CZ4042 Neural Networks and Deep Learning

Project 2

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Contents

1. Introduction

The objective of this project is to experiment with Convolutional Neural Network and Recurrent Neural Network architectures and different sets of hyperparameters to determine the optimal structure of models to target specific problems.

1.1 Part A

In this project we are required to build convolutional neural networks with different structure and hyperparameters to classify images from CIFAR-10 dataset. The dataset contains RGB images of size 32 * 32 and are categorized with 10 labels from 0 to 9. The training data contains 10,000 training samples and testing data contains 2,000 testing samples.

The default structure of the network consists an input layer, two pairs of convolution layer and max pooling layer which we will implement grid search to determine their optimal number of channels, one fully connected layer with no activation and one fully connected layer with Softmax activation. We will also explore the effects of different optimizers on the performance of the models.

1.2 Part B

In this project we are required to build convolutional neural networks and recurrent neural networks which takes characters and words as inputs respectively to classify texts from the dataset. The output layer of the model is a Softmax layer.
The dataset contains the first paragraphs collected from Wikipage entries and are categorized with different labels.
We will experiment the performances of the model on the word-level input and character-level input. We will also explore the effects of a dropout layer before the output layer and the effects of different network structure and optimizers on the performance of the networks. We have selected the accuracy, loss, and training time of a model as metrics to evaluate its performance.

2. Method

2.1. Part A

2.1.1. Model Development

We start with a default convolutional neural network model with the following architecture:

- An Input layer of 32x32x3 dimensions.
- A convolution layer $C1$ with 50 channels, window size 9x9, VALID padding, and ReLU activation.
- A max pooling layer $S1$ with a pooling window of size 2x2, stride = 2, and VALID padding.
- A convolution layer $C2$ with 60 channels, window size 5x5, VALID padding, and ReLU activation.
- A max pooling layer $S2$ with a pooling window of size 2x2, stride = 2, and VALID padding.
- A fully connected layer $F3$ of size 300 with no activation.
- A fully connected layer $F4$ of size 10 with Softmax activation.

The hyperparameters we will explore with the networks are:

1. The number of channels in convolution layer C1.

2. The number of channels in convolution layer C2.
3. Whether to apply dropout layers with drop rate of 50% to the fully connected layers.
4. Different optimizers like SGD, SGD with momentum (0.1), RMSProp, and Adam.

2.1.2. Hyperparameter Optimization

We will adopt the accuracy on the testing data set as the metric for determining the performance of the model.

We adopted grid search and limited the range of possible number of channels of the first convolution layer to [10, 30, 50, 70, 90] and the possible number of channels of the second convolution layer to [20, 40, 60, 80, 100], this will give us a combination of 25 models.

The performances of the models will be compared and analyzed in the conclusion section in the Experiments and Results section of Part A.

2.2. Part B

2.2.1. Model Development

In this project we develop four baseline models, which are Character CNN, Word CNN, Character RNN, Word RNN.

For character-level networks, we implement one-hot encoding for the input data for a total vocabulary size of 256. For word-level networks, we implement an embedding layer of size 20 before feeding the data to the network.

Architecture for Character CNN:

• A convolution layer $C1$ of 10 filters of window size 20x256, VALID padding, and ReLU neurons. A max pooling layer $S1$ with a pooling window of size 4x4, with stride = 2, and padding = 'SAME'.

• A convolution layer $C2$ of 10 filters of window size 20x1, VALID padding, and ReLU neurons. A max pooling layer $S2$ with a pooling window of size 4x4, with stride = 2 and padding = 'SAME'.

Architecture for Word CNN:

• A convolution layer $C1$ of 10 filters of window size 20x20, VALID padding, and ReLU neurons. A max pooling layer $S1$ with a pooling window of size 4x4, with stride = 2, and padding = 'SAME'.

• A convolution layer $C2$ of 10 filters of window size 20x1, VALID padding, and ReLU neurons. A max pooling layer $S2$ with a pooling window of size 4x4, with stride = 2 and padding = 'SAME'.

Architecture for Character RNN:

• A recurrent layer R1 with GRU cell and a hidden layer size of 20.

Architecture for Word RNN:

• A embedding layer of size 20 for data to pass before following layers.

• A recurrent layer R1 with GRU cell and a hidden layer size of 20.

2.1.2. Hyperparameter Optimization

We will adopt the accuracy on the testing data set and total training time as the metric for determining the performance of the model.

We will experiment with adding dropout layers with drop rate of 0.5 before the output layer to analyze its effect on the performance on the model.

We will also experiment with the types of RNN layers, the number of layers and hyperparameters like gradient clipping threshold for optimizers.

The performances of the models will be compared and analyzed in the conclusion section in the Experiments and Results section of Part B.

3. Experiments and Results

3.1. Part A

3.1.1. Question 1 Training the network

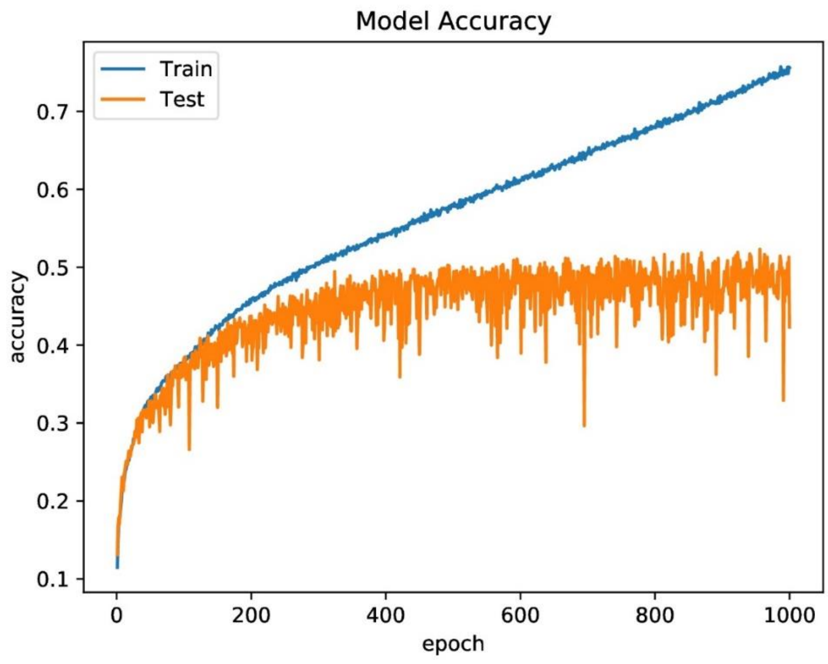
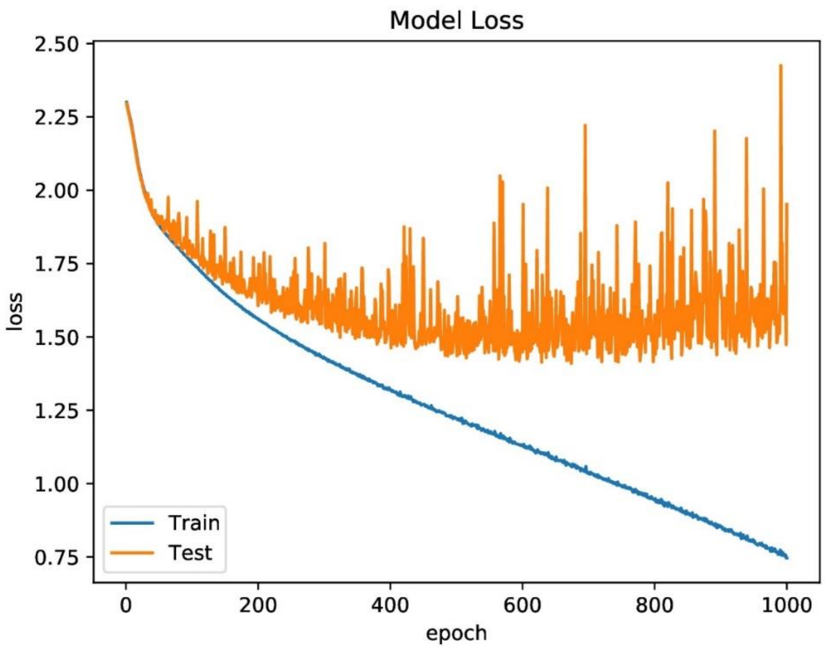
We developed the model using the following code:

```
def make_model(num_ch_c1, num_ch_c2, use_dropout):
    model = tf.keras.Sequential()
    # Input layer
    model.add(layers.Input(shape=(3072,)))
    model.add(layers.Reshape(target_shape=(32, 32, 3),
input_shape=(3072,)))  # why not just input(shape=(32, 32,
3))?

    # First pair of convolution layer and max pooling layer
    model.add(layers.Conv2D(num_ch_c1, 9, activation='relu',
input_shape=(None, None, 3)))  # default padding is VALID
    model.add(layers.MaxPooling2D(pool_size=(2, 2),
strides=2))  # default padding is VALID

    # Second pair of convolution layer and max pooling layer
    model.add(layers.Conv2D(num_ch_c2, 5, activation='relu',
input_shape=(None, None, 3)))
    model.add(layers.MaxPooling2D(pool_size=(2, 2),
strides=2))

    model.add(layers.Flatten())

    # Add dropout layer with dropout rate of 0.5 depending on
the paramter use_dropout
    if use_dropout:
        model.add(layers.Dropout(0.5))
    model.add(layers.Dense(300))

    if use_dropout:
        model.add(layers.Dropout(0.5))
    model.add(layers.Dense(10, use_bias=True,
input_shape=(300,)))
    # Here no softmax because we have combined it with the
loss(from_logits=True)
    return model
```

The function takes in three parameters, **num_ch_c1**, **num_ch_c2**, and **use_dropouts**. **num_ch_c1** and **num_ch_c2** indicates the number of channels in the convolution layers This will serve as a baseline for the following sections.

3.1.1.(a)Plot the accuracies and loss of training and testing against training epoch

The accuracies and loss of the model against each training epoch is given below:

Model Accurac y	
Model Loss	

3.1.1.(b) For the first two test images, plot the feature maps at both convolution layers and pooling layers along with the test images.

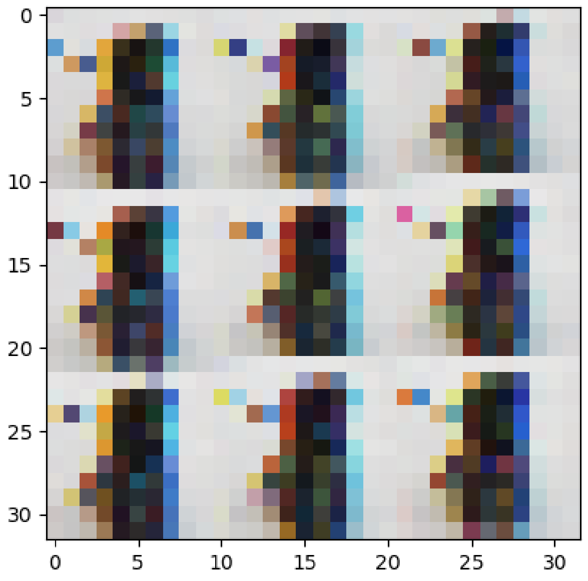
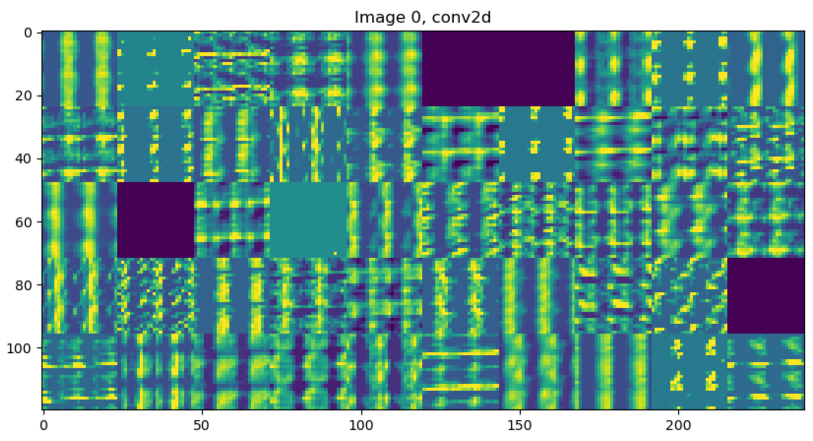
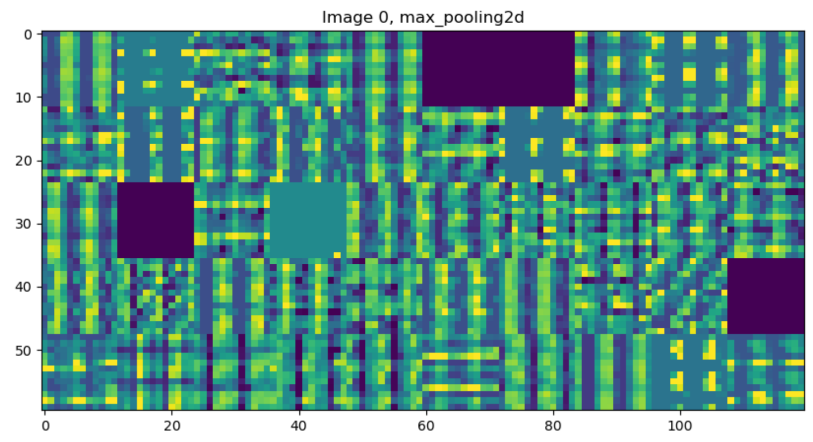
We used the following code to display the images:

```
test_imgs = x_test[0:2]  # test the first two images

for i, img in enumerate(test_imgs):
    img = tf.reshape(img, [32, 32, 3])
    plt.imshow(img, interpolation='nearest')
    plt.savefig(f'./results/testImage_{i}.png')
```

The after training the model, we used the following section of code to display the intermediate results:

```
for img_idx in [0, 1]:
    for layer_name, layer_activation in zip(layer_names,
activations):
        n_features = layer_activation.shape[-1]
        size = layer_activation.shape[1]
        n_cols = n_features // images_per_row
        display_grid = np.zeros((size * n_cols, images_per_row
* size))

        for col in range(n_cols):
            for row in range(images_per_row):
                channel_img = layer_activation[img_idx, :, :,
col * images_per_row + row]
                channel_img -= channel_img.mean()
                channel_img /= channel_img.std()
                channel_img *= 64
                channel_img += 128
                channel_img = np.clip(channel_img, 0,
255).astype('uint8')
                display_grid[col * size:(col + 1) * size, row
* size:(row + 1) * size] = channel_img
        scale = 1. / size
        plt.figure(figsize=(scale * display_grid.shape[1],
                            scale * display_grid.shape[0]))
        plt.title("Image " + str(img_idx) + ", " + layer_name)
        plt.grid(False)
        plt.imshow(display_grid, aspect='auto')
        plt.savefig(
            f'./results/Image_{img_idx}_{layer_name}.png')
        plt.clf()
```

The result of the first two images and their intermediate results after the convolution layers and polling layers are given below:

Image 0	
Feature Map at C1	
Feature Map at S1	

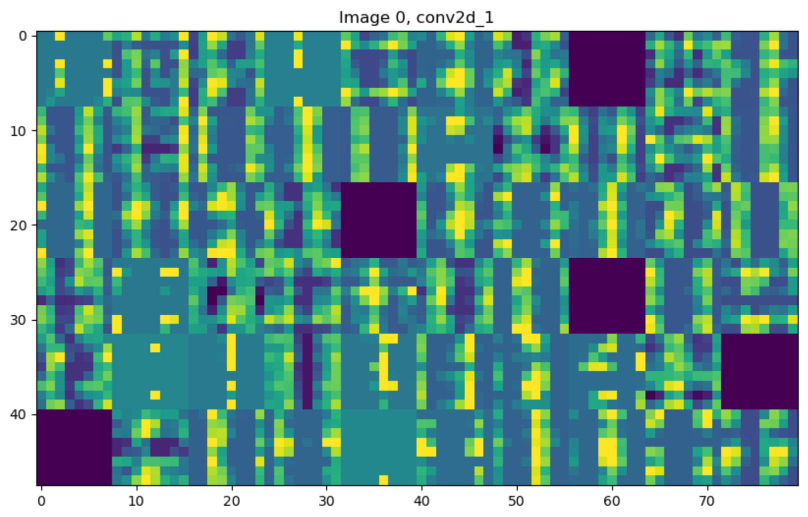
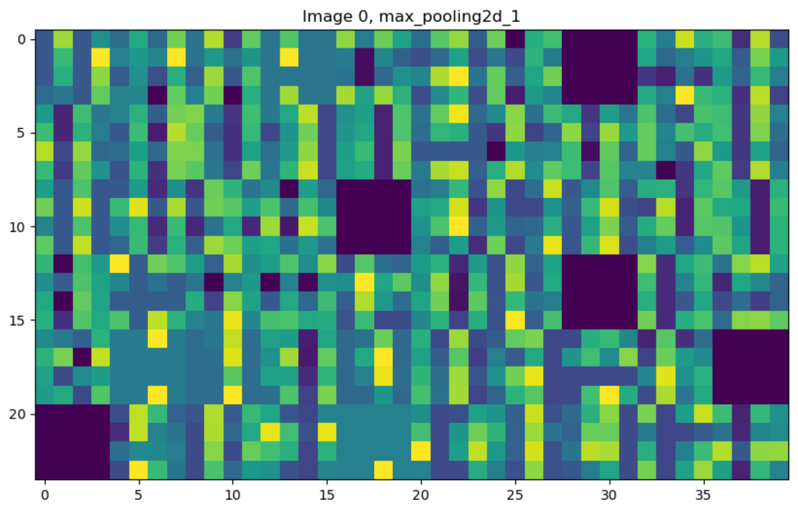
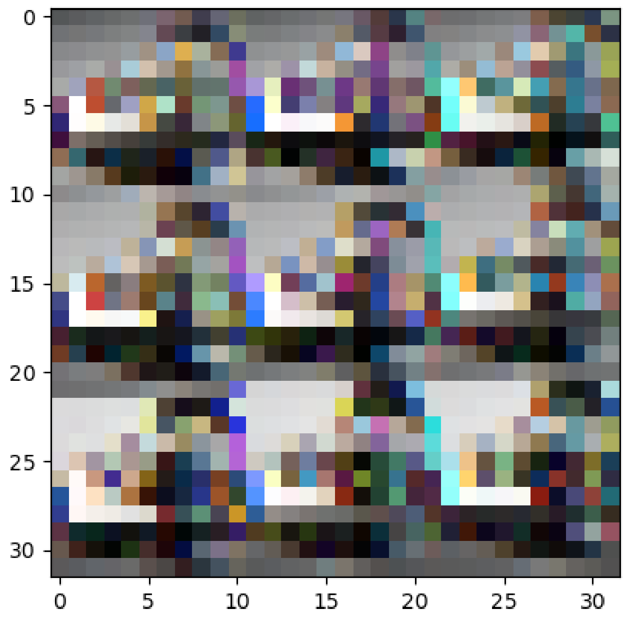
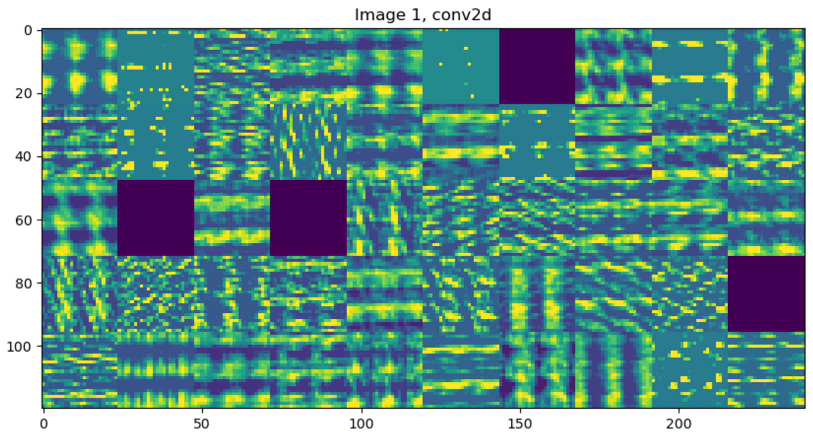
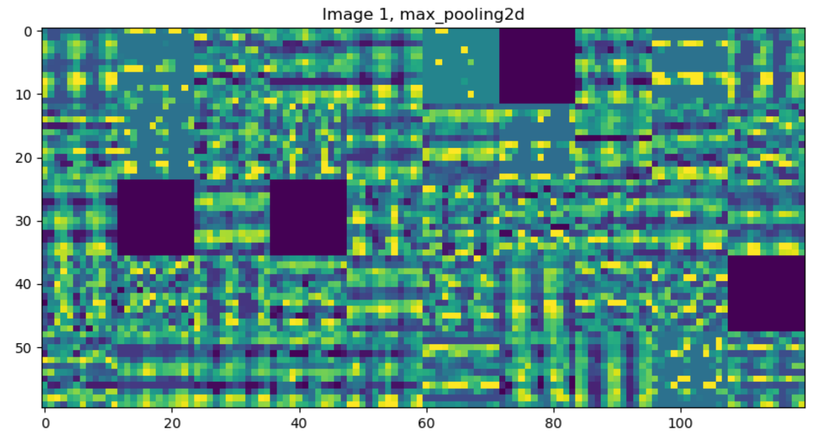
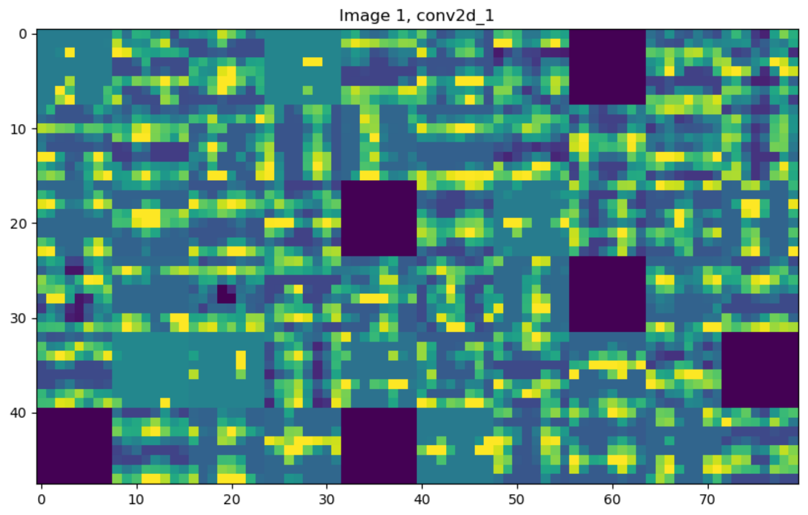
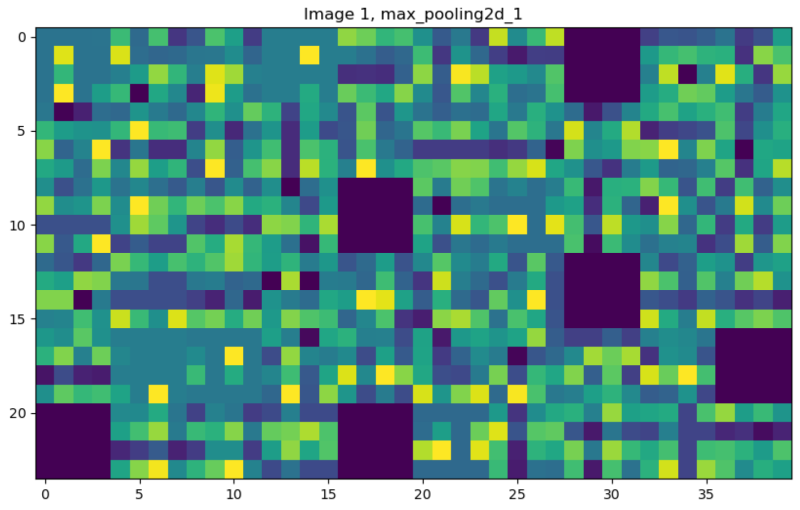
Feature Map at C2	
Feature Map at S2	

Image 1	
Feature Map at C1	
Feature Map at S1	

Featur e Map at C2	
Featur e Map at S2	

3.1.2. Question 2 Use a grid search to find the optimal combination of the numbers of channels at the convolution layers.

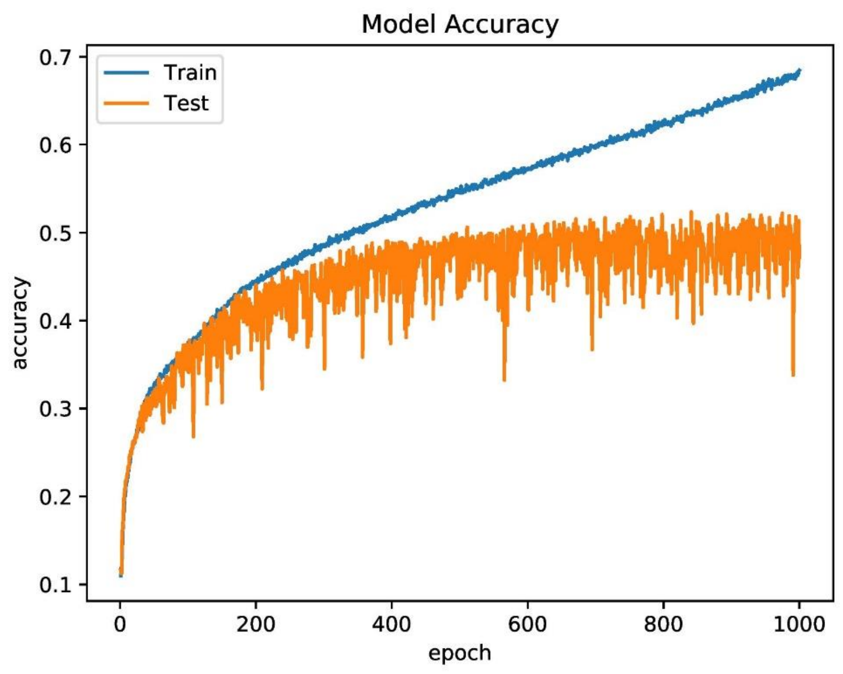
We applied the grid search to train the 25 models aforementioned in the method section and recorded their accuracy and loss as following:

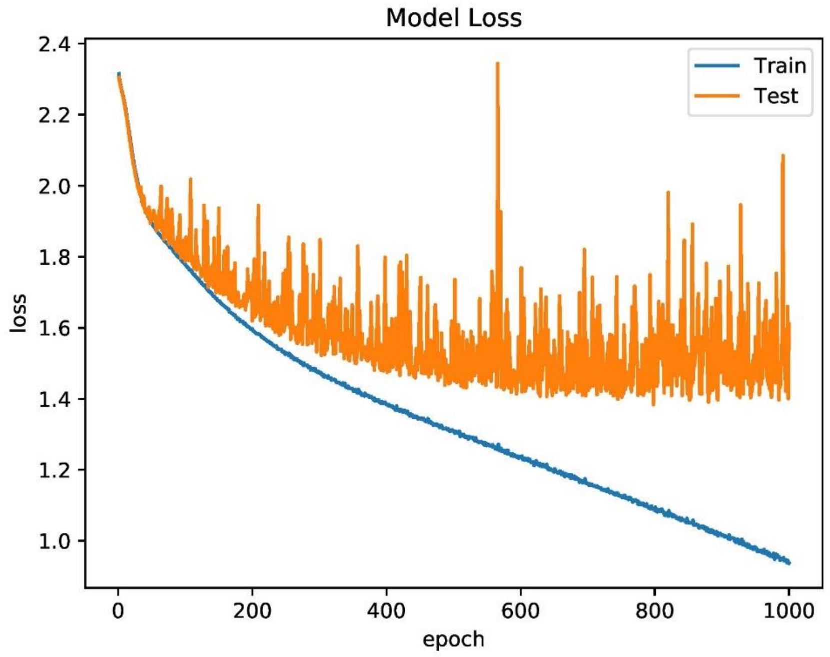
C1	C2	Accuracy	Loss
10	20	0.4335	1.600266547203064
10	40	0.474	1.6105144748687743
10	60	0.447	1.722028130531311
10	80	0.395	2.060461317062378
10	100	0.4495	1.728692039489746
30	20	0.4625	1.571728699684143
30	40	0.404	1.9098822059631348
30	60	0.425	1.8802436389923096
30	80	0.3745	2.206295244216919
30	100	0.4145	2.1070687370300294
50	20	0.461	1.6028640966415406

50	40	0.4675	1.7147203922271728
50	60	0.4525	1.9518405380249024
50	80	0.4105	1.7616415233612062
50	100	0.448	1.96665834236145
70	20	0.474	1.5943922576904297
70	40	0.455	1.8243213157653808
70	60	0.3975	1.9165659065246583
70	80	0.455	1.9572435817718505
70	100	0.4455	1.9626891288757324
90	20	0.442	1.7560296392440795
90	40	0.4465	1.887927869796753
90	60	0.4475	2.029411937713623
90	80	0.443	2.12908487701416
90	100	0.3925	1.8592973976135254

By observing from the evaluation data, we can conclude that the model with 70 channels in the first convolution layer and 20 channels in the second convolution layer has the highest accuracy and lowest validation loss. We will use this setting as the baseline for the following questions.

The accuracies and loss of training and testing against epochs for the (70, 20) model are given below:

Model Accurac y	

Model Loss	

3.1.3. Question 3 Experiments with variations

We adopted the (70, 20) pair as the optimal model for this section.

The following variations are experimented:

a. adding the momentum term with momentum $\gamma = 0.1$,

b. using RMSProp algorithm for learning,

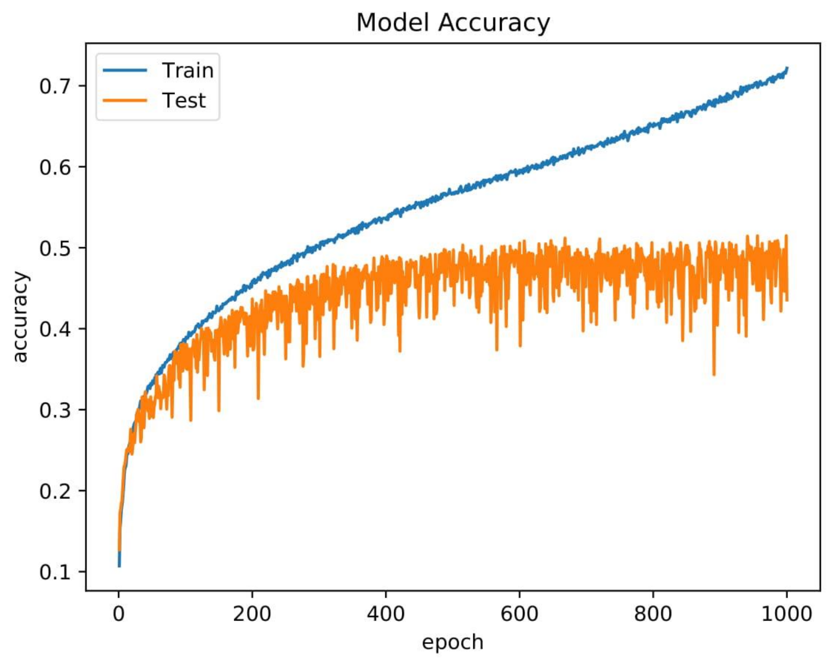
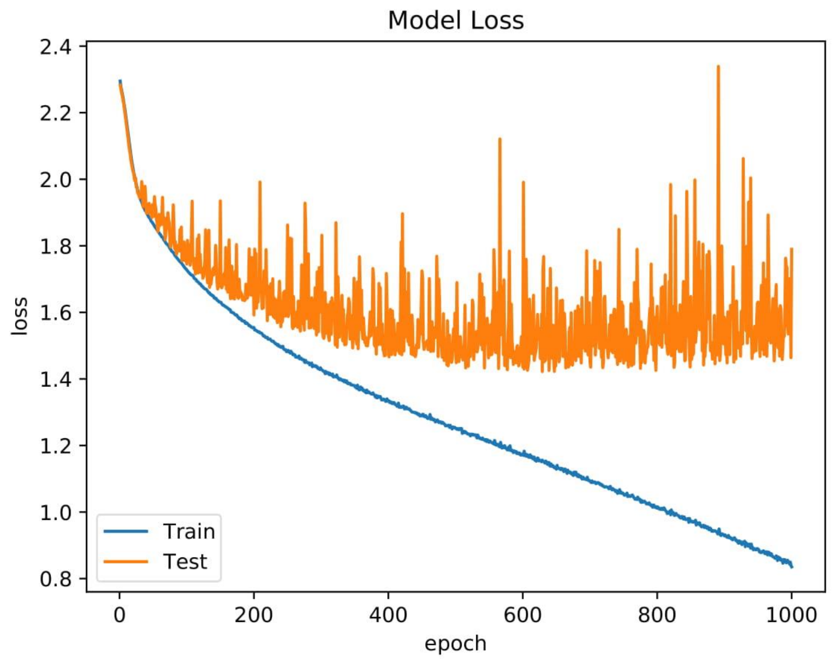
c. using Adam optimizer for learning,

d. adding dropout (probability=0.5) to the two fully connected layers.

3.1.3.(a) adding the momentum term with momentum $\gamma = 0.1$

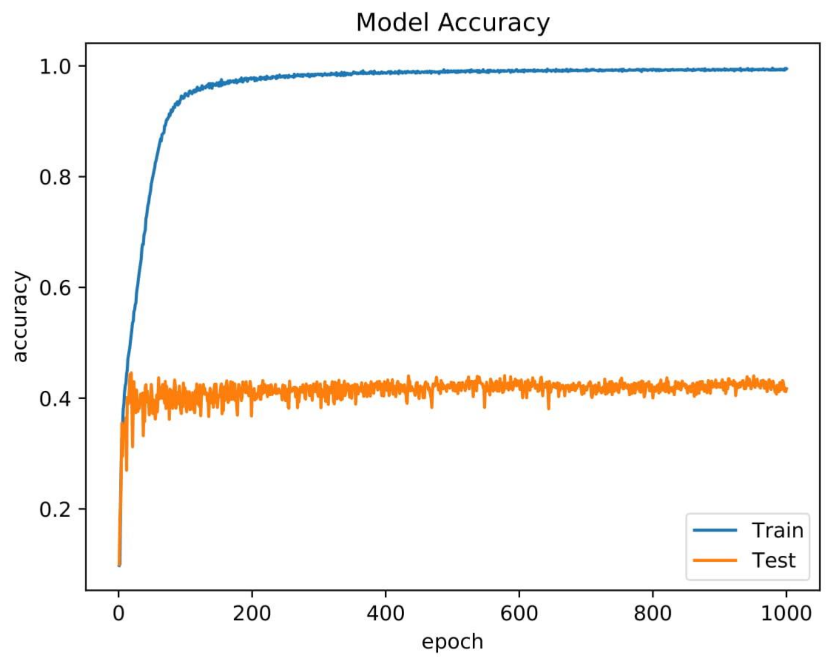
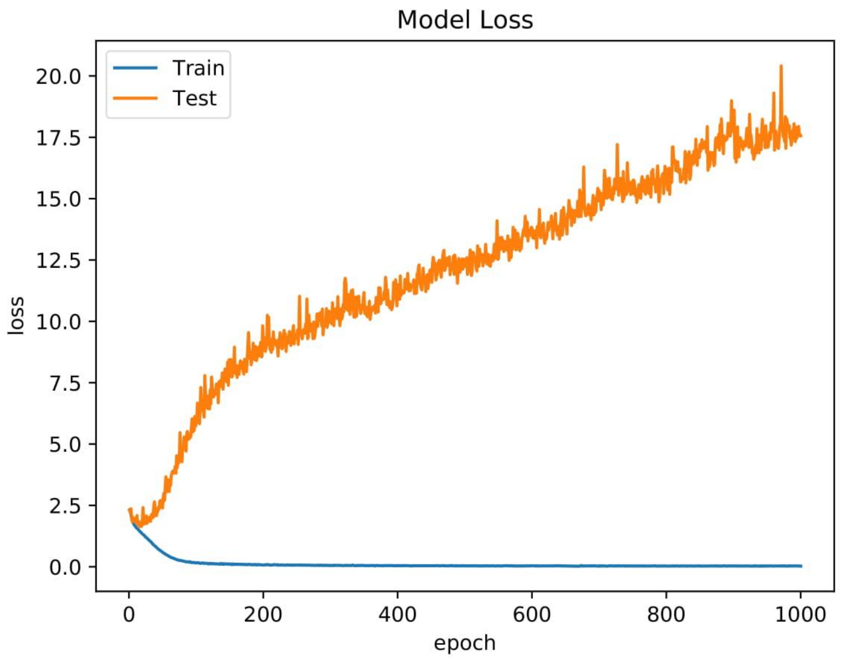
Accuracy	Loss
0.4355	1.7893178691864013

The plots for accuracies and loss of training and testing against training epochs are given below:

Model Accurac y	
Model Loss	

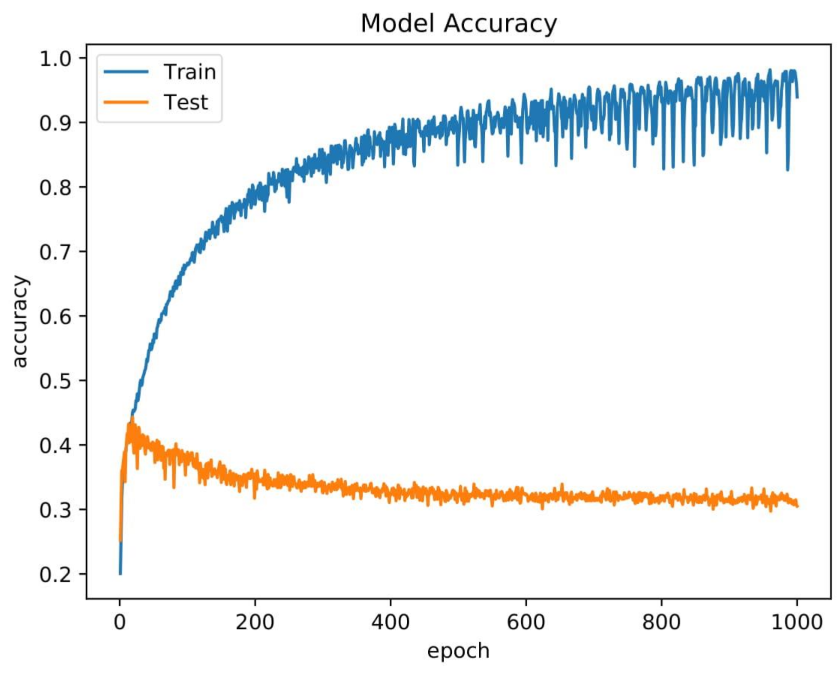
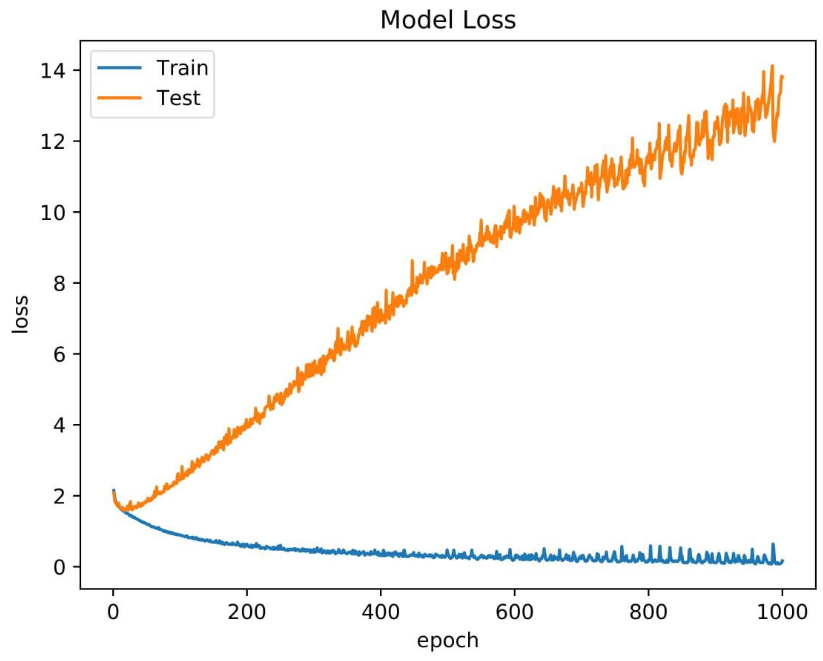
3.1.3.(b) using RMSProp algorithm for learning

Accuracy	Loss
0.417	17.560549850463868

Model Accurac y	
Model Loss	

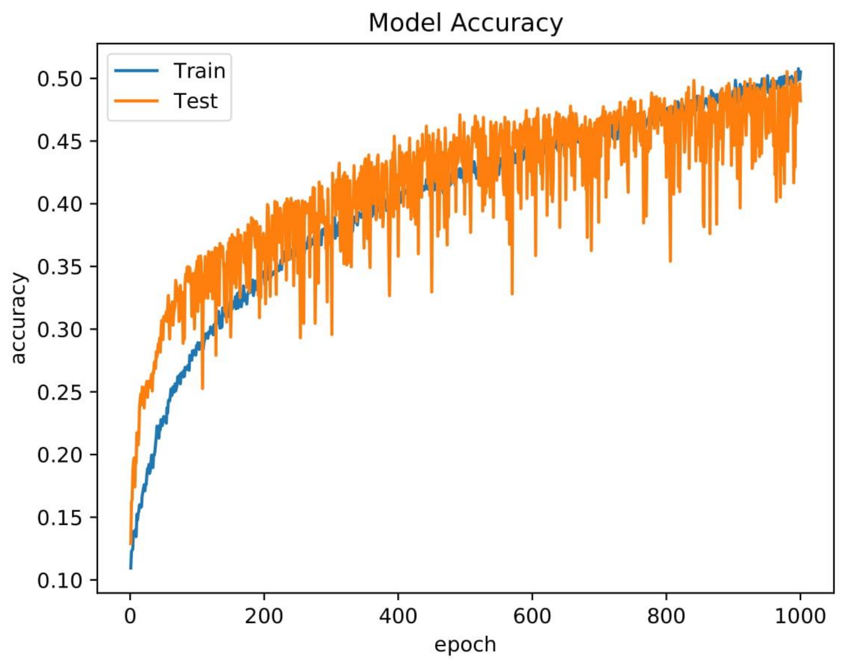
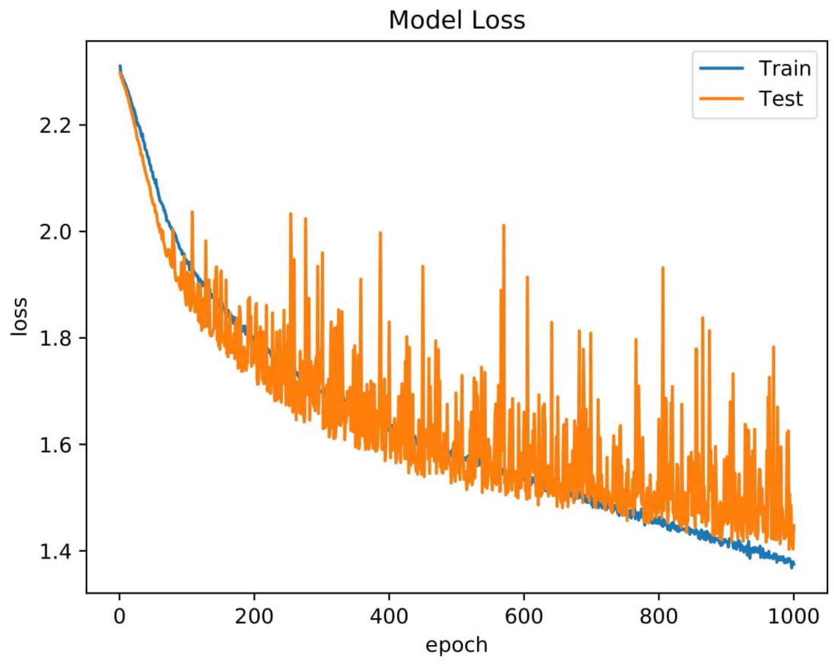
3.1.3.(c) using Adam optimizer for learning

Accuracy	Loss
0.305	13.802277282714844

Model Accuracy	
Model Loss	

3.1.3.(d) adding dropout (probability=0.5) to the two fully connected layers

Accuracy	Loss
0.482	1.4474995489120484

Model Accuracy	
Model Loss	

3.1.4. Question 4 Compare the accuracies of all the models from parts (1) - (3) and discuss their performances.

We aggregated the performances from models developed from part (2) – part (3) to better observe the effects of hyperparameter optimization and different optimizers. The accuracies for models from part (1) are recorded in the section itself.

Model Architecture	Accuracy
Gradient Descent (c1=70, c2=20, same for below)	0.474
Gradient Descent with momentum = 0.1	0.4355
RMSProp Algorithm	0.417
Adam Algorithm	0.305

Adding Dropout layer with drop rate of 0.5	0.482

We can analyse the observations from the following perspectives:

- From the experiments we did in section (1) we can conclude that adding more channels to both convolution layers does not necessarily increase the accuracy of the models. The optimal settings of both hyperparameters still rely on experiments like grid search.
- From the accuracies we recorded above we can conclude that GD with the dropout layer achieved the highest accuracy of 48.2% followed by the vanilla GD model of 47.4%, while other variations including adding momentum, using RMSProp Algorithm, and using Adam Algorithm did not seem to improve the accuracy of the model significantly.
- Following the conclusion above, we can observe the models with RMSProp, and Adam algorithm converges significantly earlier than GD algorithm variations. Both algorithms converge in the first 200 epochs, while the continuation of training actually led to a decrease in testing accuracy. This is because overfitting has happened and the model, along with more training epochs, biases towards the training data which lead to a decrease in accuracy for testing data. To tackle this problem, early stopping can be applied to the training process and we could expect to witness a higher accuracy for these two algorithms.
- In this CNN architecture, momentum does not seem to pose an observable impact on the testing accuracy of the model.
- Adding dropouts to the CNN model generally result a higher accuracy.

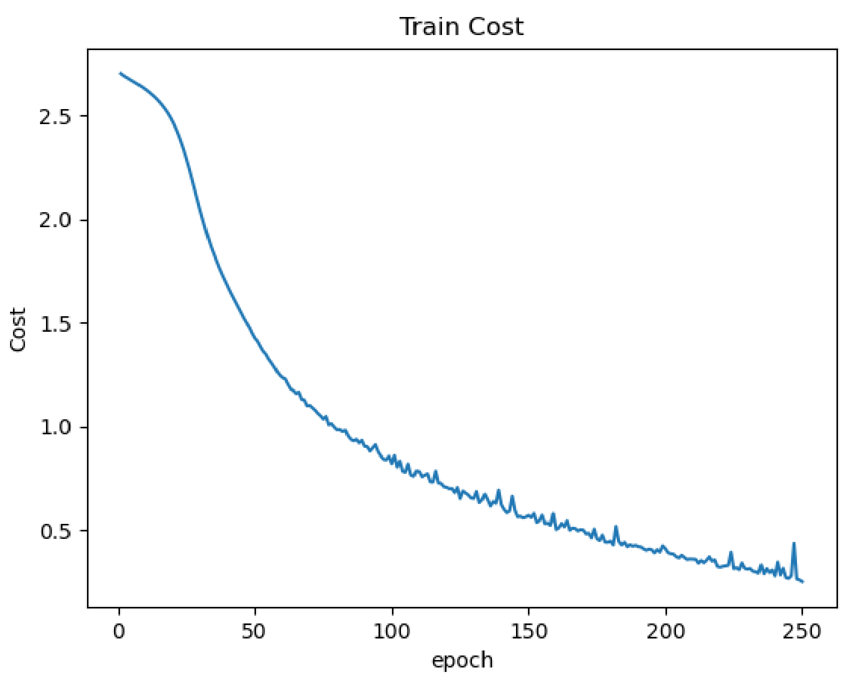
3.2. Part B

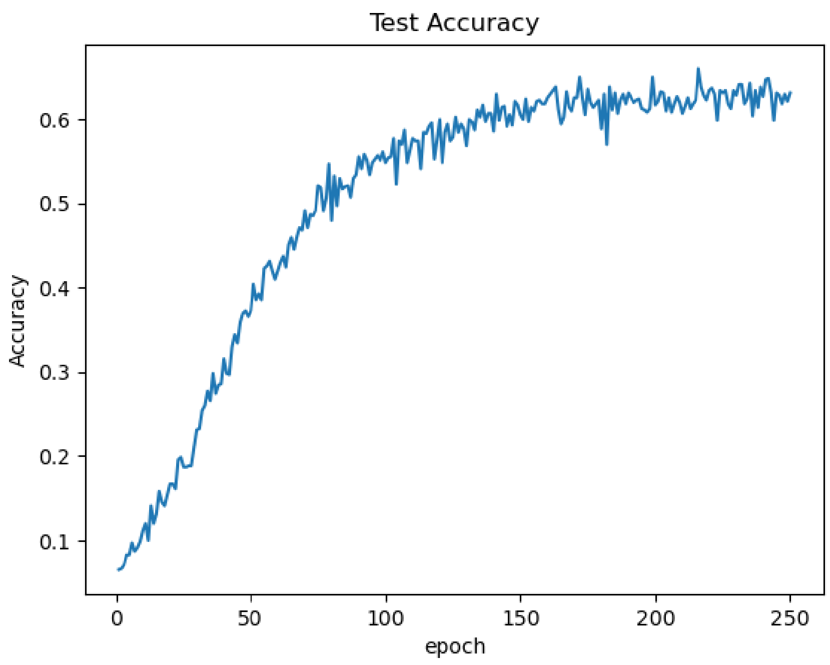
3.2.1. Question 1 Design a Character CNN Classifier that receives character ids and classifies the input

We used the following code to build the required model:

```
class CharCNN(Model):
    def __init__(self, vocab_size=256):
        super(CharCNN, self).__init__()
        self.vocab_size = vocab_size
        # Weight variables and RNN cell
        self.conv1 = layers.Conv2D(N_FILTERS, FILTER_SHAPE1,
padding='VALID', activation='relu', use_bias=True)
        self.pool1 = layers.MaxPool2D(POOLING_WINDOW,
POOLING_STRIDE, padding='SAME')
        self.conv2 = layers.Conv2D(N_FILTERS, FILTER_SHAPE2,
padding='VALID', activation='relu', use_bias=True)
        self.pool2 = layers.MaxPool2D(POOLING_WINDOW,
POOLING_STRIDE, padding='SAME')
        self.flatten = layers.Flatten()
        self.dense = layers.Dense(MAX_LABEL,
activation='softmax')

    def call(self, x, drop_rate=0.5):
        # forward
        x = tf.one_hot(x, one_hot_size)
        x = x[..., tf.newaxis]
        x = self.conv1(x)
        x = self.pool1(x)
        x = self.conv2(x)
        x = self.pool2(x)
        x = self.flatten(x)
        x = tf.nn.dropout(x, drop_rate)
        logits = self.dense(x)
        return logits

model = CharCNN(256)
```

The plots the entropy cost on the training data and the accuracy on the testing data against training epochs are given below:

Training Cost	

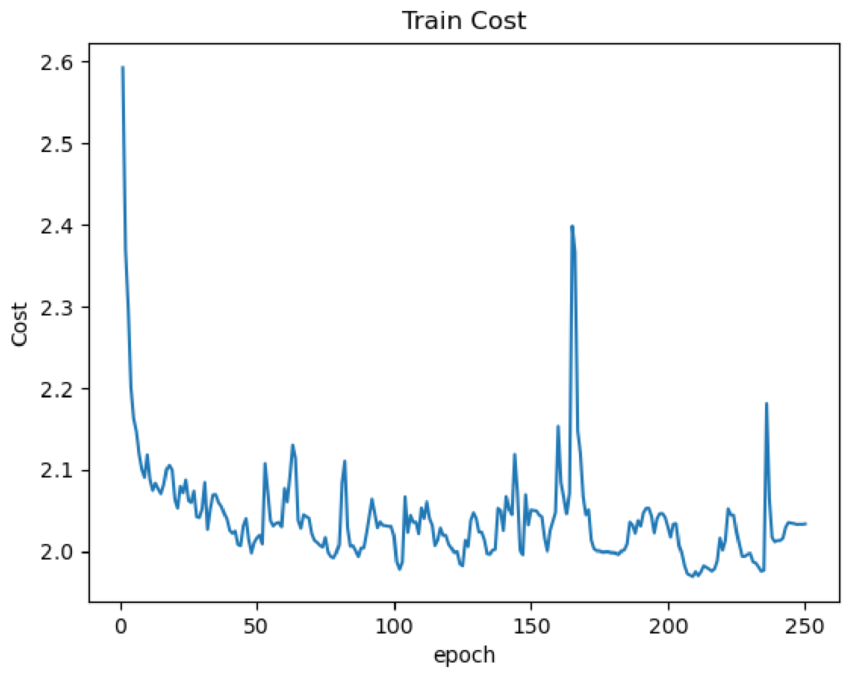
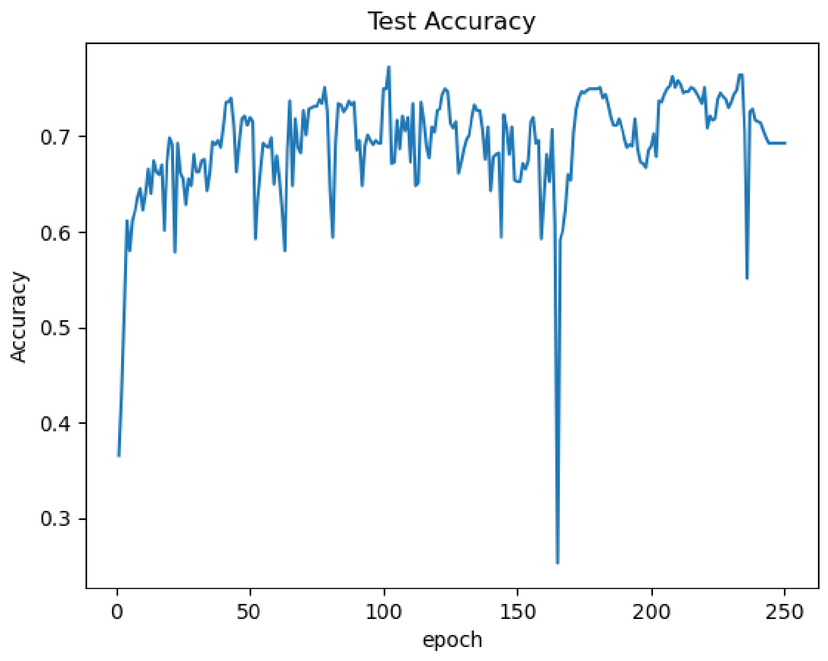
Testing Accurac y	

3.2.2. Question 2 Design a Word CNN Classifier that receives word ids and classifies the input

We used the following code to build the required model:

```
class WordCNN(Model):

    def __init__(self, vocab_size):
        super(WordCNN, self).__init__()
        self.vocab_size = vocab_size
        # Weight variables and RNN cell
        self.embedding = layers.Embedding(vocab_size,
EMBEDDING_SIZE, input_length=MAX_DOCUMENT_LENGTH)

        self.conv1 = layers.Conv2D(N_FILTERS, FILTER_SHAPE1,
padding='VALID', activation='relu', use_bias=True)
        self.pool1 = layers.MaxPool2D(POOLING_WINDOW,
POOLING_STRIDE, padding='SAME')
        self.conv2 = layers.Conv2D(N_FILTERS, FILTER_SHAPE2,
padding='VALID', activation='relu', use_bias=True)
        self.pool2 = layers.MaxPool2D(POOLING_WINDOW,
POOLING_STRIDE, padding='SAME')

        self.flatten = layers.Flatten()
        self.dense = layers.Dense(MAX_LABEL,
activation='softmax')

    def call(self, x, drop_rate):
        # forward
        x = self.embedding(x)
        x = x[..., tf.newaxis]
        x = self.conv1(x)
        x = self.pool1(x)
        x = self.conv2(x)
        x = self.pool2(x)
        x = self.flatten(x)
        x = tf.nn.dropout(x, drop_rate)
        logits = self.dense(x)
        return logits

model = WordCNN(vocab_size)
```

The plots the entropy cost on the training data and the accuracy on the testing data against training epochs are given below:

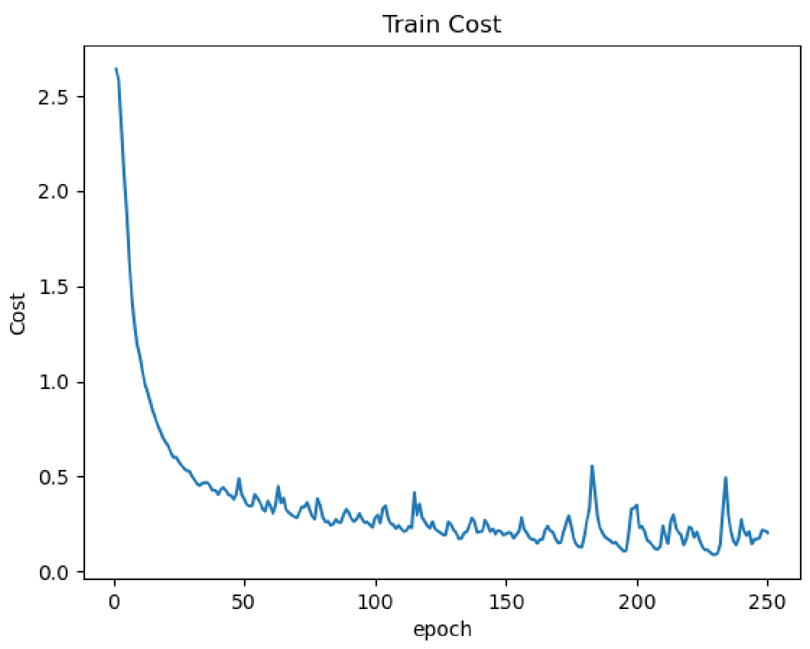
Training Cost	
Model Loss	

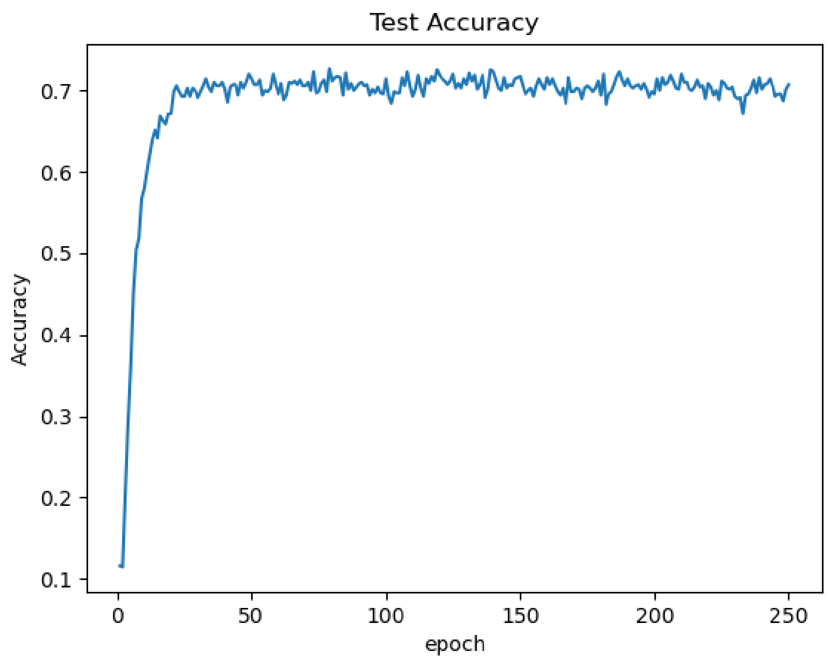
3.2.3. Question 3 Design a Character RNN Classifier that receives character ids and classify the input.

We used the following code to build the required model:

```
class CharRNN(Model):
    def __init__(self, vocab_size, hidden_dim=20):
        super(CharRNN, self).__init__()
        self.hidden_dim = hidden_dim
        self.vocab_size = vocab_size
        # Weight variables and RNN cell
        self.rnn = layers.RNN(
            tf.keras.layers.GRUCell(self.hidden_dim),
unroll=True)

        self.dense = layers.Dense(MAX_LABEL, activation=None)

    def call(self, x, drop_rate):
        # forward logic
        x = tf.one_hot(x, one_hot_size)
        x = self.rnn(x)

        x = tf.nn.dropout(x, drop_rate)
        logits = self.dense(x)

        return logits


model = CharRNN(vocab_size=256, hidden_dim=HIDDEN_SIZE)
```

The plots the entropy cost on the training data and the accuracy on the testing data against training epochs are given below:

Training Cost	

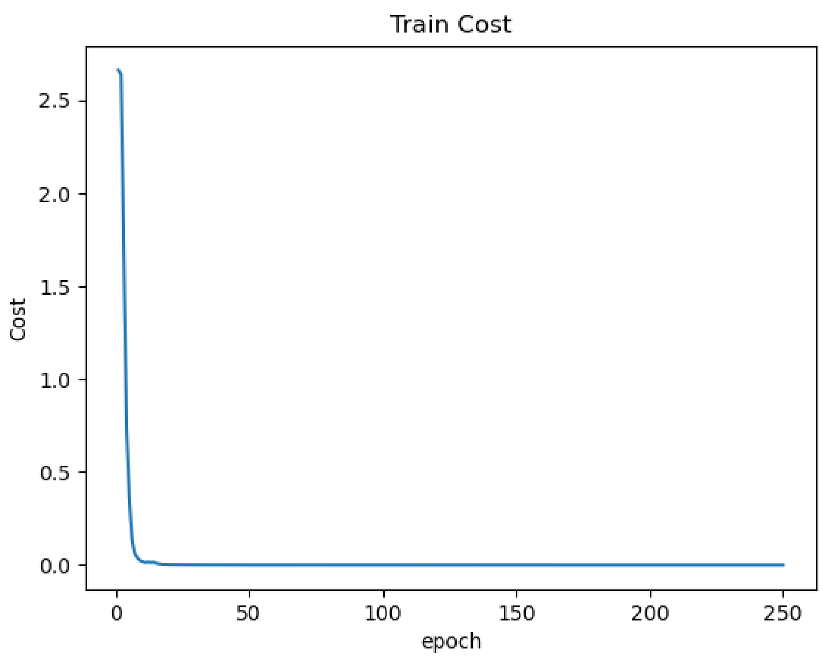
Testing Accuracy	

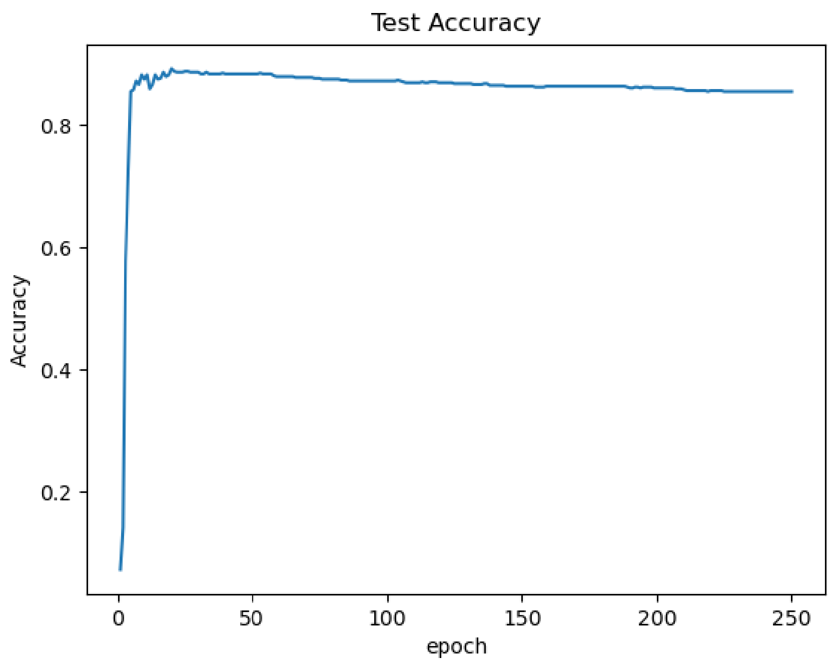
3.2.4. Question 4 Design a word RNN classifier that receives word ids and classify the input.

We used the following code to build the required model:

```
class WordRNN(Model):
    def __init__(self, vocab_size, hidden_dim=20):
        super(WordRNN, self).__init__()
        self.hidden_dim = hidden_dim
        self.vocab_size = vocab_size
        self.embedding = layers.Embedding(vocab_size,
EMBEDDING_SIZE, input_length=MAX_DOCUMENT_LENGTH)
        # Weight variables and RNN cell
        self.rnn = layers.RNN(
            tf.keras.layers.GRUCell(self.hidden_dim),
unroll=True)

        self.dense = layers.Dense(MAX_LABEL, activation=None)

    def call(self, x, drop_rate):
        # forward logic
        embedding = self.embedding(x)
        encoding = self.rnn(embedding)

        encoding = tf.nn.dropout(encoding, drop_rate)
        logits = self.dense(encoding)

        return logits


model = WordRNN(vocab_size, HIDDEN_SIZE)
```

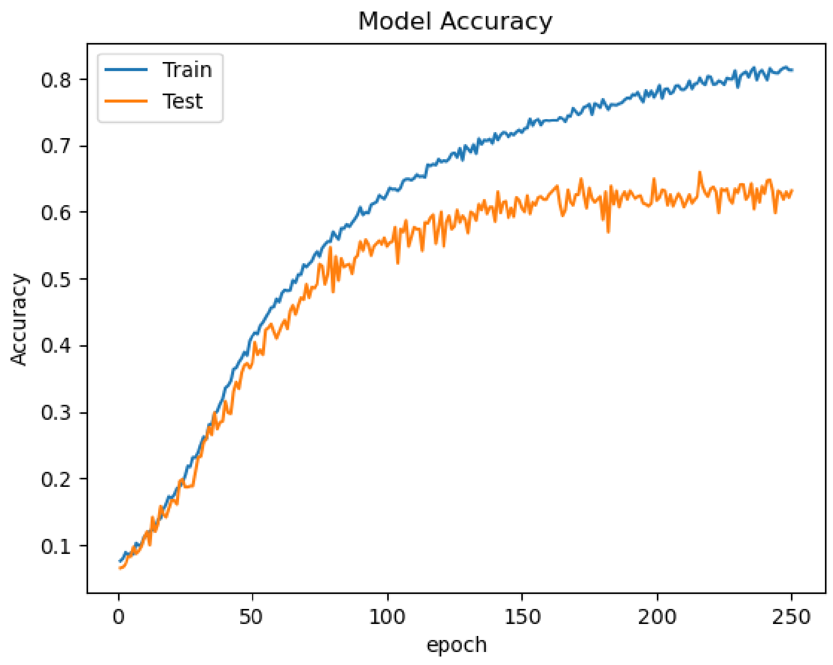
The plots the entropy cost on the training data and the accuracy on the testing data against training epochs are given below:

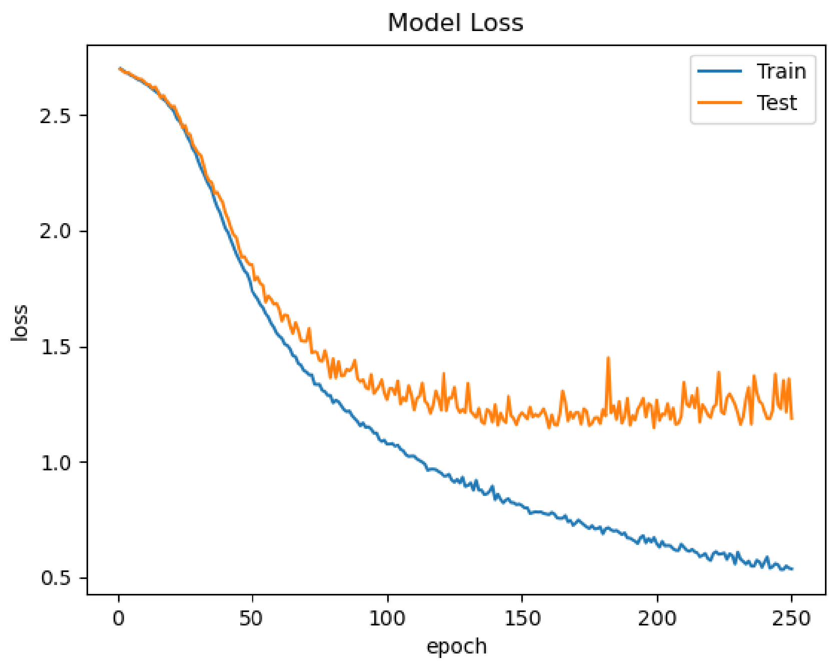
Training Cost	

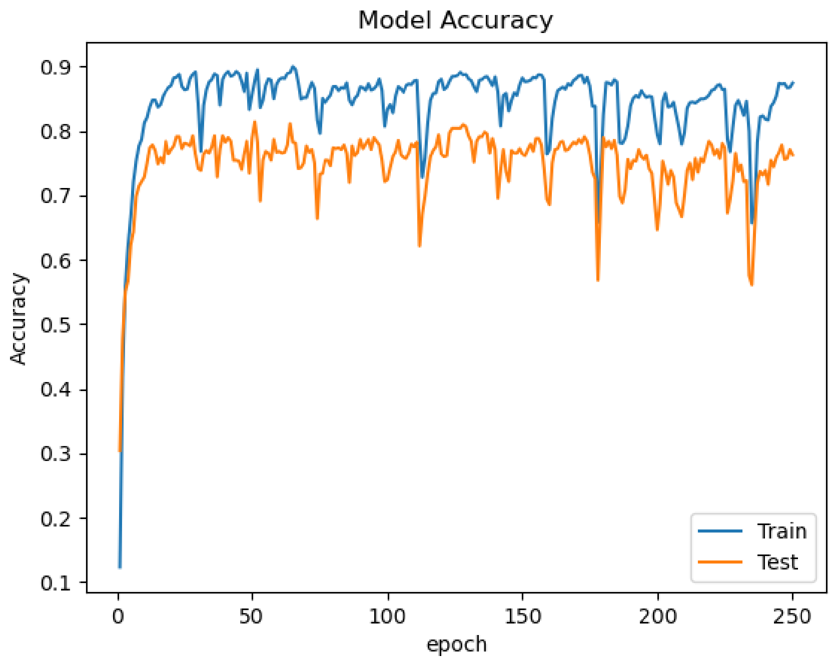
Testing Accuracy	

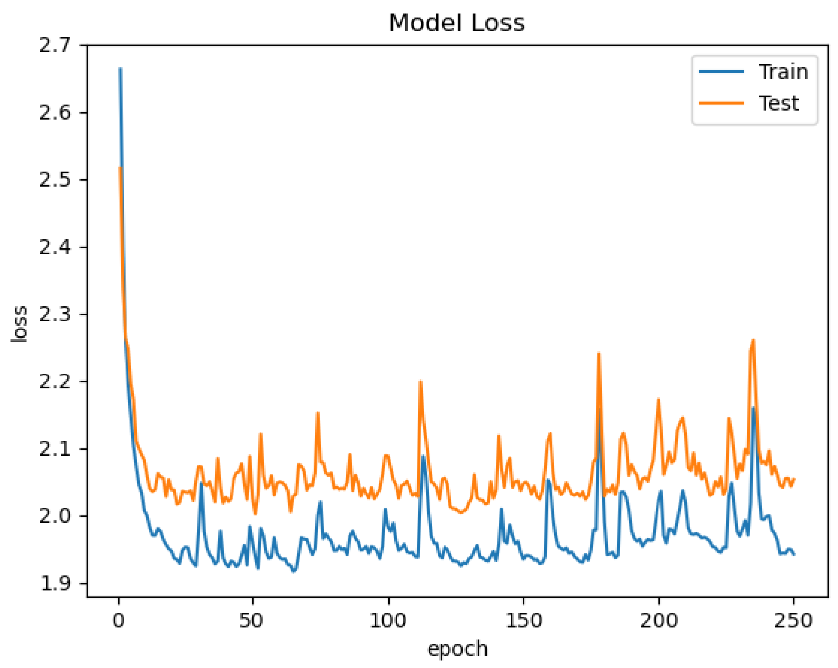
3.2.5. Question 5 Compare the test accuracies and the running times of the networks implemented in parts (1) – (4). Experiment with adding dropout to the layers of networks in parts (1) – (4) and report the test accuracies. Compare and comment on the accuracies of the networks with/without dropout.

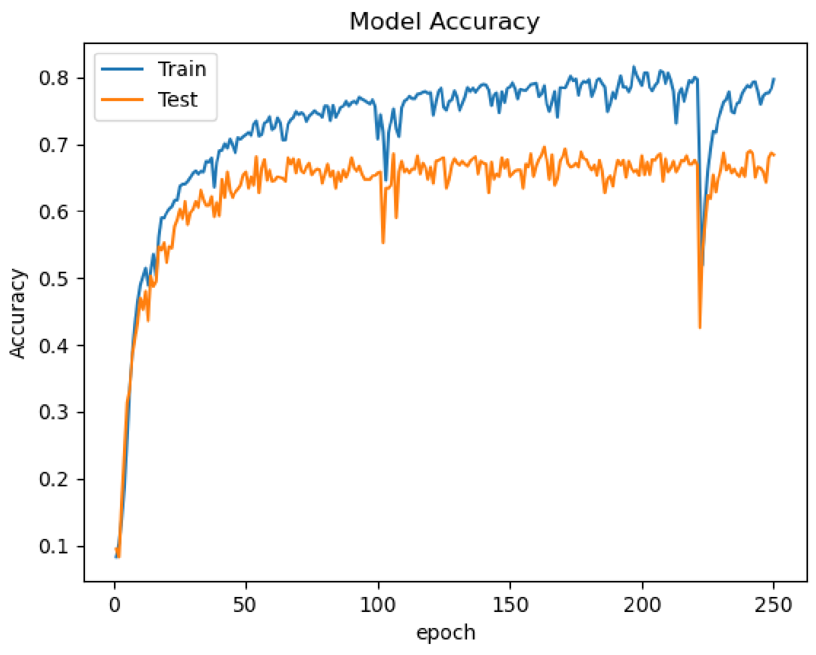
The plots for training loss and testing accuracies of each setting of model after adding the dropout layer is listed as following:

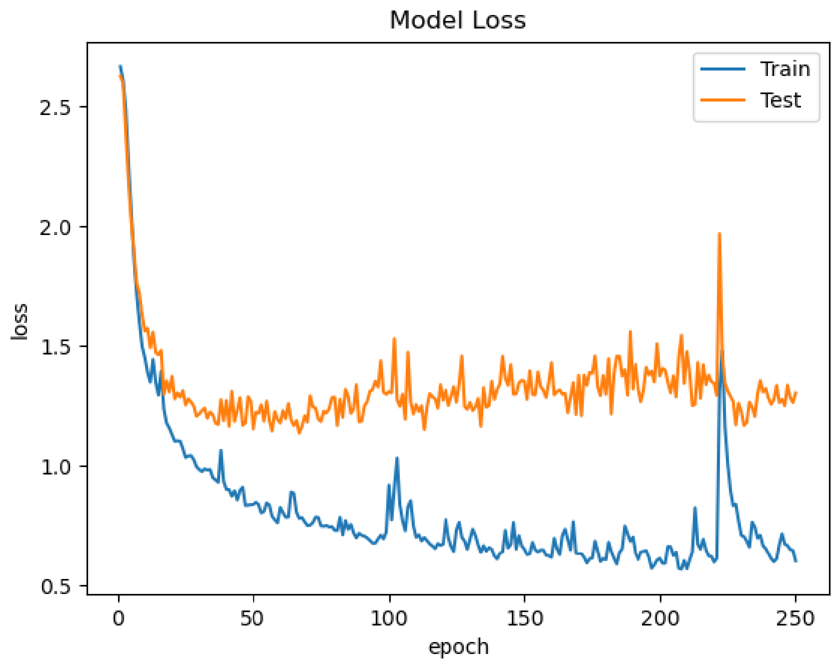
Char CNN	
Model Accuracy	

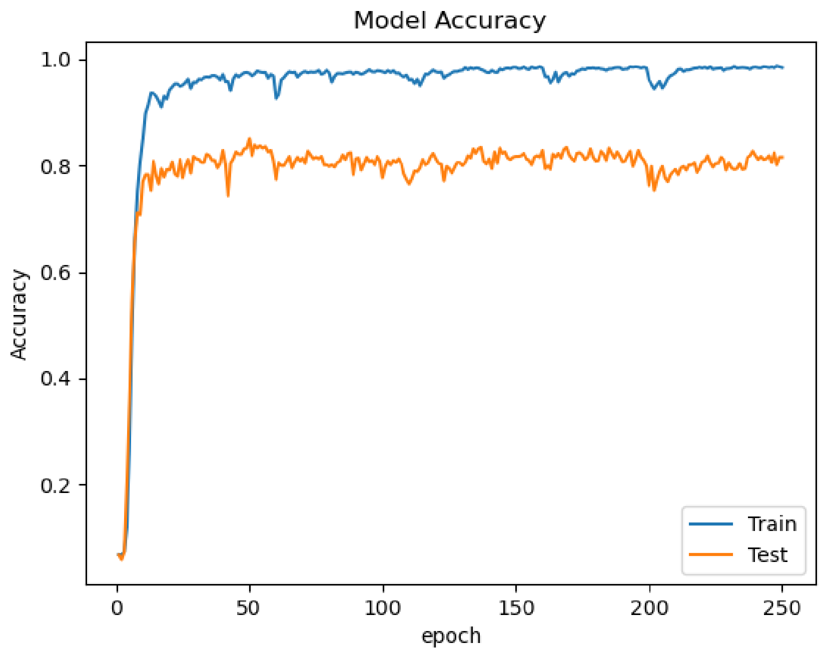
Model Loss	

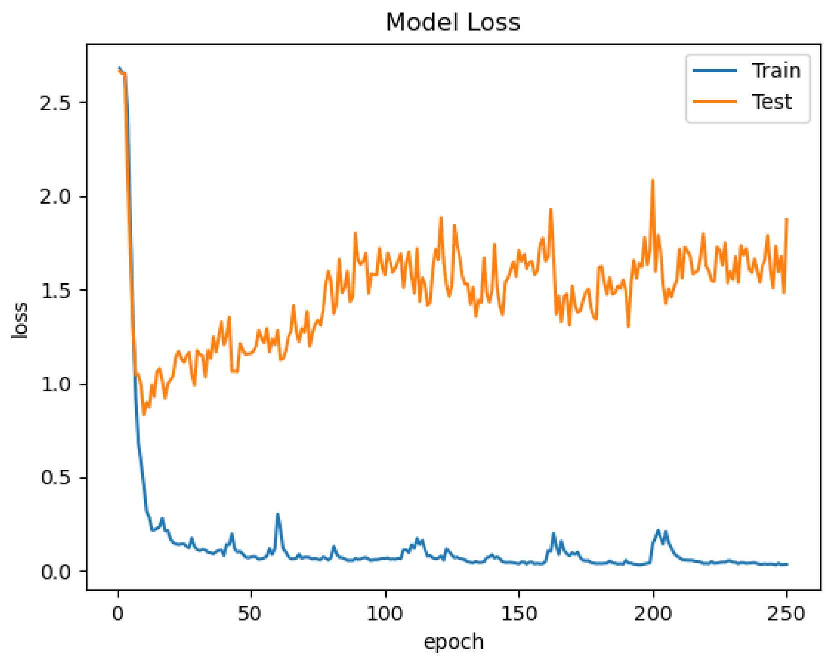
Word CNN	
Model Accuracy	

Model Loss	

Char RNN	
Model Accuracy	

Model Loss	

Word RNN	
Model Accurac y	

Model Loss	

The performances of four neural network architectures are summarised as following:

NN Architecture	Use Dropout	Testing Accuracy	Training Time in seconds
Char CNN	False	0.668571412563324	330.4538435935974
Char CNN	True	0.631428599357605	304.46557354927063
Word CNN	False	0.6928571462631226	859.0286507606506
Word CNN	True	0.7628571391105652	932.8975763320923
Char RNN	False	0.7071428298950195	2606.2206382751465
Char RNN	True	0.6842857003211975	2793.671418428421
Word RNN	False	0.8557142615318298	3058.287944793701
Word RNN	True	0.8157142996788025	3085.323560476303

From the results above we can make the following observation:

- On the perspective of time, training a character-level Neural Network generally takes less time than training a word-level Neural Network for both CNN and RNN. Training RNNs generally takes significantly longer time than training CNNs. In the case of this project, the training time for RNN could be 4-10 times to the time taken for training a CNN. Additionally, adding a dropout layer does not seem to pose an observable impact on training time.
- On the perspective of accuracy, adding a dropout layer does not seem to pose an observable impact on enhancing the testing accuracy with only one exception, the Word CNN model. One explanation to this reduction is that the network size is relatively small compared to the dataset, thus regularization would lower the capacity of the model which results in a lower performance.

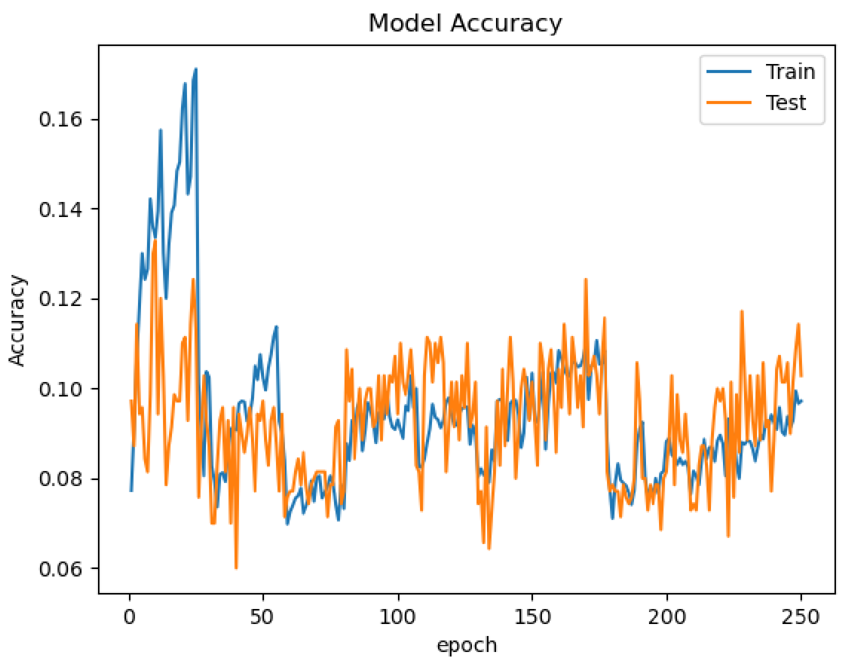
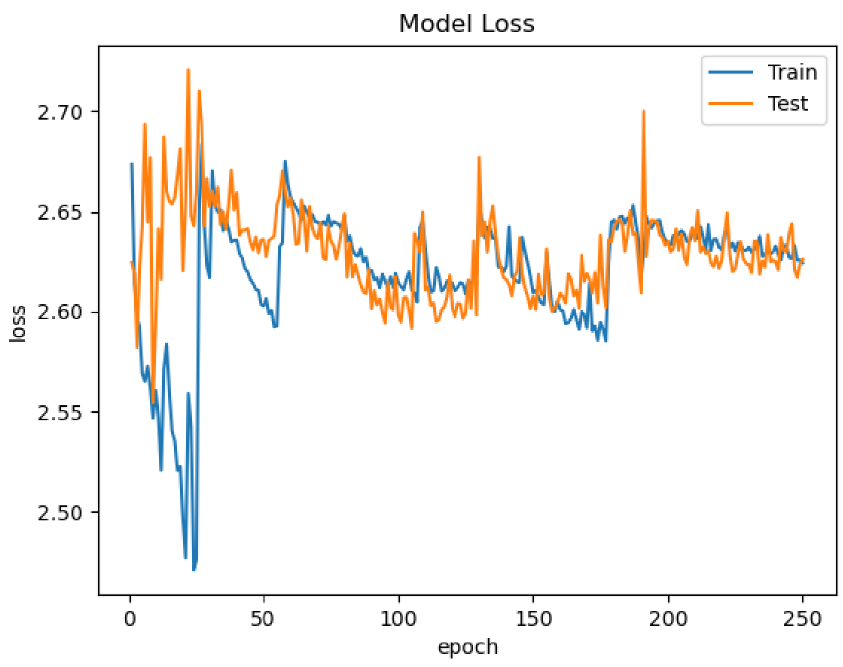
3.2.6. Question 6 For RNN networks implemented in (3) and (4), perform the following experiments with

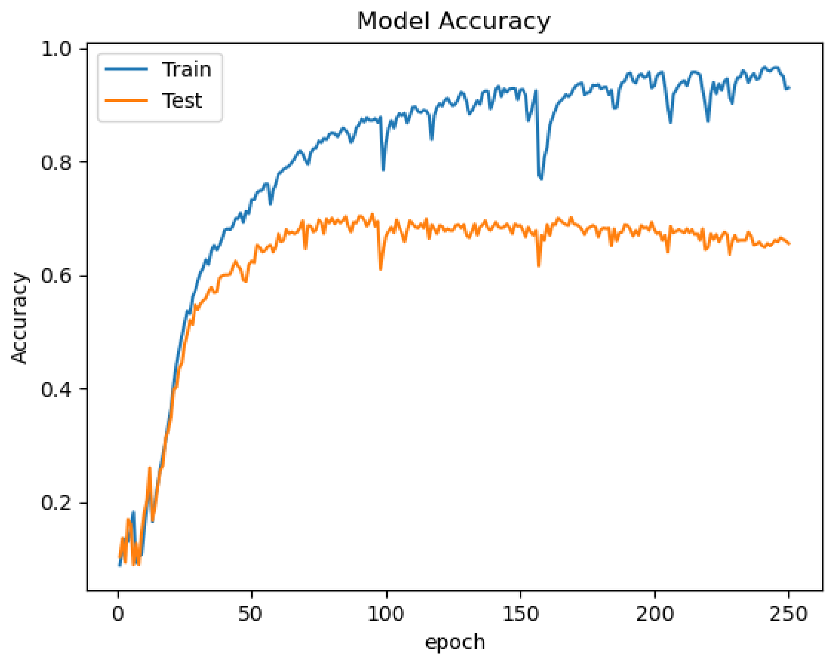
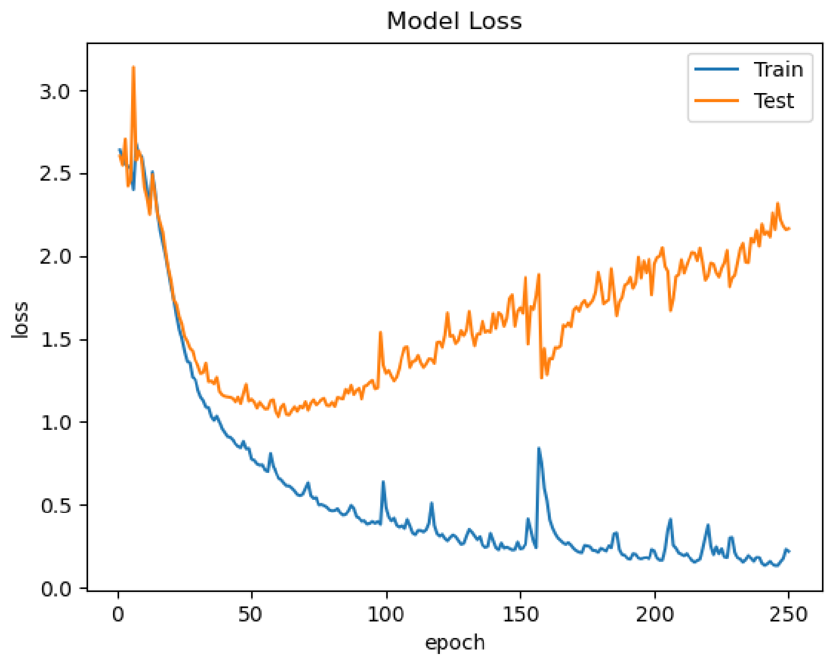
the aim of improving performances, compare the accuracies and report your findings

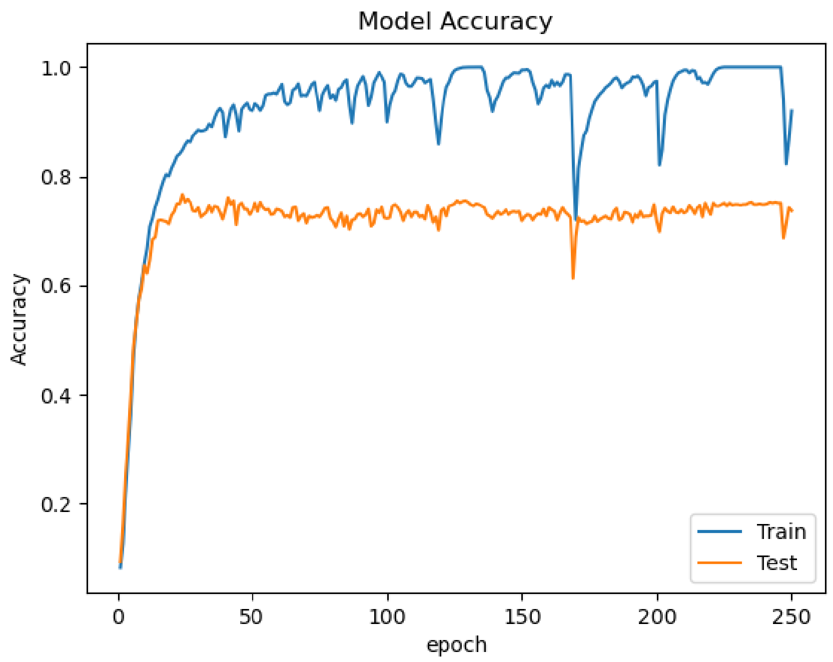
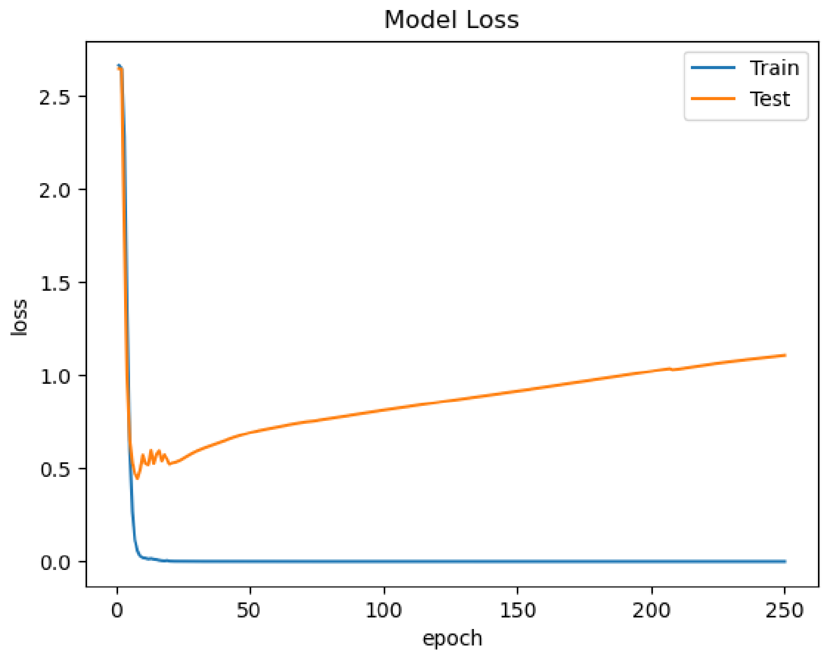
In this section we explored the following variations with the char RNN and word RNN models built in Question (3) and Question (4):

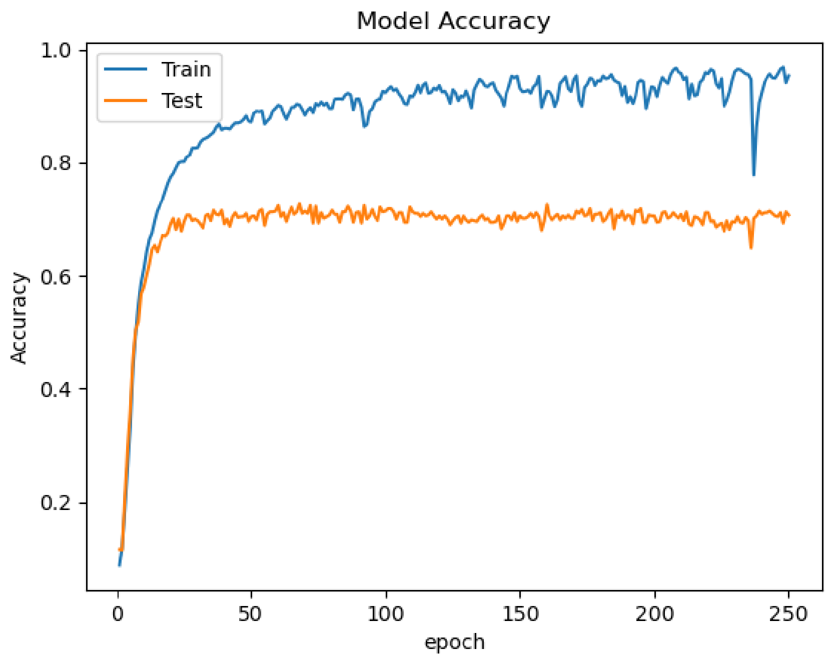
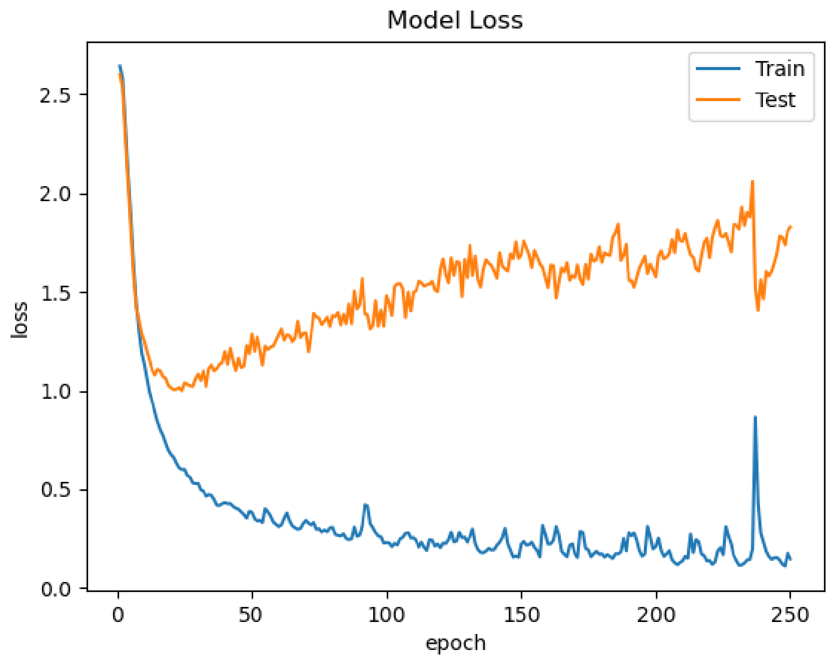
1. (i) Vanilla RNN Layer/ (ii) LSTM Layer
2. Increase the number of RNN layers to 2. For the additional layer, we used the default GRU layer.
3. Gradient clipping with threshold = 2

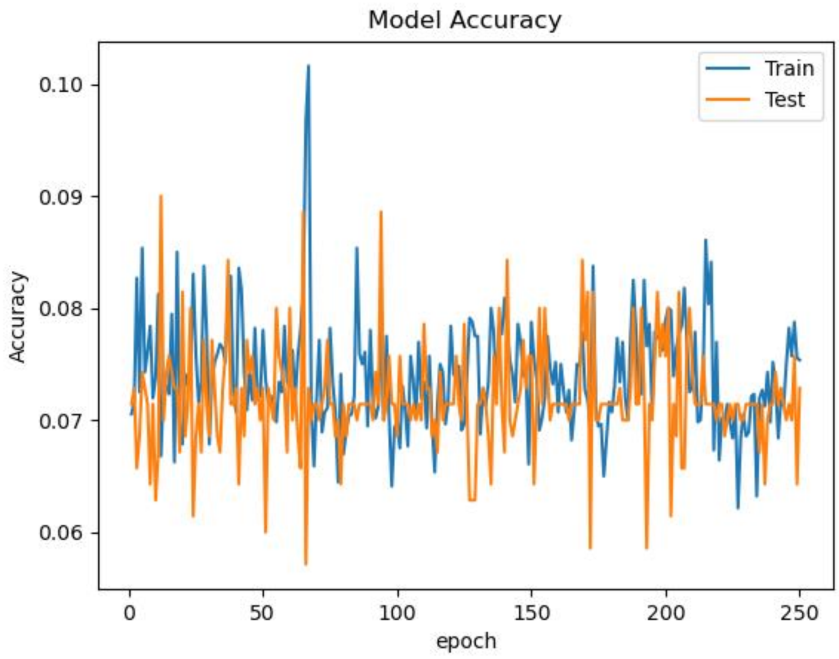
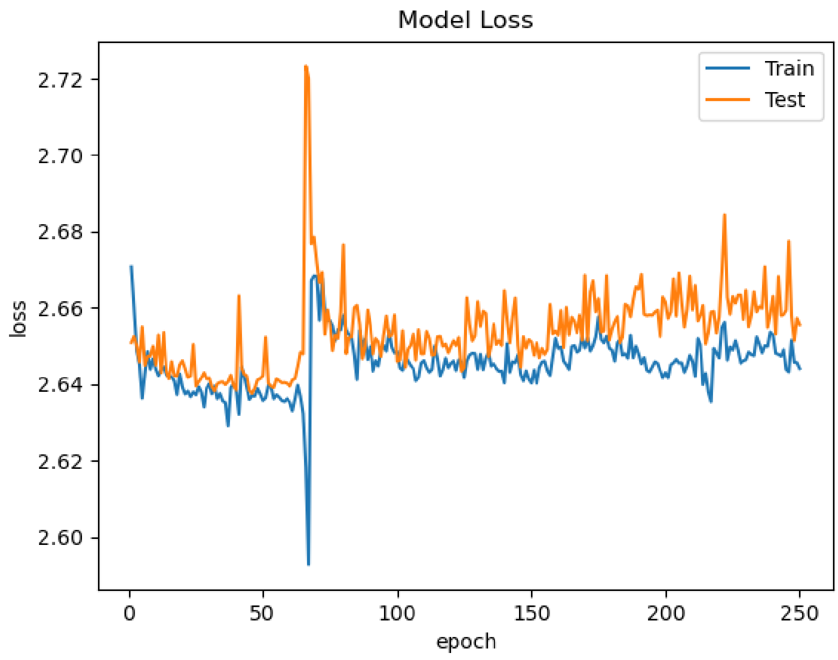
The plots of training cost and testing accuracies against each epoch are given below:

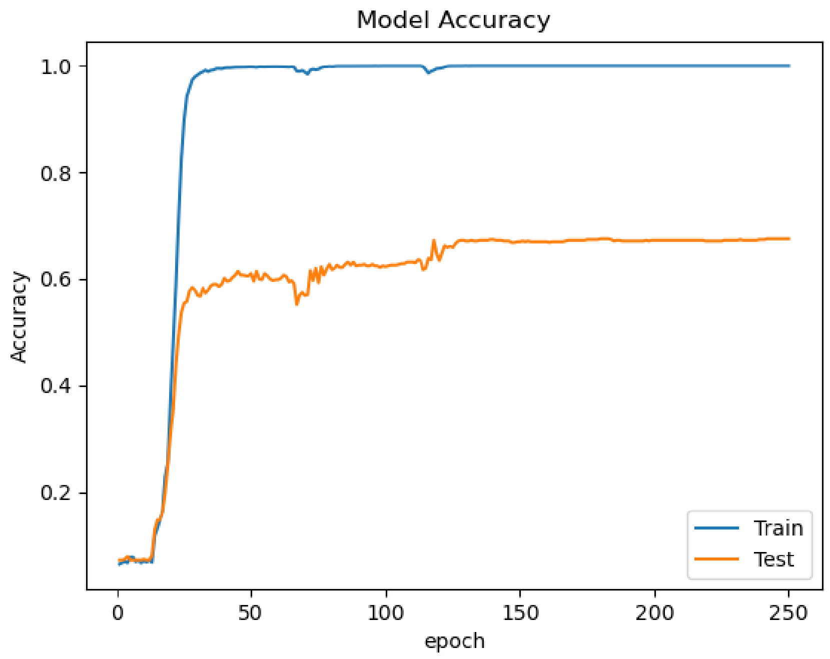
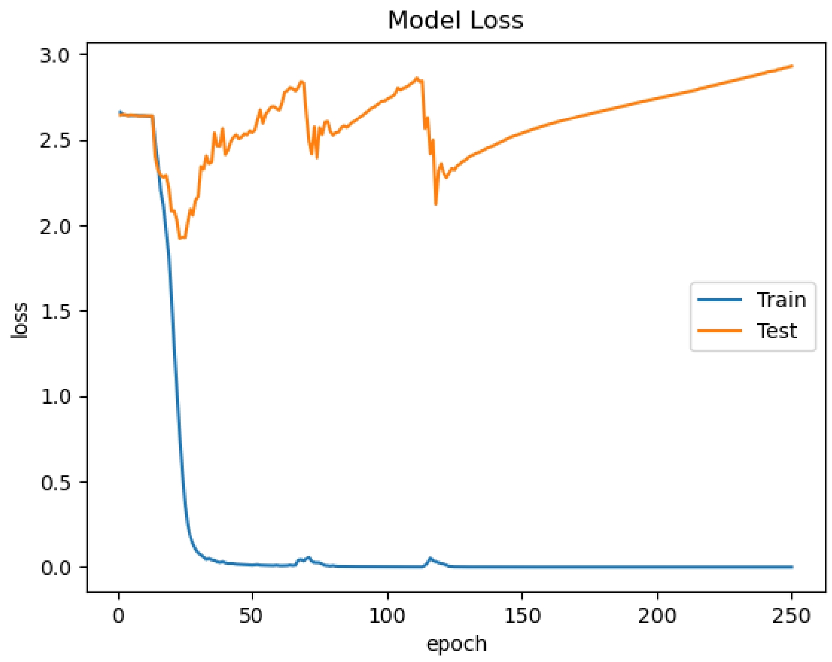
Char RNN with vanilla RNN layer	
Model Accuracy	
Model Cost	

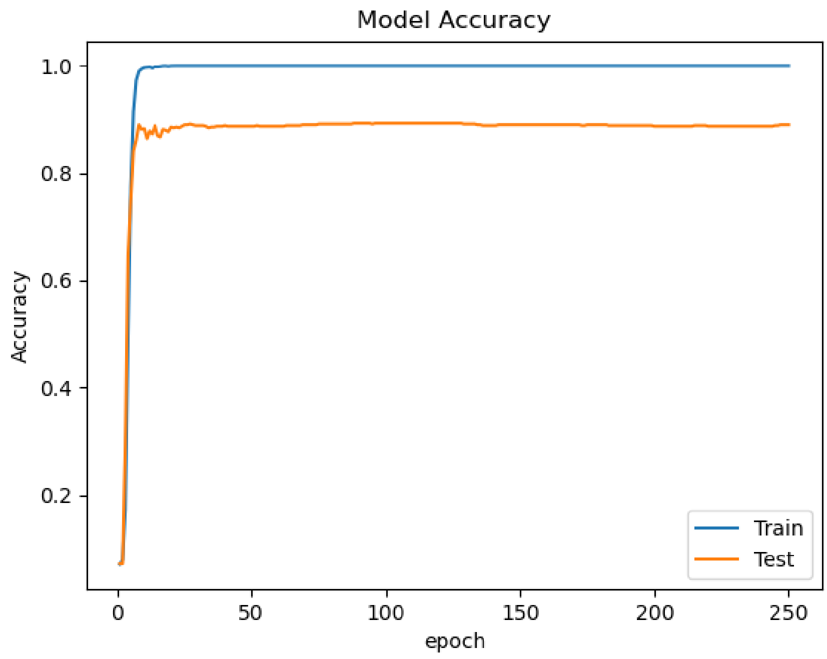
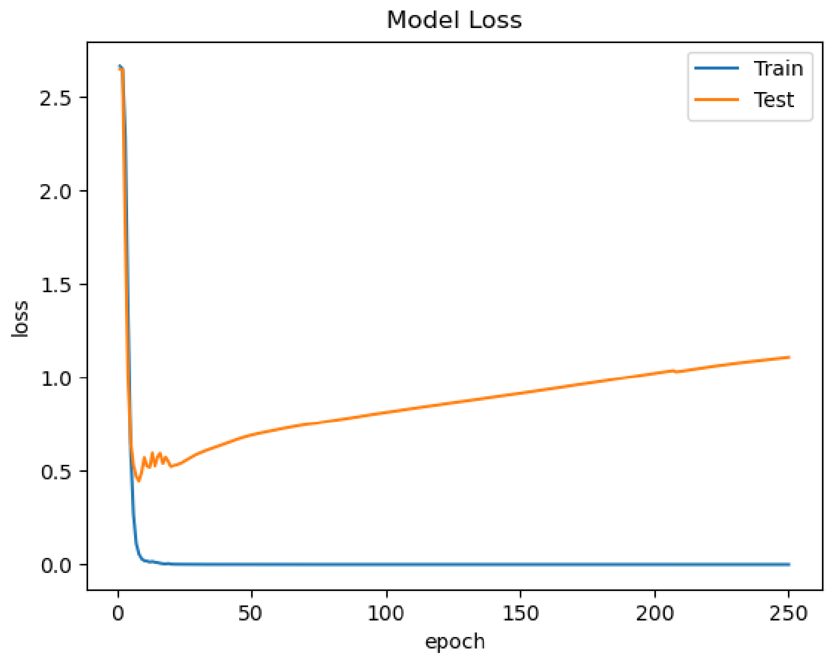
Char RNN with vanilla LSTM layer	
Model Accuracy	
Model Cost	

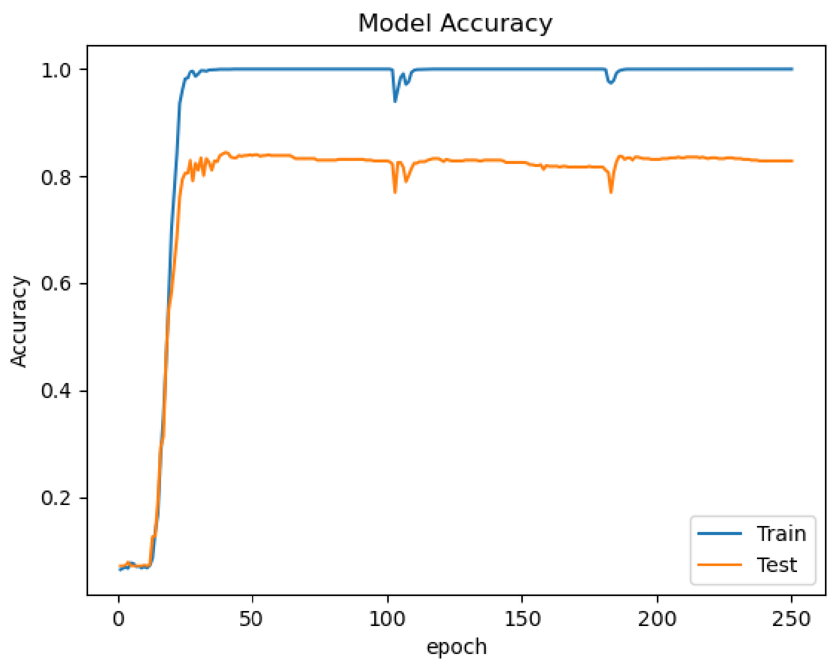
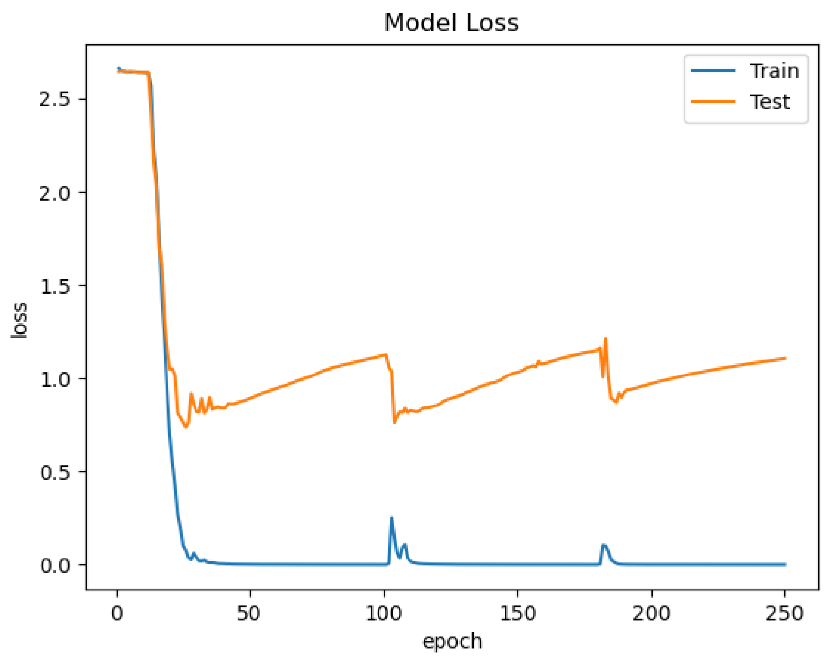
Char RNN with 2 RNN layer	
Model Accurac y	
Model Cost	

Char RNN with clipping threshold = 2	
Model Accuracy	
Model Cost	

Word RNN with vanilla RNN layer	
Model Accuracy	
Model Cost	

Word RNN with vanilla LSTM layer	
Model Accuracy	
Model Cost	

Word RNN with 2 RNN layer	
Model Accurac y	
Model Cost	

Word RNN with clipping threshold = 2	
Model Accuracy	
Model Cost	

We aggregated the accuracies and training times of these variations together with the original RNN models:

Model	Testing Accuracy	Training Time in seconds
Original Char RNN	0.7071428298950195	2606.2206382751465
Char RNN with vanilla RNN layer	0.10285714268684387	817.8206958770752
Char RNN with LSTM layer	0.6557142734527588	1693.6792585849762
Char RNN with 2 RNN layers	0.74	

Char RNN with clipping threshold = 2	0.70115656444550195	2991.314649581909
Original Word RNN	0.8557142615318298	3058.287944793701
Word RNN with vanilla RNN layer	0.07285714149475098	1212.7567870616913
Word RNN with LSTM layer	0.6757143139839172	2167.067813873291
Word RNN with 2 RNN layers	0.8899999856948853	6856.745208024979
Word RNN with clipping threshold = 2	0.8285714387893677	2202.778781414032

From the recorded plots above and the accuracy and time of each model, we can make the following key observations:

1. For both Char RNN and Word RNN, applying the vanilla RNN layer SimpleRNN result in the most unstable performance (from the turbulation observed in the plots) and lowest accuracy (both around 10%). Whereas the training time was reduced significantly to around 1/3 of the original model's training time.
2. Experiments with LSTM layers also produced worse performance compared to the original RNNs. We could still observe a reduction in training time when using LSTM. This observation together with observation 1 can deduce a general conclusion of the relationship between the accuracy and training time of a model – one can be improved at the cost of sacrificing the other.
3. Implementing 2-layers with an additional GRU layer significantly improved performance for both Char RNN and Word RNN models.
4. Implementing clipping thresholds with value 2 does not seem to pose an observable improvement to both models.

4. Conclusions

4.2. Part A Conclusions

We can conclude the following key observations from the experiments:

1. The number of channels of each convolution layer in a deep convolutional neural network has important impact on the accuracy of the model. However, the enhancement of accuracy is not linearly proportional to the number of channels, which means we cannot simply increase the number of channels. Empirical Experiments are needed to determine the optimal number of channels, as well as other hyperparameters.
2. The type of optimizer applied also has important impact on the accuracy of the model. Empirically experimenting different optimization algorithm can lead to enhancement of the performance of the model.
3. Adding dropout layer to the network generally can enhance the performance of the model by preventing the model from overfitting and produce more generalized result.
4. Other hyperparameters, for instance, learning rate and number of layers can also be empirically studies to enhance the performance of the model.

4.2. Part B Conclusions

We can conclude the following key observations from the experiments:

1. It can be observed that compared to CNN models, RNN models have better performance regarding sequential textual data that are related in the context, from the result that any one of the RNN models has a higher accuracy than one from CNN models.
2. It can be observed that compared to CNN models, RNN models generally takes significantly longer time for training.
3. RNN models with more layers generally has better performance than RNN models with fewer layers. This is due to more RNN layers can capture the precedent intermediate results more accurately.
4. The type of RNN layer implemented in the RNN model has important impact on the performance of the model. Among all RNN layers, GRU layer has the best performance, followed by LSTM layer, while SimpleRNN layer has significantly low accuracy compared to other types of layers.