Model	Parameters	Size
VGG16	138,357,544	528 MB
VGG19	143,667,240	548 MB
ResNet50	25,636,712	98 MB
Inception-V3	23,851,784	92 MB
DenseNet-121	8,062,504	31 MB
Xception	22,910,480	88 MB
MobileNet	4,253,864	16 MB

Model	Depth	Trainable Parameters	Size	# of Weights	# of Biases
VGG16	16	138,357,544	528 MB	138,357,544	0
VGG19	19	143,667,240	548 MB	143,667,240	0
ResNet50	50	25,636,712	98 MB	25,583,592	53,120
Inception-V3	159	23,851,784	92 MB	23,768,712	83,072
DenseNet-121	121	8,062,504	31 MB	7,978,856	83,648
Xception	126	22,910,480	88 MB	22,855,840	54,640
MobileNet	88	4,253,864	16 MB	4,253,384	480

Orden de a cuerdo a cantidad de Weights:

- 1. VGG19
- 2. Resnet50
- 3. DenseNet-121
- 4. MobileNet

Orden de acuerdo a profundidad:

Inception-V3
DenseNet-121
Resnet50
Mobile Net

#### Modelos seleccionados:

- ResNet50: Este modelo tiene un alto rendimiento en la clasificación de imágenes en general, gracias a su arquitectura profunda y su capacidad para aprender características de alto nivel a partir de características de bajo nivel. La estructura de salto de conexión residual de ResNet también ayuda a prevenir el problema de desvanecimiento de gradiente, lo que puede mejorar la precisión de la clasificación. Además, ResNet50 tiene un tamaño de modelo moderado en comparación con otros modelos más grandes, lo que lo hace más fácil de entrenar y menos propenso al sobreajuste.
- DenseNet-121: Este modelo también tiene una arquitectura profunda, pero utiliza conexiones densas entre capas para mejorar aún más el flujo de información en la red. DenseNet-121 es conocido por su eficiencia y facilidad de entrenamiento, ya que el tamaño del modelo es relativamente pequeño y tiene menos parámetros que otros modelos más grandes. Además, el modelo ha demostrado ser efectivo en problemas de clasificación de imágenes, incluidos los problemas de clasificación multietiqueta.
- Inception-V3: Este modelo se enfoca en mejorar la eficiencia computacional de las redes neuronales convolucionales, al mismo tiempo que mantiene un alto rendimiento en la clasificación de imágenes. Inception-V3 utiliza una estructura de red modular y varias operaciones de convolución para mejorar la eficiencia computacional. Además, Inception-V3 tiene un tamaño de modelo moderado y es fácil de entrenar, lo que lo hace ideal para aplicaciones de clasificación de imágenes multietiqueta.
- MobileNet: Este modelo se destaca por su eficiencia en términos de uso de recursos computacionales y su capacidad para ejecutarse en dispositivos con recursos limitados. MobileNet utiliza capas convolucionales separables en profundidad para reducir el costo computacional y el tamaño del modelo, lo que lo hace adecuado para aplicaciones en dispositivos móviles o en la nube con recursos limitados. A pesar de su tamaño reducido, MobileNet ha demostrado ser efectivo en tareas de clasificación de imágenes, incluida la clasificación multietiqueta.

### **EVALUACIÓN DE ESPECTROGRAMAS**

Para la generación de los espectrogramas se decidió probar dos acercamientos:

- Uso de SFFT y specshow, función de librosa.
- Uso de melspectrogram función de librosa.

Para modificar parámetros y encontrar la mejor forma de visualización de los llamados en los espectrogramas se usó la siguiente formula: FFT Length = (Sample Rate \* Duration) / Hop Length

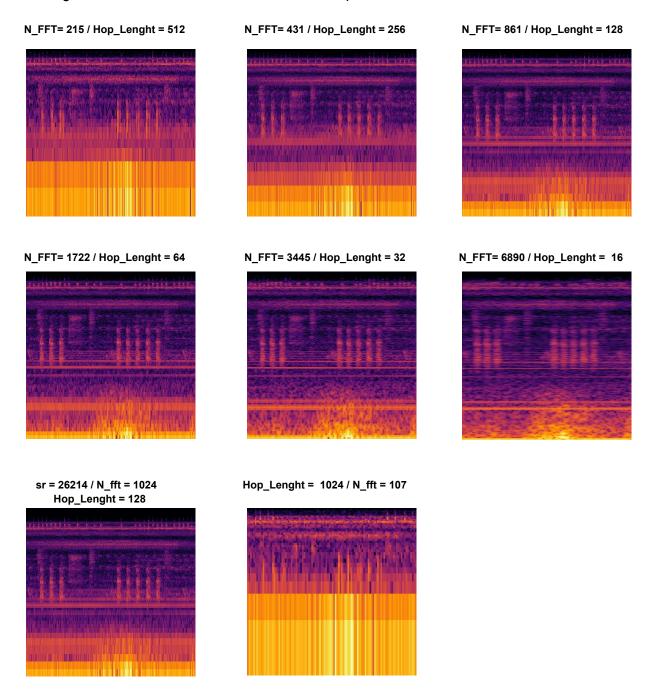
El Sample Rate de nuestros audios es = 22050Hz Nuestra duración de los audios es de = 5sec Se fué modificando el Hop Lenght en base a potencias de 2 disminuyendo desde 512 y despejando el valor de FFT Lenght con cada variación

A continuación los códigos utilizados:

#### SFFT y specshow:

```
def generate spectrogram(audio file path, output file path, sr=22050, n fft=1723, hop length=64):
    Generate spectrogram from audio file and save it as an image.
   Parameters
    audio file path : str
       Path to audio file
   output file path : str
       Path to save the generated spectrogram
    sr : int, optional
       Sampling rate of the audio file, by default 22050
    n fft : int, optional
       Length of the FFT window, by default 2048
    hop_length : int, optional
       Number of samples between successive frames, by default 512
   Returns
   y, sr = librosa.load(audio_file_path, sr=sr)
    S = np.abs(librosa.stft(y, n_fft=n_fft, hop_length=hop_length))
    log_S = librosa.amplitude_to_db(S)
    plt.figure(figsize=(8, 8))
    librosa.display.specshow(log_S, sr=sr, x_axis='time', y_axis='log', cmap='inferno')
    plt.axis('off')
    plt.savefig(output_file_path, bbox_inches='tight', pad_inches=0, dpi=100)
   plt.close()
```

Los siguientes fueron los resultados de variar los parámetros de esta función:



A partir de estas pruebas de concluyó que este método de obtención de espectrograma no es apropiado para la aplicación que se desea emplear, pues los llamados no se pueden identificar fácilmente y en algunos casos no se puede distinguir casi nada, sin embargo se concluyo que la combinación de parámetros Hop\_Lenght = 64, N\_FFT = 1722 generó la

mejor imagen de todas las pruebas, por lo que se partió de estos parámetros en la siguiente prueba con los espectrogramas de Mel

### Mel Spectrogram:

```
def generate_spectrogram(audio_file_path, output_file_path, sr=22050, n_fft=1024, hop_length=64, n_mels=256):
   Generate mel spectrogram from audio file and save it as an image.
   audio_file_path : str
   output_file_path : str
       Path to save the generated spectrogram
   sr : int, optional
       Sampling rate of the audio file, by default 22050
       Length of the FFT window, by default 2048
   hop_length : int, optional
       Number of samples between successive frames, by default 512
       Number of mel bands to generate, by default 128
   Returns
   y, sr = librosa.load(audio_file_path, sr=sr)
   S = librosa.feature.melspectrogram(y=y, sr=sr, n_fft=n_fft, hop_length=hop_length, n_mels=n_mels)
   log_S = librosa.amplitude_to_db(S)
   plt.figure(figsize=(8, 8))
   librosa.display.specshow(log_S, sr=sr, x_axis='time', y_axis='mel', cmap='jet')
   plt.axis('off')
   plt.savefig(output_file_path, bbox_inches='tight', pad_inches=0, dpi=100)
   plt.close()
```

Los siguientes fueron los resultados de variar los parámetros de esta función:

N\_FFT= 215 / Hop\_Lenght = 512 **N\_FFT= 431 / Hop\_Lenght = 256 N\_FFT= 861 / Hop\_Lenght = 128** N\_FFT= 1722 / Hop\_Lenght = 64 N\_FFT= 3445 / Hop\_Lenght = 32 N\_FFT= 6890 / Hop\_Lenght = 16 sr = 26214 / N\_fft = 1024 Hop\_Lenght = 1024 / N\_fft = 107 N\_FFT = 2048 / Hop\_Lenght = 64 /N\_Mels = 256 Hop\_Lenght = 128 N\_FFT = 1722 / Hop\_Lenght = 64 N\_FFT = 1024 / Hop\_Lenght = 64 / N\_Mels = 256 N\_Mels = 256

De estas pruebas se concluyó que el conjunto de parámetros: **N\_FFT = 1024 / Hop\_Lenght = 64 /N\_Mels = 256** fué el que mejor resultado visual entregó, por lo que se va a proceder a realizar entrenamientos de los modelos definidos con el dataset compuesto por imágenes obtenidas de esta forma.

#### **EVALUATION PLAN**

To create a testing plan for these models, we need to consider the following steps:

Data preprocessing: First, we need to preprocess the data in the same way for all the models. We will resize the images to a fixed size (224x224) and normalize the pixel values.

Splitting the data: We need to split the dataset into training, validation, and testing sets. We will use 70% of the data for training, 20% for validation, and 10% for testing.

Model selection: We will train and test four models: MobileNet, Inception-V3, DenseNet-121, and ResNet50. All the models will be pretrained on the ImageNet dataset and fine-tuned on the target dataset. We will use binary cross-entropy loss and sigmoid activation function for multi-label classification.

Hyperparameter tuning: We will perform hyperparameter tuning to find the best learning rate, batch size, and number of epochs for each model. We will use the validation set for this purpose.

Evaluation: Finally, we will evaluate the performance of each model on the testing set. We will use the following evaluation metrics: accuracy, precision, recall, F1-score, and ROC AUC, Hamming Loss. We will compare the performance of the models and select the one with the best performance(F1 score).

Here is the detailed testing plan for the models:

### Data preprocessing:

Resize the images to a fixed size of (224, 224). Normalize the pixel values to the range [0, 1].

We are currently doing this with this function:

```
#Function for preprocessing images

def preprocess_images(paths, target_size=(224,224,3)):
    X = []
    for path in paths:
        img = image.load_img(path, target_size=target_size)
        img_array = tf.keras.preprocessing.image.img_to_array(img)
        img_array = img_array/255
        X.append(img_array)
    return np.array(X)
```

Splitting the data:

Split the dataset into training, validation, and testing sets.

Use 70% of the data for training, 20% for validation, and 10% for testing.

366 folders with 11 audios each is our total dataset, we extract 37 folders and isolated from the training and validation dataset, this will be our testing dataset, we ensure we encounter here all possibilities of labels.

For the train and validation dataset we use sklearn train split function and split the dataset in 80% for training and 20% for validation, remember this is over the 329 remaining folders.

Images of the code implemented below:

Our dataset is not balanced, this may give issues in performance.

#### **Model selection:**

Train and test four models: MobileNet, Inception-V3, DenseNet-121, and ResNet50. Pretrain the models on the ImageNet dataset.

Fine-tune the models on the target dataset with binary cross-entropy loss and sigmoid activation function.

Use early stopping and model Check-Pointing to prevent overfitting.

Use the Adam optimizer with a learning rate of 0.001.

#### Hyperparameter tuning:

Perform hyperparameter tuning to find the best learning rate, batch size, and number of epochs for each model.

Use the validation set for this purpose.

Vary the learning rate from 0.00001 to 0.01 in steps of 0.1.

Vary the batch size between 16,32,64 the selected one because of memory issues was **32**. Vary the number of epochs from 10 to 100 in steps of 10, an early stopping was implemented to avoid overfitting and the epoch size fixed in 100.

Evaluation:

Evaluate the performance of each model on the testing set.

Use the following evaluation metrics: accuracy, precision, recall, F1-score, and ROC AUC. Compare the performance of the models and select the one with the best performance.

# **RESULTS**

## **MobileNet**

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
MobileN et_Reg_ L2_Ir_00 01_batch _32.h5	0.468	0.811	0.550	0.656	0.904	0.74	0.097
MobileN et_Reg_ L2_Ir_00 001_batc h_32.h5	0.5	0.798	0.593	0.680	0.927	0.768	0.094
MobileN et_lr_000 01_batch _32.h5	0.436	0.732	0.513	0.60	0.9274	0.734	0.113
MobileN et_lr_000 1_batch_ 32.h5	0.462	0.764	0.556	0.643	0.927	0.756	0.103
MobileN et_lr_001 _batch_3 2.h5	0.506	0.718	0.588	0.647	0.932	0.737	0.108

Best model: MobileNet\_Reg\_L2\_Ir\_00001\_batch\_32.h5

# ResNet50

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
Resnet5 0_Reg_L 2_lr_000 1_Batch 32.h5	0.430	0.692	0.481	0.567	0.920	0.602	0.123
Resnet5 0_Reg_L 2_Ir_000 01_Batc h32.h5	0.417	0.682	0.449	0.541	0.904	0.621	0.128
Resnet5 0_lr_000 01_Batc h32.h5	0.436	0.684	0.475	0.561	0.910	0.644	0.125
Resnet5 0_lr_000 1_Batch 32.h5	0.436	0.673	0.497	0.572	0.904	0.563	0.125
Resnet5 0_lr_001 _Batch3 _2.h5	0.120	0.814	0.117	0.205	0.909	0.646	0.153
Resnet5 0_lr_01_ Batch32. h5	0.0	0.0	0.0	0.0	0.889	0.526	0.169

Best model:Resnet50\_lr\_0001\_Batch32.h5

# InceptionV3

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
Inceptio nV3_Reg _L2_Ir00 001_Bat ch_32.h5	0.405	0.673	0.508	0.579	0.903	0.669	0.124
Inceptio nV3_Reg _L2_Ir00 01_Batc h_32.h5	0.386	0.708	0.454	0.553	0.887	0.634	0.123
Inceptio nV3_Ir00 001_Bat ch_32.h5	0.360	0.675	0.433	0.527	0.910	0.635	0.131
Inceptio nV3_Ir00 01_Batc h_32.h5	0.443	0.686	0.550	0.611	0.914	0.669	0.118
Inceptio nV3_Ir00 1_Batch _32.h5	0.392	0.723	0.4759	0.574	0.921	0.698	0.119
Inceptio nV3_Ir01 _Batch_ 32.h5	0.0	0.0	0.0	0.0	0.890	0.544	0.169

Best model: InceptionV3\_Reg\_L2\_Ir00001\_Batch\_32.h5

DenseNet121

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
DenseN et121_lr _0001_e poch_25 _batch_3 2.h5	0.405	0.743	0.465	0.572			0.11
DenseNe t_Reg_l2 _lr01.h5	0.0	0.5	0.005	0.01	0.88	0.492	0.16
DenseNe t_Reg_I2 _Ir0001.h	0.417	0.708	0.518	0.598	0.896	0.632	0.117
DenseNe t_Reg_l2 _lr001.h5	0.360	0.768	0.390	0.517	0.932	0.676	0.12
DenseNe t_Reg_l2 _lr01.h5	0.0	0.5	0.005	0.010	0.882	0.492	0.169

Best Model: DenseNet121\_lr\_0001\_epoch\_25\_batch\_32.h5

# 2+ Layers Models

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
DenseN et121_2 L_Ir_001 .h5	0.437	0.740	0.519	0.610	0.853	0.553	0.112
DenseN et121_2 L_Ir_000 1.h5	0.456	0.711	0.576	0.637	0.922	0.667	0.111
DenseN et121_2 L_Ir_000 01.h5	0.494	0.770	0.572	0.656	0.918	0.681	0.101
MobileN et_2L_lr _001.h5	0.234	0.671	0.283	0.398	0.909	0.646	0.145
MobileN et_2L_lr _0001.h 5	0.551	0.743	0.663	0.700	0.929	0.756	0.095
MobileN et_2L_lr _00001. h5	0.487	0.728	0.588	0.651	0.903	0.696	0.106
Resnet_ 2L_lr_00 1.h5	0.348	0.750	0.417	0.536	0.911	0.688	0.122
Resnet_ 2L_lr_00 01.h5	0.038	0.040	0.043	0.077	0.910	0.568	0.173
Resnet_ 2L_lr_00 001.h5	0.0	0.0	0.0	0.0	0.869	0.454	0.169
Inceptio nV3_2L_ Ir_00001 .h5	0.487	0.687	0.588	0.634	0.907	0.654	0.115

### **Best models**

Model Name	Accurac y	Precisio n	Recall	F1	ROC AUC	PR AUC	Hammin g Loss
DenseN et121_2 L_Ir_000 01.h5	0.494	0.770	0.572	0.656	0.918	0.681	0.101
MobileN et_2L_lr _0001.h 5	0.551	0.743	0.663	0.700	0.929	0.756	0.095
Inceptio nV3_2L_ Ir_00001 .h5	0.487	0.687	0.588	0.634	0.907	0.654	0.115
Resnet5 0_lr_000 1_Batch 32.h5	0.436	0.673	0.497	0.572	0.904	0.563	0.125

Best Model: MobileNet\_2L\_Ir\_0001.h5

Smaller learning rates give the best results

F1 - Score selected models

Model Name	PHYCUV _M	PHYCUV _F	BOAALB _M	BOAALB _F	BOALUN _F	BOALUN _M	NONE
DenseN et121_2 L_Ir_000 01.h5	0	0	0.4	0.703	0.685	0	0
MobileN et_2L_Ir _0001.h 5	0	0	0	0.707	0.777	0	0
Inception V3_2L_Ir _00001. h5	0	0	0	0.662	0.667	0	0
Resnet50 _lr_0001 _Batch32 .h5	0	0	0	0.636	0.578	0	0

Data augmentation Time

PHYCUV_M	364
PHYCUV_F	87
BOAALB_M	101
BOAALB_F	469
BOALUN_F	391
BOALUN_M	27
none	86

# 3 etiquetas

# F1 - Score selected models

Model Name	PHYCUV	BOAALB	BOALUN
DenseNet121_2L_Ir _00001.h5	0	0.703	0
MobileNet_2L_Ir_00 01.h5	0	0.707	0
InceptionV3_2L_Ir_0 0001.h5	0	0.662	0
Resnet50_lr_0001_B atch32.h5	0	0.636	0

Temas a tratar en próxima reunión con Director de tesis y Codirector:

- Trabajar con cross validation k fold = 5
- Conj entrenamiento y test 70 30
- usar time masking
- usar 3 labels
- borrador estructura tesis que compartió Ulloa
- Documentando bien pruebas
- formulación de hipotesis
- plan de pruebas para hacer check
- intentar frecuency masking
- intentar time stretching
- Viernes a las 10 nuevo horario

3LABELS - New Beggining

### **EVALUATION PLAN**

To create a testing plan for these models, we need to consider the following steps:

Data preprocessing: First, we need to preprocess the data in the same way for all the models. We will resize the images to a fixed size (224x224) and normalize the pixel values.

Data augmentation techniques for testing: Time masking, Frequency masking, Time stretching

Step 1

Splitting the data with no augmentation: We need to split the dataset into training, validation. We will use 70% of the data for training, 30% for validation.

Splitting the data with augmentation: We need to split the dataset in 70% 30% and then include to the 70% part the augmented data, then train with that 70%

Step 2

**Model selection:** We will train and test four models: MobileNet, Inception-V3, DenseNet-121, and ResNet50. All the models will be pretrained on the ImageNet dataset and fine-tuned on the target dataset. We will use binary cross-entropy loss and sigmoid activation function for multi-label classification.

- MobileNet
- Inception-V3
- DenseNet-121
- ResNet50

**Hyperparameter tuning:** We will perform hyperparameter tuning to find the best learning rate, and the number of epochs for each model. We will use the validation set for this purpose.

Learning Rate: 0.00001 due to previous results

Epochs: because of an implemented early stop function used to avoid over-fitting, the number of epochs will vary depending on the model, architecture, dataset, and hyperparameters selected.

Regularization: L2 selected as preferred to avoid overfitting or none

#### Architecture

1 fully connected layer 256, act relu and reg L2

2 fully connected layer 128 & 256, act relu and reg L2

Evaluation: Finally, we will evaluate the performance of each model on the testing set. We will use the following evaluation metrics: accuracy, precision, recall, F1-score, and ROC AUC, Hamming Loss. We will compare the performance of the models and select the one with the best performance(F1 score).

Here is the detailed testing plan for the models:

#### Data preprocessing:

Resize the images to a fixed size of (224, 224).

Normalize the pixel values to the range [0, 1].

Train models with selected parameters and architecture and corresponding dataset Resulting on 48 models

### Mobile Net

✓ Augmented - Frequency Masking					
One fully connected Layer					
✓ Regularization L2					
✓ Normal Training					
✓ Normal Training					
✓ Augmented - Time Masking					
One fully connected Layer					
☐ CrossValidation-5folds					
✓ Normal Training					
Two fully connected Layer					
☑ Regularization L2					
Normal Training					
✓ Not Augmented					
One fully connected Layer					
✓ Normal Training					
✓ Regularization L2					
✓ Normal Training					

## DensNet121

☐ Augmented - Frequency Masking					
☐ One fully connected Layer					
☐ Regularization L2					
☐ CrossValidation-5folds					
✓ Normal Training					
Two fully connected Layer					
☐ Regularization L2					
✓ Normal Training					
✓ Augmented - Time Masking					
One fully connected Layer					
✓ Regularization L2					
✓ Normal Training					
Two fully connected Layer					
✓ Regularization L2					
✓ Normal Training					
✓ Not Augmented					
One fully connected Layer					
✓ Regularization L2					
Normal Training					
Two fully connected Layer					
✓ Regularization L2					
Normal Training					

## Resnet50

Augmented - Frequency Masking						
One fully connected Layer						
☐ Regularization L2						
☐ CrossValidation-5folds						
☐ Normal Training						
☐ Two fully connected Layer						
Regularization L2						
☐ CrossValidation-5folds						
☐ Normal Training						
✓ Augmented - Time Masking						
One fully connected Layer						
✓ Regularization L2						
✓ Normal Training						
Two fully connected Layer						
✓ Regularization L2						
✓ Normal Training						
✓ Not Augmented						
One fully connected Layer						
✓ Regularization L2						
☐ CrossValidation-5folds						
Normal Training						
Two fully connected Layer						
✓ Regularization L2						
☐ CrossValidation-5folds						
Normal Training						

# InceptionV3

✓ Augmented - Frequency Masking					
One fully connected Layer					
✓ Regularization L2					
✓ Normal Training					
✓ Regularization L2					
Normal Training					
✓ Augmented - Time Masking					
One fully connected Layer					
✓ Regularization L2					
✓ Normal Training					
✓ Regularization L2					
✓ Normal Training					
✓ Not Augmented					
One fully connected Layer					
☐ CrossValidation-5folds					
□ Normal Training					
☐ CrossValidation-5folds					
☐ Normal Training					

Distribución 65% - 35% de dataset original para entrenamientos con data aumentada

```
Train label counts: NAME
                              INCT41_20201028_194500_10INCT41_20201028_23450...
          ._/SCRIPTS/TDL/PHYCUV/AUSPEC/INCT41 20201028 1...
PHYCUV
BOAALB
                                                         193
BOALUN
                                                         145
dtype: object
                             INCT41 20201028 204500 7INCT41 20201028 034500...
Test label counts: NAME
          ../SCRIPTS/TDL/PHYCUV/AUSPEC/INCT41 20201028 2...
PHYCUV
                                                          60
BOAALB
                                                         361
BOALUN
                                                         272
dtype: object
```

cantidad de datos por label una vez la data aumentada por time masking se adicionó al conjunto de 65%

Cantidad de datos una vez la data aumentada por Frequency Masking junto al conjunto de 65%

PHYCUV 609 BOAALB 601 BOALUN 602 dtype: int64

Detail & Screenshots of Results

**DenseNet:** 

### PRUEBA #1:

Model name: DenseNet121\_lr\_0001\_epoch\_25\_batch\_32.h5

```
5/5 [===============] - 10s 2s/step
Test accuracy: 0.4050632911392405
Test precision: 0.7435897435897436
Test recall: 0.46524064171123
Test f1 score: 0.5723684210526316
Test hamming loss: 0.11754068716094032
```

Model Name: DenseNet121\_lr\_0001\_epoch\_25\_batch\_32.h5 **Test:** 

```
5/5 [==========] - 9s 2s/step
Test accuracy: 0.4050632911392405
Test precision: 0.7435897435897436
Test recall: 0.46524064171123
Test f1 score: 0.5723684210526316
Test hamming loss: 0.11754068716094032
ANOTHER METRICS
Test F1 score: 0.5723684210526316
Test precision: 0.7435897588729858
Test recall: 0.46524062752723694
Test ROC AUC: 0.9071881175041199
Test PR AUC: 0.6472712725783859
```

PRUEBA #3:

Model Name: DenseNet Reg 12 Ir01.h5

### Test:

### PRUEBA #4

Model Name: DenseNet Reg | 12 | Ir0001.h5

```
5/5 [=======] - 9s 2s/step
Test accuracy: 0.4177215189873418
Test precision: 0.708029197080292
Test recall: 0.5187165775401069
Test f1 score: 0.5987654320987654
Test hamming loss: 0.11754068716094032
ANOTHER METRICS
Test F1 score: 0.5987654320987654
Test precision: 0.7080292105674744
Test recall: 0.51871657371521
Test ROC AUC: 0.8965917825698853
Test PR AUC: 0.6321914026454407
```

### PRUEBA #5

## Model Name: DenseNet\_Reg\_l2\_lr001.h5

```
5/5 [=======] - 9s 2s/step
Test accuracy: 0.36075949367088606
Test precision: 0.7684210526315789
Test recall: 0.39037433155080214
Test f1 score: 0.5177304964539008
Test hamming loss: 0.12296564195298372
ANOTHER METRICS
Test F1 score: 0.5177304964539008
Test precision: 0.7684210538864136
Test recall: 0.3903743326663971
Test ROC AUC: 0.9327448606491089
Test PR AUC: 0.6760729872929301
```

```
| Figure | 14: val_loss improved from 2.448/5 to 1.56578, saving model to ../SCRPTS/TDL/PHYCUN/MODELS/DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\DenseNet121\
```

### Model name: DenseNet\_Reg\_I2\_Ir01.h5

### **INCEPTIONV3:**

### Prueba con Regularización:

### PRUEBA #1:

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```

Model Name: <u>InceptionV3\_Reg\_L2\_Ir00001\_Batch\_32.h5</u> **test:** 

```
5/5 [==================] - 5s 718ms/step
Test accuracy: 0.4050632911392405
Test precision: 0.6737588652482269
Test recall: 0.5080213903743316
Test f1 score: 0.5792682926829269
Test hamming loss: 0.12477396021699819
ANOTHER METRICS
Test F1 score: 0.5792682926829269
Test precision: 0.673758864402771
Test recall: 0.5080214142799377
Test ROC AUC: 0.9034552574157715
Test PR AUC: 0.6690698881877418
```

### PRUEBA#2

### Model Name: Inception V3 Reg L2 Ir0001 Batch 32.h5

### Test:

```
5/5 [=======] - 5s 731ms/step
Test accuracy: 0.3860759493670886
Test precision: 0.7083333333333334
Test recall: 0.454545454545453
Test f1 score: 0.5537459283387622
Test hamming loss: 0.12386980108499096
ANOTHER METRICS
Test F1 score: 0.5537459283387622
Test precision: 0.7083333134651184
Test recall: 0.4545454680919647
Test ROC AUC: 0.887619137763977
Test PR AUC: 0.6348686765166647
```

PRUEBA#3

### Model name: Inception V3 Ir00001 Batch 32.h5

#### Test:

```
5/5 [==================] - 5s 739ms/step
Test accuracy: 0.36075949367088606
Test precision: 0.675
Test recall: 0.43315508021390375
Test f1 score: 0.5276872964169381
Test hamming loss: 0.13110307414104883
ANOTHER METRICS
Test F1 score: 0.5276872964169381
Test precision: 0.675000011920929
Test recall: 0.4331550896167755
Test ROC AUC: 0.910103440284729
Test PR AUC: 0.6351922305747805
```

#### PRUEBA #4

Model name:InceptionV3 Ir0001 Batch 32.h5

#### Test:

```
5/5 [=======] - 5s 749ms/step
Test accuracy: 0.4430379746835443
Test precision: 0.6866666666666
Test recall: 0.5508021390374331
Test f1 score: 0.6112759643916914
Test hamming loss: 0.11844484629294756
ANOTHER METRICS
Test F1 score: 0.6112759643916914
Test precision: 0.6866666674613953
Test recall: 0.5508021116256714
Test ROC AUC: 0.9146044254302979
Test PR AUC: 0.66699455829427674
```

#### PRUEBA #5

```
| Epoch | 1/180 | Epoch | 1/180 | ETA: 0s - loss: 3.7699 - precision | 12: 0, 3807 - recall | 12: 0, 4219 - auc | 12: 0, 6782 - PR AUC: 0, 3319 - binary_accuracy: 0.7922 | Epoch | 1: val_loss improved from inf to 0,64462, saving model to ._/SCRIPIS/IDI/ENYCUV/PXXXELS/Incention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/X/lincention/
```

### Model Name: InceptionV3 Ir001 Batch 32.h5

#### test:

```
5/5 [========] - 5s 737ms/step
Test accuracy: 0.3924050632911392
Test precision: 0.723577235778
Test recall: 0.47593582887700536
Test f1 score: 0.5741935483870968
Test hamming loss: 0.11934900542495479
ANOTHER METRICS
Test F1 score: 0.5741935483870968
Test precision: 0.7235772609710693
Test recall: 0.47593581676483154
Test ROC AUC: 0.921188473701477
Test PR AUC: 0.6982516823071688
```

PRUEBA#6

```
Epoch 1: val_loss improved from inf to 2.39155, saving model to ../SCRIPTS/TDL/PPYCUN/MODELS/Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception/3\Inception
```

### Model name: <a href="mailto:lnceptionV3\_lr01\_Batch\_32.h5">lnceptionV3\_lr01\_Batch\_32.h5</a>

```
5/5 [=======] - 5s 726ms/step
Test accuracy: 0.0
Test precision: 0.0
Test recall: 0.0
Test f1 score: 0.0
Test hamming loss: 0.16907775768535263
ANOTHER METRICS
Test F1 score: 0.0
Test precision: 0.0
Test recall: 0.0
Test ROC AUC: 0.8907408714294434
Test PR AUC: 0.5440759042397165
```

## Resnet50:

### Con Regularizacion

#### PRUEBA #1:

Model name: Resnet50\_Reg\_L2\_Ir\_0001\_Batch32.h5 test:

```
5/5 [========] - 8s 1s/step
Test accuracy: 0.43037974683544306
Test precision: 0.6923076923076923
Test recall: 0.48128342245989303
Test f1 score: 0.5678233438485805
Test hamming loss: 0.12386980108499096
ANOTHER METRICS
Test F1 score: 0.5678233438485805
Test precision: 0.692307710647583
Test recall: 0.48128342628479004
Test ROC AUC: 0.9204057455062866
Test PR AUC: 0.602525935327927
```

Test ROC AUC: 0.843002200126648 Test PR AUC: 0.49826752820902626

#### PRUEBA #2:

Model name: Resnet50\_Reg\_L2\_Ir\_00001\_Batch32.h5 test:

```
5/5 [======] - 8s 1s/step
Test accuracy: 0.4177215189873418
Test precision: 0.6829268292682927
Test recall: 0.44919786096256686
Test f1 score: 0.5419354838709678
Test hamming loss: 0.12839059674502712
ANOTHER METRICS
Test F1 score: 0.5419354838709678
Test precision: 0.6829268336296082
Test recall: 0.4491978585720062
Test ROC AUC: 0.9043979048728943
Test PR AUC: 0.6219763751331561
```

### PRUEBA#3

Model Name: Resnet50 Ir 00001 Batch32.h5

#### test:

```
5/5 [=======] - 8s 1s/step
Test accuracy: 0.43670886075949367
Test precision: 0.6846153846153846
Test recall: 0.47593582887700536
Test f1 score: 0.5615141955835963
Test hamming loss: 0.1256781193490054
ANOTHER METRICS
Test F1 score: 0.5615141955835963
Test precision: 0.6846153736114502
Test recall: 0.47593581676483154
Test ROC AUC: 0.9109995365142822
Test PR AUC: 0.6440103676442863
```

PRUEBA #4

```
Output exceeds the <u>size limit</u>. Open the full output data <u>in a text editor</u>

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```

## Model name: Resnet50\_Ir\_0001\_Batch32.h5

#### Test:

```
5/5 [======] - 8s 1s/step
Test accuracy: 0.43670886075949367
Test precision: 0.6739130434782609
Test recall: 0.49732620320855614
Test f1 score: 0.5723076923076923
Test hamming loss: 0.1256781193490054
ANOTHER METRICS
Test F1 score: 0.5723076923076923
Test precision: 0.6739130616188049
Test recall: 0.49732619524002075
Test ROC AUC: 0.9047063589096069
Test PR AUC: 0.5630085825595499
```

#### PRUEBA #5

```
Output exceeds the size limit, Open the full output data in a text editor

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| FIA: 05 - loss: 1.1500 - precision_4: 0.2930 - recall_4: 0.4003 - auc_4: 0.6377 - PR AUC: 0.2460 - binary_accuracy: 0.7427
| Epoot h: val_loss improved from inf to 0.40105, saving model to __/SCRIPTS/PEL/PRICE/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL/PRICE/SCRIPTS/PEL
```

Model Name: Resnet50 Ir 001 Batch32.h5

Test:

```
5/5 [=======] - 8s 1s/step
Test accuracy: 0.12025316455696203
Test precision: 0.8148148148148148
Test recall: 0.11764705882352941
Test f1 score: 0.205607476635514
Test hamming loss: 0.15370705244122965
ANOTHER METRICS
Test F1 score: 0.205607476635514
Test precision: 0.8148148059844971
Test recall: 0.11764705926179886
Test ROC AUC: 0.9093382358551025
Test PR AUC: 0.646481683067916
```

#### PRUFBA #6

#### model name:Resnet50 Ir 01 Batch32.h5

#### Test:

#### PRUEBAs con layer 256 and 128

```
# Add a custom output layer for multilabel classification
x = Flatten()(base_model.output)
x = Dense(256, activation='relu')(x)
x = keras.layers.Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
x = keras.layers.Dropout(0.5)(x)
output = Dense(7, activation='sigmoid')(x)
```

#### **MOBILENET:**

#### code:

#### PRUEBA#1:

model name: MobileNet\_Reg\_L2\_Ir\_0001\_batch\_32.h5
Test

```
5/5 [============] - 3s 427ms/step
Test accuracy: 0.46835443037974683
Test precision: 0.8110236220472441
Test recall: 0.5508021390374331
Test f1 score: 0.6560509554140127
Test hamming loss: 0.09764918625678119
ANOTHER METRICS
Test F1 score: 0.6560509554140127
Test precision: 0.8110235929489136
Test recall: 0.5508021116256714
Test ROC AUC: 0.9047877788543701
Test PR AUC: 0.7495851630388455
```

#### PRUEBA#2

```
| State | Second | Fig. | Seco
```

# model name: MobileNet\_Reg\_L2\_Ir\_00001\_batch\_32.h5 Test

```
5/5 [==========] - 3s 464ms/step
Test accuracy: 0.5
Test precision: 0.7985611510791367
Test recall: 0.5935828877005348
Test f1 score: 0.6809815950920246
Test hamming loss: 0.09403254972875226
ANOTHER METRICS
Test F1 score: 0.6809815950920246
Test precision: 0.798561155796051
Test recall: 0.5935828685760498
Test ROC AUC: 0.927699863910675
Test PR AUC: 0.7685870322815206
```

#### PRUEBA #3

```
Output exceeds the size limit, Open the full output data in a text editor
from 1/180

| Fix: 6s - loss; 0.5686 - precision_14: 0.3649 - recall_14: 0.4666 - aux_15: 0.7144 - PR ARC: 0.3045 - binary_accuracy: 0.7861
from 1: val_loss improved from inf to 0.46075, waving model to __SCRIPS/IND_PROCOMPOSISMS interval interval. PR ARC: 0.3045 - binary_accuracy: 0.7861 - val_loss: 0.4007 - val_precision_14: 0.5259 - val_recall_14: 0.3790 - val_unc_15
from 1: val_loss improved from 6.040075, universal interval. PR ARC: 0.5005 - 0.7144 - PR ARC: 0.3045 - binary_accuracy: 0.7861 - val_loss: 0.4007 - val_precision_14: 0.5259 - val_recall_14: 0.3790 - val_unc_15
from 1: val_loss improved from 6.040075 to 0.37472, salvage model to __SCRIPS/IND_PROCOMPOSISMS interval inter
```

# Model name: MobileNet\_Ir\_00001\_batch\_32.h5 Test

```
5/5 [========] - 2s 418ms/step
Test accuracy: 0.43670886075949367
Test precision: 0.732824427480916
Test recall: 0.5133689839572193
Test f1 score: 0.6037735849056604
Test hamming loss: 0.11392405063291139
ANOTHER METRICS
Test F1 score: 0.6037735849056604
Test precision: 0.732824444770813
Test recall: 0.5133689641952515
Test ROC AUC: 0.9274787306785583
Test PR AUC: 0.7344947627132411
```

#### PRUEBA#4

```
Output exceeds the <u>size limit</u>, Open the full output data in a text editor

1998

1918 (8 - loss; 8 .0969 - precision_16; 8 .4469 - recall_16; 8 .4469 - recall_16; 8 .4460 - re
```

# model name: MobileNet\_Ir\_0001\_batch\_32.h5 test

```
5/5 [=========] - 3s 437ms/step
Test accuracy: 0.4620253164556962
Test precision: 0.7647058823529411
Test recall: 0.5561497326203209
Test f1 score: 0.6439628482972136
Test hamming loss: 0.10397830018083183
ANOTHER METRICS
Test F1 score: 0.6439628482972136
Test precision: 0.7647058963775635
Test recall: 0.5561497211456299
Test ROC AUC: 0.9274119138717651
Test PR AUC: 0.7561683999446828
```

#### PRUEBA#5

# model name: <u>MobileNet\_Ir\_001\_batch\_32.h5</u> Test

```
5/5 [========] - 2s 409ms/step
Test accuracy: 0.5063291139240507
Test precision: 0.7189542483660131
Test recall: 0.5882352941176471
Test f1 score: 0.6470588235294118
Test hamming loss: 0.10849909584086799
ANOTHER METRICS
Test F1 score: 0.6470588235294118
Test precision: 0.7189542651176453
Test recall: 0.5882353186607361
Test ROC AUC: 0.9325878024101257
Test PR AUC: 0.7372595789538927
```

#### PRUEBA#6

# Model name: MobileNet\_Ir\_01\_batch\_32.h5 Test

```
5/5 [=========] - 2s 412ms/step
Test accuracy: 0.3860759493670886
Test precision: 0.717948717948718
Test recall: 0.44919786096256686
Test f1 score: 0.5526315789473684
Test hamming loss: 0.12296564195298372
ANOTHER METRICS
Test F1 score: 0.5526315789473684
Test precision: 0.7179487347602844
Test recall: 0.4491978585720062
Test ROC AUC: 0.9126200675964355
Test PR AUC: 0.6505656174831768
```

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 224, 224, 3)]	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
<pre>conv1_bn (BatchNormalizatio n)</pre>	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
<pre>conv_dw_1_bn (BatchNormaliz ation)</pre>	(None, 112, 112, 32)	128
	•	
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
flatten_1 (Flatten)	(None, 50176)	0
dense_2 (Dense)	(None, 256)	12845312
dropout_1 (Dropout)	(None, 256)	0
dense_3 (Dense)	(None, 3)	771

Total params: 16,074,947
Trainable params: 12,846,083

Non-trainable params: 3,228,864