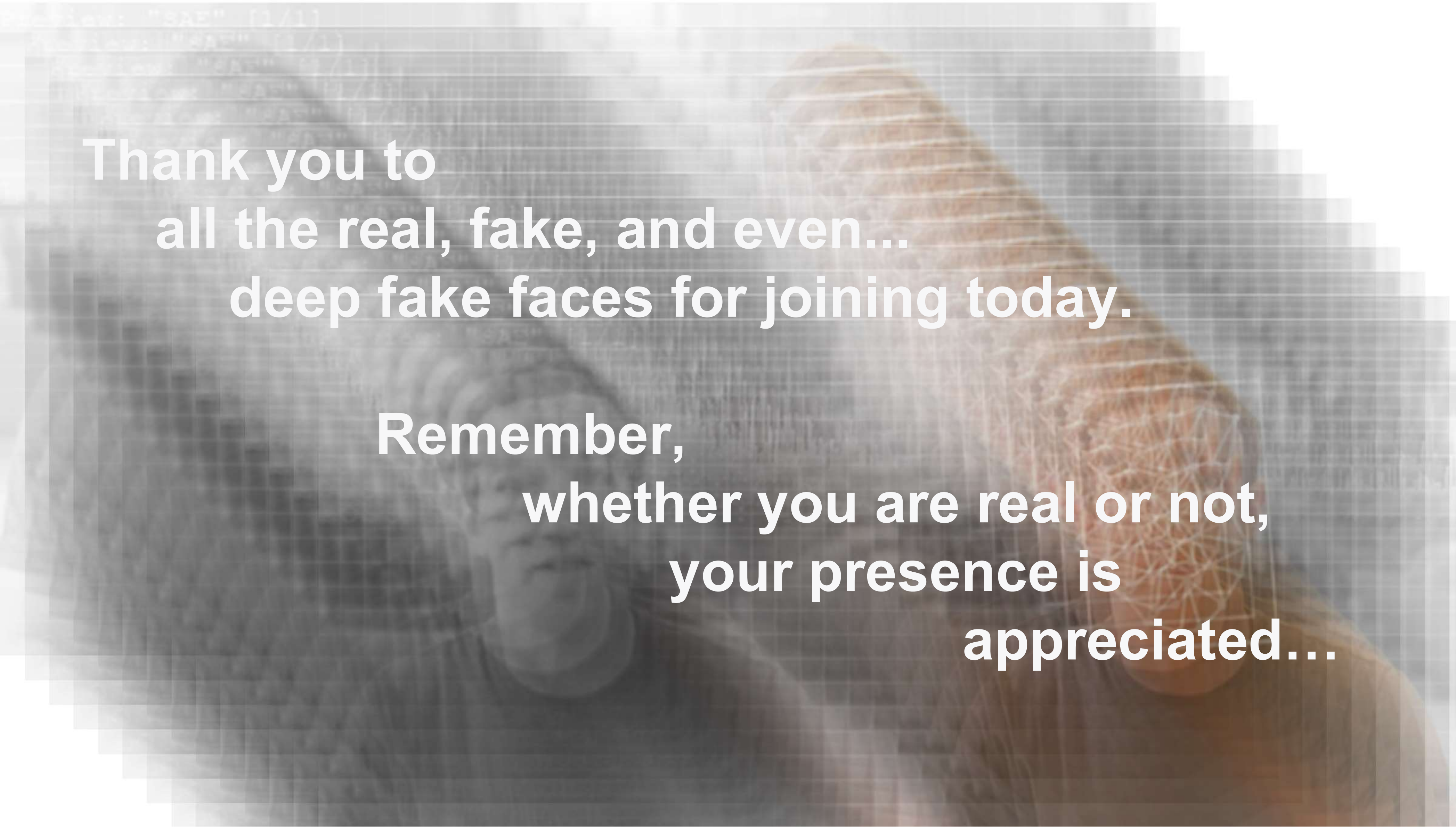
- Model effectively learnt during training and achieved high accuracy in both training and validation datasets.

4. Limitation

- Model’s impressive accuracy and generalization could be attributed to the limited dataset.
- A larger and more diverse dataset might provide a better understanding of the model’s performance.

5. Github

- Code link: https://github.com/HL-Kim/Deep-Learning


Thank you to
all the real, fake, and even...
deep fake faces for joining today.
Remember,
whether you are real or not,
your presence is
appreciated…