Movie Genre Prediction Using Multi-Label Image Classification

Presented By Group - 12

The Team

Adithya Nair

AM.EN.U4CSE19103

Akshay Hari

AM.EN.U4CSE19104

Sreejith K Pai

AM.EN.U4CSE19153

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Background

Brief Introduction & Aim of our Project

Posters are more than just a promotional material, that captures a viewer’s attention.

It is a reflection of how the audience is able to perceive an image about the movie.

Therefore a model which can extract the features of a movie poster and identify the genres can become handy for both the film-makers as well as the designers.

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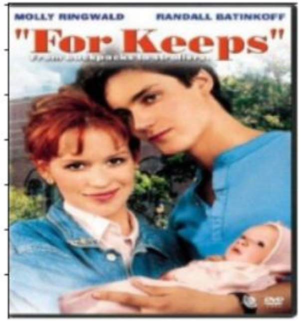
Problem Definition

A Model to Predict Movie Genres

Problem definition

Movie posters cannot be labelled to just one pinpoint genre. Thus, determining the genre of a Movie poster is a Multi-label classification problem. The objective is to solve this problem using Neural Networks.



→ Drama / Romance

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Related Works

Related Works

Identifying Multiple Objects in an Image

Early work from Barnard and Forsyth focused on identifying objects in particular sub-sections of an image.

Multi-Label Classification of Satellite Images

Work from Daniel Gardner & David Nichols focused on classification of Satellite Images using multiple models.

04. Contributions

- A model for multi label image classification using Feed Forward neural network architecture.
- Used different loss functions including Cross Entropy, BCELoss etc.
- Tried different pre-trained CNN models like Resnet-50, VGG-16, InceptionV3, EfficientNet etc.
- Used different optimizers like Adam, SGD etc.

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Solution Approach

Neural Network Models

Neural Network models

Feed Forward Neural Network

Convolutional Neural Network

Data Preprocessing

Data Preparation

Image layer

Images with 3 RGB channels with varying sizes

Dimension

Resize all images to 350*350 dimension for easy training and efficiency

Splitting

Splitting dataset into train (85%) and test (15%)

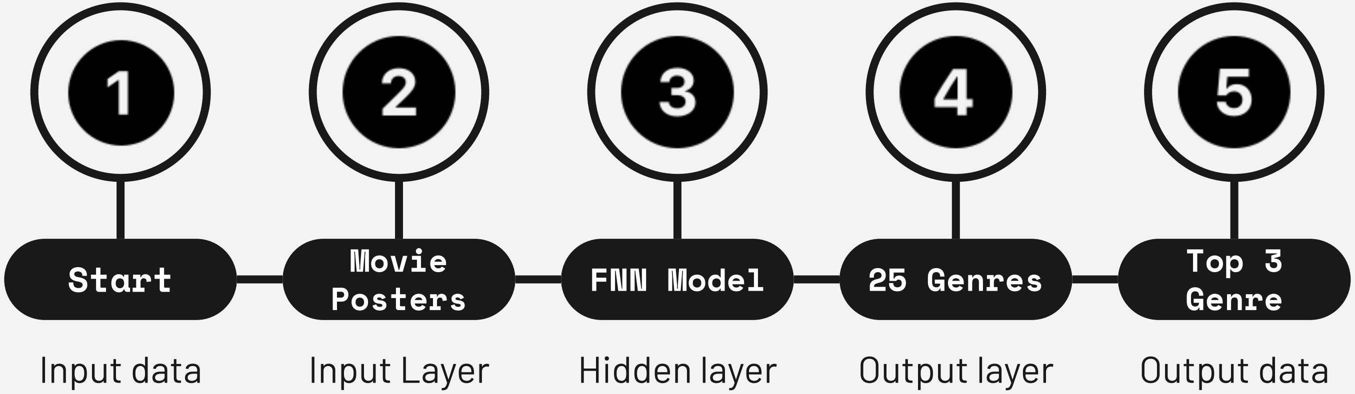
Dataloader

Load images into training and test data loader with batch size of 33.

Feed Forward Neural Network

Model

- Each layer consist of neurons which are triggered based on activation functions.
- Architecture consist of single linear layer , three hidden layer and an Output layer.
- **ReLU activation function** is used for input and hidden layers
- Output layer is activated using **Sigmoid function**
- Sigmoid function converts each value into probability score between 0 and 1



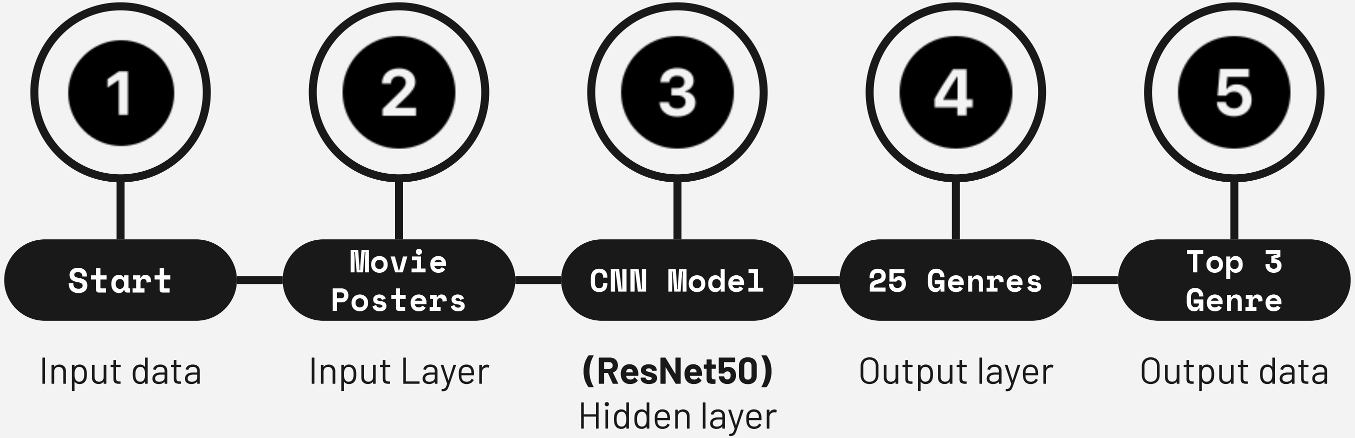
Implementation of FFN

```
class FirstModel(Base):

    def __init__(self):

        super().__init__()
         # input layer
        self.linear1 = nn.Linear(input_size, hidden_size[0])
         # hidden layer
        self.linear2 = nn.Linear(hidden_size[0], hidden_size[1])
        self.linear3 = nn.Linear(hidden_size[1], hidden_size[2])

        self.linear4 = nn.Linear(hidden_size[2], output_size)

    def forward(self, xb):

        # Flatten images into vectors
        out = xb.view(xb.size(0), -1).requires_grad_()
        # Get intermediate outputs using hidden layer
        out = self.linear1(out)
        # Apply layers & activation function
        out = F.relu(out)
        out = self.linear2(out)
        out = F.relu(out)
        out = self.linear3(out)
        out = F.relu(out)

        # Get predictions using output layer
        out = self.linear4(out)

        y_pred = torch.sigmoid(out)

        return y_pred
```

Convolutional Neural Network - ResNet50

Model

- Based on pre-trained CNN Resnet50 Architecture..
- Solves problem of Vanishing/Exploding of gradients.
- Introduction of skip connection for freezing the intermediate layers.
- Capable of learning deeper networks in an optimised way by reducing the no. of parameters.
- Sigmoid function converts each value into probability score between 0 and 1



Implementation of CNN

```
resnet = models.resnet50(pretrained=True)
```

```
for param in resnet.parameters():
    param.requires_grad = False
```

```
in_features = resnet.fc.in_features
resnet.fc = nn.Linear(in_features, num_classes)
```

```
resnet = resnet.to(device)
opt = optim.Adam(resnet.parameters(), lr=0.0001)
loss_fn = nn.BCELoss()
```

```
outputs = resnet(inputs)
outputs = torch.sigmoid(outputs)
```

Loss Function

Model

- We used Binary Cross Entropy Loss (BCE Loss).
- Used along with Sigmoid function
- Compares each of the predicted probabilities to actual class output which can be either 0 or 1.
- Calculates the score that penalizes the probabilities based on the distance from expected value.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Binary Cross-Entropy / Log Loss

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Dataset

Movie Poster Dataset

7867

Number of Image Data Samples

Dataset

IMDB Data

1980-2015

Our dataset is taken from IMDB collection of movie posters.

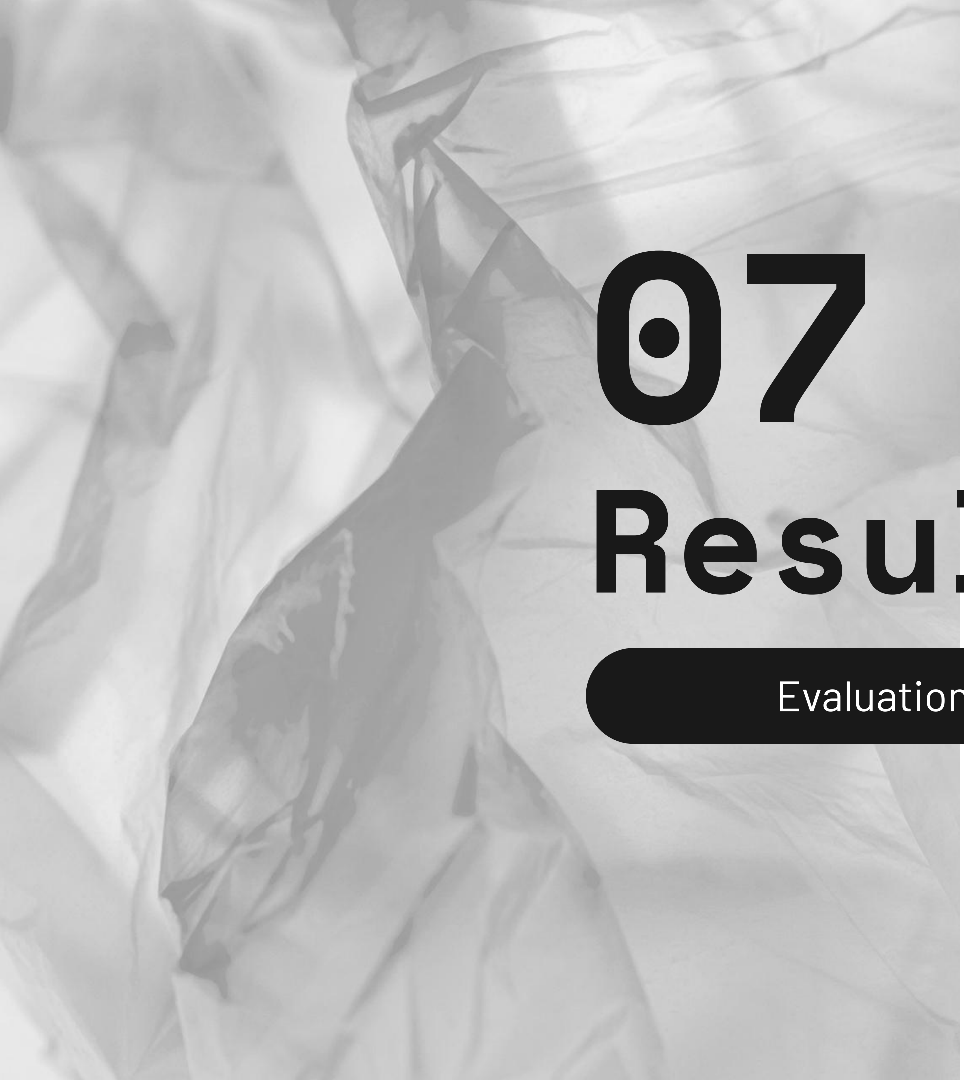
Features

27 Columns

Features include ID of images & labels along with their corresponding genres.

Movie Poster Dataset

	Id	Genre	Action	Adventure	Animation	Biography	Comedy	Crime	Documentary	Drama	Family	Fantasy	History	Horror
0	tt0086425	['Comedy', 'Drama']	0	0	0	0	1	0	0	1	0	0	0	0
1	tt0085549	['Drama', 'Romance', 'Music']	0	0	0	0	0	0	0	1	0	0	0	0
2	tt0086465	['Comedy']	0	0	0	0	1	0	0	0	0	0	0	0
3	tt0086567	['Sci-Fi', 'Thriller']	0	0	0	0	0	0	0	0	0	0	0	0
4	tt0086034	['Action', 'Adventure', 'Thriller']	1	1	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
7249	tt2409818	['Action', 'Crime', 'Thriller']	1	0	0	0	0	1	0	0	0	0	0	0
7250	tt2062622	['Animation', 'Comedy', 'Family']	0	0	1	0	1	0	0	0	1	0	0	0
7251	tt2442502	['Comedy']	0	0	0	0	1	0	0	0	0	0	0	0
7252	tt3455850	['Documentary']	0	0	0	0	0	0	1	0	0	0	0	0
7253	tt4179482	['Animation']	0	0	1	0	0	0	0	0	0	0	0	0



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Result

Evaluation & Observations

Evaluation

- The training as well as the testing datasets were evaluated separately.
- The probability scores obtained as output after **Sigmoid activation** in the final layer, were converted into one-hot encoded values based on a condition.
- The top three probability scores were converted into 1's and the remaining scores were converted into 0's.
- This ensured prediction of three top genres for each sample.
- The accuracy rates were then calculated based on the predicted outputs and the actual labels (1's at the same index of both the outputs were only included).

Accuracy Rates

21.93%

Feed Forward with Multiple Layers

60.21%

CNN using ResNet50 model

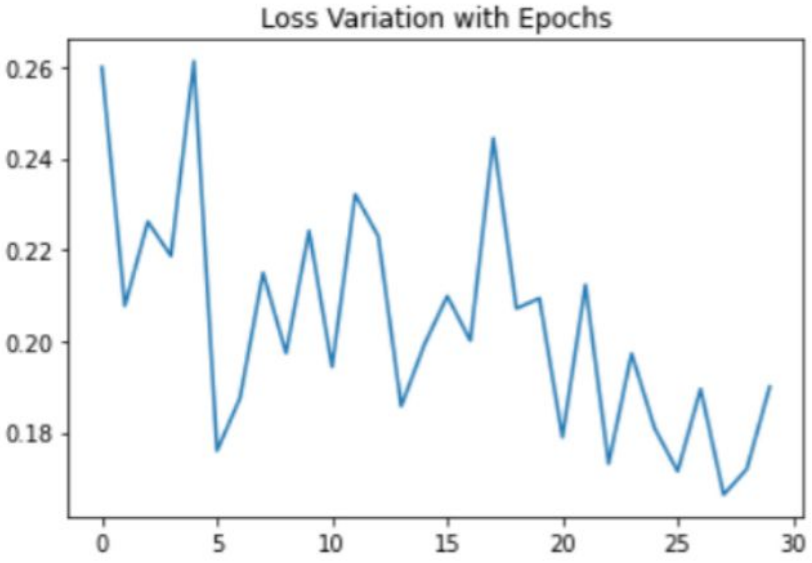
Feed Forward Neural Network - Observations

```
TRAIN LOSS:  0.2542370557785034
Epoch [0], val_loss: 0.2555, val_acc: 21.9061
TRAIN LOSS:  0.2609313726425171
Epoch [1], val_loss: 0.2506, val_acc: 21.9506
TRAIN LOSS:  0.2470485270023346
Epoch [2], val_loss: 0.2505, val_acc: 21.9108
TRAIN LOSS:  0.23429888486862183
Epoch [3], val_loss: 0.2481, val_acc: 21.9342
TRAIN LOSS:  0.24423915147781372
Epoch [4], val_loss: 0.2467, val_acc: 21.9310
```

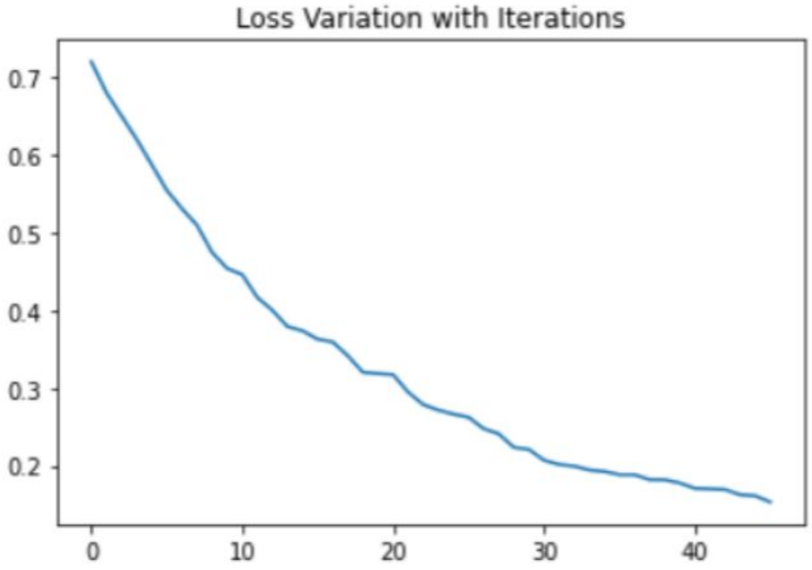
Convolutional Neural Network - Observations

```
Epoch: 24/30, Test acc: 59.93, Train acc: 61.28
CORRECT: 1507
TOTAL: 2513
CORRECT: 8821
TOTAL: 14361
Epoch: 25/30, Test acc: 59.97, Train acc: 61.42
CORRECT: 1513
TOTAL: 2513
CORRECT: 8841
TOTAL: 14361
Epoch: 26/30, Test acc: 60.21, Train acc: 61.56
CORRECT: 1493
TOTAL: 2513
CORRECT: 8836
TOTAL: 14361
Epoch: 27/30, Test acc: 59.41, Train acc: 61.53
CORRECT: 1495
TOTAL: 2513
CORRECT: 8848
TOTAL: 14361
Epoch: 28/30, Test acc: 59.49, Train acc: 61.61
CORRECT: 1493
TOTAL: 2513
CORRECT: 8900
TOTAL: 14361
Epoch: 29/30, Test acc: 59.41, Train acc: 61.97
```

Convolutional Neural Network - Observations



Graph comparing the change in Loss function with respect to the number of Epochs.



Variation of Loss Function with increase in number of iterations.

08. Hyper parameter Tuning

Strategies

- The gradient descent optimizers used to update the model parameter are :
- Stochastic gradient descent with a learning rate of 0.05 in FNN.
- Adam Gradient Optimization with a learning rate of 0.0001 in CNN.

Activation Function

- ReLu activation function was used in hidden layers of FNN model
- Sigmoid function used in the output layer of both FNN and CNN model

09. Comparisons

- Below 4 CNN Architectures were applied :

Model	Test Accuracy	Training Accuracy
VGG-16	54.98%	60.78%
ResNet50	60.21%	61.56%
InceptionV3	46.27%	46.85%
EfficientNet	45.19%	74.48%

- ResNet was the best model with an accuracy of 60.21 on test dataset and 61.56 on train dataset.

References

- Multi-label Classification of Satellite Images with Deep Learning by Daniel Gardner, David Nicols

- Movie Posters' Classification into Multiple Genres.
  Vaibhav Narawade,Aneesh Potnis,Vishwaroop Ray

- Residual Attention: A Simple but Effective Method for Multi-Label Recognition.·Ke Zhu, Jianxin. Wu.

- Research on Multi-label Clothing Image Classification
  Based on Convolutional Neural Network.
  Ying Hong, DOI:10.1007/978-3-030-63784-2-1,05

- Movie genre classification using convolutional neural networks. Luka Popovic,Santiago Cepeda,Nino Scherrer

Thank You