CS6910
Deep Learning (Spring 2024)
Programming Assignment 2

Image Classification, Captioning and Machine Translation

Instructor: Prof. Chandra Shekhar Chellu
Group: Team #4

Students:
ME20B059 Dharani Govindasamy
ME20B087 Janmenjaya Panda
ME20B122 Nishant Sahoo
ME20B143 Raghav Jangid

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Department of Computer Science & Engineering
Indian Institute of Technology Madras

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1 Task 1

Image classification using a MLFFNN with two hidden layers, and with Deep CNN features for an image as the input to the MLFFNN, with

1. VGGNet as Deep CNN, and
2. GoogLeNet as Deep CNN.

In this section, we will study and compare the results of image classification using a multilayer feedforward neural network (MLFFNN) with two hidden layers. The input to the MLFFNN consists of deep convolutional neural network (CNN) features extracted from images. We will use VGGNet and GoogLeNet as the deep CNN models for feature extraction, and contrast their performance in this context.

1.1 Introduction

Image classification is a crucial task in the field of computer vision, where the objective is to assign a label to an input image from a fixed set of categories. Deep convolutional neural networks (CNNs) have significantly advanced the state of the art in image classification by automatically learning hierarchical features from raw images. In this study, we explore the efficacy of using deep CNN features as inputs to a multilayer feedforward neural network (MLFFNN) with two hidden layers. Specifically, we employ VGGNet[4] and GoogLeNet [5], two well-established deep CNN architectures, to extract features from images. We then feed these features into the MLFFNN and compare the classification performance of the two approaches. This comparison aims to shed light on the effectiveness of different CNN architectures in conjunction with a simple feedforward neural network for image classification tasks.

1.2 VGGNet as Deep CNN

VGGNet is a convolutional neural network (CNN) architecture that was proposed by Karen Simonyan and Andrew Zisserman [4] from the Visual Geometry Group at the University of Oxford. It was introduced in their 2014 paper entitled *Very Deep Convolutional Networks for Large-Scale Image Recognition."*

1.2.1 Key Features of VGGNet

Followingly, we discuss some key features of VGGNet.

- **Depth:** VGGNet is known for its depth, featuring networks with 16 to 19 layers. This deep architecture helps the network to learn complex features and achieve high performance on image recognition tasks.
- **Simplicity of Design:** The architecture is characterized by its simplicity and uniformity. It uses small 3x3 convolution filters throughout the network, stacked on top of each other. This contrasts with earlier architectures that used larger filters.

- **Receptive Field:** Despite using small filters, VGGNet achieves a large effective receptive field by stacking multiple layers. For example, two 3x3 convolutions have a combined receptive field of 5x5.
- **Performance:** VGGNet demonstrated superior performance in various image recognition benchmarks. It was one of the top-performing models in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014.
- **Transfer Learning:** Due to its performance and the generality of its learned features, VGGNet has been widely used for transfer learning. Pre-trained VGG models are often fine-tuned for various computer vision tasks beyond image classification, such as object detection and segmentation.

1.2.2 Variants of VGGNet

The original paper presented several variants of the network, with the most well-known being VGG16 and VGG19, named after the number of layers (16 and 19, respectively). These models differ mainly in the number of convolutional layers and fully connected layers.

1.2.3 Impact

VGGNet's architecture has had a significant impact on the design of subsequent deep learning models. Its use of small, uniform convolutional filters has become a common practice in modern CNN architectures. While newer models have surpassed VGGNet in performance, its simplicity and effectiveness have made it a foundational model in the field of deep learning.

In summary, VGGNet is a landmark in the evolution of CNN architectures, demonstrating that increasing network depth using small convolution filters can significantly enhance performance in image recognition tasks. Its influence continues to be felt in the design of modern neural networks.

1.2.4 Model Architecture

For the given task we shall be using the VGGNet16 Architecture. Figure 1 captures the overall framework of the Deep Neural Network concerning the model [2].

The architecture of VGGNet16 comprises 16 layers, featuring a combination of 13 convolutional layers and 3 fully connected layers. This design principle is elegantly simple yet highly effective, relying on the consistent use of small 3x3 convolutional filters across the entire network. By employing such uniformity, VGGNet16 systematically extracts features from input images at various levels of abstraction. Throughout the architecture, max-pooling layers are strategically inserted to decrease the spatial dimensions of feature maps, thereby enlarging the receptive field. The profound depth of VGGNet16 empowers it to discern intricate patterns and hierarchical representations within images with remarkable efficiency. In summary, VGGNet16's hallmark lies in its deep structure and the pervasive utilization of compact convolutional filters, establishing it as a cornerstone model in the landscape of deep learning research and application.

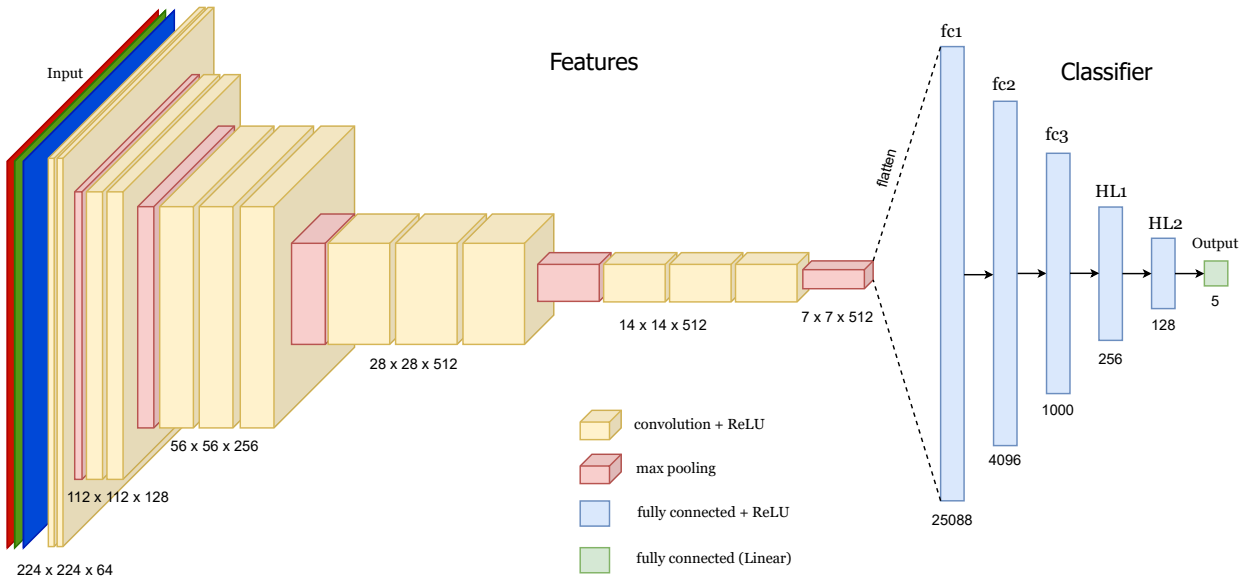


Figure 1: VGGNet Architecture

Also note that here, fc1, fc2, and fc3 represent the fully connected layers from the VGG16 Architecture, and HL1 and HL2 are the two hidden layers of MLFFNN. The reason for taking the three fully connected layers from the VGG16 Classifier (pretrained) is to reduce the parameters from 25088×256 to 1000×256.

1.3 GoogLeNet as Deep CNN

GoogLeNet, also known as Inception V1, is a convolutional neural network (CNN) architecture developed by researchers at Google, including Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke. It was introduced in their 2014 paper [5] entitled *"Going Deeper with Convolutions."* GoogLeNet was designed to address the challenges of deep neural networks, such as computational complexity and overfitting, while maintaining high accuracy in image classification tasks.

1.3.1 Key Features of GoogLeNet

Followingly, we discuss some key aspects of GoogLeNet.

- **Inception Module:** The hallmark of GoogLeNet is the Inception module, which replaces traditional convolutional layers with parallel convolutional operations of different filter sizes (1x1, 3x3, 5x5), along with max pooling. This allows the network to capture features at multiple scales efficiently.
- **Reduced Parameters:** By using multiple filter sizes in parallel, the Inception module reduces the number of parameters compared to traditional convolutional layers with large filters. This leads to a more efficient use of computational resources and helps prevent overfitting.
- **Global Average Pooling:** Instead of fully connected layers at the end of the network, GoogLeNet uses global average pooling, which averages the features across spatial dimensions. This further reduces the number of parameters and helps improve generalization.

- **Auxiliary Classifiers:** GoogLeNet introduces auxiliary classifiers at intermediate layers of the network during training. These auxiliary classifiers provide additional supervision signals and help alleviate the vanishing gradient problem by providing gradients through the network.
- **Deep Network Architecture:** Despite its high accuracy, GoogLeNet has a relatively shallow architecture compared to other contemporary models like VGGNet. This is achieved by using the Inception modules to capture complex features effectively.

1.3.2 Impact

GoogLeNet significantly advanced the state-of-the-art in image classification and introduced innovative architectural components that have since become standard in deep learning models. Its efficient use of parameters and computational resources paved the way for deeper and more complex neural network architectures.

1.3.3 Success in Competitions

GoogLeNet's performance was demonstrated in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2014, where it achieved top results in the classification task, demonstrating its effectiveness in real-world scenarios.

In summary, GoogLeNet, with its Inception module and innovative design choices, represents a milestone in the development of deep neural networks. Its architectural innovations have inspired subsequent research and continue to influence the design of modern CNN architectures.

1.3.4 Architecture

In this section, we shall be discussing the architecture concerning GoogLeNet.

1.3.4.1 Model Architecture

Figure 2 captures the architecture of GoogLeNet.

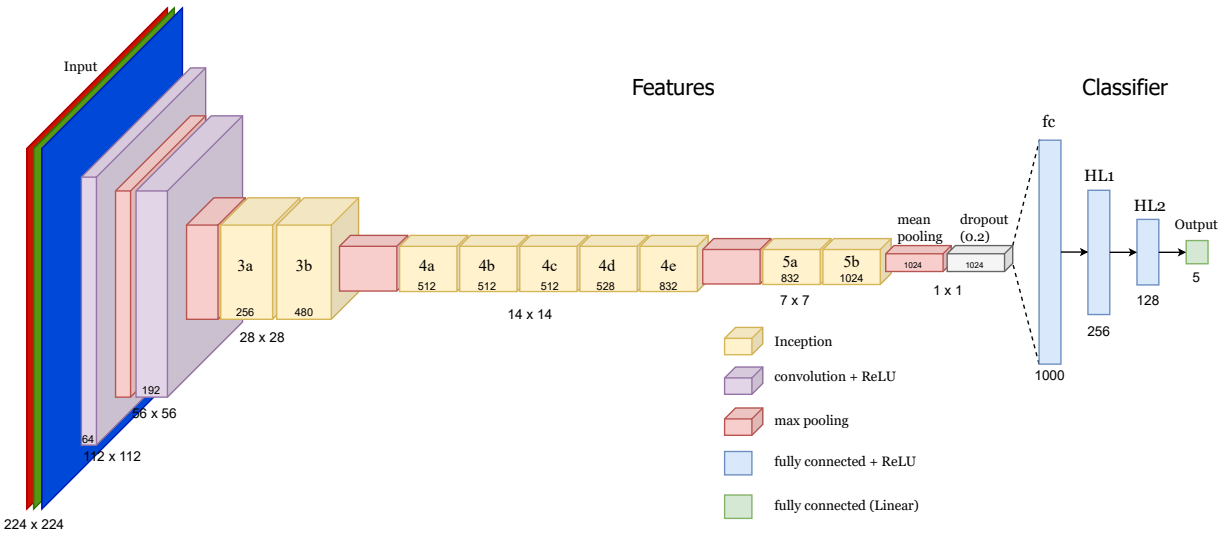


Figure 2: GoogLeNet Architecture

1.3.4.2 Inception Modules

The Inception modules, introduced in the GoogLeNet architecture, represent a key innovation in designing deep convolutional neural networks (CNNs). These modules are designed to capture features at multiple scales efficiently, promoting better representation learning while maintaining computational efficiency.

- **Inception Module (3a):** In the Inception Module 3a of GoogLeNet, various filter sizes are employed in parallel to capture features at different spatial scales. Specifically, the module consists of multiple convolutional layers with filter sizes of 1x1, 3x3, and 5x5, along with max pooling operations. This design choice allows the network to extract features at different levels of granularity, enabling it to learn diverse and rich representations from the input data.

- **Inception Module (3b):** Similarly, Inception Module 3b continues the theme of capturing features at multiple scales. It builds upon the concept introduced in Module 3a by further expanding the parallel pathways. In Module 3b, additional convolutional layers with varying filter sizes are added to enhance the network's ability to extract intricate patterns and structures from the input images.

- **Inception Module (4a):** In Inception Module 4a, the architecture focuses on increasing the depth and complexity of feature extraction while maintaining computational efficiency. This is achieved by introducing additional convolutional layers and pooling operations. The module aims to further enrich the network's representation learning capabilities by exploring a wider range of receptive fields and feature combinations.

- **Inception Module (4b):** Building upon the advancements of Module 4a, Inception Module 4b continues to refine the network's feature extraction capabilities. It explores different combinations of convolutional filters and pooling operations to capture a diverse range of features from the input data. By incorporating these variations, Module 4b aims to enhance the network's discriminative power and generalization ability.

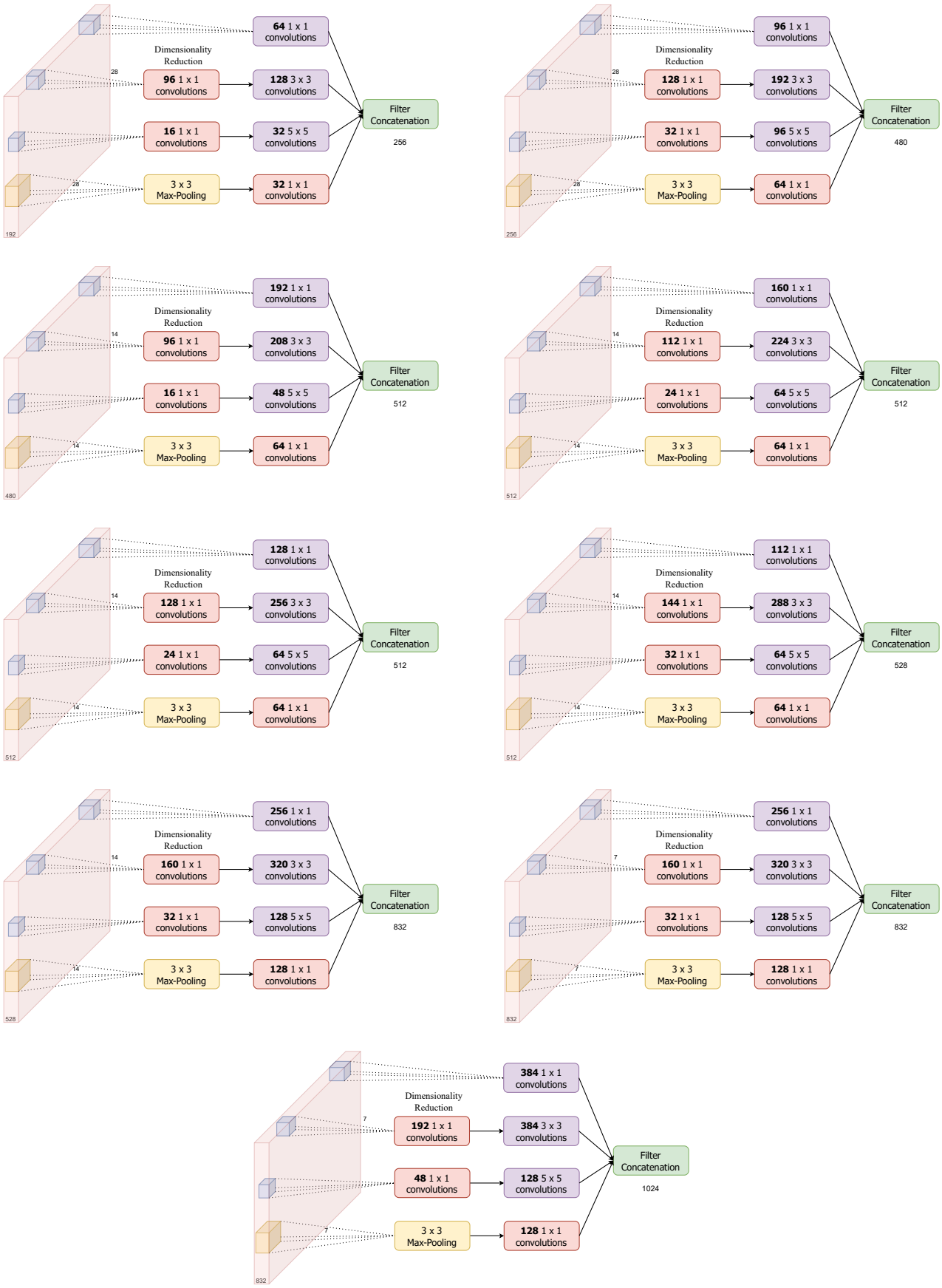


Figure 3: Inception Modules (**3***a* to **5***b* in order)

- **Inception Module (5a and 5b):** In the final stages of the GoogLeNet architecture, Inception Modules 5a and 5b further refine the learned features and prepare them for classification. These modules focus on consolidating the extracted information and reducing the dimensionality of the feature maps. By combining various convolutional operations and pooling strategies, Modules 5a and 5b aim to distill the essential information from the input data and provide a compact yet informative representation for the subsequent classification layers.

In summary, the Inception modules in GoogLeNet revolutionized the design of deep CNN architectures by introducing parallel pathways with different filter sizes. These modules enable efficient feature extraction at multiple scales, leading to improved performance and representational capacity while maintaining computational efficiency.

Figure 3 represents the Inception Modules of GoogLeNet with $3a$ to $5b$ in order.

1.4 Implementation

The details regrading the implementation goes as follows:

1. **Importing Libraries:** The code begins by importing necessary libraries, including `PyTorch` modules for building and training neural networks, as well as other utilities like `tqdm` for progress tracking, `seaborn` for plotting, and `numpy` for numerical operations.

2. **Loading and Preprocessing Dataset:** The dataset is loaded using `PyTorch`'s `ImageFolder` class, which automatically assigns labels based on directory structure. Three sets are created: training, validation, and testing, each containing images and their corresponding labels. Images are preprocessed using transformations like resizing, normalization, and conversion to tensors.

3. **Defining ImageClassification Class:** This class encapsulates the functionality for training, evaluating, and testing the models. It also includes methods for plotting confusion matrices, losses, and accuracies.

4. **Training and Evaluating VGGNet Model:**

   (a) *Loading Pretrained VGGNet:* The pretrained VGG-16 model is loaded from `torchvision.models` and modified to remove the fully connected layers, leaving only the convolutional layers (feature extractor).

   (b) *Defining MLFFNN Architecture:* An MLFFNN is defined with three fully connected layers and ReLU activation functions. The input size is determined by the output of the VGGNet feature extractor.

   (c) *Training and Evaluation:* The model is trained using the ImageClassification class, which handles the training loop, loss calculation, and parameter updates. Training progress is monitored using metrics like loss and accuracy. After training, the model is evaluated on the test dataset, and performance metrics are displayed.

   (d) *Visualization:* Confusion matrices, losses, and accuracies are plotted to visualize the model's performance and training progress.

5. **Training and Evaluating GoogLeNet Model:**

(a) *Loading Pretrained GoogLeNet:* Analogous to VGGNet, the pretrained GoogLeNet model is loaded from `torchvision.models`.

(b) *Defining MLFFNN Architecture:* An MLFFNN with three fully connected layers is defined, taking the output of GoogLeNet as input.

(c) *Training and Evaluation:* The model is trained and evaluated using the same procedure as VGGNet.

(d) *Visualization:* Similar visualizations are generated to analyze the performance of the GoogLeNet model.

6. **Loss Function and Optimizer:** The Cross Entropy Loss function is used as the loss criterion, suitable for multi-class classification tasks. The Adam optimizer is employed to update the model parameters, with a learning rate of 0.001.

7. **Evaluation Metrics:** During training and validation, metrics such as loss and accuracy are calculated and monitored to assess the model's performance. These metrics are then visualized using plots to analyze the training progress and identify any overfitting or underfitting issues.

8. **Results:** After training, the models are evaluated on the test dataset to assess their generalization performance. Additionally, confusion matrices are generated for both training and testing datasets to visualize the performance of the models across different classes. Losses and accuracies are also plotted over epochs to provide insights into the training process and model convergence.

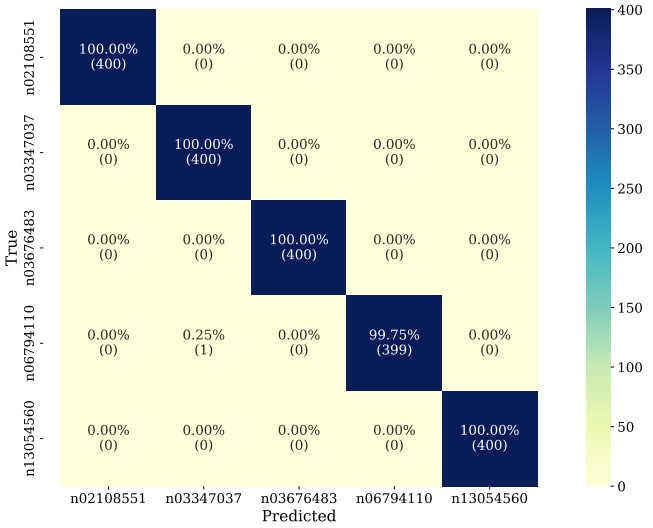
9. **Conclusion:** The code demonstrates the implementation of image classification using MLFFNN with VGGNet and GoogLeNet as feature extractors. Through training, evaluation, and visualization, the code provides insights into the performance of these architectures on the given dataset.

1.5 Plots

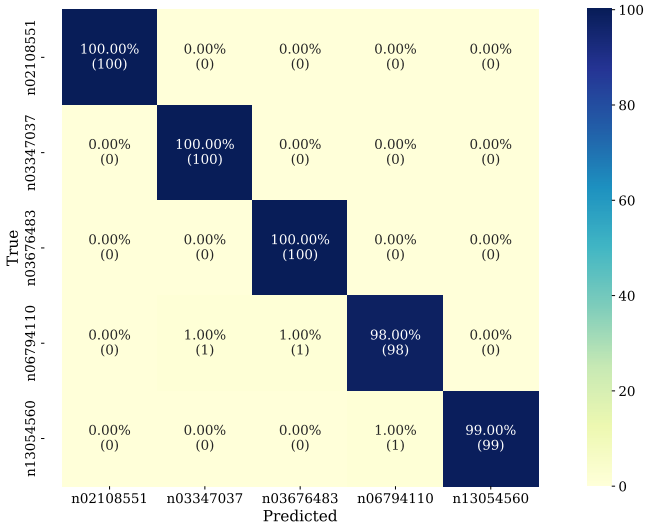
In this section, we present the plots obtained from the implementation.

1.5.1 VGGNet

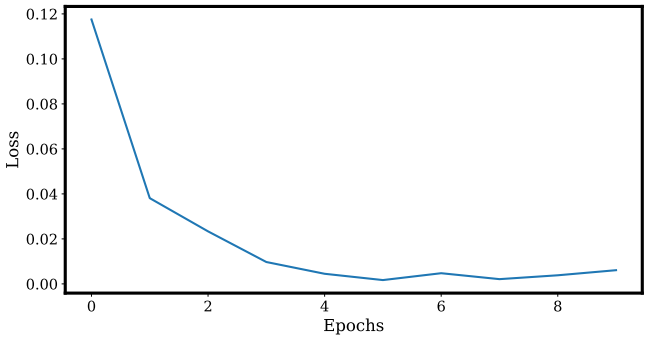
This section displays the plots concerning the confusion matrix, losses and accuracy vs epochs across train, validation and test dataset concerning the VGGNet architecture.



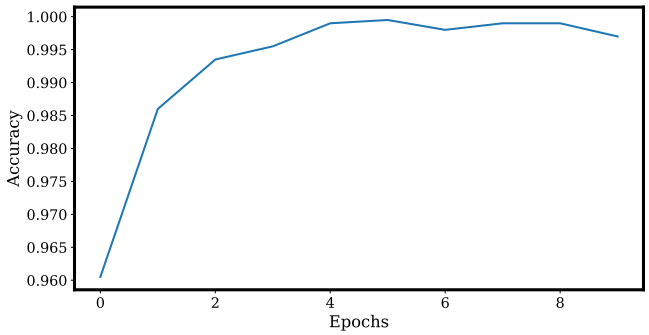
(a) Confusion Matrix (Train)



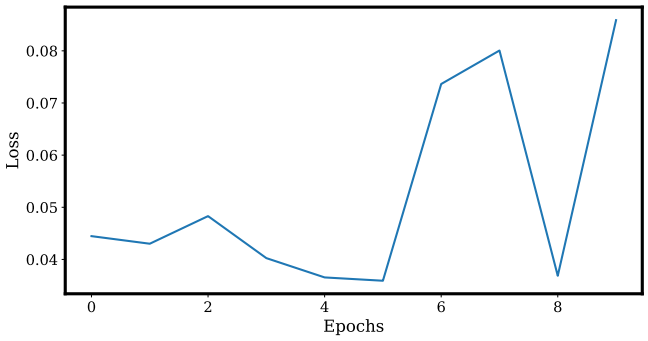
(b) Confusion Matrix (Test)



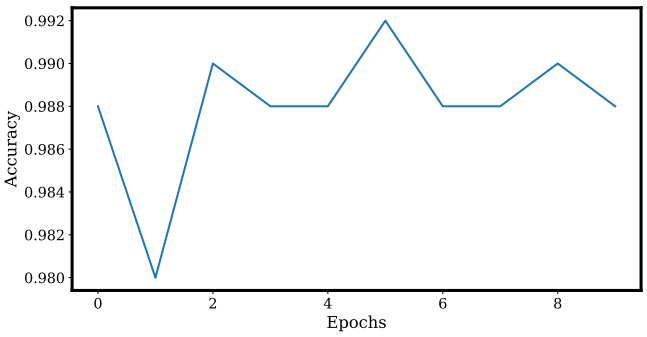
(c) Train Losses



(d) Train Accuracy



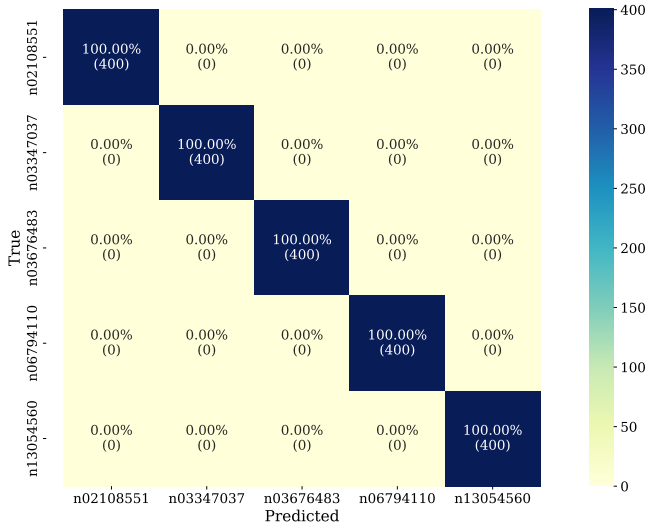
(e) Validation Losses



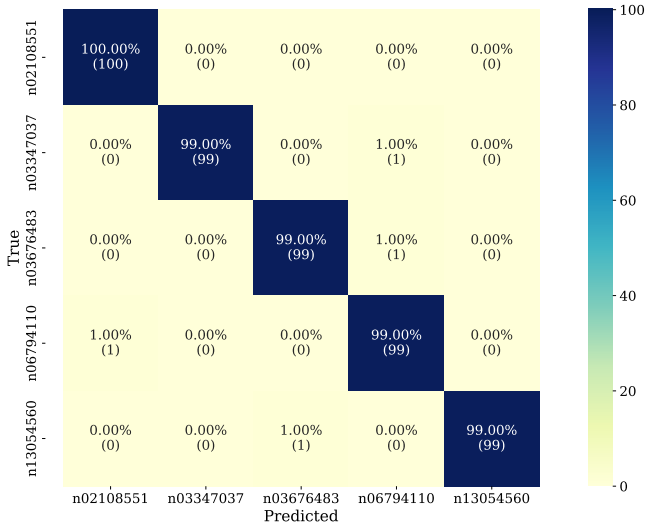
(f) Validation Accuracy

1.5.2 GoogLeNet

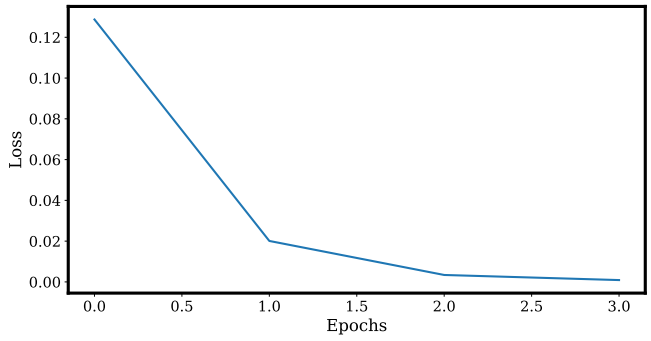
This section displays the plots concerning the confusion matrix, losses and accuracy vs epochs across train, validation and test dataset concerning the GoogleNet architecture.



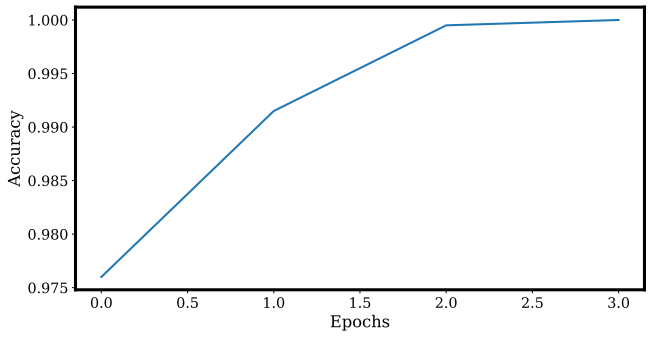
(a) Confusion Matrix (Train)



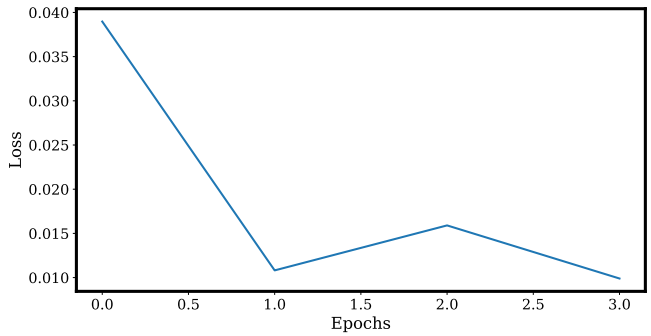
(b) Confusion Matrix (Test)



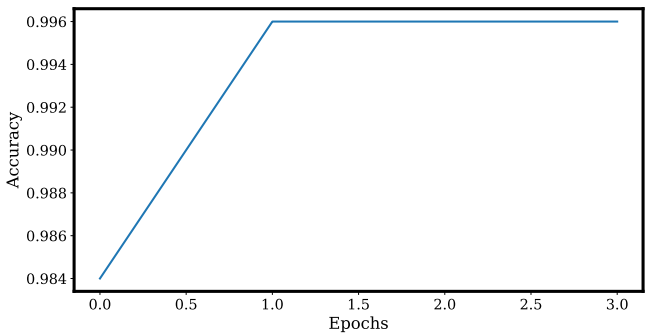
(c) Train Losses



(d) Train Accuracy



(e) Validation Losses



(f) Validation Accuracy

1.6 Observations and results

In this section we shall be comparing the results obtained thru VGGNet16 and GoogLeNet.

1. **A comparison on Confusion Matrices:**

- *Model Training Performace:* It is clear that both the models are well trained as far as the training dataset is concerned as both of them achieved an absolute precision of 100% concerning each of the labelling on the training dataset. This indicates that both models have learned to correctly classify images within the training set with high accuracy.
- *Label-specific Test Performance:* It is worth noting that, in test dataset even though both of the model achieved 100% correct labelling for `n02108551` and `n02108551` and 99% for `n13054560`, VGGNet16 achieved 100% correct labelling for `n03676483` in contrast with 99% thru the GoogLeNet and GoogLeNet achieved 99% precision for `n06794110` in contrast with 98% by VGGNet.
- *Differences in Performance:* The paragraph highlights that there are differences in precision between the two models for specific labels. For instance:
  (a) VGGNet16 achieved higher precision for the label `n03676483` compared to GoogLeNet.
  (b) GoogLeNet achieved higher precision for the label `n06794110` compared to VGGNet16.

2. **A comparison on Training Loss:** Comparing the training loss vs. epoch curves for VGGNet and GoogLeNet, we can draw several inferences:

   - *Convergence Rate:* From the plot, it seems that VGGNet converges more gradually compared to GoogLeNet. VGGNet's loss decreases steadily over multiple epochs, indicating a slower convergence rate, while GoogLeNet achieves lower loss values more rapidly, suggesting a faster convergence.
   - *Initial Loss:* At epoch 1, VGGNet has a lower initial loss (0.1175) compared to GoogLeNet (0.1287), implying that VGGNet starts with a slightly better performance in terms of training loss.
   - *Stability:* GoogLeNet's loss curve appears to be relatively stable throughout the epochs, with almost no fluctuations. On the other hand, VGGNet's loss curve exhibits fluctuations, especially in the tail of the epochs. This could indicate that GoogeLeNet's training process might be more stable or less sensitive to small changes in the training data.
   - *Final Loss:* Despite the initial difference in loss values, both models achieve very low final training losses. However, it seems that GoogLeNet reaches a lower final loss compared to VGGNet, as indicated by the last available loss values for both models.
   - *Convergence Point:* While VGGNet shows a consistent decrease in loss over the epochs provided, GoogLeNet's loss curve indicates a rapid decrease (below a resonable threshold within 3 epochs as compared to 9 epochs in VGGNet), possibly indicating that GoogLeNet reaches its convergence point earlier than VGGNet. Also in VGGNet there has been an increase in the loss after epoch 7 suggesting potential fluctuations.

3. **A comparison on Training Accuracy:** Let's analyze the training accuracy for both GoogLeNet and VGGNet:

   - *Initial Training Accuracy:* At the first epoch, both GoogLeNet and VGGNet have relatively high training accuracies. GoogLeNet starts with a training accuracy of 0.976, while VGGNet starts slightly lower at 0.9605.

- *Convergence Rate:* Both models show an increasing trend in training accuracy over the epochs. However, GoogLeNet seems to converge faster to near-perfect accuracy compared to VGGNet. By the fourth epoch, GoogLeNet achieves perfect training accuracy (1.0), while VGGNet is at 0.9955.
- *Final Training Accuracy:* GoogLeNet achieves perfect training accuracy by the fourth epoch, while VGGNet reaches very high accuracy but does not quite reach perfect accuracy even after ten epochs. The final training accuracy for VGGNet is 0.997, slightly lower than that of GoogLeNet.
- *Stability:* Both models exhibit stable behavior in terms of training accuracy, with consistent increases over the epochs. There are no significant fluctuations observed in either case. It is worth noting that after achieving the peak value of 0.999 VGGNet tends to move down at the tail of the epochs suggesting potential fluctuation.

  Overall Performance: GoogLeNet demonstrates faster convergence and achieves higher final training accuracy compared to VGGNet. While both models achieve high accuracy, GoogLeNet's ability to reach perfect accuracy in fewer epochs suggests that it may be more effective for this particular task.

4. **A comparison on Validation Loss:** Let's analyze the validation loss for both VGGNet and GoogLeNet:

   - *Initial Validation Loss:* At the first epoch, VGGNet has a slightly more validation loss (0.0445) compared to GoogLeNet (0.0390). This suggests that GoogLeNet starts with a slightly better performance in terms of validation loss.
   - *Convergence Rate:* Note that GoogLeNet's validation loss suffers from a long interval minor amplitute (a gap of $\sim$ **0.005**) fluctuation towards the tail of the epochs before settling down at 0.009. On the other hand, VGGNet suffers high fluctuation (a consecutive gap of $\sim$ **0.04** between epoch 5 and epoch 6) towards the tail of the epoch starting from epoch 5. Also at the very end the validation loss seems to be increasing.
   - *Final Validation Loss:* The fluctuations in VGGNet's validation loss leads to its final validation loss being 0.0859, that is significantly pooer than that of GoogLeNet (0.0099). Also, it's essential to note that GoogLeNet achieves a significantly lower final validation loss compared to VGGNet.
   - *Stability:* GoogLeNet's validation loss curve appears to be more stable and consistently decreasing compared to VGGNet, which exhibits more fluctuations and irregular patterns.
   - *Convergence Point:* GoogLeNet reaches a lower validation loss much faster than VGGNet. By the fourth epoch, GoogLeNet has already achieved a very low validation loss, while VGGNet continues to fluctuate without reaching a similarly low loss value.
   - *Overall Performance:* Based on the validation loss, GoogLeNet outperforms VGGNet, achieving lower validation loss values consistently and more rapidly.

5. **A comparison on Validation Accuracy:** Let's analyze the validation accuracy for both GoogLeNet and VGGNet:

   - *Initial Validation Accuracy:* At the first epoch, VGGNet has a slightly higher validation accuracy (0.988) compared to GoogLeNet (0.984).

- *Convergence Rate:* Both models show an increasing trend in validation accuracy over the epochs. However, GoogLeNet's validation accuracy reaches a plateau after the second epoch, remaining constant at 0.996 for the last two epochs. In contrast, VGGNet's validation accuracy fluctuates slightly over the epochs, with some minor increases and decreases.
- *Final Validation Accuracy:* GoogLeNet achieves a final validation accuracy of 0.996, which it maintains for the last two epochs. On the other hand, VGGNet's final validation accuracy fluctuates between 0.988 and 0.992 over the last few epochs, with the highest being 0.992.
- *Stability:* GoogLeNet's validation accuracy remains stable after the second epoch, showing no significant fluctuations. In contrast, VGGNet's validation accuracy exhibits some fluctuations, although they are relatively minor.
- *Overall Performance:* GoogLeNet achieves a slightly higher final validation accuracy compared to VGGNet. Additionally, GoogLeNet's validation accuracy stabilizes earlier and remains constant for the last two epochs, indicating a more consistent performance.

1.7 Conclusion

We conclude that GoogLeNet perfomed better on the test data set, exhibited better, faster convergence on loss and accuracy with more stablity and lesser fluctuations in both training and testing. Several factors could contribute to why GoogLeNet performed better than VGGNet based on the provided data. GoogLeNet's innovative inception modules, allowing for more efficient use of computational resources and capturing a broader range of features and relationships within images, contribute to its depth and complexity, which in turn enables it to discriminate between classes more effectively. Additionally, GoogLeNet's efficient parameter usage, regularization techniques, and optimization dynamics likely enhance its generalization performance, leading to faster convergence and better accuracy on both validation and test datasets. Furthermore, the observed differences in precision for specific labels suggest that GoogLeNet's architecture excels at capturing label-specific features, further reinforcing its superiority over VGGNet in this scenario.

2 Task 2

Image classification using a CNN with CL1, PL1, CL2 and PL2 as the layers. Use kernels of size 3×3, stride of 1 in the convolutional layers. Use the mean pooling with a kernel size of 2×2 and stride of 2 in the pooling layers. Use 4 feature maps in CL1. The number of feature maps in CL2 is a hyperparameter.

2.1 Introduction

Note that this task is in the analogous spirit with the previous task with a different model architecture.

2.2 Model Architecture

The following figure represents the model architecture implemented.

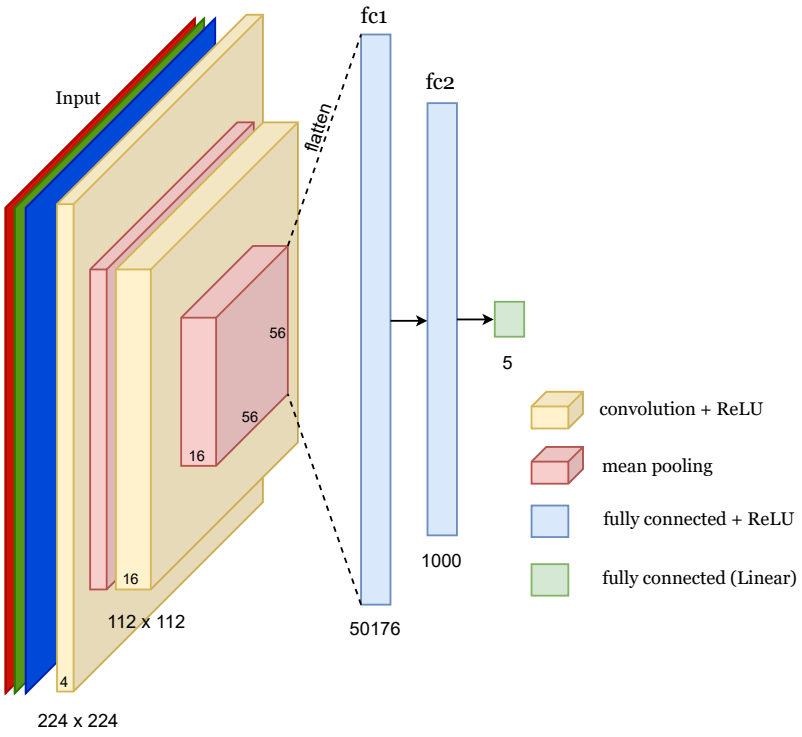


Figure 6: Image Classification Architecture

2.3 Implementation

1. **Prepare the Dataset:** First, we loaded the image dataset (train, test, validation). Then, we preprocessed the images by normalizing the pixel values and resizing them to a fixed size.

2. **Define the Model Architecture:** We created a convolutional neural network (CNN) model with the following layers:

   - **Convolutional Layer 1 (CL1):** used 4 feature maps, applied kernels of size 3×3, used a stride of 1, and applied ReLU activation function.
   - **Pooling Layer 1 (PL1):** used mean pooling with a kernel size of 2×2 and a stride of 2.
   - **Convolutional Layer 2 (CL2):** We used a specified number of feature maps (as a hyperparameter). We applied kernels of size 3×3 and a stride of 1, and applied ReLU activation function.
   - **Pooling Layer 2 (PL2):** used mean pooling with a kernel size of 2×2 and a stride of 2.

   We flattened the output of the last pooling layer to feed into fully connected layers, added fully connected (dense) layers as needed. Finally, we added an output layer with the number of units equal to the number of classes in the dataset, using a linear activation function. We didn't use softmax activation even though it is a classification problem due to the fact that we are using the Cross-Entropy loss criterion.

3. **Compiling the Model:** We define the loss function as Cross-Entropy loss for classification, an optimizer as Adam and we specified evaluation metrics like accuracy and confusion matrix.

4. **Training:** We fed the training data into the model, used the validation data to monitor the training process and tuned hyperparameters. After tuning, we chose the best hyperparameter (number of feature maps in CL2 = 16) and trained the model for 10 epochs. Early stopping was not needed in this case as the model converged in just 10 epochs.

5. **Evaluation:** We used the test dataset to evaluate the model's performance. Then, we computed relevant metrics such as accuracy and confusion matrix for both training and testing datasets.

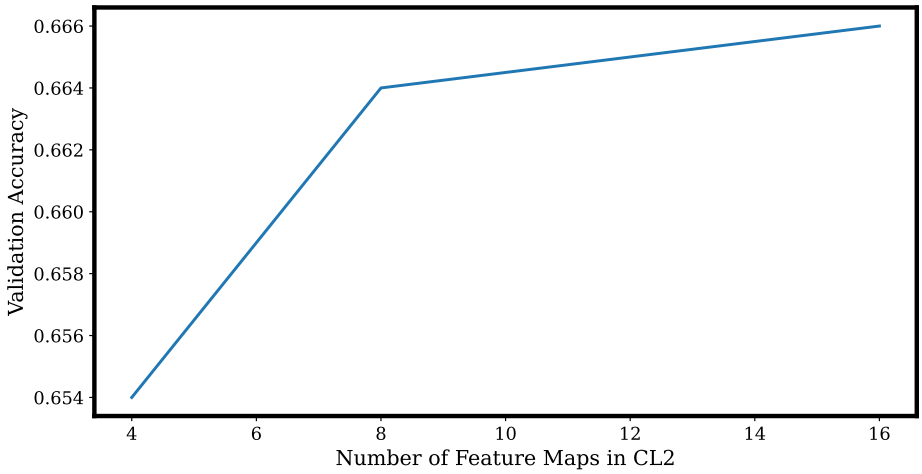
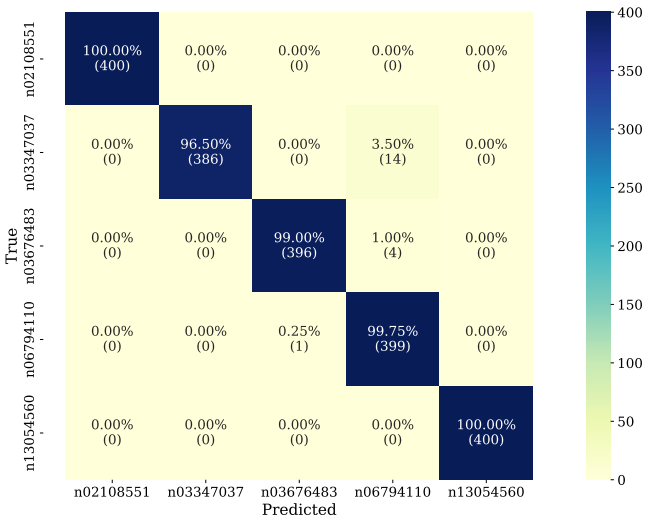
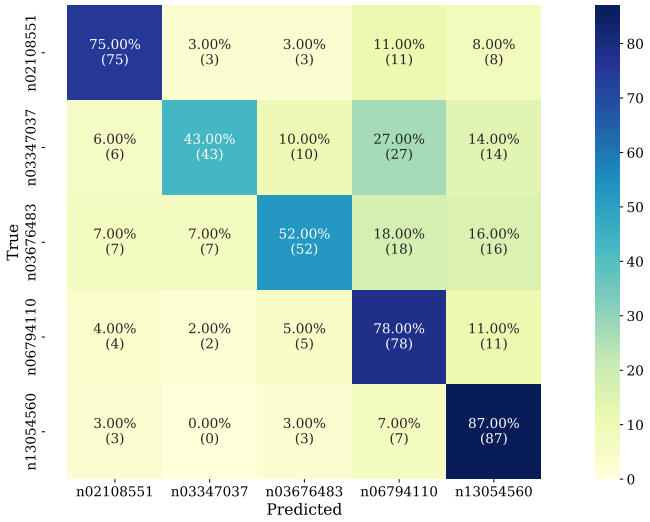


Figure 7: Hyperparameter Tuning

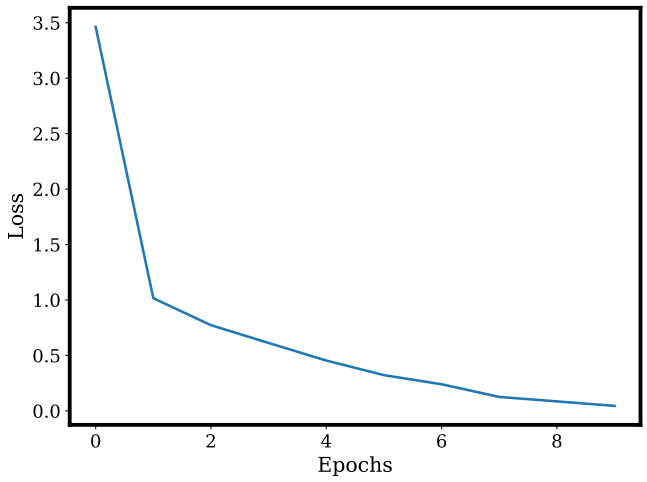
2.4 Plots



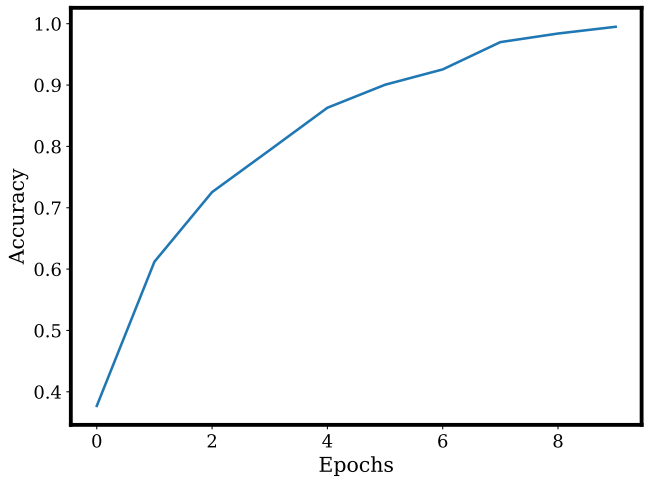
(a) Confusion Matrix (Train)



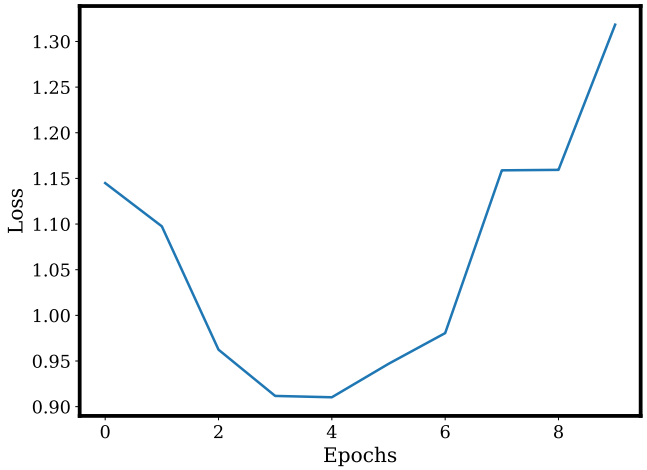
(b) Confusion Matrix (Test)



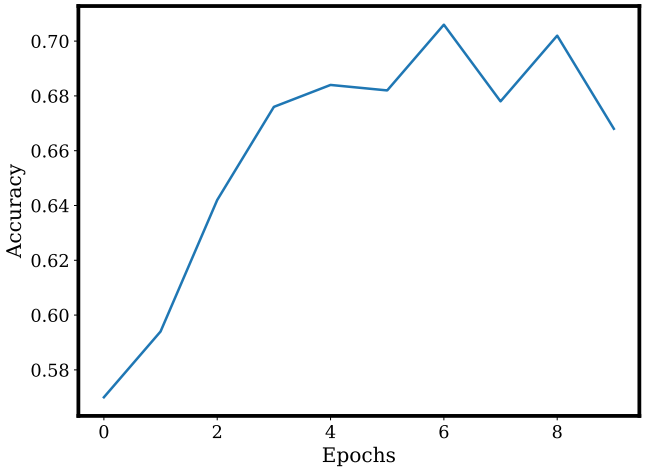
(c) Train Losses



(d) Train Accuracy



(e) Validation Losses



(f) Validation Accuracy

2.5 Observations and Results

- The above plots are based on the optimal hyperparameter, specifically the number of features in CL2, which is set to 16.
- As we increase the number of features in CL2, the performance tends to improve; however, the computational complexity also increases significantly. Therefore, a balance must be struck between performance and computational cost.
- Although the training plots appear satisfactory, the validation plots are not ideal. We observe that the validation loss initially decreases but then starts to increase, which is contrary to the expected behaviour.
- The confusion matrix for the training data looks very good, but this is not the case for the testing confusion matrix.
- These results indicate that Task 2 is performing worse than Task 1, where we used VGG16 and GoogLeNet as the deep CNN features for classification.
- Task 1 significantly outperforms Task 2 due to the more advanced architecture and feature extraction capabilities of VGG16 and GoogLeNet.

3 Task 3

Image captioning using a CNN with NetVLAD as encoder and a single hidden layer RNN based decoder.

3.1 Introduction

Image captioning, a task at the intersection of computer vision and natural language processing, aims to generate textual descriptions for images automatically. In recent years, convolutional neural networks (CNNs) have been widely adopted for extracting visual features from images due to their ability to learn hierarchical representations. These visual features are then typically fed into a decoder network, often based on recurrent neural networks (RNNs), to generate descriptive captions. In particular, a single hidden layer RNN-based decoder is a common choice for its simplicity and effectiveness in sequential data generation tasks. This approach forms the backbone of many image captioning systems, where the encoder-decoder architecture is crucial for transforming visual information into coherent textual descriptions. One such encoder-decoder architecture employs NetVLAD, a CNN-based encoder, to extract visual features, coupled with a single hidden layer RNN-based decoder to generate captions based on these features. In this context, exploring the performance and limitations of such architectures provides valuable insights into the capabilities of current image captioning systems.

3.2 NetVLAD

NetVLAD, short for Network with Vector of Locally Aggregated Descriptors, is a neural network architecture primarily used for visual feature aggregation and representation learning in computer vision tasks. It was introduced by Arandjelović and Zisserman in their 2016 paper "NetVLAD: CNN Architecture for Weakly Supervised Place Recognition" [1].

At its core, NetVLAD is designed to address the challenge of recognizing and localizing places in images without requiring precise annotations. It operates on top of a convolutional neural network (CNN) and aggregates local image descriptors into a global representation, enabling robust and discriminative place recognition.

NetVLAD Architecture: NetVLAD consists of the following key components:

1. **CNN Backbone:** A CNN is employed to extract local image descriptors, typically in the form of feature maps, from an input image.
2. **VLAD Layer:** The Vector of Locally Aggregated Descriptors (VLAD) layer aggregates the local descriptors across spatial locations into a single global descriptor. This is achieved through a process of vector quantization and aggregation, resulting in a fixed-size representation.
3. **Fully Connected Layers:** The aggregated descriptor from the VLAD layer is then passed through fully connected layers to perform further feature transformation and dimensionality reduction.
4. **Normalization:** L2 normalization is often applied to the final representation to ensure that it is invariant to changes in scale and illumination.

3.3 The BLEU score

In this section, we shall discuss about the BLEU score. We consider the Wikipedia article as our reference.

The *BLEU* score, aka ***Bi**Lingual **E**valuation **U**nderstudy*, is an algorithm for evaluating the quality of text which has been machine-generated. The quality is considered to be the correspondence between a machine's output and that of a human in the sense that the closer a machine translation is to a professional human translation, the better it is — this is the central idea behind BLEU. Invented at IBM by Kishore Papineni et al. [3] in 2002, BLEU was one of the first metrics to claim a high correlation with human judgements of quality, and remains one of the most popular automated and inexpensive metrics.

3.3.1 The basic setup

Let's try to define the BLEU score; firstly, it shall consider two arguments:

1. a candidate string $\hat{y}$, and
2. a list of reference strings $(y^1, y^2, \cdots, y^N)$.

The idea is that $\text{BLEU}(\hat{y}; y^1, y^2 \cdots, y^N)$ should be close to 1 when $\hat{y}$ is similar to $y^1, y^2, \cdots, y^N$, and close to 0 if not.

Since in natural language processing, one should evaluate a large set of candidate strings, one must generalize the BLEU score to the case where one has a list of M candidate strings, aka in a corpus $(\hat{y}^1, \hat{y}^2 \cdots, \hat{y}^M)$, and for each candidate string $\hat{y}^i$, a list of reference candiate strings $S_i := (y_i^1, y_i^2, \cdots, y_i^{N_i})$.

Given a string $s := s_1, s_2, \cdots, s_K$, and any integer $1 \leqslant n \leqslant K$, we define the set of n-grams corresponding to the string s as:

$$G(s, n) := \{s_1 s_2 \cdots s_n, s_2 s_3 \cdots s_{n+1}, \cdots, s_{K-n+1} s_{K-n+2} \cdots s_K\}$$

Note that it is a set of unique elements, not a multiset allowing redundant elements, so that, for instance, $G('abab', 2) = \{'ab', 'ba'\}$.

For any two given strings, s and y, we define the substring count $C(s, y)$ to be the number of appearances of s as a substring of y. For instance: $C('ab', 'abcbab') = 2$.

Now, we fix a candidate corpus $\hat{S} := (\hat{y}^1, \hat{y}^2, \hat{y}^3, \cdots, \hat{y}^M)$, and for reference candidate corpus $S := (S_1, S_2, \cdots, S_M)$, where each $S_i := (y_i^1, y_i^2, \cdots, y_i^{N_i})$.

3.3.2 Modified n-gram precision

We define the modified n-gram precision function to be:

$$p(\hat{S}; S, n) := \frac{\sum_{i=1}^{M} \sum_{s \in G(\hat{y}^i, n)} \min\left(C(s, \hat{y}^i), \max_{y \in S_i} C(s, y)\right)}{\sum_{i=1}^{M} \sum_{s \in G(\hat{y}^i, n)} C(s, \hat{y}^i)}$$

The modified n-gram, which looks complicated, is merely a straightforward generalization of the prototypical case: one candidate sentence and one reference sentence. In this case, it is

$$p(\{\hat{y}\};\{y\},n) := \frac{\sum_{s\in G(\hat{y},n)} \min\left(C(s,\hat{y}),C(s,y)\right)}{\sum_{s\in G(\hat{y},n)} C(s,\hat{y})}$$

To work up to this expression, we start with the most obvious n-gram count summation:

$$\sum_{s\in G(\hat{y},n)} C(s,y) = \#\text{ of } n\text{-substrings in } \hat{y} \text{ that appear in } y$$

This quantity measures how many n-grams in the reference sentence are reproduced by the candidate sentence. Note that we count the n-substrings, not n-grams. For example, when $\hat{y} =' aba'$, $y =' abababa'$ and $n = 2$, all the 2-substrings in $\hat{y}$ ($'ab'$ and $'ba'$) appear in y 3 times each, so the count is 6, not 2.

In the above situation, however, the candidate string is too short. Instead of 3 appearances of ab it contains only one, so we add a minimum function to correct for that, that is — $\sum_{s\in G(\hat{y},n)} \min\left(C(s,\hat{y},C(s,y))\right)$.

This count summation cannot be used to compare between sentences, since it is not normalized. If both the reference and the candidate sentences are long, the count could be big, even if the candidate is of very poor quality. So we normalize it, that is — $\frac{\sum_{s\in G(\hat{y},n)} \min\left(C(s,\hat{y},C(s,y))\right)}{\sum_{s\in G(\hat{y},n)} C(s,\hat{y})}$.

The normalization is such that it is always a number in $[0,1]$, allowing meaningful comparisons between corpora. It is zero if and only if none of the n-substrings in candidate is in reference. It is one if and only if every n-gram in the candidate appears in reference, for at least as many times as in candidate. In particular, if the candidate is a substring of the reference, then it is one.

3.3.3 Brevity penalty

The modified n-gram precision unduly gives a high score for candidate strings that are 'telegraphic', that is, containing all the n-grams of the reference strings, but for as few times as possible.

In order to punish candidate strings that are too short, define the *brevity penalty* to be

$$BP(\hat{S};S) := \exp\left(-\max(0,\frac{r}{c}-1)\right)$$

Here

1. c denotes the length of the candidate corpus, that is —

$$c := \sum_{i=1}^{M} \left|\hat{y}^i\right|, \text{ and}$$

2. r is the effective reference corpus length, that is —

$$r := \sum_{i=1}^{M} \left|y_j^i\right|$$

where $y_j^i := \arg\min_{y \in S_i} \left| |y| - |\hat{y}^i| \right|$, that is a sentence from S_i whose length is as close to $|\hat{y}^i|$ as possible.

Observe that

1. when $r \leqslant c$, the brevity penalty BP equals to one, signifying the fact that we don't punish long candidates, and only punish short candidates, and
2. when $r > c$, the brevity penalty BP equals to $\exp(1 - \frac{r}{c})$

3.3.4 The formulation

There is not a single definition of BLEU, but a whole family of them, parametrized by the weighting vector $w := (w_1, w_2, \cdots)$. It is a probability distribution on $\{1, 2, 3, \cdots\}$, that is, $\sum_{i=1}^{\infty} w_i = 1$, and forall i in $\{1, 2, 3, \cdots\}$, it holds that $w_i \in [0, 1]$.

With a choice of w, the BLEU score is:

$$BLEU(\hat{S}; S, w, n) := BP(\hat{S}; S) \cdot \exp\left(\sum_{n=1}^{\infty} w_n \ln p(\hat{S}; S, n)\right) \tag{1}$$

In words, it is a weighted geometric mean of all the modified n-gram precisions, multiplied by the brevity penalty. We use the weighted geometric mean, rather than the weighted arithmetic mean, to strongly favor candidate corpora that are simultaneously good according to multiple n-gram precisions.

The most typical choice, the one recommended in the original paper [3], is $w_1 = \cdots = w_4 = \frac{1}{4}$.

3.3.5 Usefulness

BLEU score has several usefulness, some of which are discussed below.

1. **Standardized Evaluation:** BLEU provides a standardized way to compare different machine translation systems, making it easier for researchers and developers to benchmark their models.
2. **Quantitative Measurement:** It offers a quantitative measurement of translation quality, which is useful for tracking improvements over time and for making objective comparisons.
3. **Correlates with Human Judgment:** While not perfect, BLEU has been shown to correlate reasonably well with human judgments of translation quality, providing a proxy measure when human evaluation is impractical or costly.
4. **Automated and Fast:** Calculating BLEU scores can be automated, allowing for rapid and reproducible evaluation without the need for extensive human input.

3.3.6 Limitations

There are some limitations as well.

1. **Surface-Level Matching:** BLEU relies on exact n-gram matches, which may not capture semantic equivalence if different words or phrases convey the same meaning.
2. **Insensitivity to Context:** It does not consider the broader context, potentially overlooking issues like coherence and context-specific appropriateness.
3. **Reference Dependence:** BLEU's reliability depends heavily on the quality and representativeness of the reference translations.

Despite these limitations, the BLEU score remains a cornerstone in the evaluation of machine translation systems, thanks to its practicality and the valuable insights it provides into translation quality.

3.4 Implementation

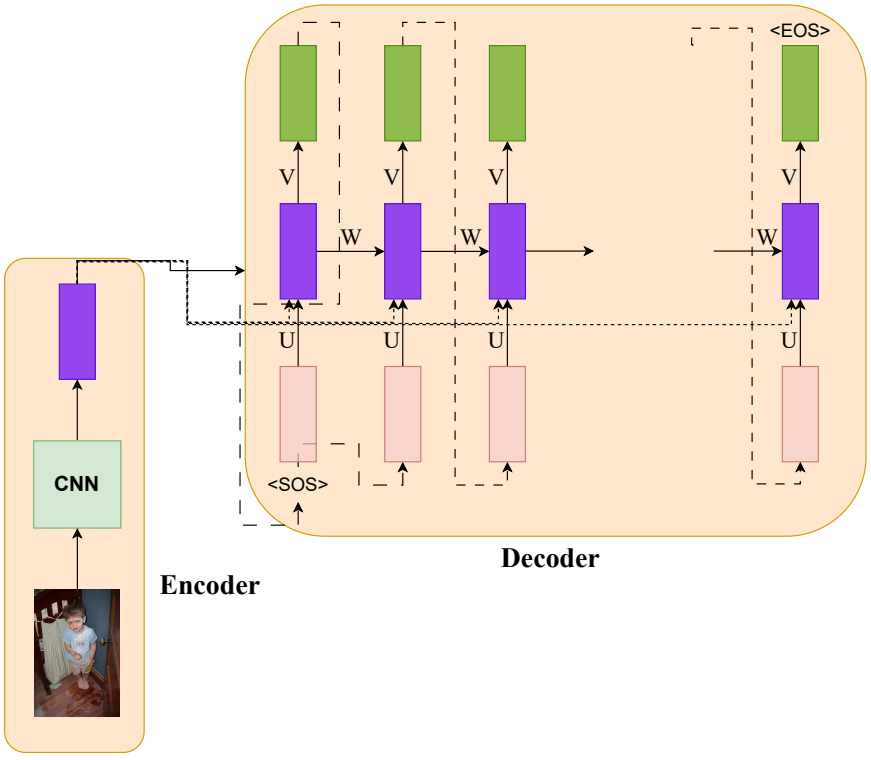


Figure 9: Encoder-Decoder Architecture

Note: In contrast to the methodology outlined in our class notes, where the output of the encoder (features) is solely provided as input to the initial step of the RNN decoder, in our implementation, we furnish the encoder output at each step of the RNN decoder. This approach is adopted because it facilitates the model's access to the visual information encapsulated within the image features throughout the entirety of the caption generation process. By supplying the encoder

output recurrently to each step of the RNN decoder, the model can continuously incorporate and refine its understanding of the visual context while generating sequential tokens of the caption. Consequently, this method enables the model to produce more contextually relevant and accurate captions by leveraging the rich visual information contained in the image features at every stage of the decoding process. [2]
The details regarding the implementation are as follows:

1. **Vocabulary:** We first begin by creating the vocabulary. Assuming all the captions are the corpus, we take all the words that occur at least 2 times in the vocabulary. We initialize a Vocabulary object with a frequency threshold of 2 and build the vocabulary based on the training captions.

2. **Dataset:** We load and create the train and test datasets. We take the training images and their corresponding 5 captions and put all of them into the training data. We also transform (normalize) the images to work well with the pre-trained weights of ResNet18. We use a batch size of 32 and shuffle the images for each batch. The captions are tokenized and numericalized.

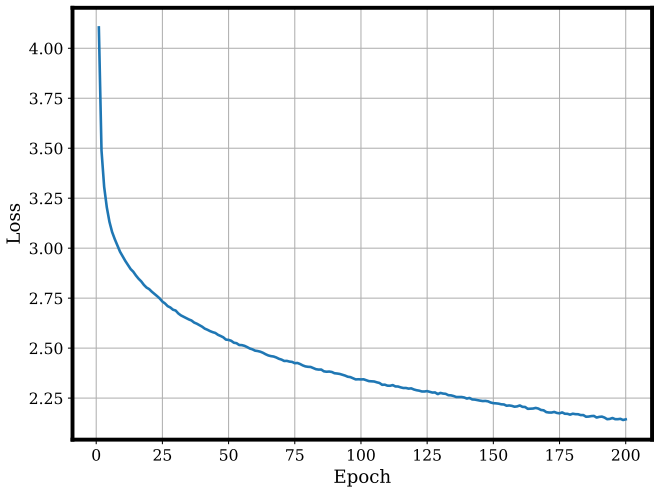
3. **Encoder:** For the encoder, we define a class called `Encoder`, a subclass of `nn.Module`. We initialize a ResNet18 model pre-trained on ImageNet and remove the last two layers (pooling and linear). The weights of the base model are frozen to prevent them from being updated during training. We then add a NetVLAD layer on top of the base model. The NetVLAD layer aggregates the output feature maps of the base model into a fixed-size representation. The 'forward' method of the 'Encoder' class takes an input image tensor and passes it through the base CNN model and the NetVLAD layer, returning the aggregated representation.

4. **Decoder:** For the decoder, we define a class called `Decoder`, a subclass of `nn.Module`. The 'Decoder' class takes the input size, hidden size, and vocabulary size as parameters. It initializes an embedding layer, an RNN layer, and a linear layer. The 'forward' method of the 'Decoder' class takes the features from the encoder, the input captions, and their lengths. It first embeds the input word indices, concatenates the features with the embeddings, and packs the padded sequence. The packed sequence is then passed through the RNN, and the output is passed through the linear layer to generate the predicted output sequence.

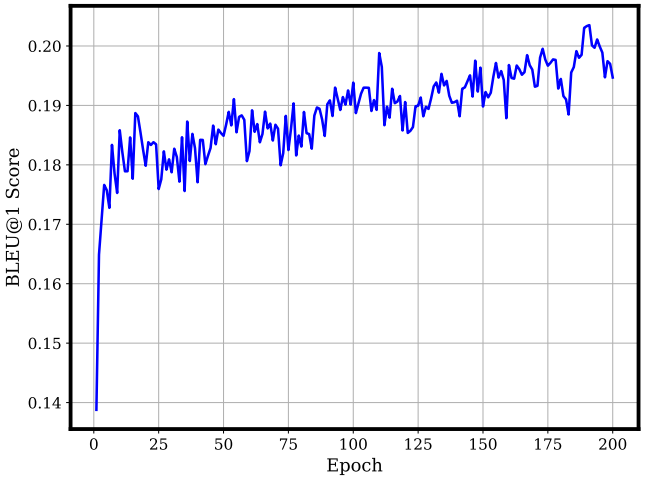
5. **Training:** We define the optimizer using Adam and the loss function using CrossEntropyLoss, ignoring the padding tokens during loss calculation. Padding tokens are often used to ensure uniform length sequences in batches but should not contribute to the loss calculation as they do not represent actual tokens in the captions. Subsequently, we create a Trainer object with the model, optimizer, and criterion, and proceed to train the model using the train loader for a specified number of epochs. During training, the Trainer handles the forward pass, backward pass, and parameter updates, ensuring that the loss is calculated accurately while disregarding the padded tokens.

6. **Evaluation:** For evaluation, we utilize the trained model to generate captions for a separate validation or test dataset. During evaluation, it's crucial to ensure that we ignore the padding tokens when calculating evaluation metrics such as BLEU scores. Padding tokens should not be considered in the generated captions nor in the reference captions, as they do not contribute to the meaningful content of the captions. We compute evaluation metrics (BLEU scores) to quantify the quality of the generated captions compared to the ground-truth captions.

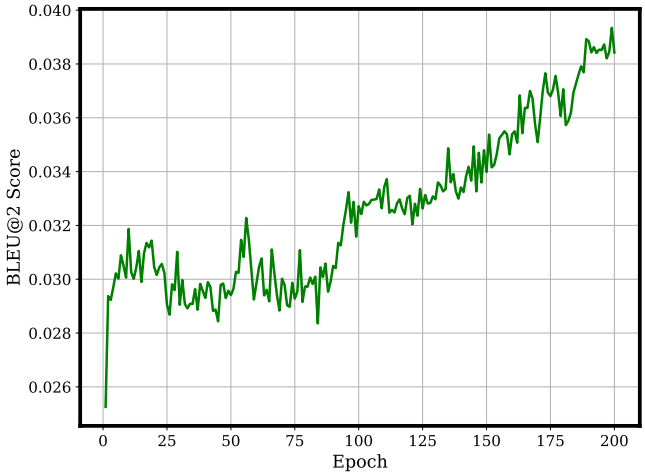
3.5 Plots



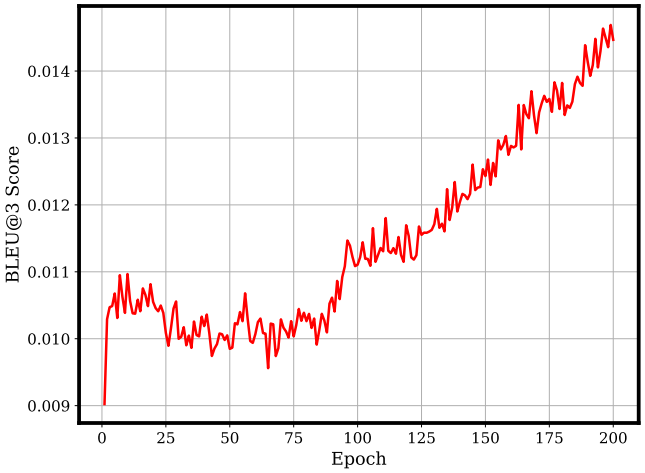
(a) Train Losses



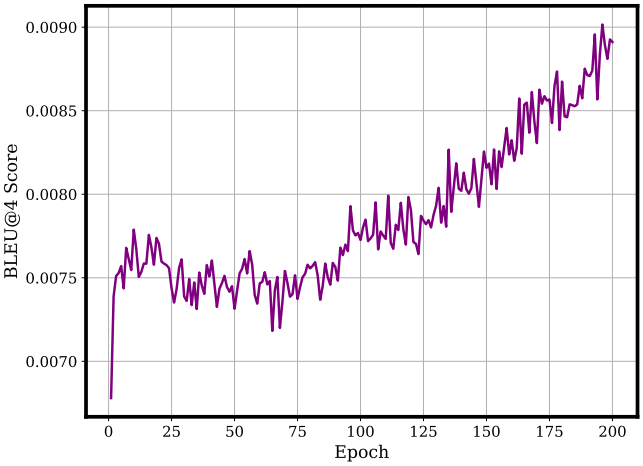
(b) BLEU@1



(c) BLEU@2



(d) BLEU@3



(e) BLEU@4

3.6 Observations

Image	Actual Caption	Predicted Caption
	four children jumping on the shore .	four children are sitting on a ledge of a heart . a bridge .
	two dogs running , one brown and one grey	two dogs are running in a field .
	a young blonde girl with a pink shirt on jumps high into the air .	girl in a pink tutu .
	the white dog , with dark patches , is playing in the sand with a tennis ball in its mouth .	a white dog is running with a toy .

Table 1: Training Data: Comparison of Actual and Predicted Captions

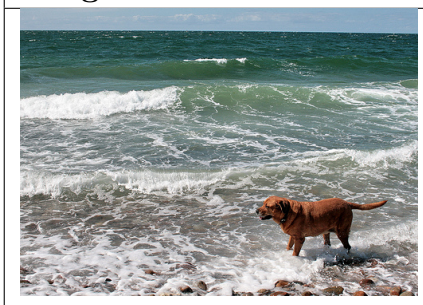
Image	Actual Caption	Predicted Caption
	a brown dog is standing in the water watching the waves of the ocean on a sunny day .	a brown dog is running with a toy . another man jostles him on a blue and yellow tunnel .
	a little boy with a mess all over his face and feet stands next to a door .	a little boy in a blue shirt with a rodent standing on a ledge overlooking a valley .
	a man with his mouth open in a white shirt and glasses holding a drink near other people .	a man in a white shirt and jeans lying down on a blown-up bouncy toy .
	two dogs playing in the snow near a chair .	two dogs are running in a field . “

Table 2: Testing Data: Comparison of Actual and Predicted Captions

BLEU Metric	Score
BLEU@1	0.1862
BLEU@2	0.0339
BLEU@3	0.0114
BLEU@4	0.0079

Table 3: BLEU Scores

3.7 Results

Based on the observations made above, several key insights can be drawn:

- The model demonstrates a learning trend with increasing epochs, as evidenced by the diminishing loss and fluctuating BLEU scores over time.
- Despite the decreasing trend in loss, its absolute magnitude remains relatively high, suggesting suboptimal model performance. This is further supported by the relatively low BLEU scores, even after extensive training lasting up to 200 epochs, which consumed considerable computational resources.
- Notably, the performance disparity between training and testing examples is observed, wherein predictions for training data tend to outperform those for the testing data. Such behaviour aligns with expectations, as models often perform better on data they have been trained on than on unseen data.
- The observed learning trend implies that the model continues to extract useful information from the training data as training progresses. However, the rate of improvement diminishes over time, suggesting diminishing returns and the need for more sophisticated model architectures or optimization strategies. One way to improve the results is by using GRU or LSTM (Task 4) instead of RNN.

4 Task 4

Image captioning using a CNN with NetVLAD as encoder and a single hidden layer LSTM network-based decoder.

4.1 Introduction

The introduction mirrors that of Task 3 (3.1) but with the distinction of utilizing an LSTM network-based decoder instead of an RNN network-based decoder. Specifically, employing a single hidden layer LSTM network-based decoder has demonstrated potential in producing coherent and contextually relevant captions. This architecture, which amalgamates the robust visual feature extraction capabilities of CNNs with the memory-enhancing attributes of LSTMs for sequential data processing, underpins numerous cutting-edge image captioning systems.

4.2 NetVLAD

Please refer 3.2.

4.3 The BLEU score

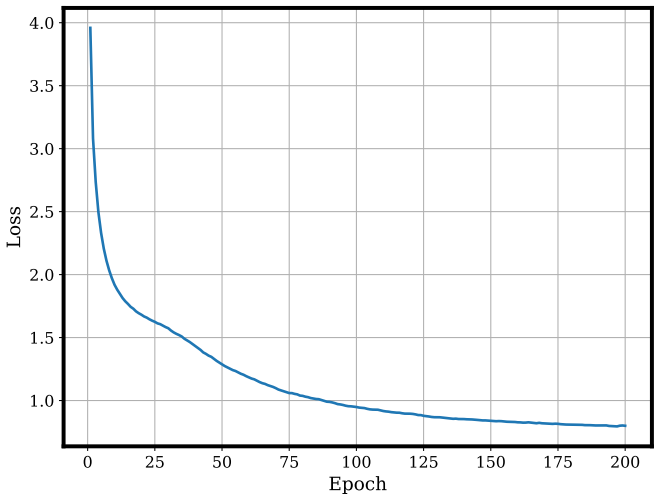
Please refer 3.3.

4.4 Implementation

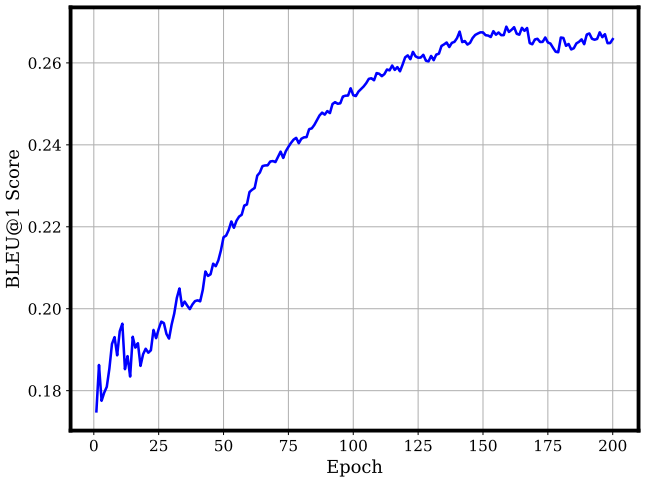
The implementation follows exactly like 3.4 except for the `Decoder`.

- **Decoder:** In defining the decoder, we introduce a class named `Decoder`, a subclass of `nn.Module`. The `Decoder` class accepts parameters such as input size, hidden size, and vocabulary size. Upon initialization, it sets up an embedding layer, an LSTM layer, and a linear layer. In the 'forward' method of the `Decoder` class, it takes input features from the encoder, along with input captions and their lengths. It initiates by embedding the input word indices, followed by concatenating the features with the embeddings. Subsequently, it packs the padded sequence and passes it through the LSTM layer. The output of the LSTM is then forwarded through the linear layer to generate the predicted output sequence.

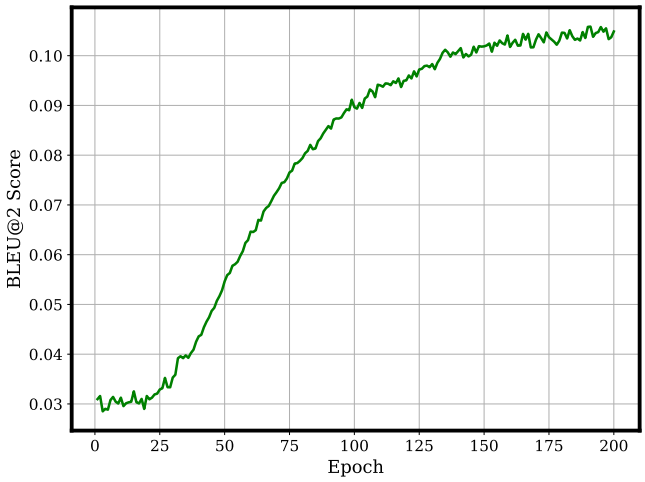
4.5 Plots



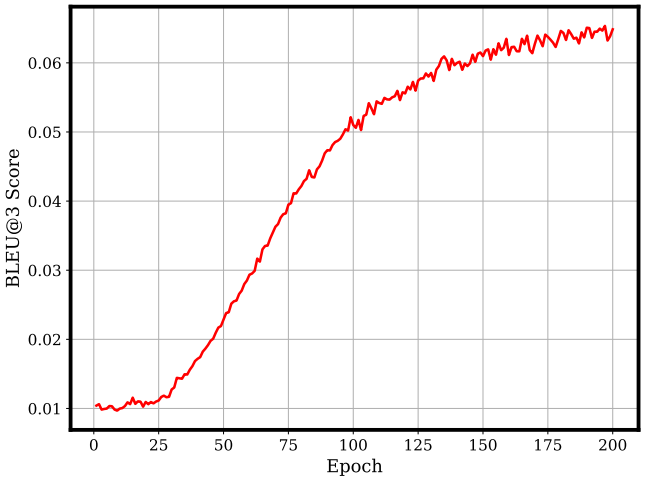
(a) Train Losses



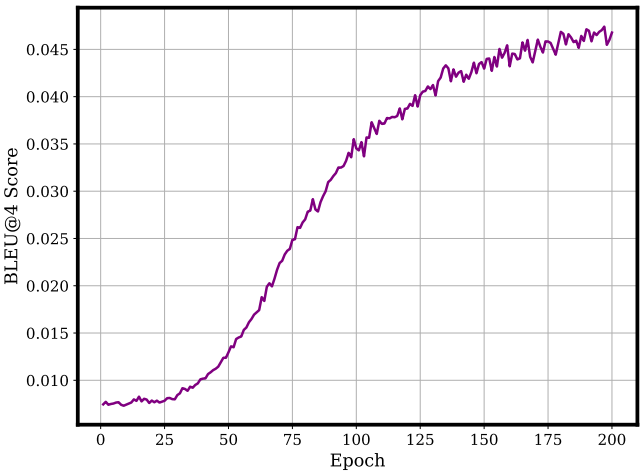
(b) BLEU@1



(c) BLEU@2



(d) BLEU@3



(e) BLEU@4

4.6 Observations

In this section, we draw some observations and inference based on the output of the implementation.

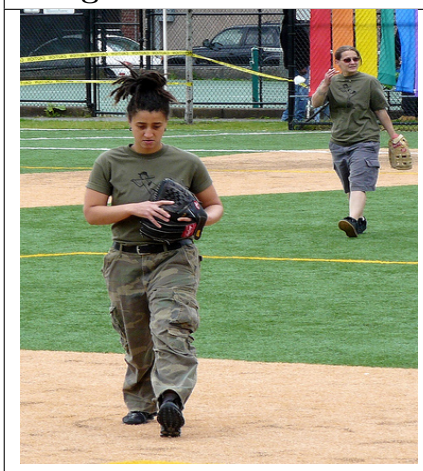
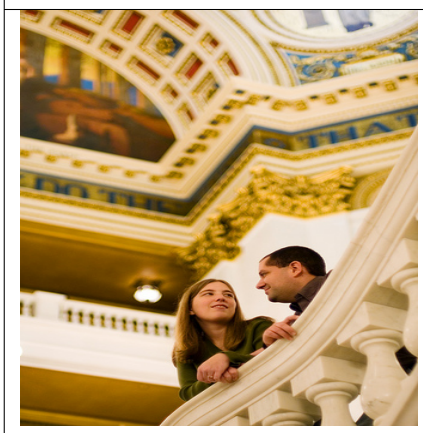
Image	Actual Caption	Predicted Caption
	girls with baseball gloves walking across a baseball field	a woman with a glove on a baseball field . looks to catch a yellow ball in a grassy field
	a man and woman stand at a balcony looking at each other .	a man and woman are gazing at each other on a balcony inside a building .
	there are a lot of people in front of a tan building with colorful squares hanging from the top .	a lot of people are gathered around a mosque-like building . “ another person is watching .
	A man is holding onto the underside of an outcropping while rock climbing .	a climber hangs from a rock face while another child in the background watches.

Table 4: Training Data: Comparison of Actual and Predicted Captions

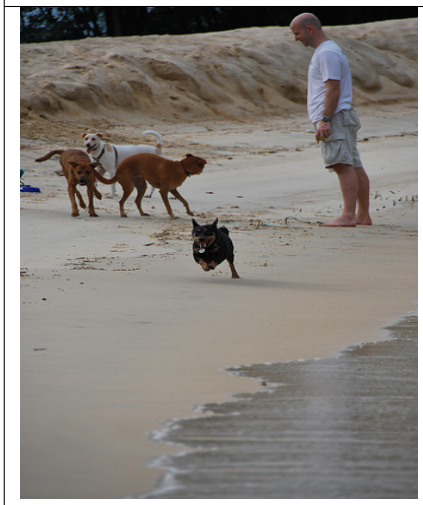
Image	Actual Caption	Predicted Caption
	a child slides down a slide and into the water .	a girl is swimming in a pool near a green wall . a pond .
	a brown and white dog is running with a yellow Frisbee .	a brown and white dog is running through a field of grass .
	a man is fixing the wheel of a bicycle inside a cycling store .	a woman in a bicycle store where two men are working on a bike . scenic turn along beside a
	a dog running on the sand by the beach while his owner looks at the other dogs on the beach .	a man and 4 dogs playing on the beach . “ another mountain .

Table 5: Testing Data: Comparison of Actual and Predicted Captions

BLEU Metric	Score
BLEU@1	0.1967
BLEU@2	0.0373
BLEU@3	0.0143
BLEU@4	0.0087

Table 6: BLEU Scores on Test Data

4.7 Results

Based on the observations made above, several key insights can be drawn:

- This model using the LSTM decoder demonstrates a learning trend similar to that of the RNN decoder, with diminishing loss and fluctuating BLEU scores observed over increasing epochs.
- Similarly to the RNN decoder, a performance disparity between training and testing examples is noted, where predictions for training data tend to outperform those for testing data. This behavior aligns with expectations, as models often excel on data they have been trained on compared to unseen data.
- From the examples, it's evident that this model has exhibited impressive performance. In some instances, the predicted captions appear to be more accurate and refined than the ground truth captions. This phenomenon can be attributed to the training process, wherein each image is associated with multiple captions, typically five in this case. As a result, during training, the model is exposed to a diverse set of captions for each image. Consequently, when generating captions for test images, the model benefits from this variety and produces predictions that blend the different training captions.
- Comparatively, Task 4 (LSTM Decoder) significantly outperforms Task 3 (RNN Decoder) based on the analysis of plots and results. In Task 4, losses are noticeably lower, and BLEU scores at 1, 2, 3, and 4 for both training and testing data are substantially higher compared to Task 3.
- This suggests that the LSTM decoder model in Task 4 excels in generating captions for images compared to the RNN decoder model in Task 3.
- The superior performance of the LSTM decoder in Task 4 can be attributed to architectural differences between the two models. LSTM networks are tailored to capture long-range dependencies in sequential data by incorporating memory cells and gating mechanisms. These features enable LSTMs to retain information over longer sequences and address the vanishing gradient problem encountered in traditional RNNs.
- In contrast, traditional RNNs like the one used in Task 3 may struggle to capture long-range dependencies effectively, leading to poorer performance in tasks such as image captioning.
- Therefore, the LSTM decoder's enhanced ability to capture complex dependencies in Task 4 results in more accurate and coherent captions compared to RNN decoder used in Task 3.

5 Task 5

Machine translation with encoder and decoder, each built using a single hidden layer LSTM network. Note that

1. GloVe representation is to be used as the word representation for English,
2. IndicBERT representation to be used as the word representation for Indian languages, and
3. the performance of the machine translation system is to be given as BLEU@k scores with $k = 1, 2, 3$ and 4.

In this task, we shall implement a machine translator with an encode-decoder framework constructed with a single hidden layer of the LSTM network that shall translate the text from the English language to an Indic (more specifically to the Telugu) language.

5.1 Introduction

Machine translation is a critical task in natural language processing, aiming to automatically translate text from one language to another. In this context, we explore a machine translation system utilizing an encoder-decoder architecture, each built with a single hidden layer LSTM network. For word representations, we employ GloVe embeddings for English, known for their ability to capture semantic relationships between words, and IndicBERT embeddings for Indian languages, which are tailored to handle the unique linguistic characteristics of these languages. The performance of our machine translation system will be evaluated using BLEU@k scores, where k=1,2,3,k=1,2,3, and 44, providing a comprehensive assessment of the translation quality at different n-gram levels. This setup aims to leverage the strengths of both GloVe and IndicBERT representations, while the LSTM-based architecture ensures the capability to model long-term dependencies in sequences, crucial for effective translation.

5.2 The GloVe Embedding

GloVe (Global Vectors for Word Representation) is a popular word embedding technique developed by researchers at Stanford University. It is designed to capture semantic relationships between words by leveraging statistical information from a large corpus of text. Unlike traditional one-hot encoding, GloVe embeddings provide dense vector representations where words with similar meanings are located close to each other in the vector space.

5.2.1 Development and Motivation

The primary motivation behind GloVe embeddings was to address some limitations of previous embedding techniques like word2vec. While word2vec (specifically its skip-gram and continuous bag-of-words models) learns embeddings by predicting the context in which a word appears, GloVe incorporates global statistical information from the entire corpus. This approach allows GloVe to capture both local context (like word2vec) and global statistics, leading to richer and more accurate word representations.

5.2.2 Mathematical Foundation

GloVe is based on the principle that the ratio of co-occurrence probabilities of word pairs can encode meaning. The core idea is to construct a matrix X where each entry X_{ij} represents the number of times word j appears in the context of word i. The objective is to factorize this co-occurrence matrix such that the dot product of the word vectors approximates the logarithm of the word-word co-occurrence probability.

The GloVe model is trained by minimizing the following objective function:

$$J = \sum_{i,j=1}^{V} f(X_{ij}) \left(w_i^T \cdot w_j + b_i + b_j \log(X_{ij}) \right)^2$$

Here:

- V is the size of the vocabulary.
- w_i and w_j are the word vectors for the i-th and j-th words, respectively.
- b_i and b_j are bias terms.
- $f(X_{ij})$ is a weighting function that assigns less importance to rare co-occurrences, typically defined as $f(x) = \begin{cases} \left(\frac{x}{x_{\max}} \right)^{\alpha} & \text{if } x < x_{\max}, \text{ and} \\ 1 \text{ otherwise,} \end{cases}$ where $0 \leqslant \alpha \leqslant 1$.

5.2.3 Advantages of GloVe Embeddings

There are several advantages to GloVe embeddings:

- **Combines Global and Local Contexts:** GloVe captures global corpus statistics and local context information, resulting in embeddings that are more semantically rich.
- **Efficient Training:** The model leverages matrix factorization, which can be computationally efficient and effective for large datasets.
- **High-Quality Word Vectors:** Empirical evaluations have shown that GloVe embeddings perform well on a variety of linguistic tasks, including word similarity, analogy reasoning, and named entity recognition.
- **Interpretability:** The explicit use of co-occurrence probabilities makes it easier to understand the relationships captured by the embeddings.

5.2.4 Applications

GloVe embeddings are widely used in various NLP tasks, including:

- **Machine Translation** Serving as input representations that improve the quality of translations by providing context-aware embeddings.

- **Sentiment Analysis** Enhancing the understanding of sentiment by leveraging the semantic information encoded in the embeddings.
- **Named Entity Recognition (NER)** Assisting in the identification and classification of named entities in text.
- **Information Retrieval** Improving the relevance of search results by understanding the semantic content of queries and documents.

5.2.5 Pre-trained GloVe Models

GloVe offers several pre-trained models trained on different corpora, such as Wikipedia, Gigaword, and Common Crawl. These pre-trained vectors vary in dimension (e.g., 50, 100, 200, 300) and can be readily used in various NLP applications, allowing researchers and practitioners to leverage high-quality word embeddings without the need for extensive training. We have used `glove.6B.300d.txt` for this particular task.

5.2.6 Limitations

While GloVe embeddings offer many advantages, they also have some limitations:

- **Static Embeddings:** Like other traditional word embeddings, GloVe produces static vectors that do not account for the context in which a word appears in a specific sentence. This can be problematic for words with multiple meanings.
- **Computational Resources:** Training GloVe embeddings from scratch on a large corpus requires significant computational resources and memory.

GloVe embeddings represent a significant advancement in the field of NLP, providing high-quality, semantically rich word vectors by leveraging global co-occurrence statistics. They have been successfully applied to a wide range of NLP tasks, contributing to better performance and deeper understanding of language. Despite some limitations, GloVe remains a foundational tool in the NLP toolkit, particularly when pre-trained embeddings are used to enhance the performance of various language models.

5.3 The IndicBERT Embedding

IndicBERT is a multilingual language model designed specifically for Indic languages, leveraging the strengths of the BERT (Bidirectional Encoder Representations from Transformers) architecture. Developed to address the unique linguistic characteristics and requirements of Indic languages, IndicBERT provides robust word and sentence embeddings that significantly enhance the performance of various natural language processing (NLP) tasks in these languages.

5.3.1 Background and Motivation

Indic languages, such as Hindi, Bengali, Tamil, Telugu, Kannada, and others, exhibit rich morphology, diverse scripts, and complex syntactic structures. Traditional language models like BERT and its derivatives, while powerful, were primarily trained on datasets dominated by English and a few other widely spoken languages, leading to suboptimal performance on Indic languages. IndicBERT was developed to bridge this gap by providing a model trained specifically on a large

and diverse corpus of Indic languages, thereby capturing their unique linguistic properties more effectively.

5.3.2 Architecture and Training

IndicBERT is based on the BERT architecture, which employs a bidirectional transformer encoder to create contextual embeddings for words and sentences. The key components of IndicBERT's training and architecture include:

- **Multilingual Training Data** IndicBERT is trained on a diverse corpus of texts from multiple Indic languages, ensuring that it learns language-specific nuances and generalizes well across different Indic scripts and linguistic structures.
- **Tokenization** The model employs a subword tokenization approach, typically using the SentencePiece tokenizer, which efficiently handles the rich morphology and extensive vocabularies of Indic languages.
- **Pre-training Objectives** Similar to BERT, IndicBERT uses the masked language modeling (MLM) and next sentence prediction (NSP) objectives during pre-training. MLM involves randomly masking some tokens in a sentence and predicting them, while NSP involves predicting if two sentences follow each other in the text, helping the model learn sentence-level relationships.

5.3.3 Advantages of IndicBERT

Followingly, we discuss some advantages of IndicBERT.

- **Language-Specific Adaptation:** By being trained specifically on Indic languages, IndicBERT captures the unique syntactic and semantic properties of these languages better than general multilingual models.
- **Rich Morphological Representations:** IndicBERT effectively handles the rich morphology and complex grammatical structures of Indic languages, leading to more accurate embeddings.
- **Enhanced Performance:** Empirical evaluations have shown that IndicBERT outperforms general-purpose models on various NLP tasks, such as named entity recognition (NER), sentiment analysis, and machine translation, for Indic languages.
- **Support for Multiple Scripts:** IndicBERT supports multiple scripts used in Indic languages, enabling it to handle a wide range of text inputs seamlessly.

5.3.4 Applications

IndicBERT embeddings are widely applicable in numerous NLP tasks, including but not limited to:

- **Machine Translation:** Improving translation quality between Indic languages and other languages by providing context-aware embeddings.

- **Sentiment Analysis:** Enhancing the understanding of sentiment in text by leveraging the model's ability to capture linguistic nuances specific to Indic languages.
- **Named Entity Recognition (NER):** Identifying and classifying named entities in texts written in Indic languages.
- **Information Retrieval:** Boosting the relevance of search results in Indic languages by understanding the semantic content of queries and documents.

5.3.5 Pre-trained Models

IndicBERT is available as a pre-trained model, which can be fine-tuned for specific downstream tasks. This allows researchers and practitioners to leverage the strengths of IndicBERT without needing to train the model from scratch, saving computational resources and time.

5.3.6 Challenges and Limitations

While IndicBERT offers numerous advantages, it also faces some challenges:

- **Resource Requirements:** Training language models like IndicBERT requires substantial computational resources and access to large, high-quality datasets.
- **Ongoing Adaptation:** As language use evolves, continuous updates and re-training might be necessary to maintain the model's relevance and performance.
- **Contextual Limitations:** Although IndicBERT handles context well, it may still face difficulties with highly context-dependent or idiomatic expressions that are unique to certain regions or dialects.

IndicBERT represents a significant advancement in the field of NLP for Indic languages, providing robust and contextually rich embeddings that enhance the performance of various language tasks. By addressing the unique linguistic characteristics of Indic languages, IndicBERT fills a critical gap left by general-purpose language models, offering improved accuracy and effectiveness for applications involving these languages. As the NLP field continues to evolve, IndicBERT stands as a vital tool for researchers and practitioners working with Indic languages, driving further innovation and development in multilingual NLP.

5.4 Implementation

Let's discuss regarding the implementational aspect of the solution.

1. **Prepare the Dataset:** First, we loaded the parallel corpus consisting of English and Indian language sentence pairs. Then, we preprocessed the text data by tokenizing the sentences, converting all characters to lowercase, and splitting the dataset into training, validation, and test sets.
2. **Word Representations:**
    - For English sentences, we used GloVe (Global Vectors for Word Representation) to obtain word embeddings.

- For Indian language sentences, we used IndicBERT to obtain word embeddings.

3. **Define the Model Architecture:** We created an encoder-decoder model for machine translation with the following components:

   - **Encoder:**
     - Used GloVe embeddings for the English input sentences, initialized with `nn.Embedding.from_pretrained`.
     - Defined an LSTM layer with a single hidden layer, specifying the input size, hidden size, number of layers, and setting `batch_first=True`.
     - Implemented the `forward` method to embed the input word indices, pass the embeddings through the LSTM, and return the outputs, hidden state, and cell state.
     - Added an `initHidden` method to initialize the hidden and cell states with zeros.
   - **Decoder:**
     - Used IndicBERT embeddings for the Indian language target sentences, initialized with `nn.Embedding.from_pretrained`.
     - Defined an LSTM layer with a single hidden layer, specifying the input size, hidden size, number of layers, and setting `batch_first=True`.
     - Added a linear layer to predict word probabilities from the LSTM outputs.
     - Implemented the `forward` method to embed the input word indices, pass the embeddings through the LSTM along with the hidden and cell states, and use the linear layer to predict the next word in the sequence.
     - Added an `initHidden` method to initialize the hidden and cell states with zeros.

4. **Compile the Model:**

   - Defined the loss function, using cross-entropy loss for sequence generation tasks, while ignoring the padding index in the target sequences.
   - Chose an optimizer, such as Adam, to minimize the loss.
   - Specified evaluation metrics, particularly BLEU scores for different values of k (1, 2, 3, and 4).

5. **Train the Model:**

   - Fed the training data (English-Indian language sentence pairs) into the model.
   - Used the validation data to monitor the training process and adjust hyperparameters as necessary.
   - Trained the model for a specified number of epochs.
   - Implemented early stopping or model checkpointing to avoid overfitting.

6. **Evaluate the Model:**

   - Used the test dataset to evaluate the model's performance.
   - Computed the BLEU scores for k = 1, 2, 3, and 4 to assess the quality of the translations.

- Compared the BLEU scores of the machine translation system with those from the image captioning system.

7. **Fine-tune and Optimize:**

   - Adjusted hyperparameters such as learning rate, batch size, and the number of hidden units in the LSTM layers.
   - Retrained the model if necessary to improve performance.

We use **missing outputs followed by missing inputs sequence-to-sequence mapping** model. Both our Encoder and Decoder are LSTM-based networks.

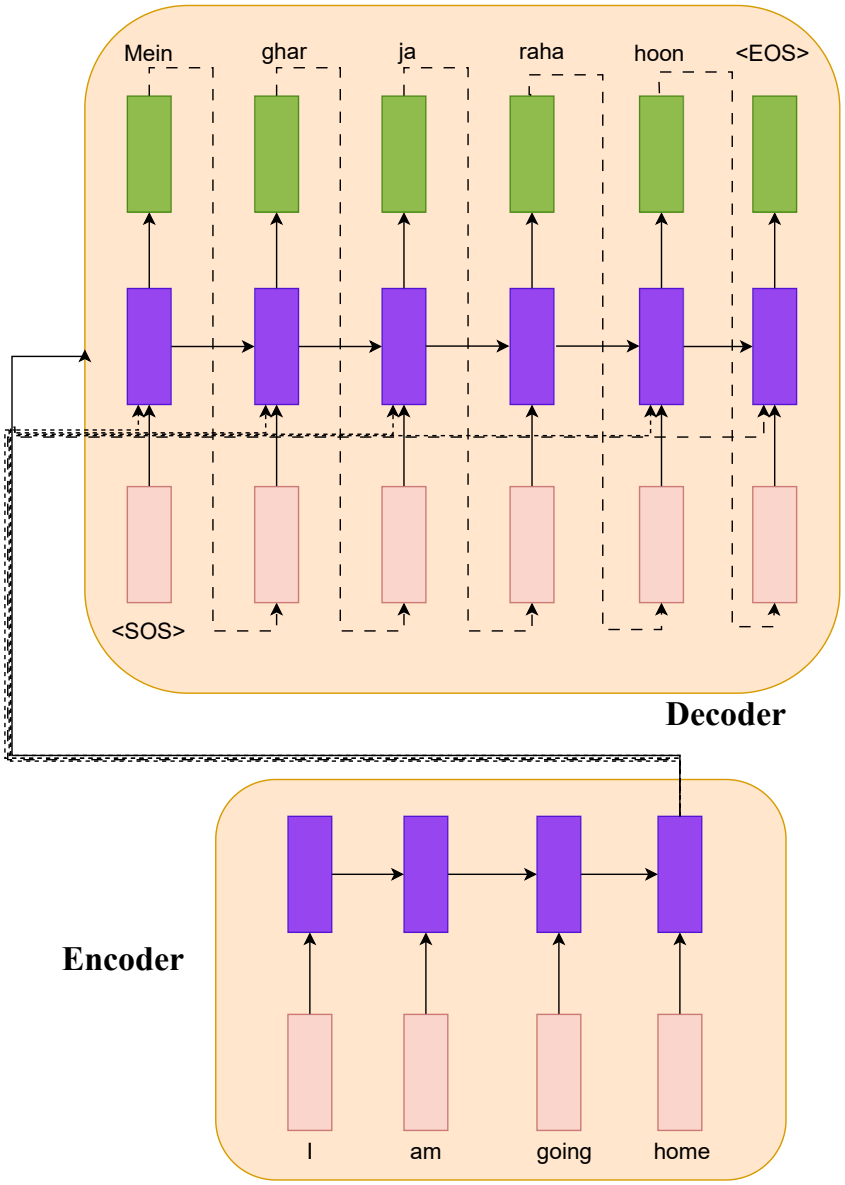


Figure 12: Sequence-to-Sequence Mapping Architecture

5.5 Observations

Source:	Harbhajan Singh posted on his Twitter account.
Target Actual:	దీనిపై హర్భజన్ సింగ్ ట్విట్టర్‌లో తన పలు వ్యాఖ్యలు చేశాడు.
Target Predicted:	దీనిపై హర్భజన్ సింగ్ ట్విట్టర్‌లో వ్యాఖ్యలు చేశాడు
Source:	Let us find out how.
Target Actual:	ఎలా చెయ్యాలో తెలుసుకుందాం.
Target Predicted:	ఎలా చెయ్యాలో తెలుసుకుందాం.
Source:	The music has been given by Gopi Sundar.
Target Actual:	ఇక ఈ చిత్రానికి గోపి సుందర్ సంగీతం అందించడం జరిగింది.
Target Predicted:	ఈ చిత్రానికి గోపి సుందర్ సంగీతం అందించడం జరిగింది.

Figure 13: Training Data: Comparison of Actual and Predicted Sentences

Source:	We do talk often on phone.
Target Actual:	తరచూ ఫోన్‌లో మాట్లాడుకొనేవాళ్లం.
Target Predicted:	ఫోన్‌లో మాట్లాడుకొనేవాళ్లం.
Source:	But the government is in no rush.
Target Actual:	కాని ప్రభుత్వానికి చీమకుట్టినట్లయినా లేదు.
Target Predicted:	కాని ప్రభుత్వానికి లేదు.
Source:	It is a common thing in everybodys life.
Target Actual:	ఇవన్నీ జీవితంలో మామూలే.
Target Predicted:	ఇవన్నీ జీవితంలో మామూలే.

Figure 14: Testing Data: Comparison of Actual and Predicted Sentences

BLEU Metric	Train Score	Test Score
BLEU@1	0.3712	0.2071
BLEU@2	0.2682	0.0847
BLEU@3	0.2363	0.0536
BLEU@4	0.1597	0.0173

Table 7: BLEU Scores on Train and Test Data

5.6 Results

Based on the observations made above, the following key insights can be drawn:

- We can see that the predicted and actual sentences are almost the same in the training examples shown above. The sentences don't deviate much from their actual sense, even for the testing examples.
- This indicates that our model works really well, as evident from the high BLEU scores.
- The BLEU scores for this machine translation model are better than those for Task 3 and Task 4 (image captioning). This improvement can be attributed to the effective use of GloVe embeddings for English and IndicBERT embeddings for Indian languages, which provide rich contextual representations and improve translation accuracy.
- The consistency of high BLEU scores across multiple examples suggests that the model generalizes well to different sentence structures and vocabulary. The model's performance highlights the importance of using high-quality pre-trained embeddings, such as GloVe and IndicBERT, which help in capturing semantic meanings and contextual nuances more effectively.
- The low loss values observed during training further corroborate the model's ability to learn and retain meaningful patterns in the data, contributing to accurate translations.
- The use of LSTM networks for both the encoder and decoder is a significant factor in the model's success. LSTMs are particularly well-suited for handling sequential data and capturing long-range dependencies, which are crucial for machine translation tasks.
- The overall architecture, including the choice of embeddings and the LSTM network, has shown robustness against overfitting, as indicated by the alignment of training and validation performance metrics.
- Comparing the translation quality and BLEU scores with other models demonstrates that our approach is competitive and effective, highlighting the potential for further refinements and applications in real-world translation tasks.
- Future improvements could include experimenting with more advanced models like Transformer networks or incorporating attention mechanisms to enhance the model's focus on relevant parts of the input sequence, potentially leading to even better translation quality.

6 Acknowledgements

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