Facial Emotion Detection

MIT Applied Data Science Program: Leveraging AI for Effective Decision-Making

Capstone Project on Facial Emotion Detection based on the domain - Deep Learning

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Facial Emotion Detection

Computer Vision: enables computers to understand and analyze visual data from the world

model

Happy

- **Facial expression**
  - Width
  - Height
  - Color channels
- **Emotion**
  - Label

Objective: Recognize four emotional states - **happiness**, **sadness**, **surprise**, and **neutrality** - in facial expressions.

Applications across various domains:

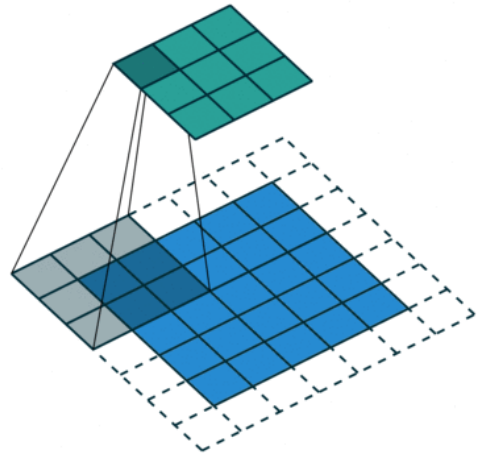
- Human-Machine Interaction
- Healthcare and therapy
- Education and Learning Environments
- Human-Centric Marketing
- Entertainment and Gaming
- Autonomous Vehicles and Driver Monitoring

Data science and Machine Learning:

- **Problem:** Multiclass classification problem
- **Input data:** Visual data
- **Model:** Convolutional Neural Network, a Supervised machine learning algorithm well suited to analyzing visual data

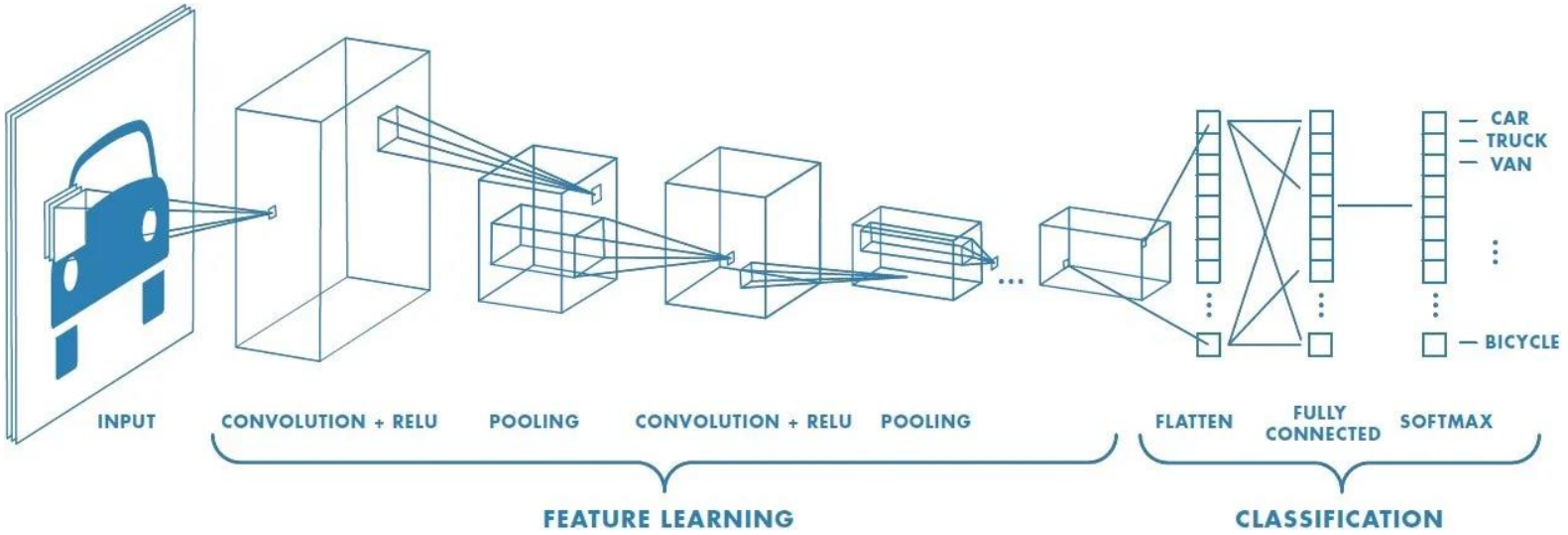
Convolution Neural Networks (CNN)

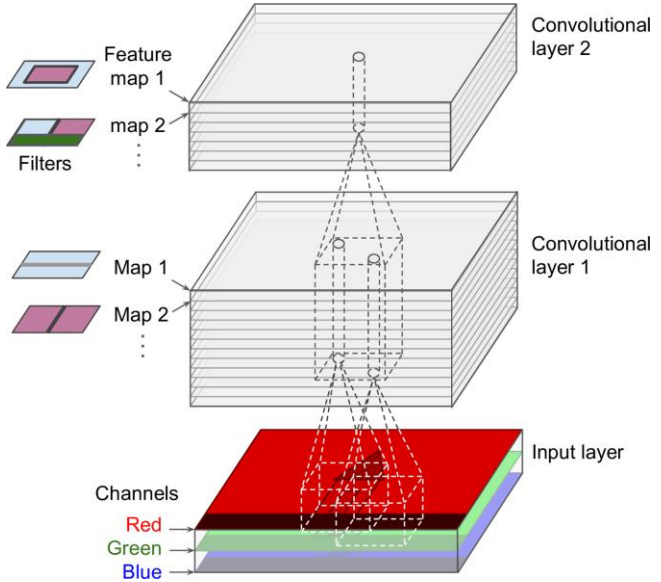
- **Convolutional layers**
  - Neurons respond to a restricted region known as the **receptive field**
  - Neurons in the **same convolutional layer** share the **same parameters**
  - Apply **filters (kernels)** to the input image to extract **low/high-level features**



- **Pooling layers** downsample the image to reduce computation

- A **Fully connected layer** makes the final prediction





Sources: Aurélien Géron (978-1-492-03264-9), www.towardsdatascience.com

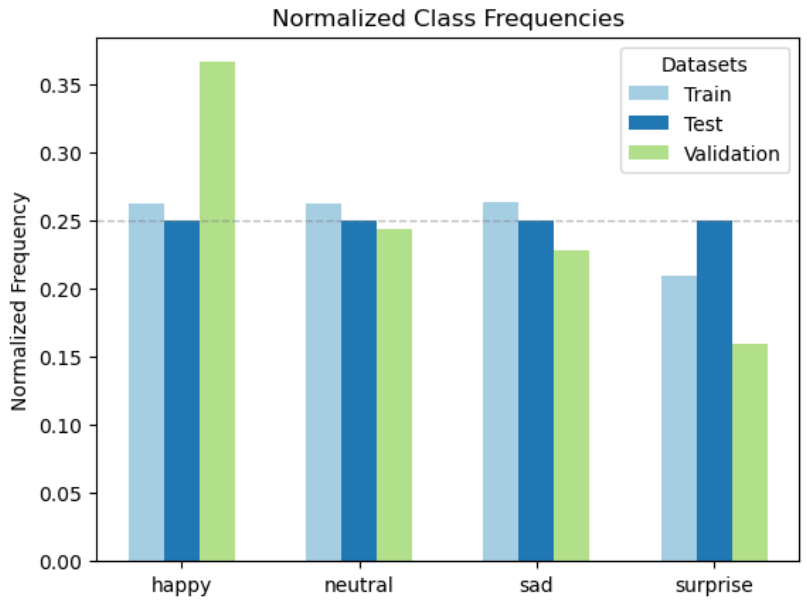
Dataset Overview: Training, Testing, and Validation Sets

Happy

Sad

Neutral

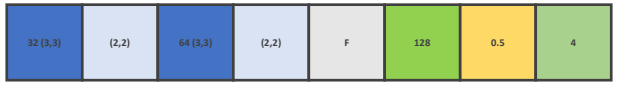
Surprise



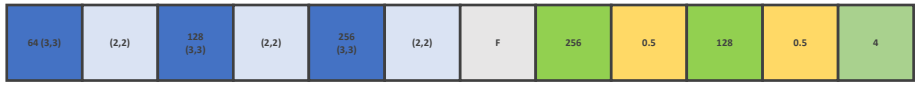
- **Datasets:**
  - Training - 15109 images
  - Testing - 128 images
  - Validation - 4977 images
- (48,48) gray scale images

Models and Architectures

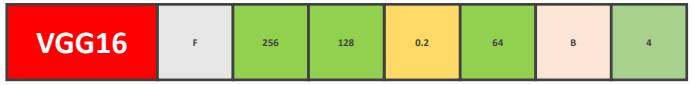
Model 1



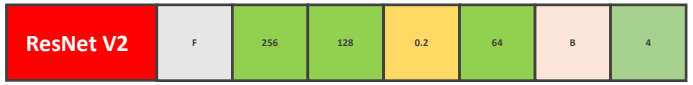
Model 2



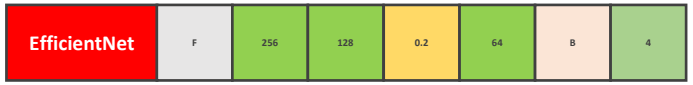
Model 3



Model 4



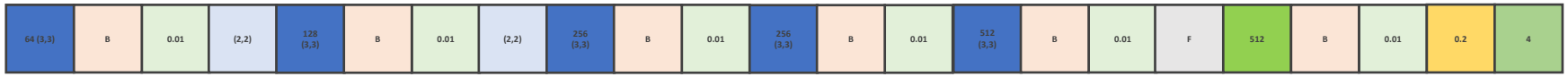
Model 5



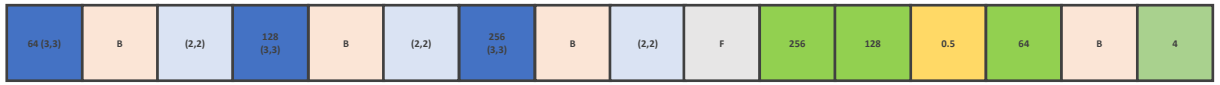
Pre-trained models:

- VGG16
- ResNet v2
- Efficient Net

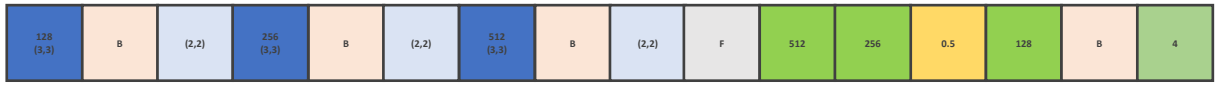
Model 6



Model 7



Model 8



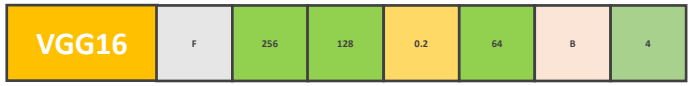
Model 2 + architecture + hyperparameter tuning

Model 9

Model 10

Model 6 + architecture + hyperparameter tuning

Model 11

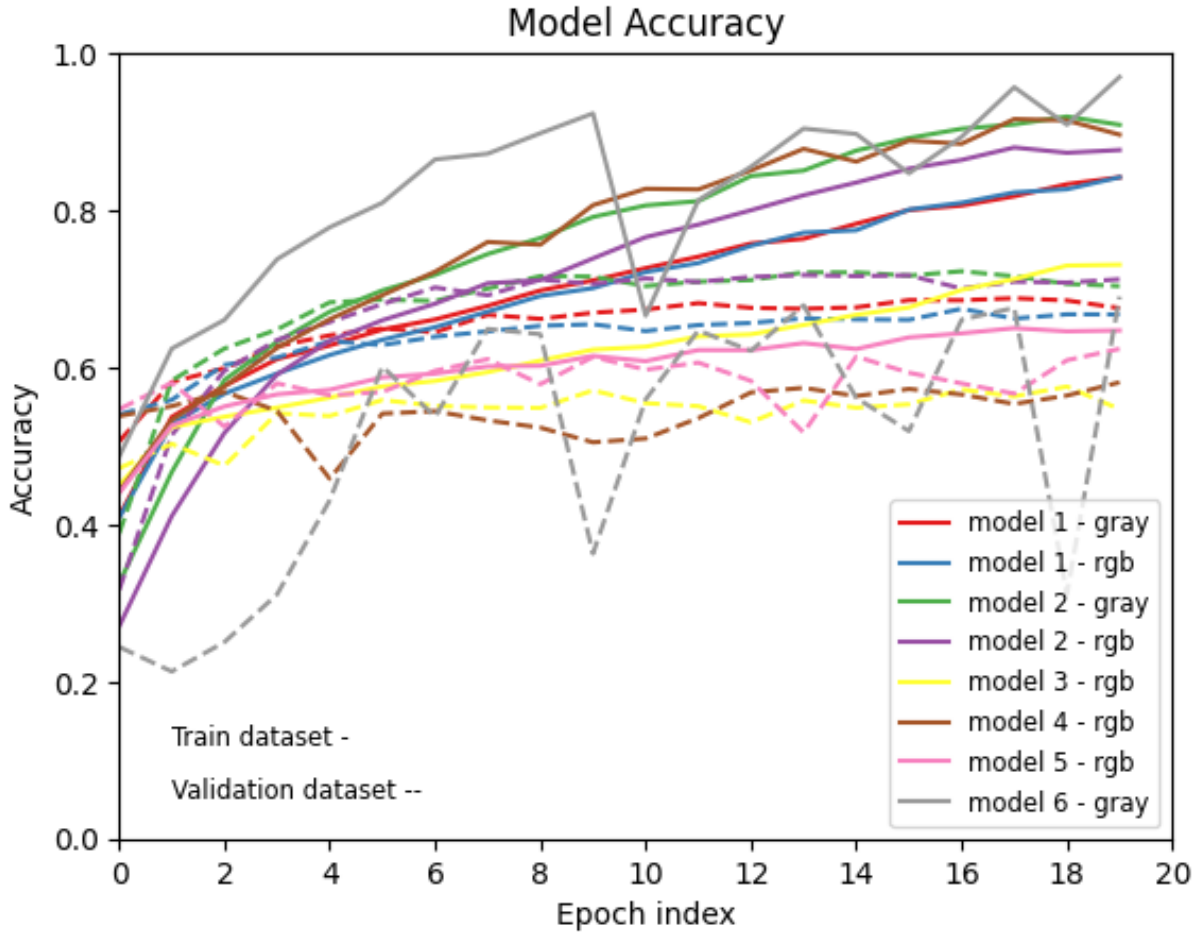


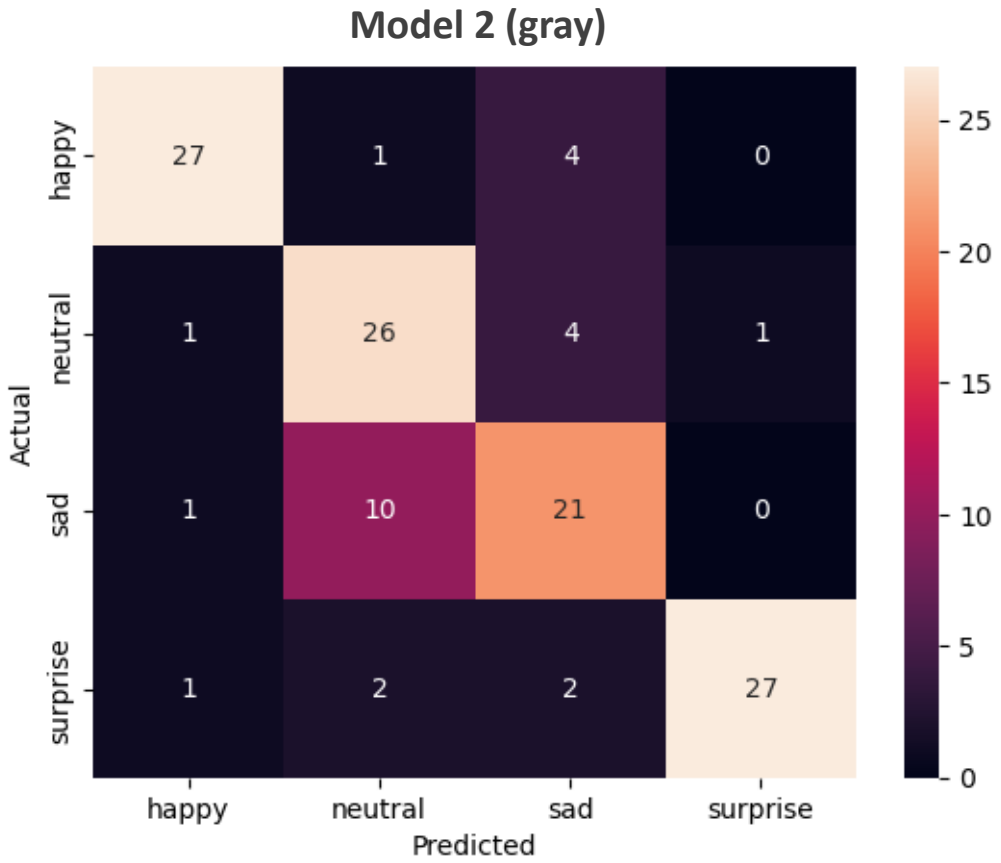
Model 3 + fine-tuning (conv5_3 block)

- Conv2D()
- MaxPooling2D()
- Dense() relu
- Dense() softmax
- LeakyReLU()
- Dropout()
- Pre-trained models
- BatchNormalization()
- Fine-tuning
- Flatten()

epochs= 20
optimizer='adam'
metrics='accuracy'
loss='categorical_crossentropy'

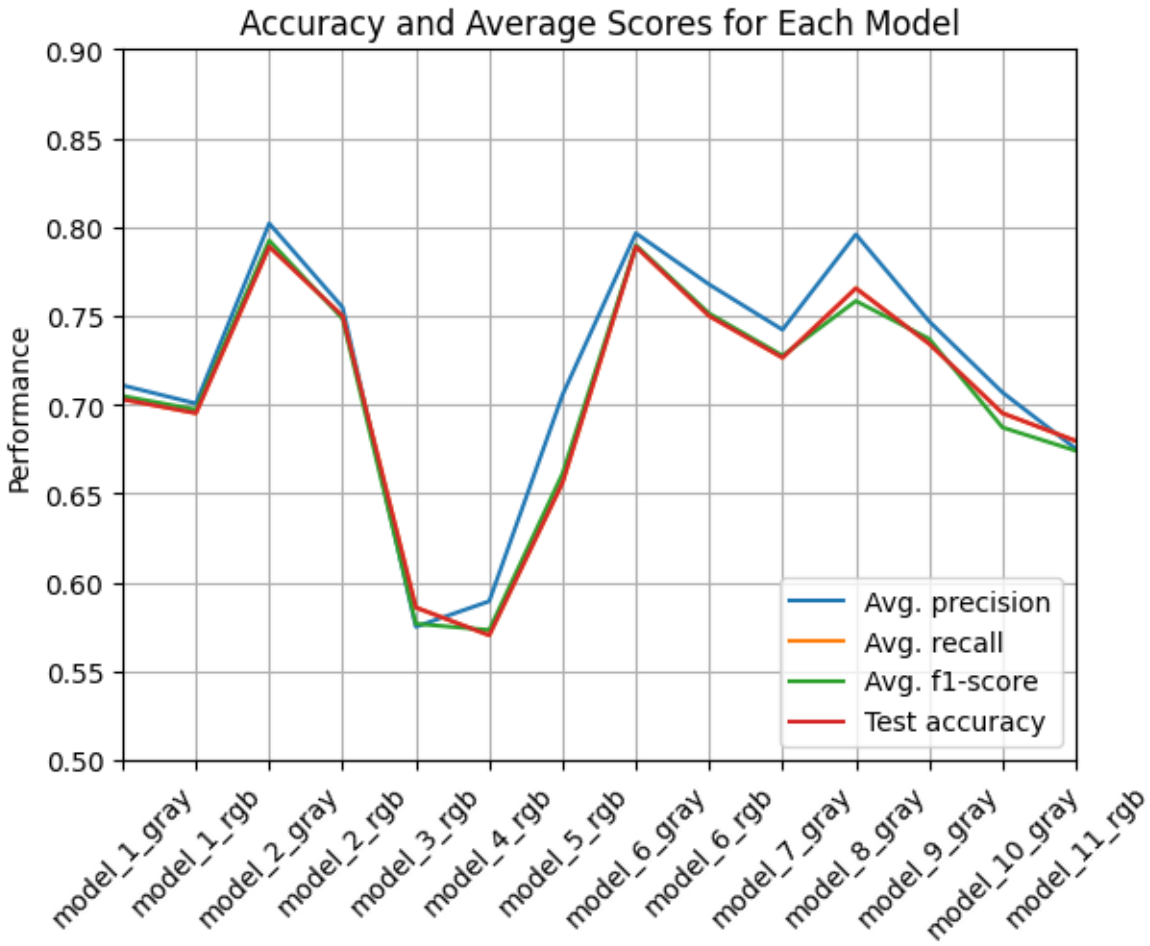
Accuracy and performance

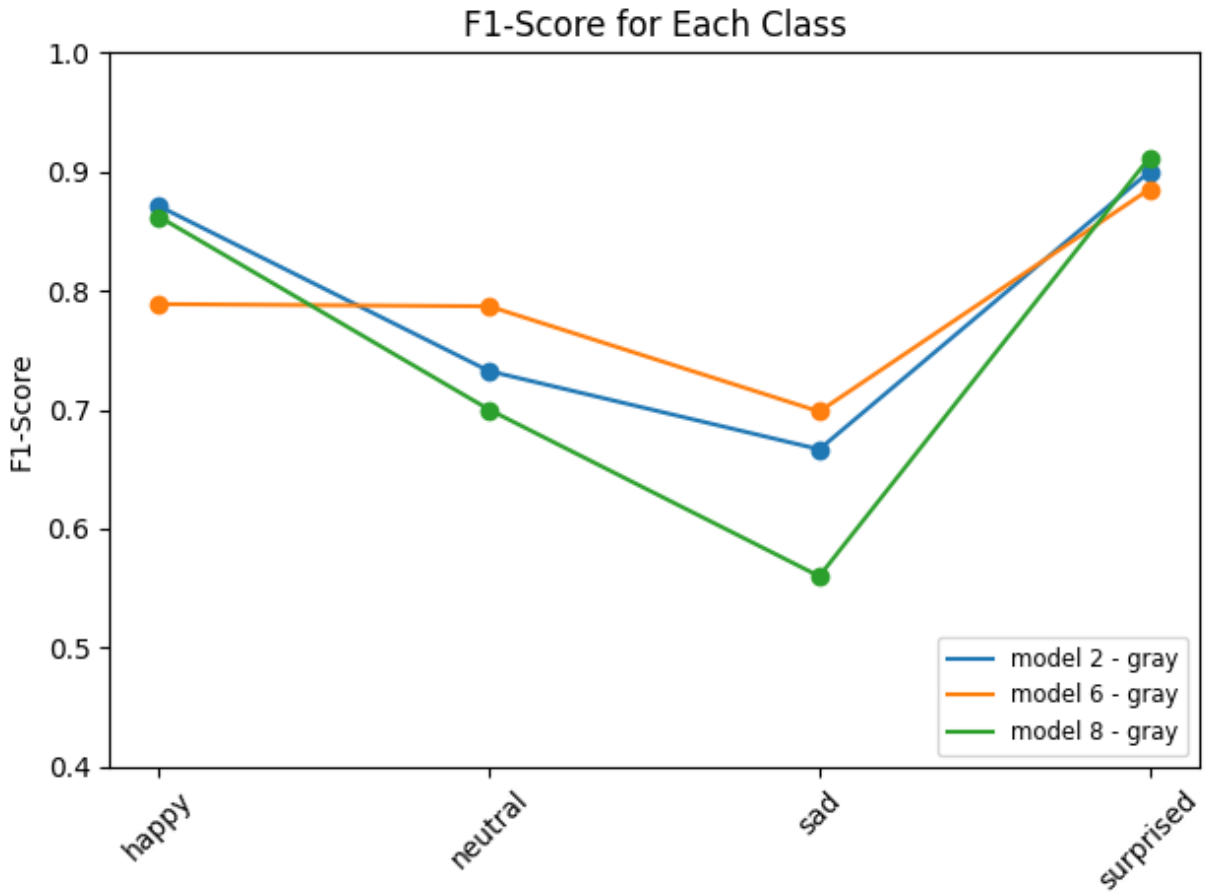




	precision	recall	f1-score
happy	0.90	0.84	0.87
neutral	0.67	0.81	0.73
sad	0.68	0.66	0.67
surprise	0.96	0.84	0.90
accuracy			0.79

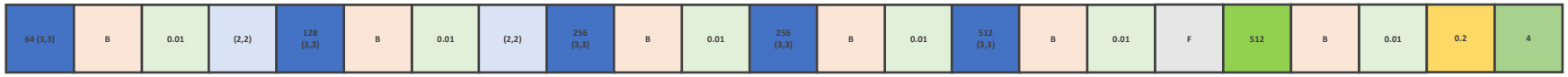
Performance for each model and emotion





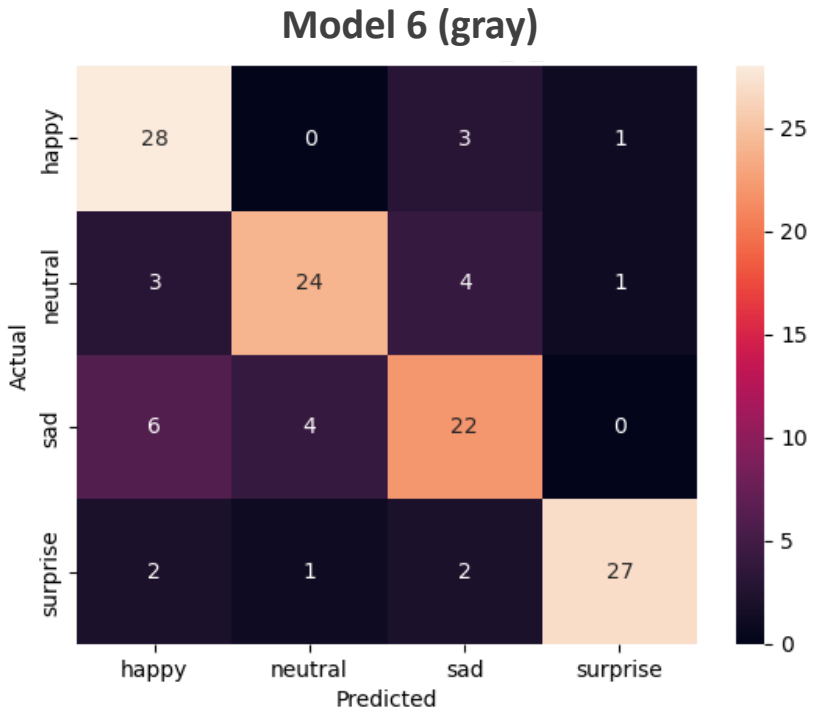
Final conclusions

Model 6



- We recommend adopting **Model 6 (gray)**
  - Strong overall performance (accuracy – 0.79 and average F1-score)
  - Well-balanced F1-score profile

- **Future implementations to enhance model's performance:**
  - Balancing Strategies:
    - Data augmentation for underrepresented classes
    - Under-sampling for overrepresented classes
    - Data cleaning
  - Hyperparameter tuning
  - Fine-tuning of transfer learning architectures
  - Regularization techniques
  - Batch normalization
  - Architecture modifications
  - Learning rate scheduling
  - Ensemble learning



Thank you for your attention