This Project focuses on developing a CNN model to categorise movie posters by their genres accurately. The goal is to create a robust classification system capable of predicting movie genres effectively.

Data Processing

The initial step involves loading the dataset, containing movie posters and their corresponding genres, from a CSV file. The dataset is split into training and testing subsets, and labels are converted into arrays. File locations are established for the images and leverage TensorFlow's tf. data API to construct efficient input pipelines. Various techniques, such as caching and prefetching, are utilised to enhance data loading performance.

Model Definition

Using the Keras Functional API, the CNN model architecture is defined according to the provided model summary. The model comprises convolutional layers, max-pooling layers, dropout layers, and dense layers. Each layer is configured with appropriate parameters, and activation functions are chosen to introduce non-linearity. Dropout layers are incorporated to mitigate overfitting. Finally, the model is compiled with the Adam optimizer, binary cross-entropy loss function, and precision and recall metrics.

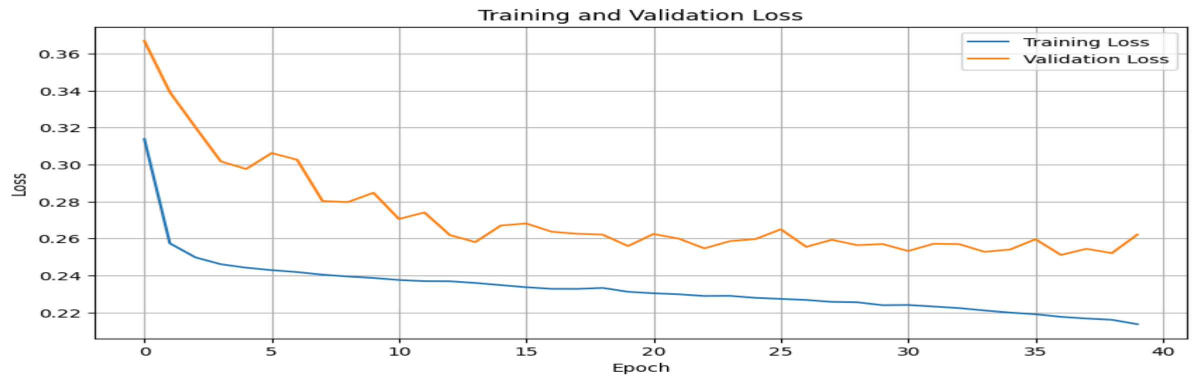
Model Training and Evaluation

The model undergoes training for 40 epochs using the training dataset. Two callbacks, namely ModelCheckpoint and LearningRateScheduler, are implemented during training. The ModelCheckpoint callback saves the weights of the best performing epoch based on validation loss, while the LearningRateScheduler dynamically adjusts the learning rate throughout training. Losses and metrics are then stored for subsequent analysis.
A comprehensive evaluation of the model's performance is conducted using various metrics and visualisations:

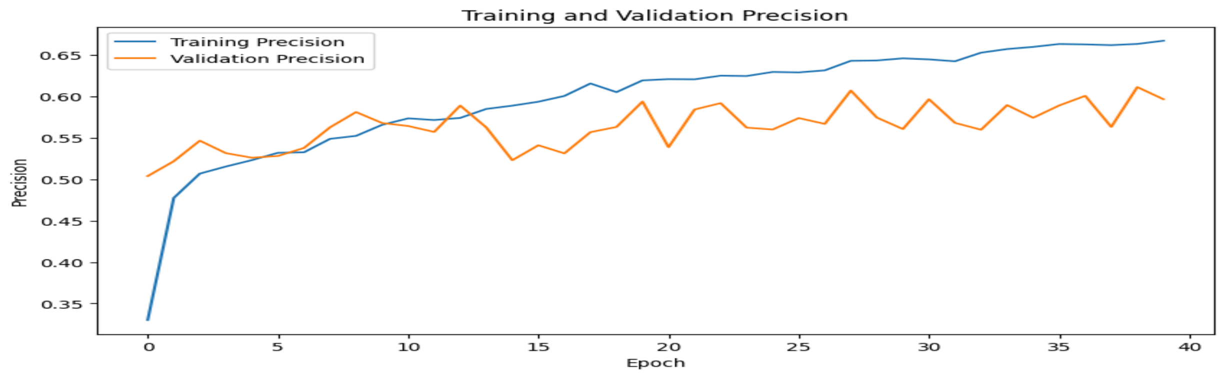
- Plotting of training and validation losses to assess model convergence and identify potential overfitting.
- Precision and recall metrics are plotted to evaluate classification performance across epochs.
- Visualisation of the confusion matrix provides insights into classification errors and areas of confusion between genres.
- Analysis of genre distribution aids in understanding class balance within the dataset and identifying potential biases and also Genre-specific metrics (precision, recall, F1-score) are computed and visualised to assess performance for individual genres.

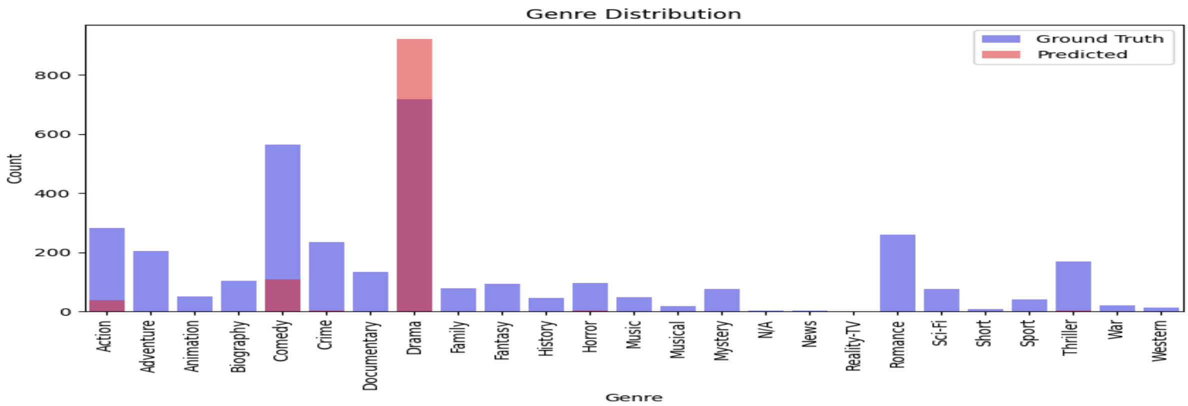
Results

The results of the model demonstrate promising performance. Overall, the model achieves competitive precision and recall metrics, indicating its effectiveness in genre classification. However, there are variations in performance across different genres, with some genres exhibiting higher precision and recall than others. The confusion matrix analysis provides valuable insights into classification errors and areas of confusion between genres. The genre-specific metrics reveal the model's ability to accurately classify certain genres while highlighting challenges in others. Precision-recall curves and ROC curves further illustrate the model's performance across different classification thresholds. These results showcase the effectiveness of the CNN model in genre classification while highlighting areas for further improvement and optimization. The precision score of approximately 0.579 indicates that, on average, when the model predicts a genre for a movie poster, it is correct about 57.9% of the time. This metric is important for assessing the model's ability to avoid false positives, i.e., correctly identifying relevant genres. The recall score of around 0.201 suggests that the model is able to correctly identify approximately 20.1% of all instances of each genre in the dataset. A recall is crucial for assessing the model's ability to capture all relevant instances of a particular genre, minimising false negatives. the model shows some capability in predicting certain genres accurately, there are areas for improvement, particularly in genres with lower precision and recall scores. Further analysis and potential model refinement may be necessary to address these issues and improve overall performance.



Both training and validation loss curves decrease and stabilise over epochs; it indicates that the model is converging and learning effectively.





If certain genres are significantly overrepresented compared to others, the model might prioritise learning to classify the frequent genres during training. For example, for the model, the Drama genre is overrepresented. This can lead to a class imbalance and poor performance in the less frequent genres.

Conclusion and Critical Evaluation

The developed CNN model exhibits promising results in classifying movie genres from posters. While the model demonstrates good overall performance, there are variations in performance across different genres, indicating areas for improvement.
Insights from the confusion matrix and error analysis highlight the need for further refinement and fine-tuning. Continued experimentation with model architecture, hyperparameters, and data augmentation techniques could lead to enhancements in classification accuracy and generalisation capability.

In summary, this report provides a comprehensive overview of the Project, encompassing data processing, model definition, training, evaluation, and critical analysis of the model's performance. It identifies strengths and weaknesses of the Convolutional Neural Network model and offers recommendations for future enhancements.