UNIVERSIDAD DE SANTIAGO DE CHILE
DEPARTAMENTO DE MATÉMATICA Y CIENCIAS DE LA COMPUTACIÓN
INGENIERÍA ESTADÍSTICA

DEEP LEARNING

CLASIFICACIÓN INTELIGENTE DE IMÁGENES DE HONGOS: UNA APLICACIÓN DE REDES NEURONALES CONVOLUCIONALES

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ÍNDICE

OBJETIVO GENERAL

- HACER CLASIFICACIÓN BINARIA MULTI-ETAPA Y MULTICLASE DE IMÁGENES MICROSCÓPICAS DE HONGOS VÍA CNN

OBJETIVOS ESPECÍFICOS

- IMPLEMENTAR AL MENOS DOS MODELOS DE CNN PARA LA CLASIFICACIÓN DE HONGOS
- ENTRENAR LOS MODELOS DESDE CERO
- EVALUAR EL ACCURACY DE LOS MODELOS
- HACER LA COMPARACIÓN

DESCRIPCIÓN DE LA BASE DE DATOS

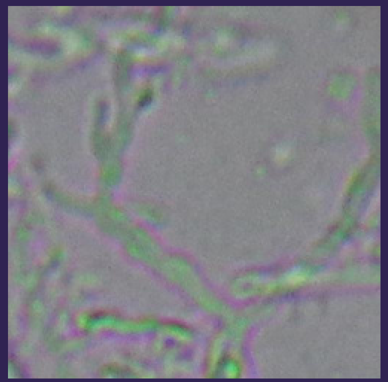
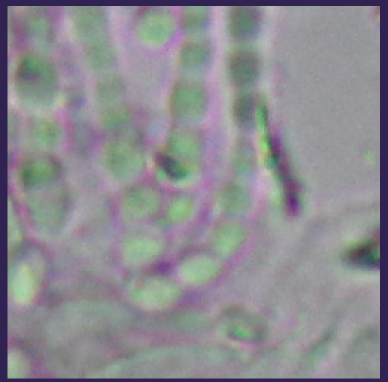
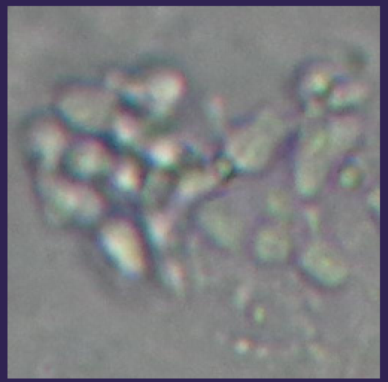
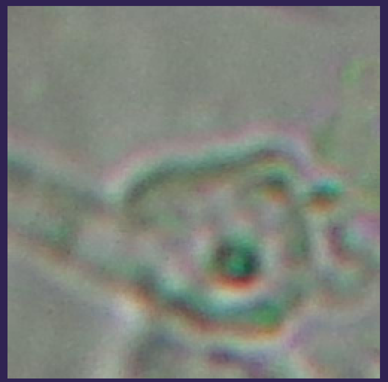
HIFAS HIALINAS SEPTADAS TORTUOSAS (H1) → 4404 FOTOS

HIFAS HIALINAS SEPTADAS EN CUENTAS (H2) → 2334 FOTOS

GRUPOS O MOSAICOS DE ARTROCONIDIAS (H3) → 819 FOTOS

HIFAS HIALINAS SEPTADAS CON CHLAMYDIOCONIDIAS (H5) → 818 FOTOS

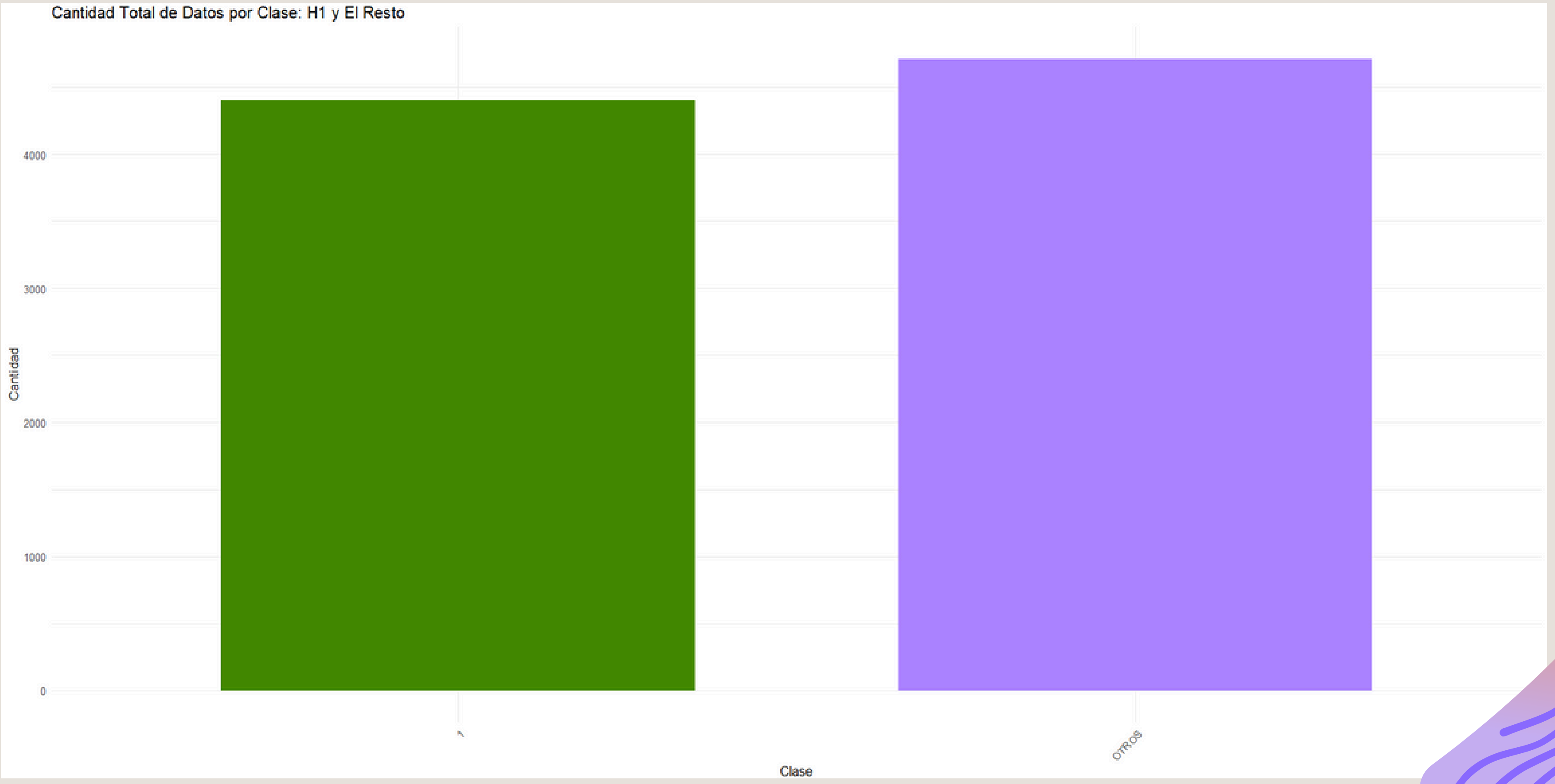
HIFAS ANCHAS MARRONES (H6) → 739 FOTOS


DESCRIPCIÓN DE LA BASE DE DATOS: H1 Y NO H1

HONGO	CANTIDAD
H1	4404
H2	2334
H3	819
H5	818
H6	739
TOTAL	**9114**

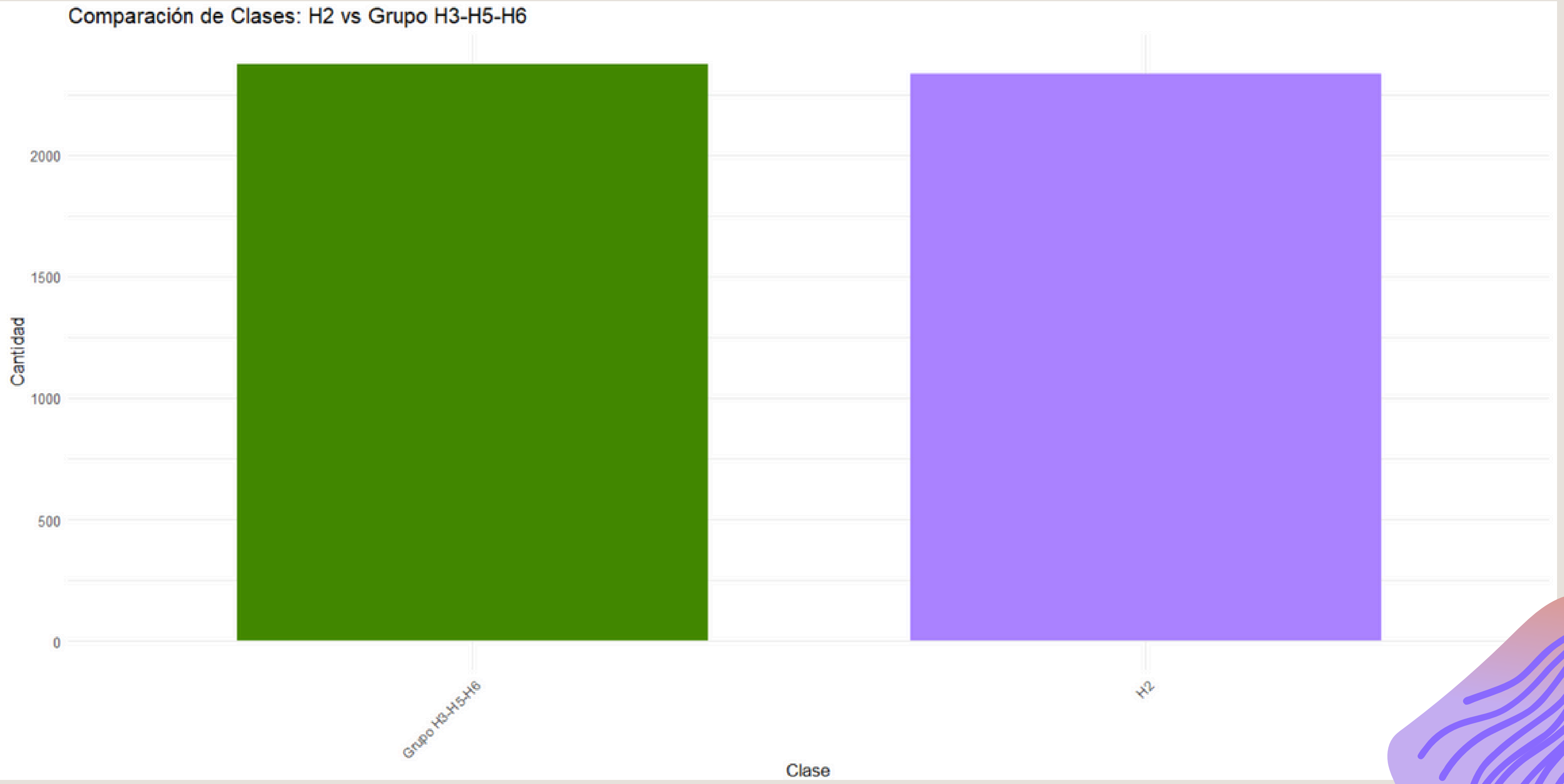
HONGO	CANTIDAD	PORCENTAJE
H1	4404	48,321264
OTROS	4710	51,678736
TOTAL	9114	100



DESCRIPCIÓN DE LA BASE DE DATOS: H2 Y NO H2

HONGO	CANTIDAD	PORCENTAJE
H2	2334	49,5541401
OTROS	2376	50,4458599
TOTAL	4710	100

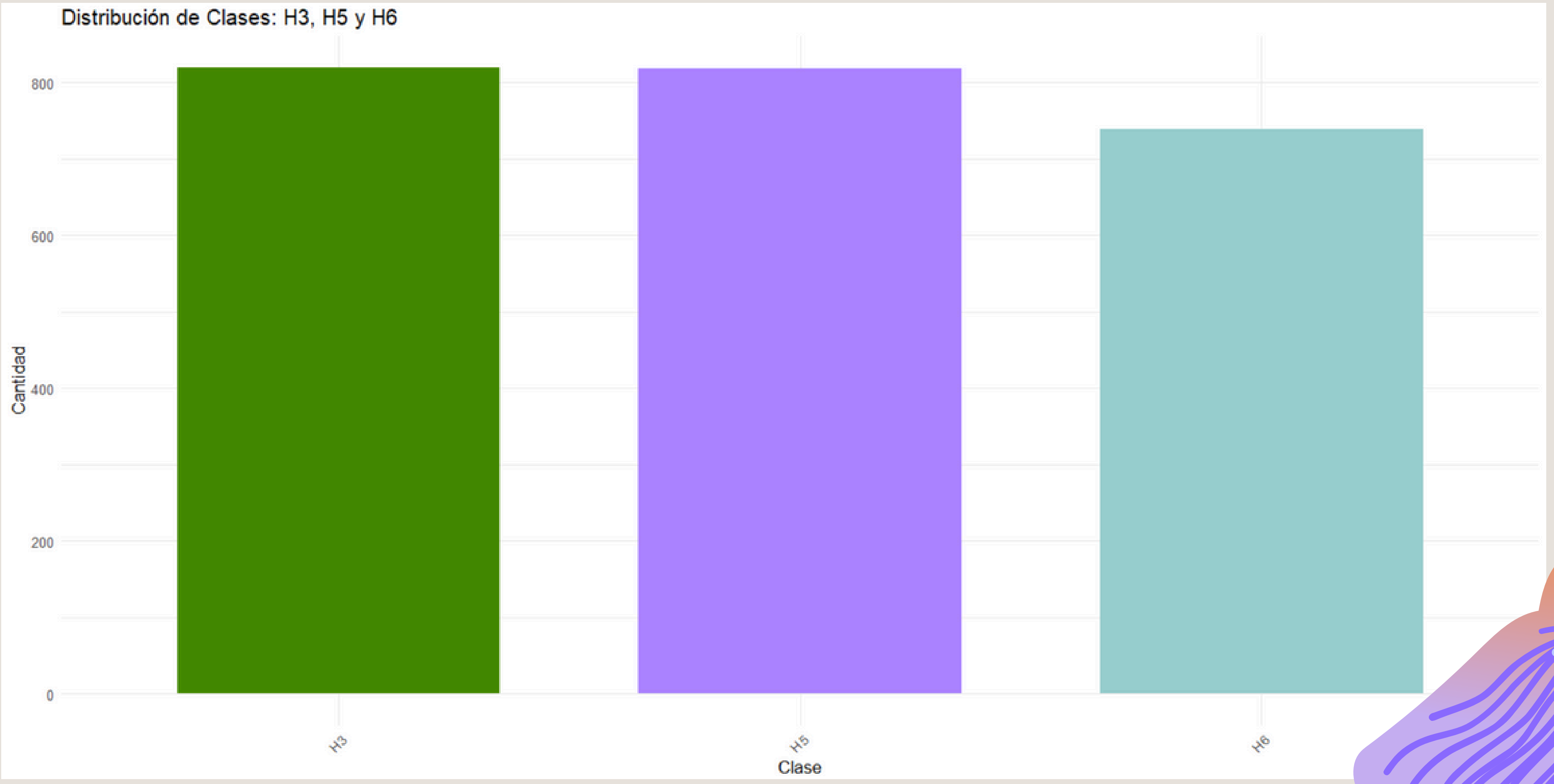
HONGO	CANTIDAD
H1	4404
H2	2334
H3	819
H5	818
H6	739
TOTAL	**9114**



DESCRIPCIÓN DE LA BASE DE DATOS: H3, H5, H6

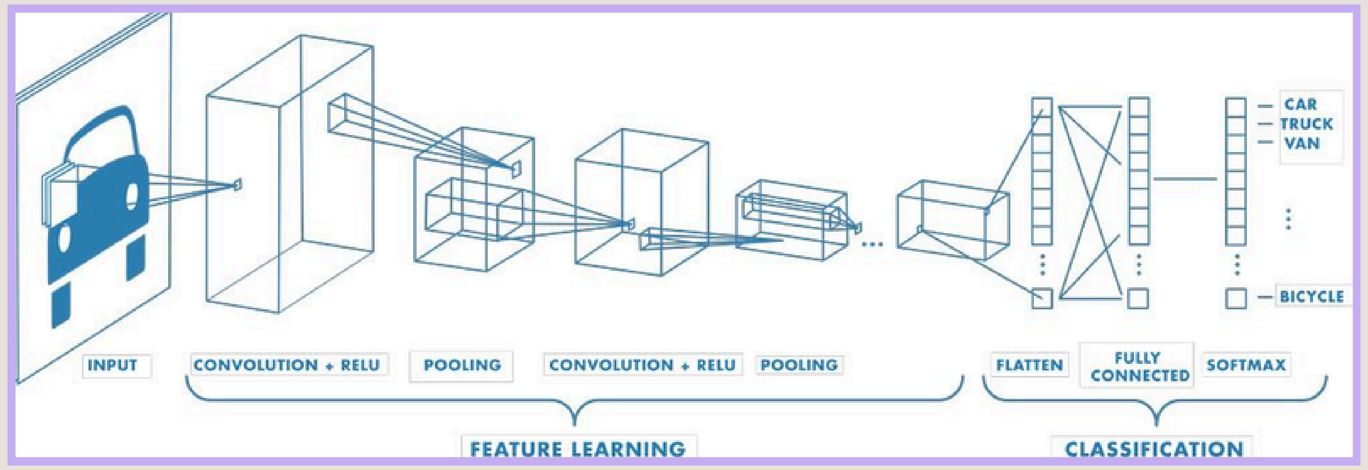
HONGO	CANTIDAD	PORCENTAJE
H3	819	34,469697
H5	818	34,4276094
H6	739	31,1026936
TOTAL	2376	100

HONGO	CANTIDAD
H1	4404
H2	2334
H3	819
H5	818
H6	739
TOTAL	**9114**



Esquema metodológico

MODELO DE RED NEURONAL CONVOLUCIONAL

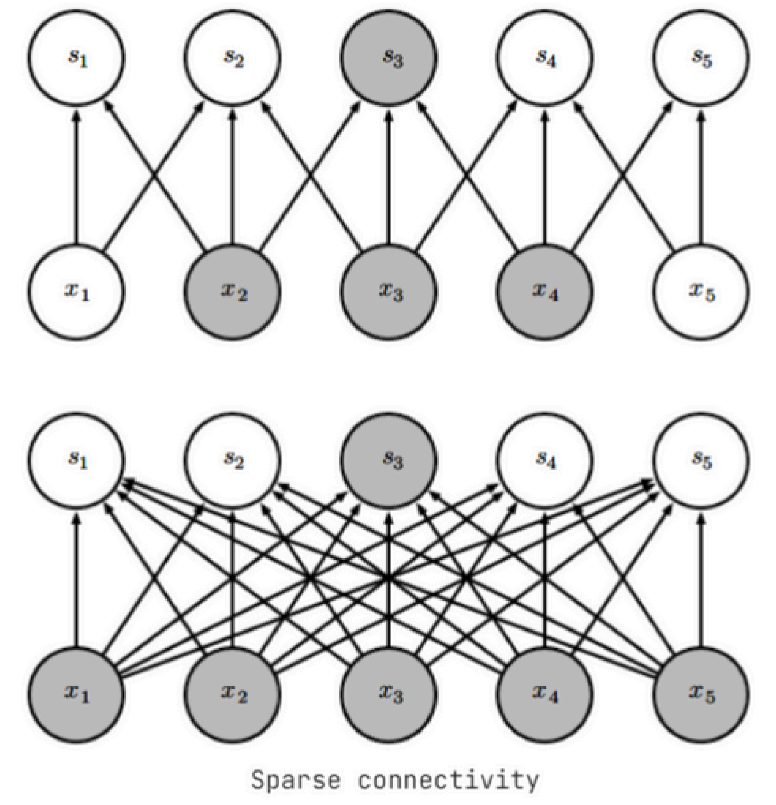


- CONVOLUCION

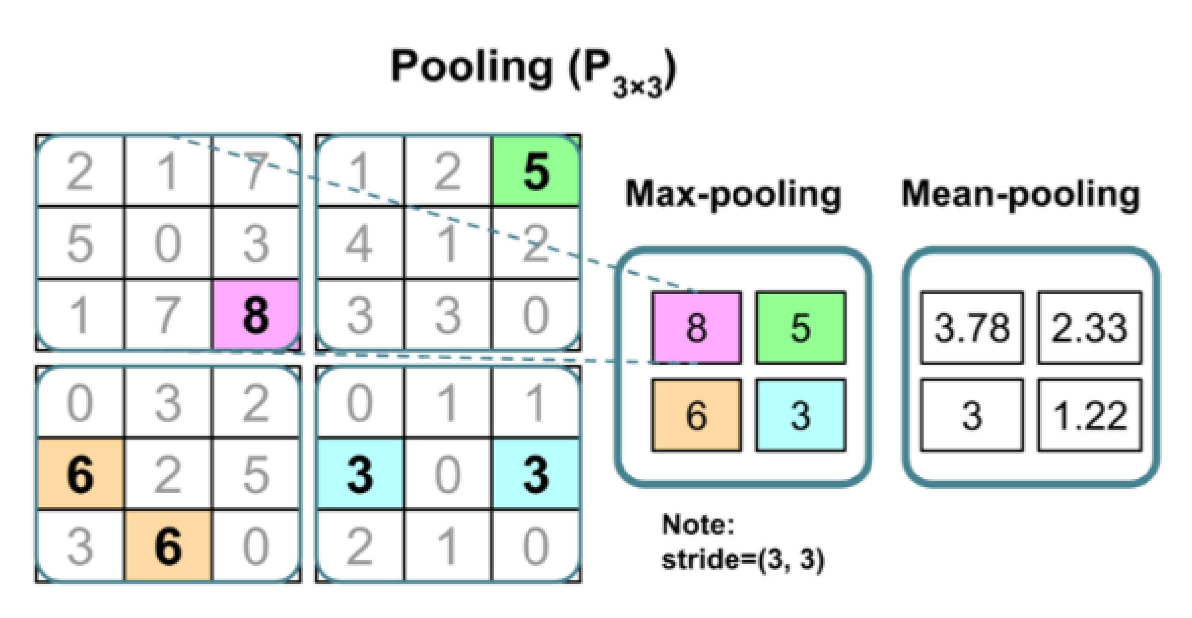
$$S(i,j) = (I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m, j-n)$$

$$S(i,j) = (K * I)(i,j) = \sum_m \sum_n I(i-m, j-n)K(m,n)$$

- SPARSE CONNECTIVITY



- POOLING



POST PROCESAMIENTO

- EL OBJETIVO ES HACER PREDICCIÓN MULTICLASE (5 CATEGORÍAS), HAY QUE TRANSFORMAR EL INPUT DEL MODELO EN UN VECTOR DE 5 PROBABILIDADES

- FUNCIÓN DE SALIDA - SOFTMAX

$$\sigma: \mathbb{R}^K \to (0,1)^K$$

$$\sigma(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

$$\mathbf{z} = (z_1, \ldots, z_K) \in \mathbb{R}^K$$

- FUNCIÓN DE PÉRDIDA - CATEGORICAL CROSS ENTROPY

$$L(y, \hat{y}) = -\frac{1}{N}\sum_{i}^{N}\sum_{j}^{C} y_{ij} \log(\hat{y}_{ij})$$

PROPUESTA 1: ANÁLISIS MULTICLASE (B&N)

```r
layer_input(shape = c(150, 150, 1), name = "input_layer") %>%
layer_conv_2d(filters = 32L, kernel_size = c(3, 3), activation = "relu",
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool1") %>%
layer_conv_2d(filters = 64L, kernel_size = c(3, 3), activation = "relu",
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool2") %>%
layer_conv_2d(filters = 128L, kernel_size = c(3, 3), activation = "relu"
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool3") %>%
layer_flatten(name = "flatten") %>%
layer_dense(units = 512L, activation = "relu", name = "dense1") %>%
layer_dense(units = 5L, activation = "softmax", name = "output")
```

PROPUESTA 1: RESULTADOS

- ACCURACY: 20.1%

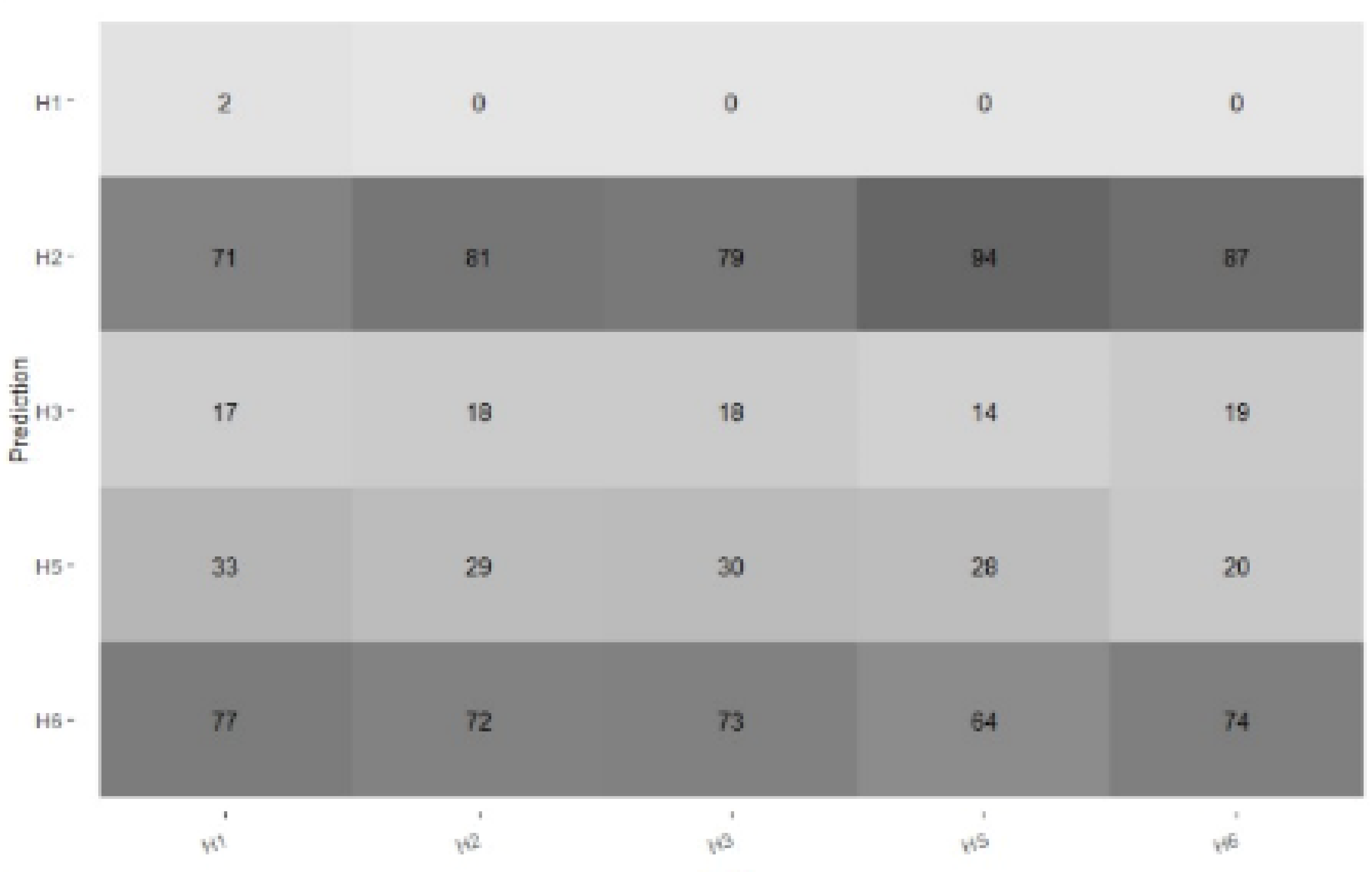
Prediction \ Truth	H1	H2	H3	H5	H6
H1	0	0	0	0	0
H2	0	0	0	0	0
H3	170	170	171	172	165
H5	7	15	15	11	16
H6	23	15	14	17	19

PROPUESTA 2: ANÁLISIS MULTICLASE (RGB)

```r
layer_input(shape = c(150, 150, 3), name = "input_layer") %>%
layer_conv_2d(filters = 32L, kernel_size = c(3, 3), activation = "relu",
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool1") %>%
layer_conv_2d(filters = 64L, kernel_size = c(3, 3), activation = "relu",
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool2") %>%
layer_conv_2d(filters = 128L, kernel_size = c(3, 3), activation = "relu"
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool3") %>%
layer_flatten(name = "flatten") %>%
layer_dense(units = 512L, activation = "relu", name = "dense1") %>%
layer_dense(units = 5L, activation = "softmax", name = "output")
```

PROPUESTA 2: RESULTADOS

- ACCURACY: 20.3%

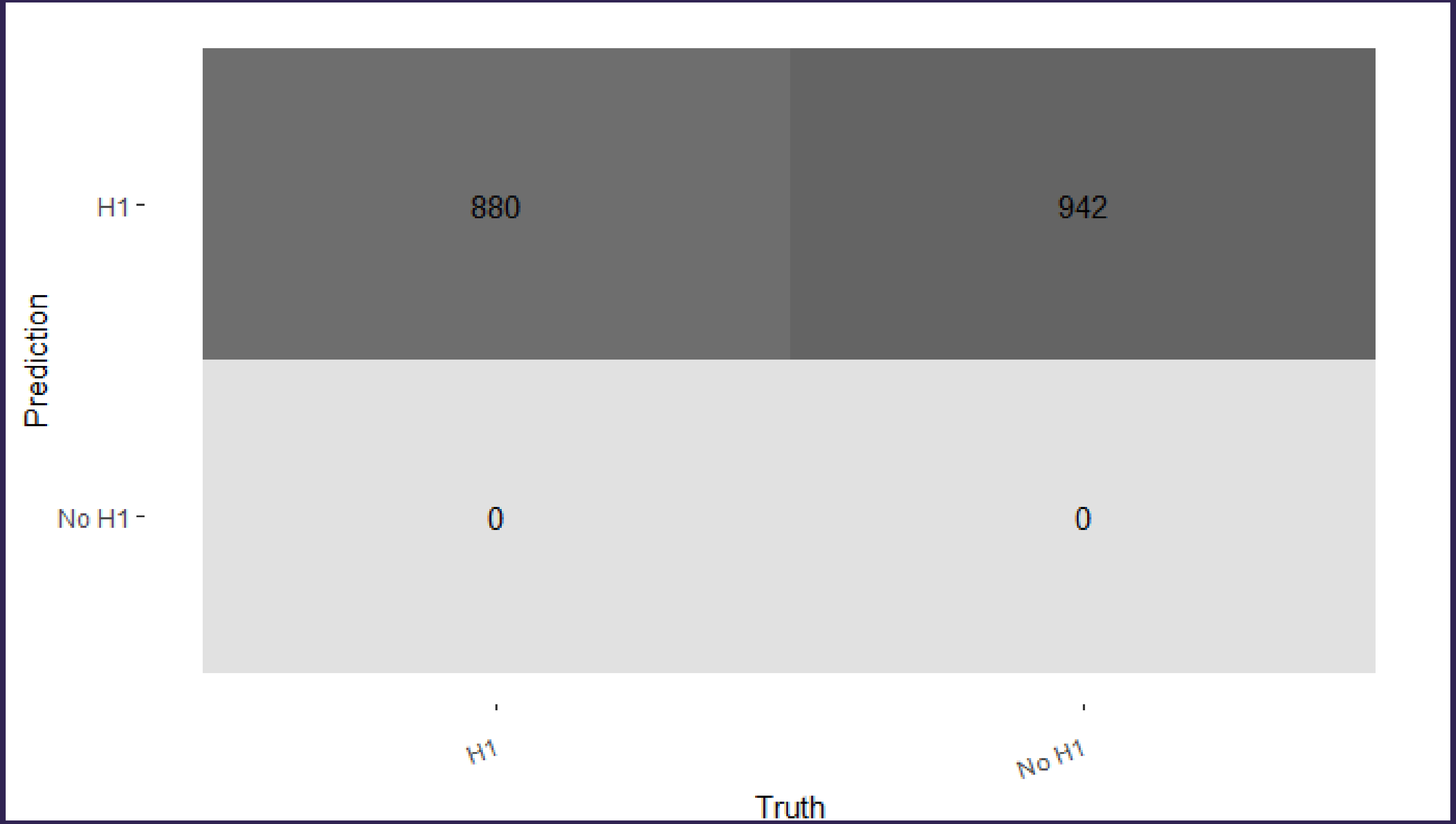


PROPUESTA 3: H1 VS NO H1 (B&N)

```
layer_input(shape = c(150, 150, 1), name = "input_layer") %>%
layer_conv_2d(filters = 32L, kernel_size = c(3, 3), activation = "relu"
layer_batch_normalization(name = "batch_norm1") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool1") %>%
layer_dropout(rate = 0.3, name = "dropout1") %>%
layer_conv_2d(filters = 64L, kernel_size = c(3, 3), activation = "relu"
layer_batch_normalization(name = "batch_norm2") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool2") %>%
layer_dropout(rate = 0.3, name = "dropout2") %>%
layer_conv_2d(filters = 128L, kernel_size = c(3, 3), activation = "relu
layer_batch_normalization(name = "batch_norm3") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool3") %>%
layer_flatten(name = "flatten") %>%
layer_dense(units = 512L, activation = "relu", name = "dense1") %>%
layer_dropout(rate = 0.5, name = "dropout3") %>%
layer_dense(units = 1L, activation = "sigmoid", name = "output")
```

PROPUESTA 3: RESULTADOS

- ACCURACY: 48.19%

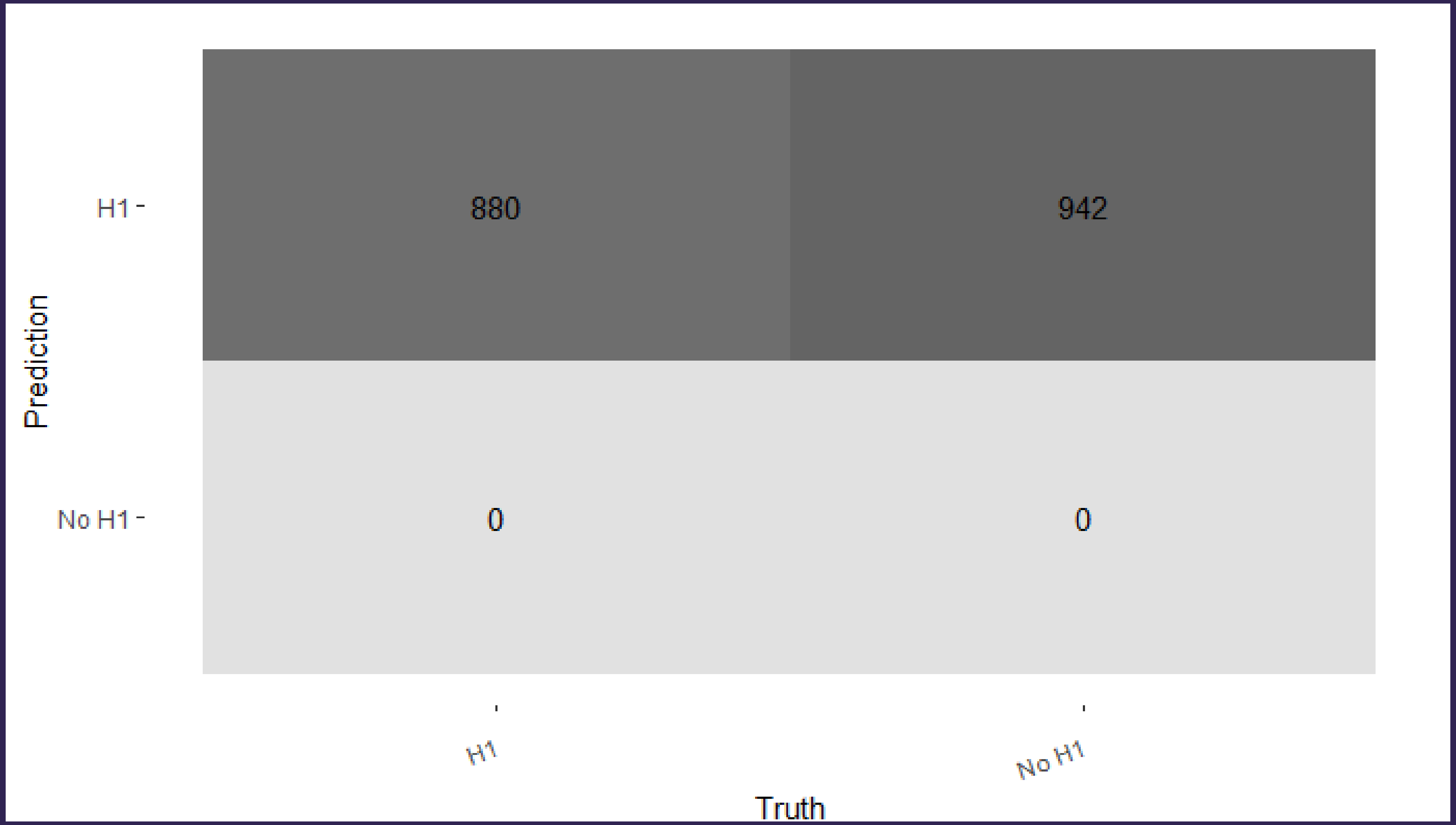


PROPUESTA 4: H1 VS NO H1 (RGB)

```
layer_input(shape = c(150, 150, 3), name = "input_layer") %>%
layer_conv_2d(filters = 32L, kernel_size = c(3, 3), activation = "relu",
layer_batch_normalization(name = "batch_norm1") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool1") %>%
layer_dropout(rate = 0.3, name = "dropout1") %>%
layer_conv_2d(filters = 64L, kernel_size = c(3, 3), activation = "relu",
layer_batch_normalization(name = "batch_norm2") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool2") %>%
layer_dropout(rate = 0.3, name = "dropout2") %>%
layer_conv_2d(filters = 128L, kernel_size = c(3, 3), activation = "relu"
layer_batch_normalization(name = "batch_norm3") %>%
layer_max_pooling_2d(pool_size = c(2, 2), name = "pool3") %>%
layer_flatten(name = "flatten") %>%
layer_dense(units = 512L, activation = "relu", name = "dense1") %>%
layer_dropout(rate = 0.5, name = "dropout3") %>%
layer_dense(units = 1L, activation = "sigmoid", name = "output")
```

PROPUESTA 4: RESULTADOS

- ACCURACY: 48.19%



RESUMEN

- LA CLASIFICACIÓN MULTICLASE TUVO RESULTADOS MUY POR DEBAJO DE LO ESPERADO PARA UNA CLASIFICACIÓN EFECTIVA.
- LA CLASIFICACIÓN BINARIA MULTI-ETAPA SE DETUVO DESPUÉS DE LA PRIMERA ETAPA POR LOS RESULTADOS INSATISFACTORIOS

CAUSAS POTENCIALES Y SUGERENCIAS

CAUSAS POTENCIALES

- VARIABILIDAD INTRACLASE
- COMPLEJIDAD DEL MODELO

SUGERENCIAS

- ANÁLISIS EXPLORATORIO PROFUNDO
- AJUSTE DE ARQUITECTURA

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