Assignment 06

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Question 01

Download and preprocess the sentiment analysis dataset from

https://www.kaggle.com/snap/amazon-fine-food-reviews. Download the Glove

word vectors from https://nlp.standford.edu/data/glove.6B.zip and extract the 100-

dimensional file (glove.6B.100d.txt) from the zipped folder.

In [3]:
```
import kagglehub


# Download latest version

path = kagglehub.dataset_download("snap/amazon-fine-food-reviews")


print("Path to dataset files:", path)
```

```
Path to dataset files: /kaggle/input/amazon-fine-food-reviews
```

In [4]:
```
import pandas as pd

import numpy as np
```

```python
df = pd.read_csv(path+'/Reviews.csv')

df.head()
```

Out[4]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe...
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i...
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...

In [5]:
```python
## Download the GLOVE vector embeddings


!wget "https://nlp.stanford.edu/data/glove.6B.zip"
```

```
--2024-11-07 13:46:55--  https://nlp.stanford.edu/data/glove.6B.zip
Resolving nlp.stanford.edu (nlp.stanford.edu)... 171.64.67.140
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:443... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: https://downloads.cs.stanford.edu/nlp/data/glove.6B.zip [following]
--2024-11-07 13:46:56--  https://downloads.cs.stanford.edu/nlp/data/glove.6B.zip
Resolving downloads.cs.stanford.edu (downloads.cs.stanford.edu)... 171.64.64.22
Connecting to downloads.cs.stanford.edu (downloads.cs.stanford.edu)|171.64.64.22|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 862182613 (822M) [application/zip]
Saving to: 'glove.6B.zip'

glove.6B.zip        100%[===================>] 822.24M  5.09MB/s    in 2m 39s

2024-11-07 13:49:35 (5.17 MB/s) - 'glove.6B.zip' saved [862182613/862182613]
```

In [6]:

```
!unzip glove.6B.zip
```

```
Archive:  glove.6B.zip
  inflating: glove.6B.50d.txt
  inflating: glove.6B.100d.txt
  inflating: glove.6B.200d.txt
  inflating: glove.6B.300d.txt
```

In [7]:

```
!rm glove.6B.zip

!rm glove.6B.50d.txt

!rm glove.6B.200d.txt

!rm glove.6B.300d.txt
```

In [8]:

```
# Map each word to its embedding



EM_DIM = 100



EM_MAP = dict()



with open('glove.6B.100d.txt', 'r') as fp:
```

```
    for line in fp.readlines():

        tokens = line.split()

        word = tokens[0]

        vec = np.array(tokens[1:], dtype=np.float32)

        EM_MAP[word] = vec
```

In [9]:
```
word = 'god'

print("Word is :-",word)



print("Embedding is :- ", EM_MAP.get(word))
```

```
Word is :- god
Embedding is :-  [ 0.43414   0.83408   0.5934   -0.27576   0.0738    1.1678   -0.81431
 -0.44566   0.107    -0.64585   0.082188 -0.21979   0.74463   0.52581
  0.30714  -1.3932    0.22689   0.87584  -1.5773    1.325    -0.17464
 -1.0626   -1.0502   -0.20297   0.57481   1.1517   -0.64222  -0.11813
  0.52094   0.10227   0.63393   0.05253  -0.24155   0.11705  -0.16385
 -0.08113  -0.40486   0.27208   0.62358  -0.78284  -0.78031   1.1003
  0.59216  -0.48685  -0.20998  -0.47734   0.03295   0.11653  -0.39919
 -0.76189   0.09318   0.84754   1.5402    1.0642   -0.62729  -1.8783
  0.67105   0.31923   0.74992   0.20445   0.76704   0.4952   -0.29807
 -0.75948   0.3302    0.44451   0.054353 -0.21146  -0.099696 -0.64717
  0.70308   0.19498   0.59476  -0.54367   0.3663    0.08349   0.090207
 -0.54985  -0.59734   0.24354  -0.36756   0.29299  -0.93052   0.103
 -1.1354    0.37565  -0.30992  -0.65516   0.82278  -0.17073  -0.049053
 -0.59641   0.35431   0.5645   -0.39342  -1.1199   -0.52763  -0.58435
  0.084958  0.26176 ]
```

Question 02

Preprocess the review dataset by considering the column “review score” > 3 as

positive reviews and others as negative reviews. For training on local machine

considers 5000 positive and negative reviews each for the training dataset.

Consider 2000 reviews for the rest dataset and validation dataset each. Strip the length of each review sentence (number of words) according to your computation

availability.

In [10]:
```python
## Create a new col_name 'verdict' in the df

## verdict is positive if review_score > 3 else negative

df['verdict'] = ['positive' if score>3 else 'negative' for score in df['Score']]



df.head()
```

Out[10]:

	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	Text	ver
0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food	I have bought several of the Vitality canned d...	posi
1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	nega
2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all	This is a confection that has been around a fe...	posi
3	4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine	If you are looking for the secret ingredient i...	nega
4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy	Great taffy at a great price. There was a wid...	posi

In [11]:

```
df.columns
```

Out[11]:

```
Index(['Id', 'ProductId', 'UserId', 'ProfileName', 'HelpfulnessNumerator',
       'HelpfulnessDenominator', 'Score', 'Time', 'Summary', 'Text',
       'verdict'],
      dtype='object')
```

In [12]:

```
df = df.drop(columns=['Id','ProductId','UserId','ProfileName','HelpfulnessNumerator','HelpfulnessDenominator','Score','Time'],a



df.head()
```

Out[12]:

	Summary	Text	verdict
0	Good Quality Dog Food	I have bought several of the Vitality canned d...	positive
1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	negative
2	"Delight" says it all	This is a confection that has been around a fe...	positive
3	Cough Medicine	If you are looking for the secret ingredient i...	negative
4	Great taffy	Great taffy at a great price. There was a wid...	positive

In [13]:

```
df['Statement']=[str(x)+str('. ')+str(y) for x,y in zip(df['Summary'],df['Text'])]


df.head()
```

Out[13]:

	Summary	Text	verdict	Statement
0	Good Quality Dog Food	I have bought several of the Vitality canned d...	positive	Good Quality Dog Food. I have bought several o...
1	Not as Advertised	Product arrived labeled as Jumbo Salted Peanut...	negative	Not as Advertised. Product arrived labeled as ...
2	"Delight" says it all	This is a confection that has been around a fe...	positive	"Delight" says it all. This is a confection th...
3	Cough Medicine	If you are looking for the secret ingredient i...	negative	Cough Medicine. If you are looking for the sec...
4	Great taffy	Great taffy at a great price. There was a wid...	positive	Great taffy. Great taffy at a great price. Th...

In [14]:

```
df = df.drop(columns=['Text','Summary'],axis=1)


df.head()
```

Out[14]:

	verdict	Statement
0	positive	Good Quality Dog Food. I have bought several o...
1	negative	Not as Advertised. Product arrived labeled as ...
2	positive	"Delight" says it all. This is a confection th...
3	negative	Cough Medicine. If you are looking for the sec...
4	positive	Great taffy. Great taffy at a great price. Th...

In [15]:
```
df['Statement']=[str(x).lower() for x in df['Statement']] # Since embeddings are done on lower-case letters


df.head()
```

Out[15]:

	verdict	Statement
0	positive	good quality dog food. i have bought several o...
1	negative	not as advertised. product arrived labeled as ...
2	positive	"delight" says it all. this is a confection th...
3	negative	cough medicine. if you are looking for the sec...
4	positive	great taffy. great taffy at a great price. th...

In [16]:
```
df.shape
```

Out[16]:
```
(568454, 2)
```

In [17]:
```
X = df['Statement']


y = df['verdict']


from sklearn.model_selection import train_test_split


X_train, X_rem, y_train,y_rem = train_test_split(X, y, test_size = 0.2, random_state = 4)
X_val, X_test, y_val,y_test = train_test_split(X_rem, y_rem, test_size = 0.5, random_state = 4)


print(X_train.shape)
print(X_val.shape)
print(X_test.shape)
```

```
(454763,)
(56845,)
(56846,)
```

In [18]:
```
## Reduce size



X_train = X_train[:80000]

X_val = X_val[:10000]

X_test = X_test[:10000]



y_train=y_train[:80000]

y_val=y_val[:10000]

y_test=y_test[:10000]
```

Question 03

iii. Train RNN model with the FC layer applied in the final hidden layer output using the following parameter:

Sl. No.	RNN	RNN Layer	LSTM Size	Activation	FC Layer	Embedding Layer
1	LSTM	1	64	ReLU	1	GloVe
2	GRU	1	64	ReLU	1	GloVe

In [19]:
```
## At first we need to create an embedding layer

# First step will be tokenization
```

```
from tensorflow.keras.preprocessing.text import Tokenizer

MAX_WORDS = 10000  # Adjust as needed
tokenizer = Tokenizer(num_words=MAX_WORDS)
tokenizer.fit_on_texts(X_train)

X_train_sequences = tokenizer.texts_to_sequences(X_train)
X_val_sequences = tokenizer.texts_to_sequences(X_val)
X_test_sequences = tokenizer.texts_to_sequences(X_test)
```

In [20]:
```
from tensorflow.keras.preprocessing.sequence import pad_sequences

MAX_LENGTH = 300 # Average review length
X_train_padded = pad_sequences(X_train_sequences, maxlen=MAX_LENGTH)
X_val_padded = pad_sequences(X_val_sequences, maxlen=MAX_LENGTH)
X_test_padded = pad_sequences(X_test_sequences, maxlen=MAX_LENGTH)
```

In [21]:
```
## Convert verdict into one hot encoded form

from tensorflow.keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder

label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
```

```python
y_val_encoded = label_encoder.transform(y_val)
y_test_encoded = label_encoder.transform(y_test)

y_train_onehot = to_categorical(y_train_encoded)
y_val_onehot = to_categorical(y_val_encoded)
y_test_onehot = to_categorical(y_test_encoded)
```

In [22]:
```python
# Create embedding matrix

embedding_matrix = np.zeros((MAX_WORDS, EM_DIM))
for word, i in tokenizer.word_index.items():
    if i < MAX_WORDS:
        embedding_vector = EM_MAP.get(word)
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector
```

In [23]:
```python
# Create embedding layer
from tensorflow.keras.layers import Embedding

embedding_layer = Embedding(MAX_WORDS,
                            EM_DIM,
                            weights=[embedding_matrix],
                            input_length=MAX_LENGTH,
                            trainable=False)
```

In [24]:
```python
# Import libraries


from tensorflow.keras import Sequential

from tensorflow.keras.layers import LSTM,GRU,Dense, Dropout

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.callbacks import EarlyStopping
```

In [ ]:
```python
## Define the RNN(LSTM) model


model = Sequential()

model.add(embedding_layer)

model.add(LSTM(64,activation='relu'))

# model.add(Dense(16,activation='relu'))

model.add(Dense(2,activation='softmax'))


model.summary()
```

Model: "sequential_2"

Layer (type)	**Output Shape**	**Param #**
embedding_2 (Embedding)	(64, 300, 100)	1,000,000
lstm_2 (LSTM)	?	0 (unbuilt)
dense_4 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)
Trainable params: 0 (0.00 B)
Non-trainable params: 1,000,000 (3.81 MB)

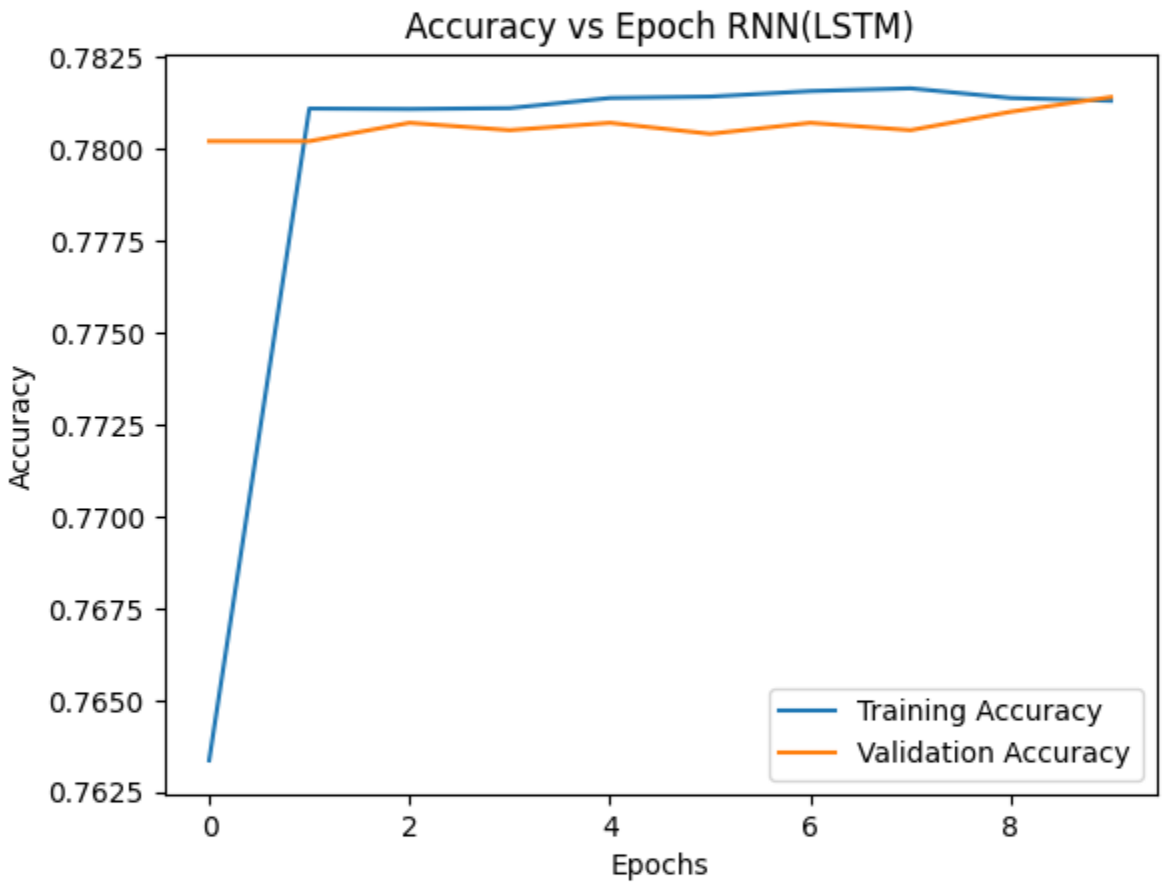
In [ ]:
```
model.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model.fit(

            X_train_padded,

            y_train_onehot,

            validation_data=(X_val_padded, y_val_onehot),

            epochs=10,

            batch_size=64,

            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]

          )


loss, accuracy = model.evaluate(X_test_padded, y_test_onehot)

print(f'Test Loss: {loss:.4f}')

print(f'Test Accuracy: {accuracy:.4f}')
```

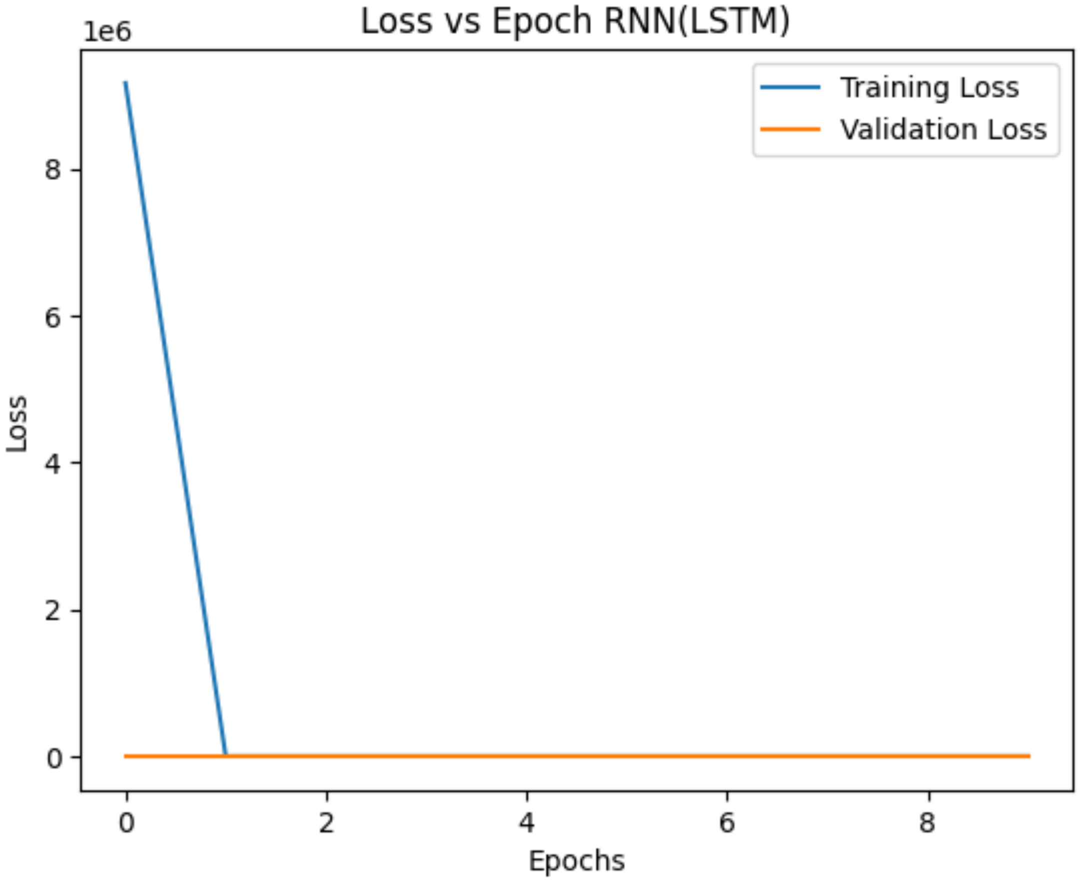
```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 54s 41ms/step - accuracy: 0.7453 - loss: 15697380.0000 - val_accuracy: 0.7802 - val_loss: 0.5083
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 44ms/step - accuracy: 0.7781 - loss: 0.5087 - val_accuracy: 0.7802 - val_loss: 0.5013
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 75s 38ms/step - accuracy: 0.7808 - loss: 0.4991 - val_accuracy: 0.7807 - val_loss: 0.4964
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 81s 37ms/step - accuracy: 0.7782 - loss: 0.4983 - val_accuracy: 0.7805 - val_loss: 0.4938
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 83s 38ms/step - accuracy: 0.7826 - loss: 0.4917 - val_accuracy: 0.7807 - val_loss: 0.4916
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 47s 37ms/step - accuracy: 0.7814 - loss: 0.4906 - val_accuracy: 0.7804 - val_loss: 0.4904
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 46s 37ms/step - accuracy: 0.7831 - loss: 0.4874 - val_accuracy: 0.7807 - val_loss: 0.4896
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 91s 44ms/step - accuracy: 0.7815 - loss: 0.4877 - val_accuracy: 0.7805 - val_loss: 0.4886
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 76s 40ms/step - accuracy: 0.7825 - loss: 0.4867 - val_accuracy: 0.7810 - val_loss: 0.4880
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 86s 43ms/step - accuracy: 0.7811 - loss: 0.4891 - val_accuracy: 0.7814 - val_loss: 0.4876
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 14ms/step - accuracy: 0.7751 - loss: 0.4908
Test Loss: 0.4902
Test Accuracy: 0.7784
```

In [ ]:

```python
import matplotlib.pyplot as plt



plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')

plt.title('Accuracy vs Epoch RNN(LSTM)')

plt.legend()

plt.show()



plt.plot(history.history['loss'], label='Training Loss')
```

```
plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(LSTM)')

plt.legend()

plt.show()
```





In [ ]:
```
## Define the RNN(GRU) model


model = Sequential()

model.add(embedding_layer)

model.add(GRU(64,activation='relu'))

# model.add(Dense(16,activation='relu'))

model.add(Dense(2,activation='softmax'))


model.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(64, 300, 100)	1,000,000
gru (GRU)	?	0 (unbuilt)
dense_5 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 1,000,000 (3.81 MB)

In [ ]:

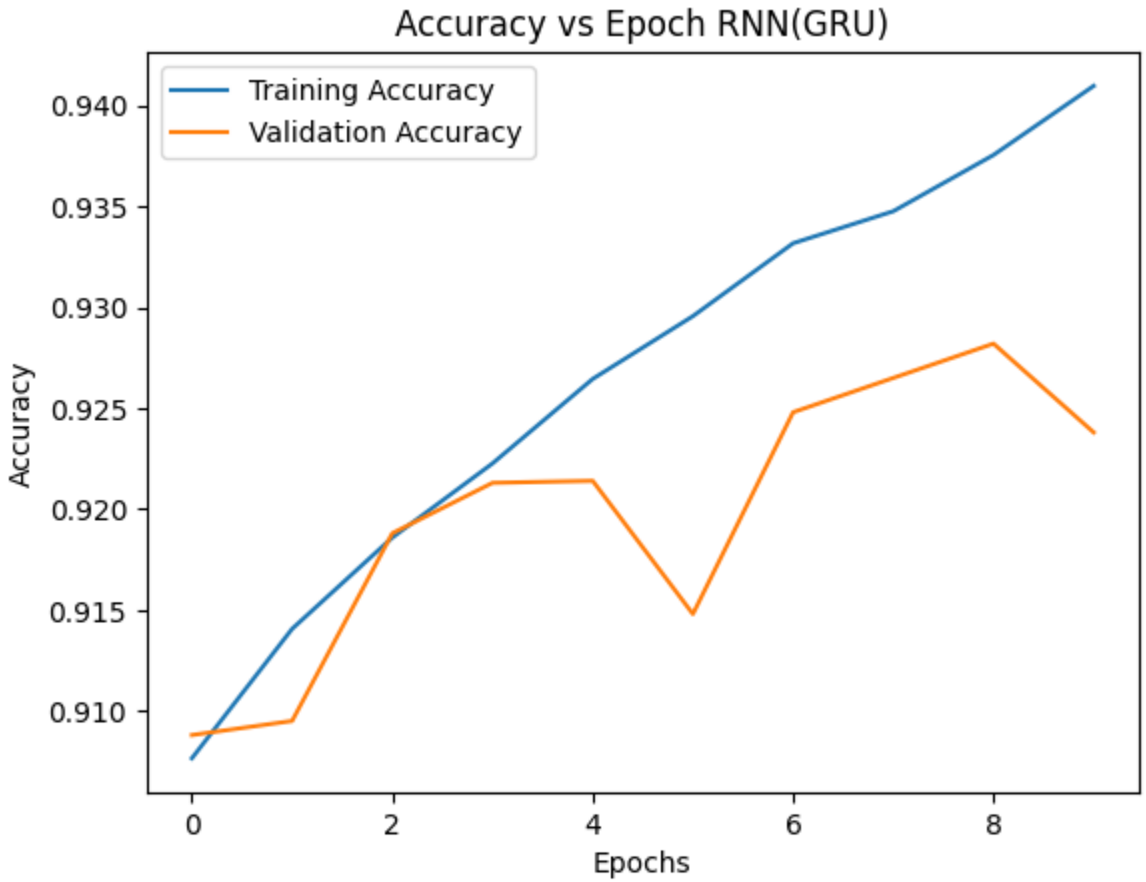
```
model.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model.fit(
            X_train_padded,
            y_train_onehot,
            validation_data=(X_val_padded, y_val_onehot),
            epochs=10,
            batch_size=64,
            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]
          )


loss, accuracy = model.evaluate(X_test_padded, y_test_onehot)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy:.4f}')
```

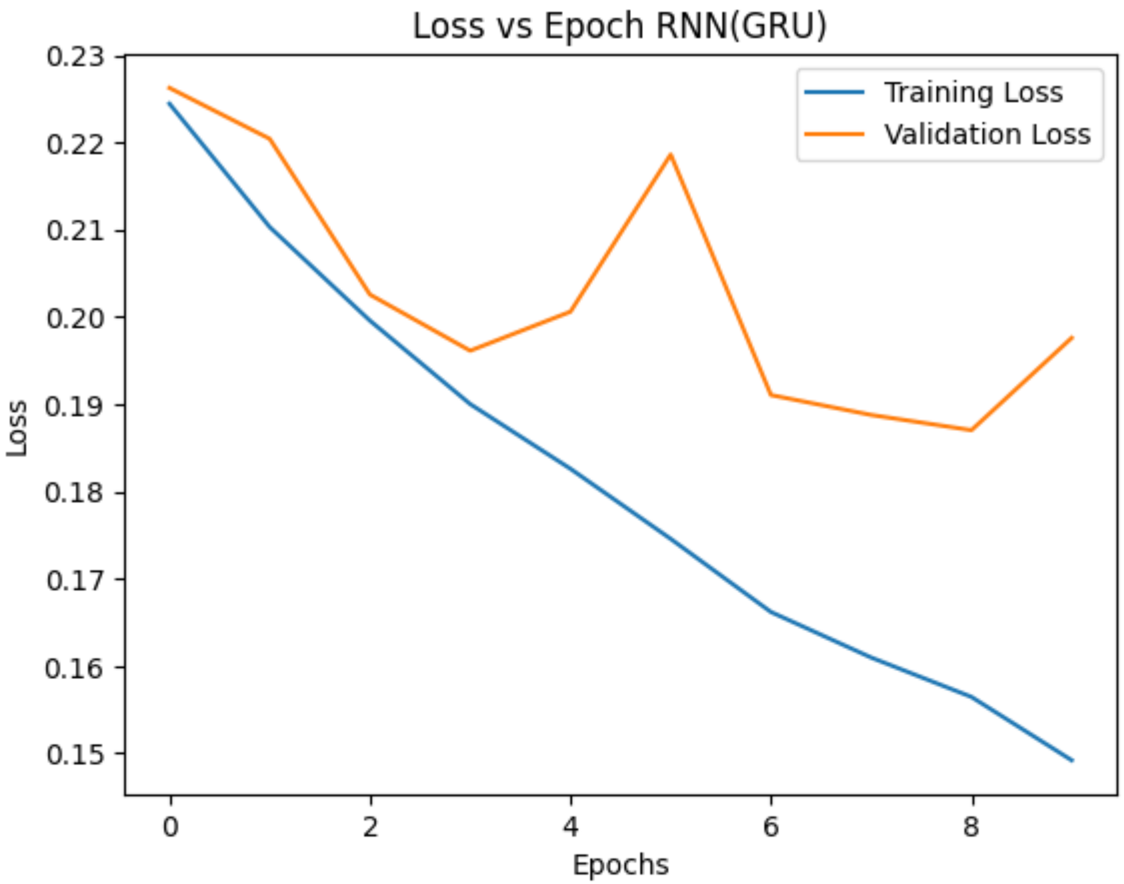
```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 68s 53ms/step - accuracy: 0.9059 - loss: 0.2259 - val_accuracy: 0.9088 - val_loss: 0.2262
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 63s 50ms/step - accuracy: 0.9145 - loss: 0.2106 - val_accuracy: 0.9095 - val_loss: 0.2204
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9184 - loss: 0.1996 - val_accuracy: 0.9188 - val_loss: 0.2026
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9217 - loss: 0.1912 - val_accuracy: 0.9213 - val_loss: 0.1961
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 64s 51ms/step - accuracy: 0.9264 - loss: 0.1837 - val_accuracy: 0.9214 - val_loss: 0.2006
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 66s 52ms/step - accuracy: 0.9309 - loss: 0.1725 - val_accuracy: 0.9148 - val_loss: 0.2186
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 79s 50ms/step - accuracy: 0.9339 - loss: 0.1677 - val_accuracy: 0.9248 - val_loss: 0.1910
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9361 - loss: 0.1590 - val_accuracy: 0.9265 - val_loss: 0.1888
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 81s 50ms/step - accuracy: 0.9378 - loss: 0.1537 - val_accuracy: 0.9282 - val_loss: 0.1870
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 83s 50ms/step - accuracy: 0.9437 - loss: 0.1447 - val_accuracy: 0.9238 - val_loss: 0.1976
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 15ms/step - accuracy: 0.9217 - loss: 0.2019
Test Loss: 0.1890
Test Accuracy: 0.9265
```

In [ ]:

```
plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')

plt.title('Accuracy vs Epoch RNN(GRU)')

plt.legend()

plt.show()



plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(GRU)')

plt.legend()

plt.show()
```





Clearly GRU performs better than LSTM

Question 04

For the best model above, vary the size of RNN: [32, 128]

In [ ]:
```
model1 = Sequential()

model1.add(embedding_layer)

model1.add(GRU(32,activation='relu'))

# model1.add(Dense(16,activation='relu'))

model1.add(Dense(2,activation='softmax'))
```

```
model1.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(64, 300, 100)	1,000,000
gru_2 (GRU)	?	0 (unbuilt)
dense_7 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 1,000,000 (3.81 MB)

In [ ]:
```
model2 = Sequential()

model2.add(embedding_layer)

model2.add(GRU(128,activation='relu'))

# model2.add(Dense(16,activation='relu'))

model2.add(Dense(2,activation='softmax'))



model2.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(64, 300, 100)	1,000,000
gru_3 (GRU)	?	0 (unbuilt)
dense_8 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

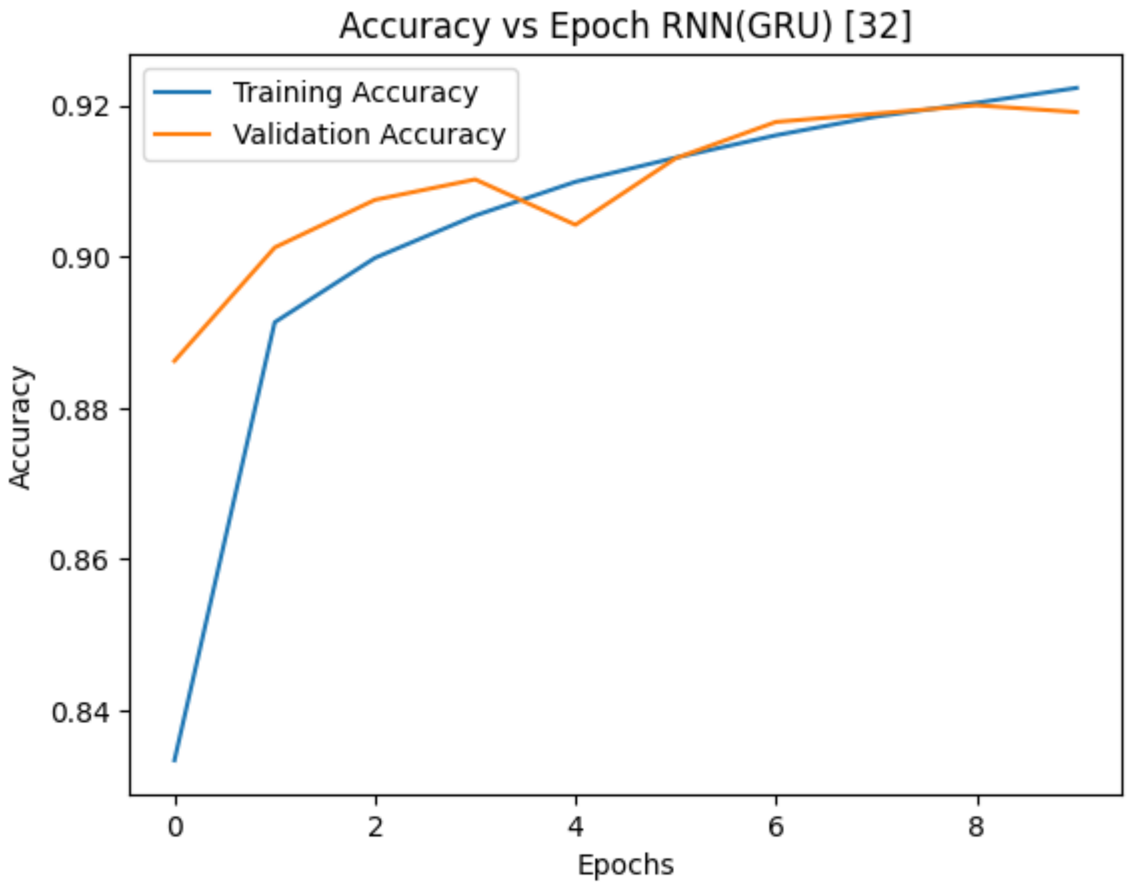
Trainable params: 0 (0.00 B)

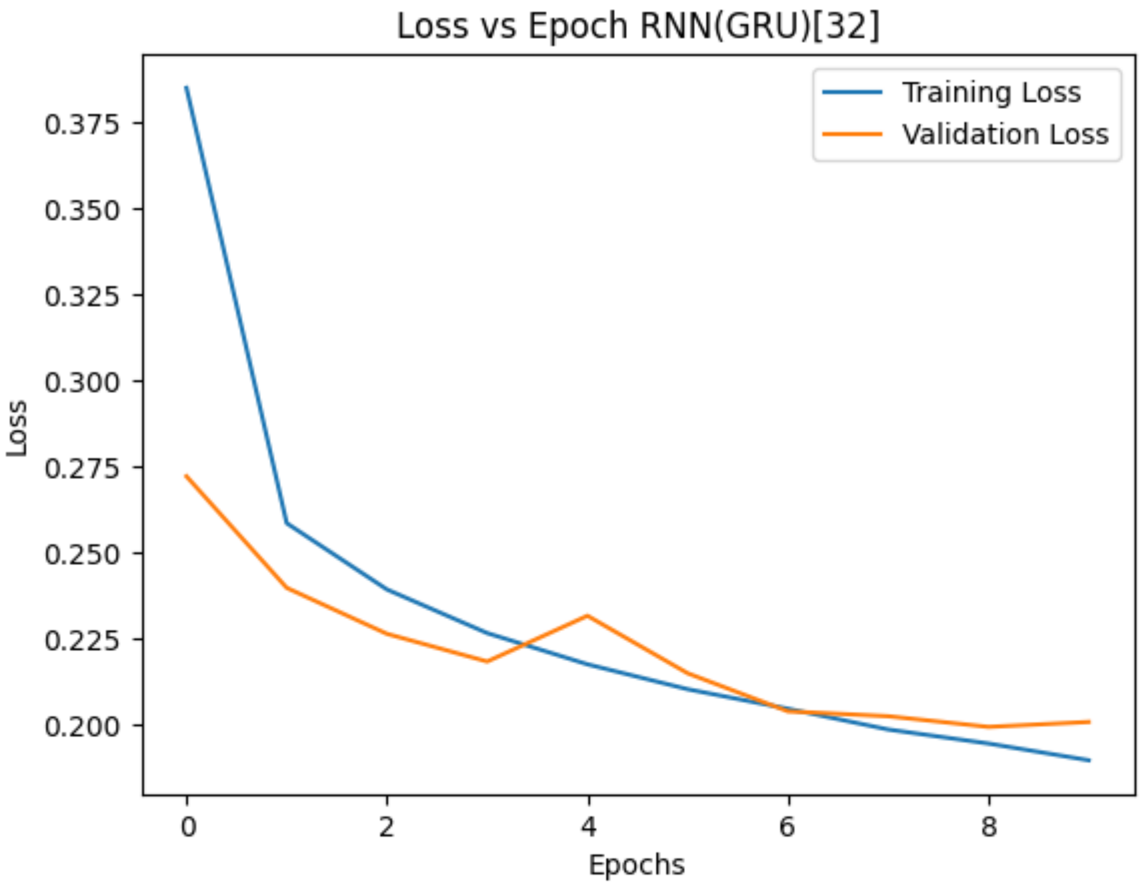
Non-trainable params: 1,000,000 (3.81 MB)

In [ ]:
```
model1.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model1.fit(
            X_train_padded,
            y_train_onehot,
            validation_data=(X_val_padded, y_val_onehot),
            epochs=10,
            batch_size=64,
            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]
          )


loss, accuracy = model1.evaluate(X_test_padded, y_test_onehot)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy:.4f}')


plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Epoch RNN(GRU) [32]')
plt.legend()
plt.show()
```

```python
plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(GRU)[32]')

plt.legend()

plt.show()
```

```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 66s 50ms/step - accuracy: 0.7917 - loss: 0.4748 - val_accuracy: 0.8862 - val_loss: 0.2722
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 60s 48ms/step - accuracy: 0.8904 - loss: 0.2634 - val_accuracy: 0.9012 - val_loss: 0.2398
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 89s 54ms/step - accuracy: 0.8985 - loss: 0.2429 - val_accuracy: 0.9075 - val_loss: 0.2264
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 74s 48ms/step - accuracy: 0.9062 - loss: 0.2255 - val_accuracy: 0.9102 - val_loss: 0.2184
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 48ms/step - accuracy: 0.9108 - loss: 0.2163 - val_accuracy: 0.9042 - val_loss: 0.2317
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 83s 49ms/step - accuracy: 0.9130 - loss: 0.2129 - val_accuracy: 0.9130 - val_loss: 0.2150
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 49ms/step - accuracy: 0.9143 - loss: 0.2088 - val_accuracy: 0.9178 - val_loss: 0.2039
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 81s 48ms/step - accuracy: 0.9188 - loss: 0.1982 - val_accuracy: 0.9189 - val_loss: 0.2025
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 83s 49ms/step - accuracy: 0.9181 - loss: 0.1988 - val_accuracy: 0.9200 - val_loss: 0.1994
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 49ms/step - accuracy: 0.9229 - loss: 0.1882 - val_accuracy: 0.9191 - val_loss: 0.2008
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 12ms/step - accuracy: 0.9144 - loss: 0.2110
Test Loss: 0.2025
Test Accuracy: 0.9182
```

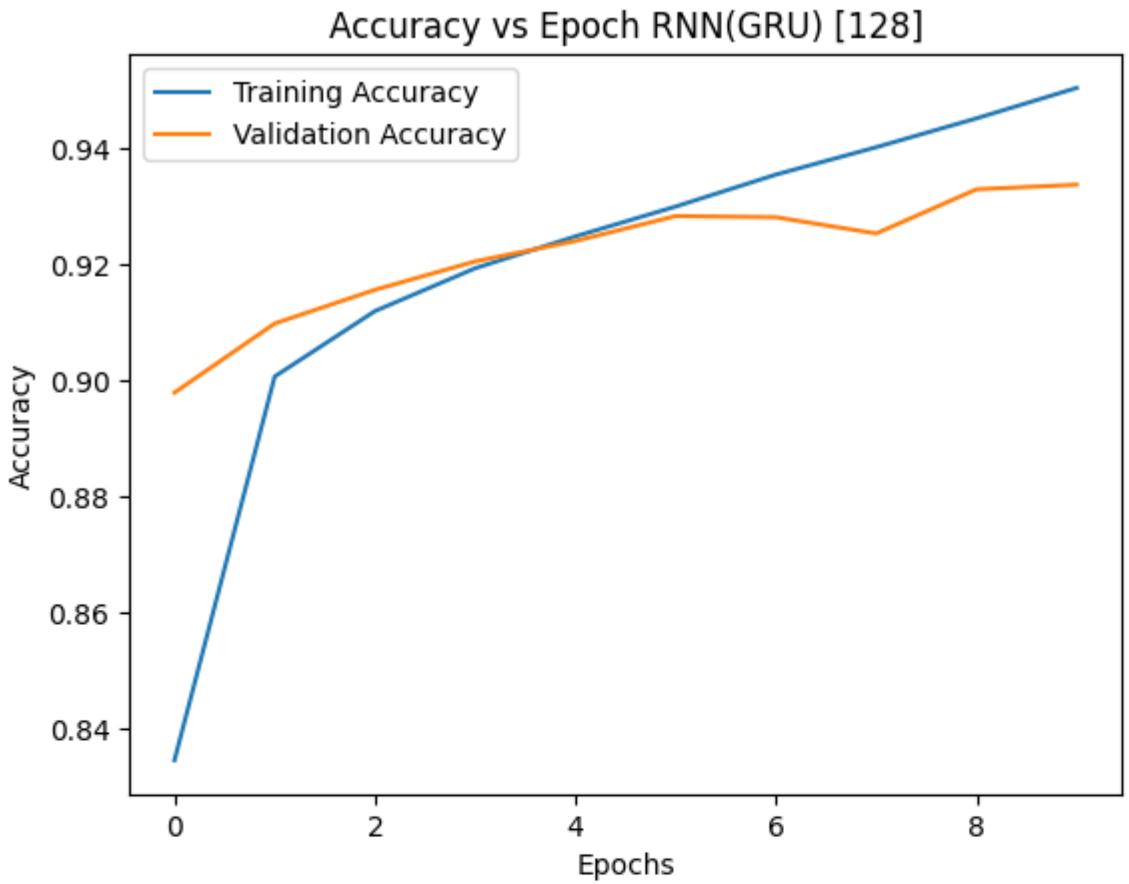

Accuracy vs Epoch RNN(GRU) [32]
Training Accuracy
Validation Accuracy
0.92
0.90
0.88
0.86
0.84
Accuracy
0
2
4
6
8
Epochs

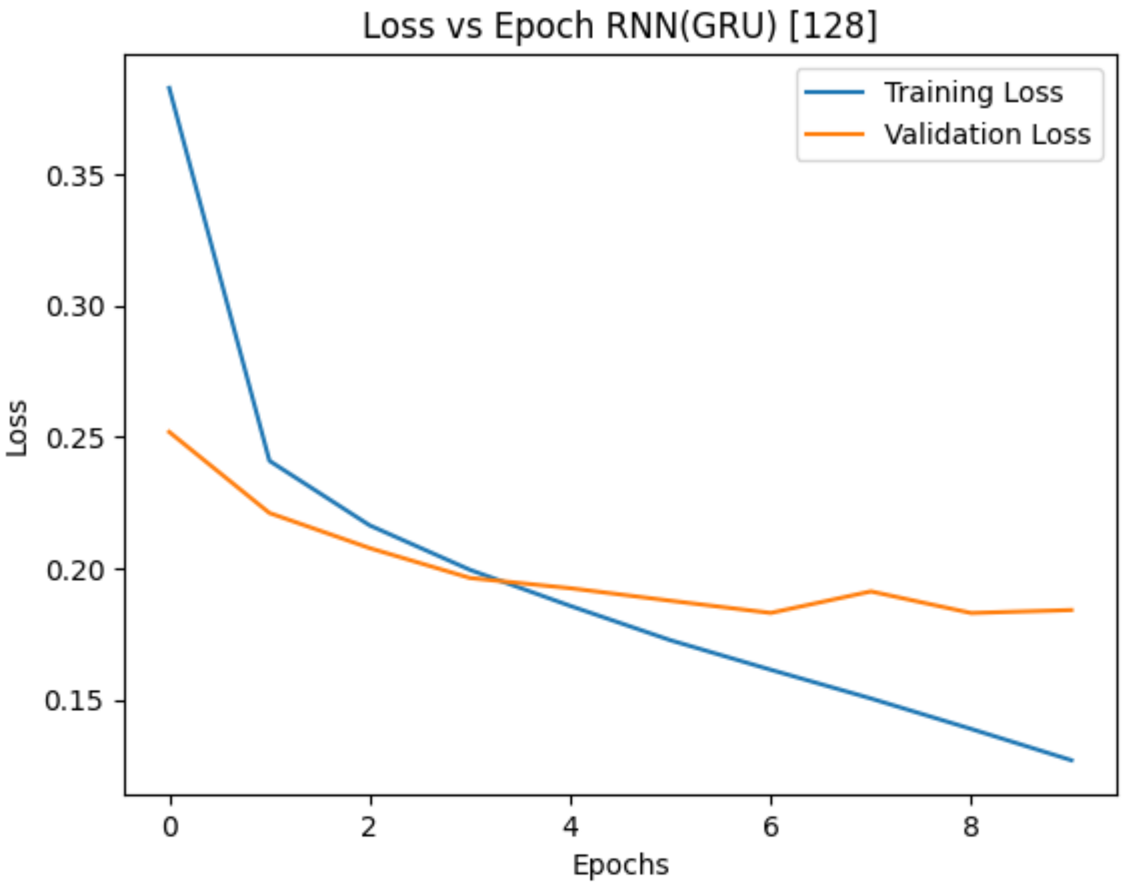


In [ ]:
```
model2.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model2.fit(
            X_train_padded,
            y_train_onehot,
            validation_data=(X_val_padded, y_val_onehot),
            epochs=10,
            batch_size=64,
            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]
```

```
        )


loss, accuracy = model2.evaluate(X_test_padded, y_test_onehot)

print(f'Test Loss: {loss:.4f}')

print(f'Test Accuracy: {accuracy:.4f}')



plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')

plt.title('Accuracy vs Epoch RNN(GRU) [128]')

plt.legend()

plt.show()



plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(GRU) [128]')

plt.legend()

plt.show()
```

```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 71s 54ms/step - accuracy: 0.7904 - loss: 0.4736 - val_accuracy: 0.8979 - val_loss: 0.2518
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 65s 52ms/step - accuracy: 0.8975 - loss: 0.2494 - val_accuracy: 0.9098 - val_loss: 0.2209
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 52ms/step - accuracy: 0.9109 - loss: 0.2183 - val_accuracy: 0.9156 - val_loss: 0.2076
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 81s 51ms/step - accuracy: 0.9199 - loss: 0.1979 - val_accuracy: 0.9205 - val_loss: 0.1962
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 81s 51ms/step - accuracy: 0.9237 - loss: 0.1861 - val_accuracy: 0.9240 - val_loss: 0.1923
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9282 - loss: 0.1758 - val_accuracy: 0.9283 - val_loss: 0.1876
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9364 - loss: 0.1606 - val_accuracy: 0.9281 - val_loss: 0.1829
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 82s 50ms/step - accuracy: 0.9400 - loss: 0.1493 - val_accuracy: 0.9253 - val_loss: 0.1911
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 62s 50ms/step - accuracy: 0.9462 - loss: 0.1372 - val_accuracy: 0.9329 - val_loss: 0.1829
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 83s 51ms/step - accuracy: 0.9512 - loss: 0.1257 - val_accuracy: 0.9337 - val_loss: 0.1840
313/313 ━━━━━━━━━━━━━━━━━━━━ 5s 12ms/step - accuracy: 0.9264 - loss: 0.2027
Test Loss: 0.1940
Test Accuracy: 0.9283
```


Accuracy vs Epoch RNN(GRU) [128]
Training Accuracy
Validation Accuracy
Accuracy
0.94
0.92
0.90
0.88
0.86
0.84
0
2
4
6
8
Epochs



128 units GRU RNN is better than 32 units GRU

In [40]:
```
best_unit=128
```

Question 05

For the best model above, vary the number of stack layers of RNN: [2, 3, 4]. One is

done previously.

In [41]:
```
model1 = Sequential()

model1.add(embedding_layer)

model1.add(GRU(best_unit,activation='relu',return_sequences=True))
```

```
model1.add(GRU(best_unit,activation='relu'))

model1.add(Dense(2,activation='softmax'))


model1.summary()


model2 = Sequential()

model2.add(embedding_layer)

model2.add(GRU(best_unit,activation='relu',return_sequences=True))

model2.add(GRU(best_unit,activation='relu',return_sequences=True))

model2.add(GRU(best_unit,activation='relu'))

model2.add(Dense(2,activation='softmax'))


model2.summary()


model3 = Sequential()

model3.add(embedding_layer)

model3.add(GRU(best_unit,activation='relu',return_sequences=True))

model3.add(GRU(best_unit,activation='relu',return_sequences=True))

model3.add(GRU(best_unit,activation='relu',return_sequences=True))

model3.add(GRU(best_unit,activation='relu'))

model3.add(Dense(2,activation='softmax'))


model3.summary()
```

Model: "sequential_15"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_45 (GRU)	?	0 (unbuilt)
gru_46 (GRU)	?	0 (unbuilt)
dense_15 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 1,000,000 (3.81 MB)

Model: "sequential_16"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_47 (GRU)	?	0 (unbuilt)
gru_48 (GRU)	?	0 (unbuilt)
gru_49 (GRU)	?	0 (unbuilt)
dense_16 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 1,000,000 (3.81 MB)

Model: "sequential_17"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_50 (GRU)	?	0 (unbuilt)
gru_51 (GRU)	?	0 (unbuilt)
gru_52 (GRU)	?	0 (unbuilt)
gru_53 (GRU)	?	0 (unbuilt)
dense_17 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

Non-trainable params: 1,000,000 (3.81 MB)

In [42]:
```
model1.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model1.fit(

            X_train_padded,

            y_train_onehot,

            validation_data=(X_val_padded, y_val_onehot),

            epochs=10,

            batch_size=64,

            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]

          )


loss, accuracy = model1.evaluate(X_test_padded, y_test_onehot)

print(f'Test Loss: {loss:.4f}')

print(f'Test Accuracy: {accuracy:.4f}')
```

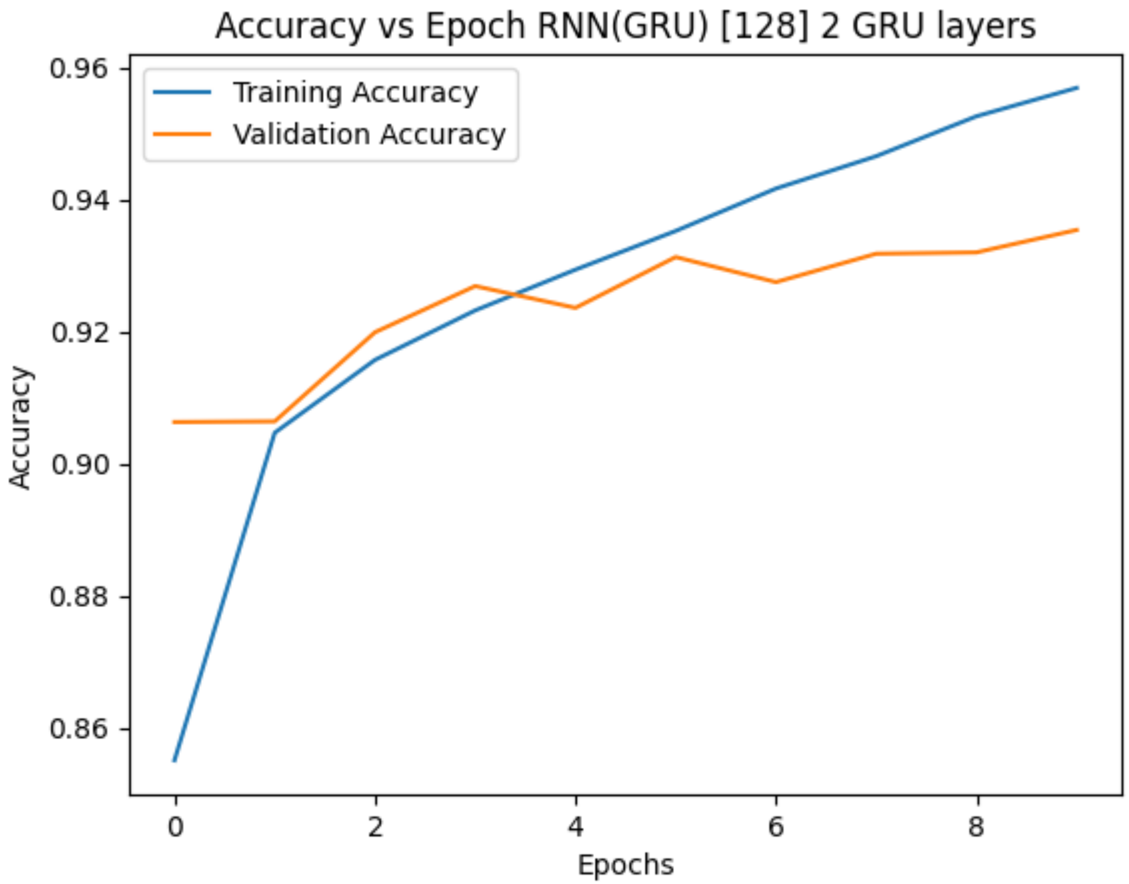
```
plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')

plt.title('Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers')

plt.legend()

plt.show()


plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(GRU) [128] 2 GRU layers')

plt.legend()

plt.show()

model2.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model2.fit(

            X_train_padded,

            y_train_onehot,

            validation_data=(X_val_padded, y_val_onehot),

            epochs=10,
```

```
            batch_size=64,
            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]
           )


loss, accuracy = model2.evaluate(X_test_padded, y_test_onehot)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy:.4f}')


plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Epoch RNN(GRU) [128] 3 GRU layers')
plt.legend()
plt.show()


plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs Epoch RNN(GRU) [128] 3 GRU layers')
plt.legend()
plt.show()
```

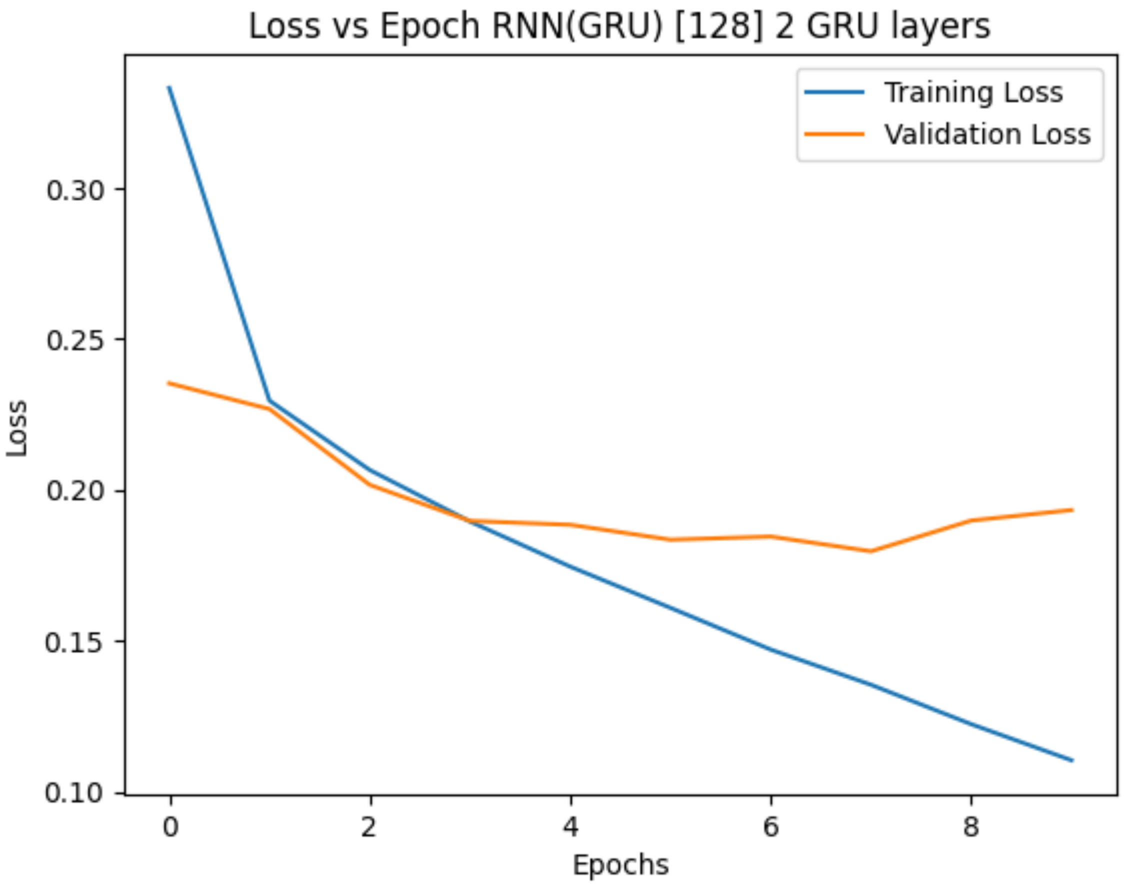
```python
model3.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])

history = model3.fit(
            X_train_padded,
            y_train_onehot,
            validation_data=(X_val_padded, y_val_onehot),
            epochs=10,
            batch_size=64,
            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]
          )

loss, accuracy = model3.evaluate(X_test_padded, y_test_onehot)
print(f'Test Loss: {loss:.4f}')
print(f'Test Accuracy: {accuracy:.4f}')

plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Accuracy vs Epoch RNN(GRU) [128] 4 GRU layers')
plt.legend()
plt.show()
```

```python
plt.plot(history.history['loss'], label='Training Loss')

plt.plot(history.history['val_loss'], label='Validation Loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.title('Loss vs Epoch RNN(GRU) [128] 4 GRU layers')

plt.legend()

plt.show()
```

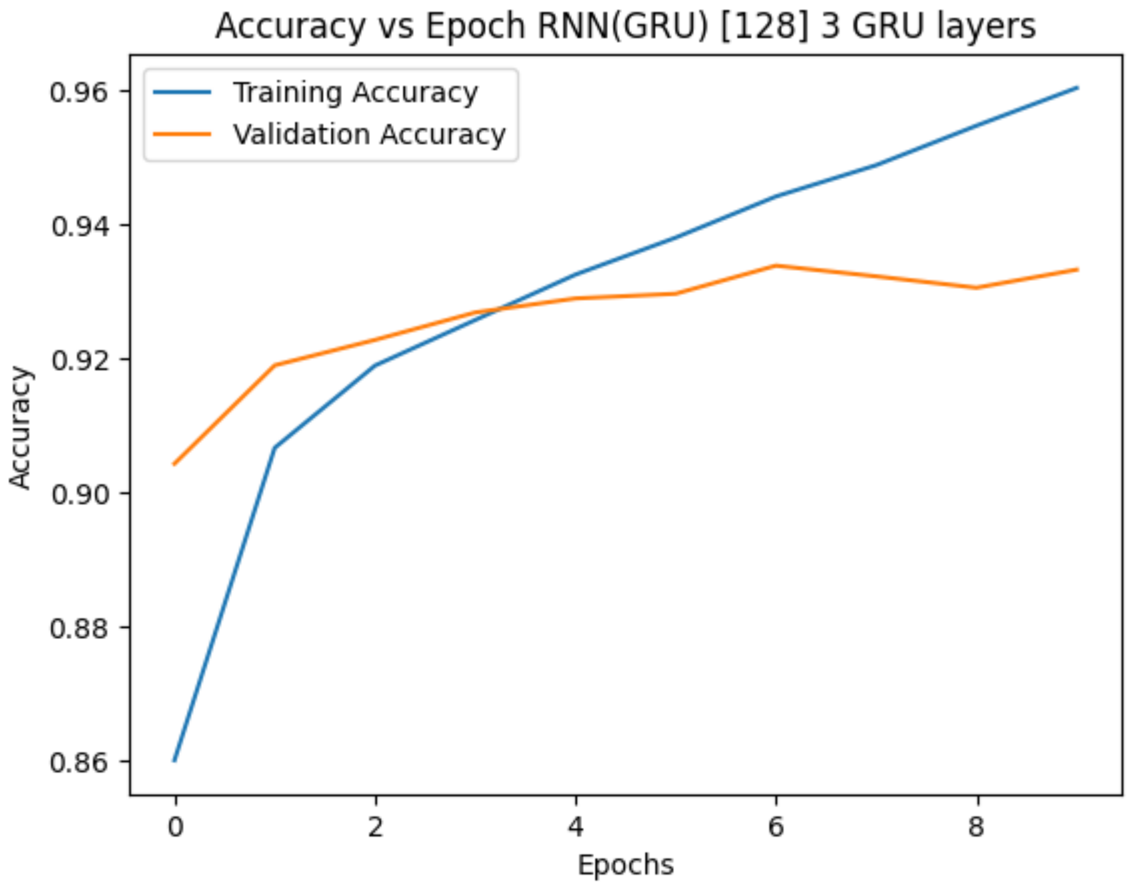
```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 89s 68ms/step - accuracy: 0.8091 - loss: 0.4238 - val_accuracy: 0.9063 - val_loss: 0.2353
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9030 - loss: 0.2336 - val_accuracy: 0.9064 - val_loss: 0.2267
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9136 - loss: 0.2093 - val_accuracy: 0.9199 - val_loss: 0.2016
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9236 - loss: 0.1898 - val_accuracy: 0.9269 - val_loss: 0.1897
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9296 - loss: 0.1765 - val_accuracy: 0.9236 - val_loss: 0.1884
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9364 - loss: 0.1595 - val_accuracy: 0.9313 - val_loss: 0.1834
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9413 - loss: 0.1477 - val_accuracy: 0.9275 - val_loss: 0.1845
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9465 - loss: 0.1338 - val_accuracy: 0.9318 - val_loss: 0.1796
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9529 - loss: 0.1201 - val_accuracy: 0.9320 - val_loss: 0.1898
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9569 - loss: 0.1093 - val_accuracy: 0.9354 - val_loss: 0.1933
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9276 - loss: 0.1877
Test Loss: 0.1773
Test Accuracy: 0.9321
```

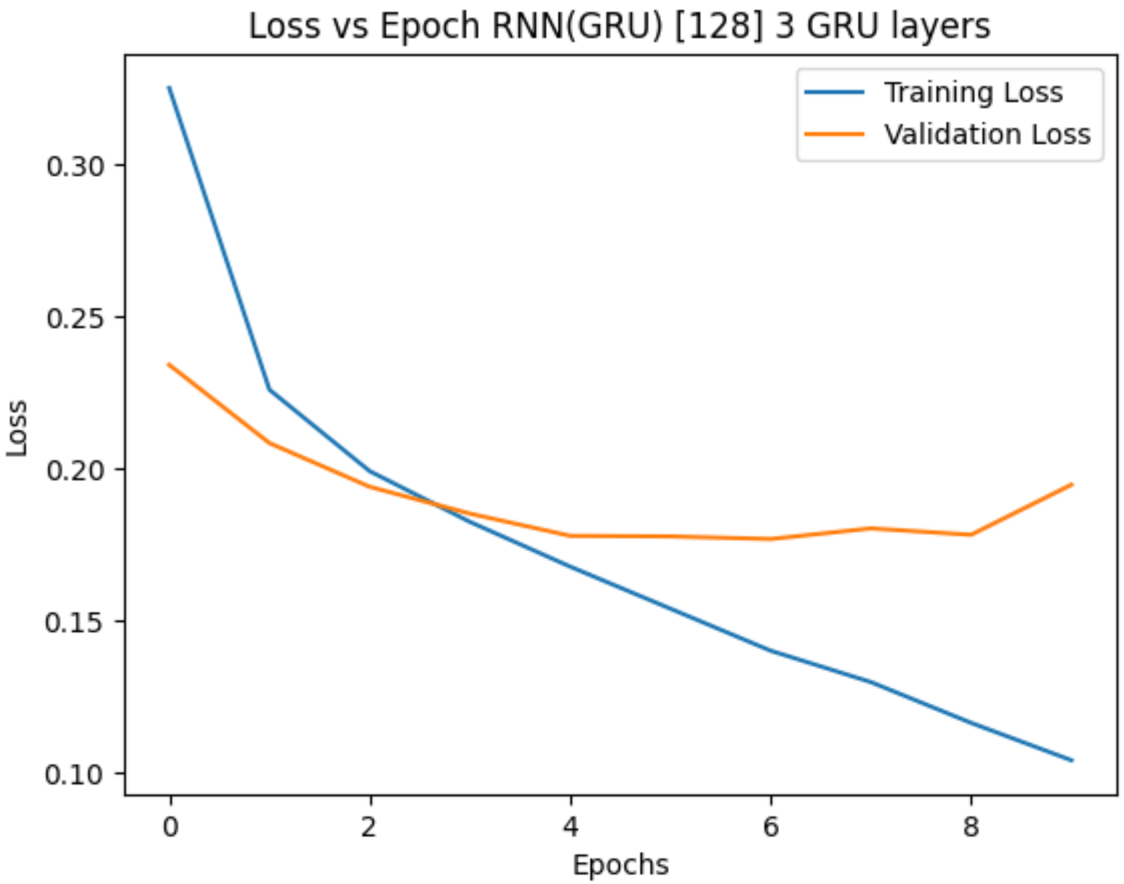


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers
Training Accuracy
Validation Accuracy
0.96
0.94
0.92
0.90
0.88
0.86
Accuracy
0
2
4
6
8
Epochs

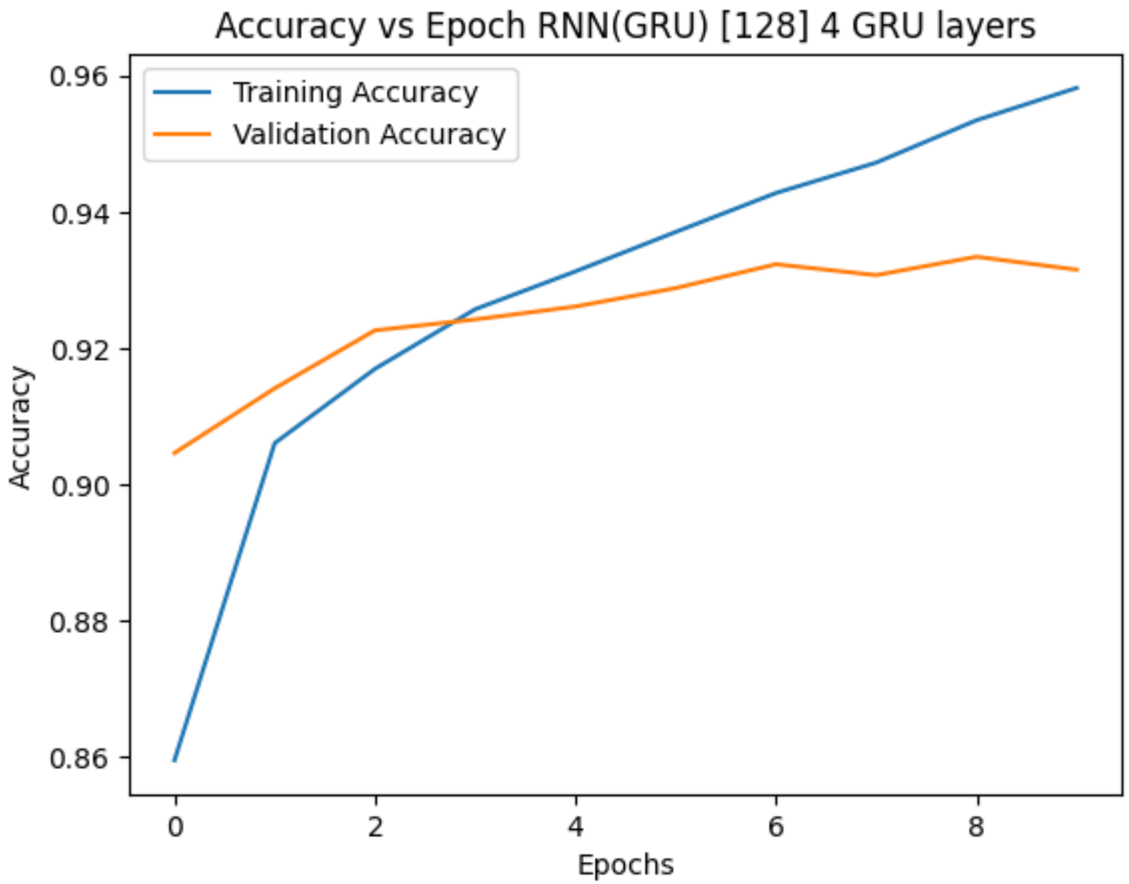

Loss vs Epoch RNN(GRU) [128] 2 GRU layers
Training Loss
Validation Loss
Loss
Epochs
0.30
0.25
0.20
0.15
0.10
0
2
4
6
8

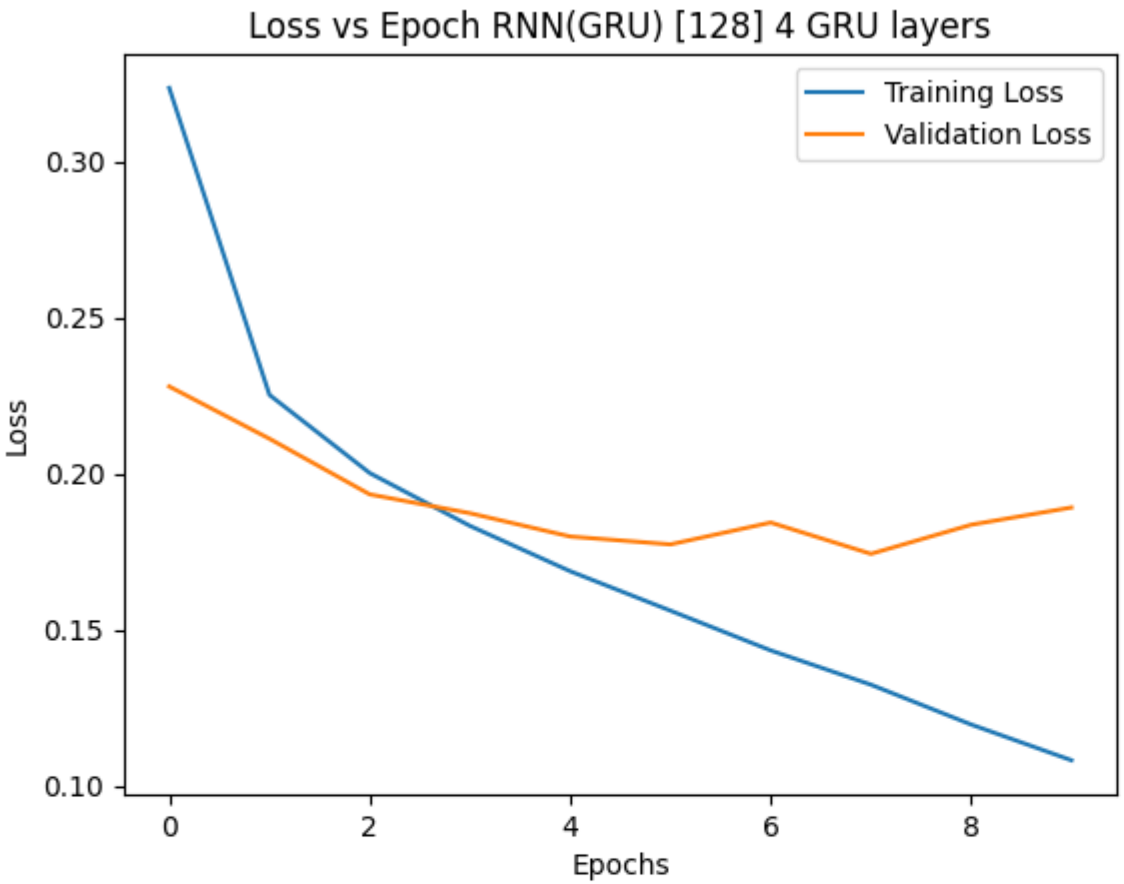
```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 133s 102ms/step - accuracy: 0.8214 - loss: 0.4132 - val_accuracy: 0.9043 - val_loss: 0.2342
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 127s 102ms/step - accuracy: 0.9064 - loss: 0.2294 - val_accuracy: 0.9190 - val_loss: 0.2084
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 127s 102ms/step - accuracy: 0.9194 - loss: 0.1982 - val_accuracy: 0.9228 - val_loss: 0.1940
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9270 - loss: 0.1803 - val_accuracy: 0.9269 - val_loss: 0.1852
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9343 - loss: 0.1658 - val_accuracy: 0.9290 - val_loss: 0.1779
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9396 - loss: 0.1511 - val_accuracy: 0.9297 - val_loss: 0.1777
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9432 - loss: 0.1424 - val_accuracy: 0.9339 - val_loss: 0.1768
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9505 - loss: 0.1257 - val_accuracy: 0.9323 - val_loss: 0.1803
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9553 - loss: 0.1147 - val_accuracy: 0.9306 - val_loss: 0.1782
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 126s 101ms/step - accuracy: 0.9621 - loss: 0.0995 - val_accuracy: 0.9333 - val_loss: 0.1947
313/313 ━━━━━━━━━━━━━━━━━━━━ 6s 18ms/step - accuracy: 0.9279 - loss: 0.1928
Test Loss: 0.1818
Test Accuracy: 0.9301
```


Accuracy vs Epoch RNN(GRU) [128] 3 GRU layers
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.96
0.94
0.92
0.90
0.88
0.86
0
2
4
6
8


Loss vs Epoch RNN(GRU) [128] 3 GRU layers
Training Loss
Validation Loss
Loss
Epochs
0.30
0.25
0.20
0.15
0.10
0
2
4
6
8

```
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 178s 137ms/step - accuracy: 0.8170 - loss: 0.4136 - val_accuracy: 0.9046 - val_loss: 0.2279
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 169s 136ms/step - accuracy: 0.9025 - loss: 0.2328 - val_accuracy: 0.9141 - val_loss: 0.2111
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 169s 136ms/step - accuracy: 0.9170 - loss: 0.2002 - val_accuracy: 0.9226 - val_loss: 0.1933
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 169s 136ms/step - accuracy: 0.9250 - loss: 0.1851 - val_accuracy: 0.9242 - val_loss: 0.1873
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 169s 136ms/step - accuracy: 0.9333 - loss: 0.1665 - val_accuracy: 0.9261 - val_loss: 0.1798
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 170s 136ms/step - accuracy: 0.9383 - loss: 0.1532 - val_accuracy: 0.9288 - val_loss: 0.1773
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 169s 136ms/step - accuracy: 0.9430 - loss: 0.1424 - val_accuracy: 0.9323 - val_loss: 0.1843
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 171s 137ms/step - accuracy: 0.9492 - loss: 0.1295 - val_accuracy: 0.9307 - val_loss: 0.1742
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 171s 137ms/step - accuracy: 0.9534 - loss: 0.1188 - val_accuracy: 0.9334 - val_loss: 0.1836
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 170s 136ms/step - accuracy: 0.9593 - loss: 0.1045 - val_accuracy: 0.9315 - val_loss: 0.1891
313/313 ━━━━━━━━━━━━━━━━━━━━ 8s 23ms/step - accuracy: 0.9259 - loss: 0.1923
Test Loss: 0.1815
Test Accuracy: 0.9290
```


Accuracy vs Epoch RNN(GRU) [128] 4 GRU layers
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.96
0.94
0.92
0.90
0.88
0.86
0
2
4
6
8



Clearly GRU with 2 layers performs better than the rest

Question 06

For the best model above, try Dropout: 0.1 and any other regularization parameters.

In [47]:
```
def train_model(
    rate
):
    model = Sequential()

    model.add(embedding_layer)

    model.add(GRU(best_unit,activation='relu',return_sequences=True))

    model.add(Dropout(rate=rate))
```

```
model.add(GRU(best_unit,activation='relu'))

model.add(Dropout(rate=rate))

model.add(Dense(2,activation='softmax'))

model.summary()

model.compile(loss='categorical_crossentropy',optimizer=Adam(learning_rate=0.0005),metrics=['accuracy'])


history = model.fit(

            X_train_padded,

            y_train_onehot,

            validation_data=(X_val_padded, y_val_onehot),

            epochs=10,

            batch_size=64,

            callbacks=[EarlyStopping(monitor='val_loss', patience=4, restore_best_weights=True)]

          )



loss, accuracy = model.evaluate(X_test_padded, y_test_onehot)

print(f'Test Loss: {loss:.4f}')

print(f'Test Accuracy: {accuracy:.4f}')



plt.plot(history.history['accuracy'], label='Training Accuracy')

plt.plot(history.history['val_accuracy'], label='Validation Accuracy')

plt.xlabel('Epochs')

plt.ylabel('Accuracy')
```

```python
    plt.title(f'Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate={rate}')

    plt.legend()

    plt.show()



    plt.plot(history.history['loss'], label='Training Loss')

    plt.plot(history.history['val_loss'], label='Validation Loss')

    plt.xlabel('Epochs')

    plt.ylabel('Loss')

    plt.title(f'Loss vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate={rate}')

    plt.legend()

    plt.show()
```

In [48]:
```python
dropout_rates = [0,0.1,0.25,0.5,0.75,0.9]

for rate in dropout_rates:
    train_model(rate)
```

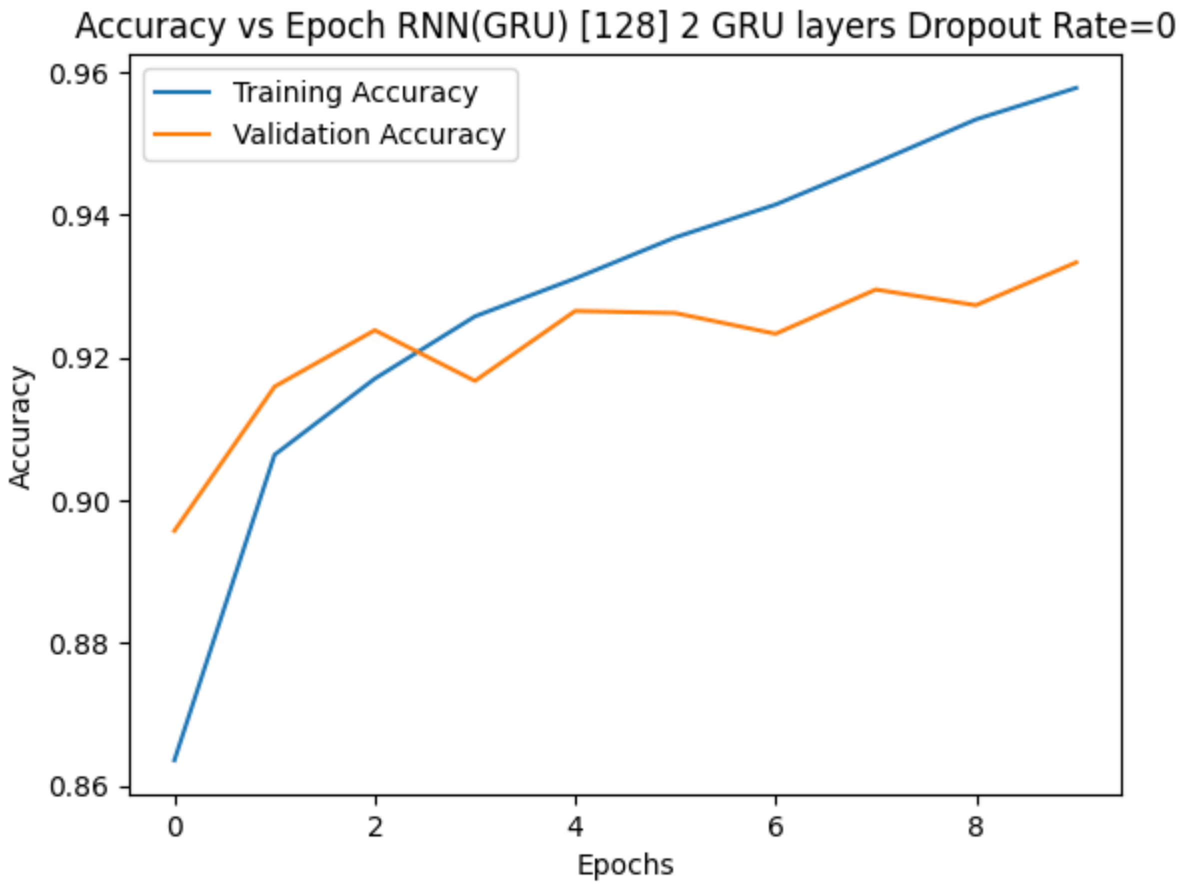
Model: "sequential_21"

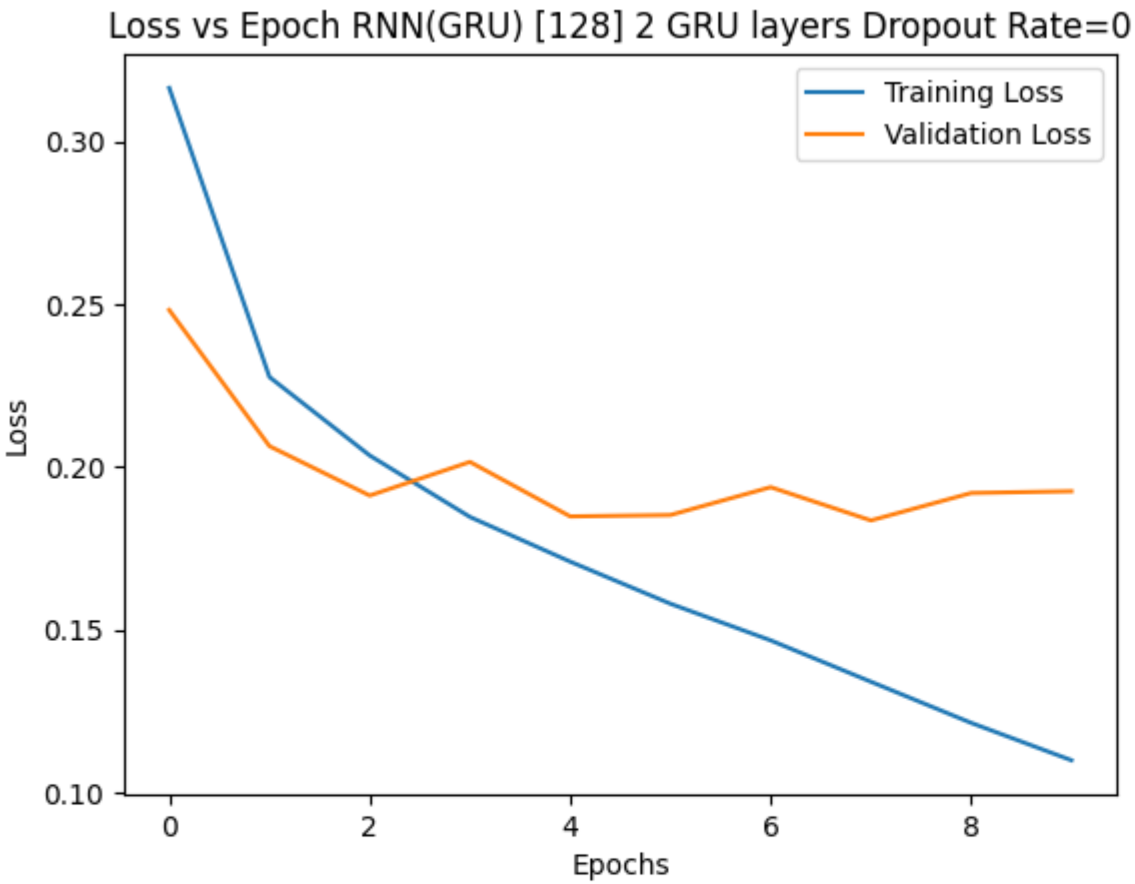
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_60 (GRU)	?	0 (unbuilt)
dropout_6 (Dropout)	?	0 (unbuilt)
gru_61 (GRU)	?	0 (unbuilt)
dropout_7 (Dropout)	?	0 (unbuilt)
dense_21 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 89s 68ms/step - accuracy: 0.8273 - loss: 0.4018 - val_accuracy: 0.8957 - val_loss: 0.2482
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9038 - loss: 0.2334 - val_accuracy: 0.9159 - val_loss: 0.2064
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9168 - loss: 0.2045 - val_accuracy: 0.9238 - val_loss: 0.1912
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9247 - loss: 0.1857 - val_accuracy: 0.9167 - val_loss: 0.2015
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9308 - loss: 0.1707 - val_accuracy: 0.9265 - val_loss: 0.1848
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9370 - loss: 0.1579 - val_accuracy: 0.9262 - val_loss: 0.1852
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9436 - loss: 0.1428 - val_accuracy: 0.9233 - val_loss: 0.1937
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9483 - loss: 0.1338 - val_accuracy: 0.9295 - val_loss: 0.1835
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9550 - loss: 0.1169 - val_accuracy: 0.9273 - val_loss: 0.1919
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9593 - loss: 0.1085 - val_accuracy: 0.9333 - val_loss: 0.1925
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9279 - loss: 0.1908
Test Loss: 0.1825
Test Accuracy: 0.9308
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.96
0.94
0.92
0.90
0.88
0.86
0
2
4
6
8



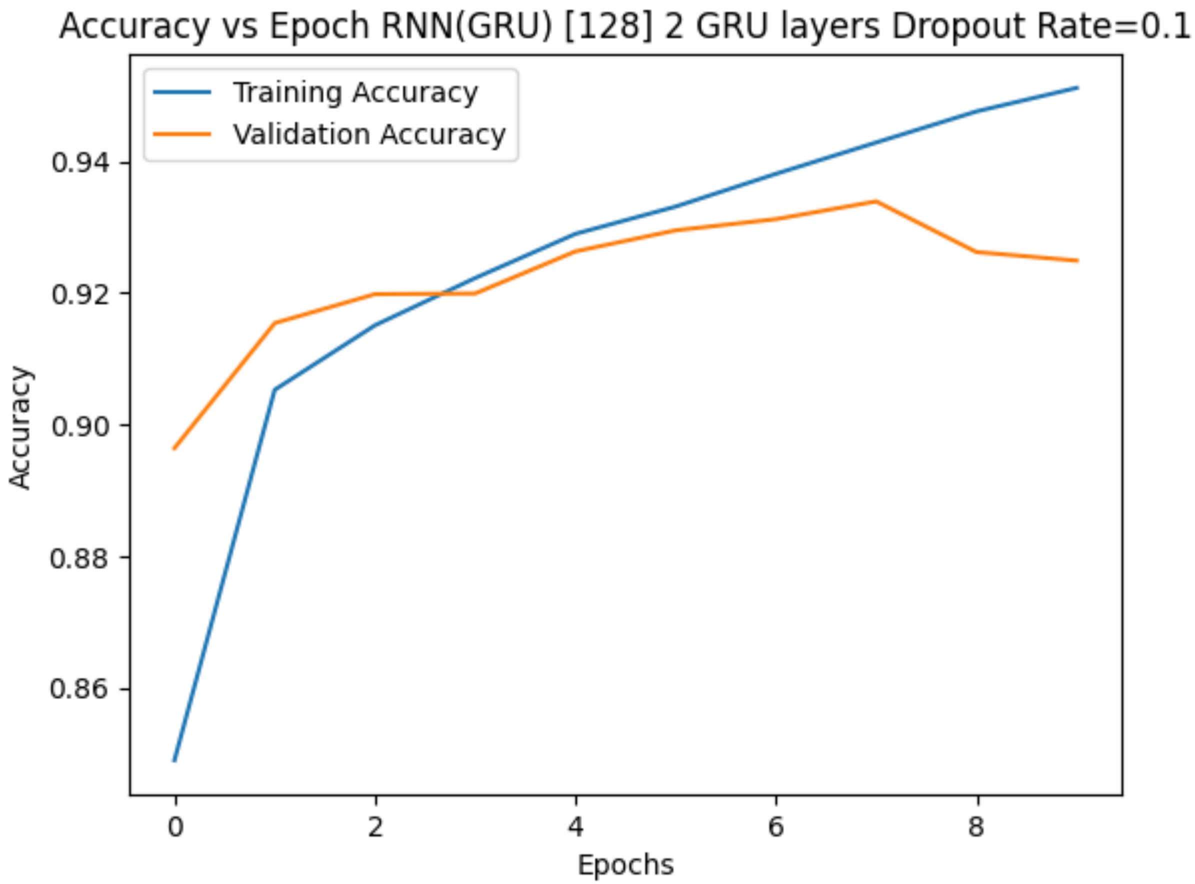
Model: "sequential_22"

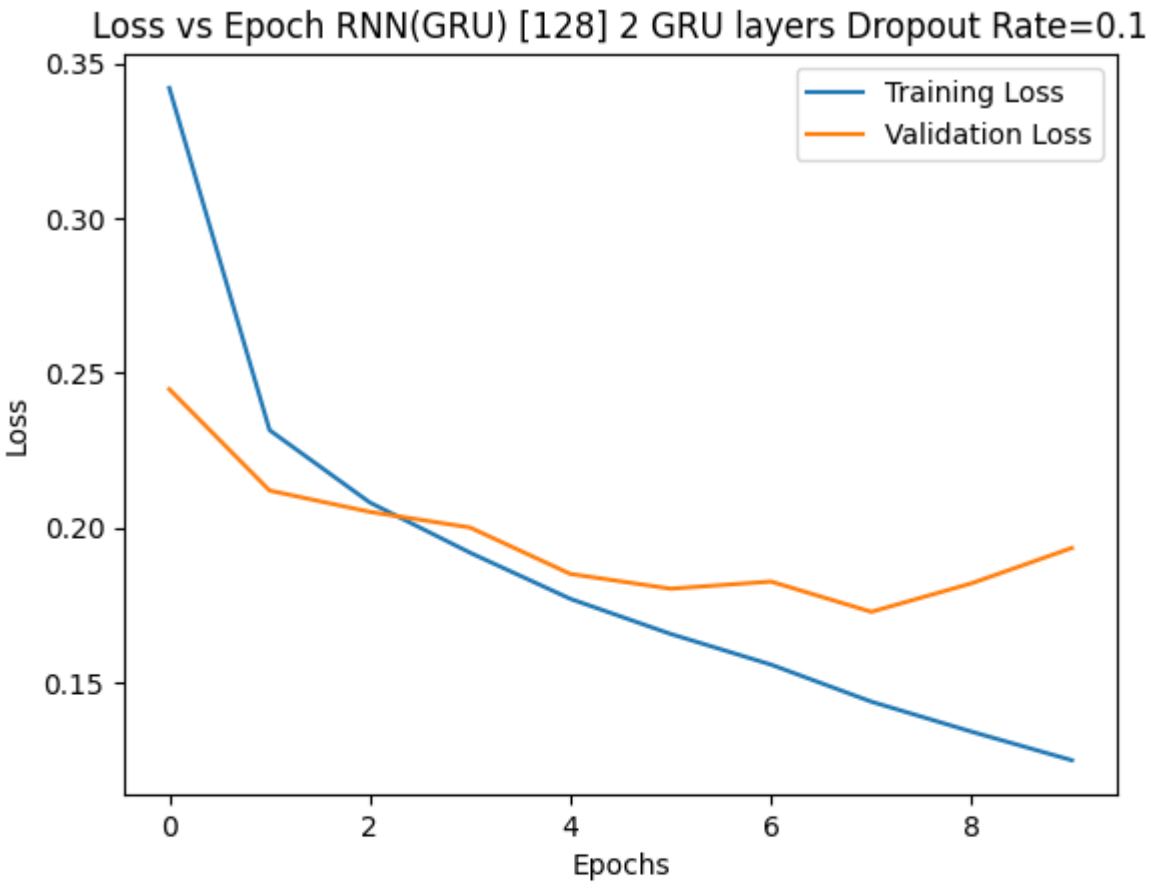
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_62 (GRU)	?	0 (unbuilt)
dropout_8 (Dropout)	?	0 (unbuilt)
gru_63 (GRU)	?	0 (unbuilt)
dropout_9 (Dropout)	?	0 (unbuilt)
dense_22 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 92s 68ms/step - accuracy: 0.8107 - loss: 0.4250 - val_accuracy: 0.8964 - val_loss: 0.2447
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9039 - loss: 0.2379 - val_accuracy: 0.9154 - val_loss: 0.2119
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9164 - loss: 0.2062 - val_accuracy: 0.9198 - val_loss: 0.2050
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9216 - loss: 0.1935 - val_accuracy: 0.9199 - val_loss: 0.1999
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9302 - loss: 0.1747 - val_accuracy: 0.9263 - val_loss: 0.1849
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9344 - loss: 0.1641 - val_accuracy: 0.9295 - val_loss: 0.1802
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9390 - loss: 0.1550 - val_accuracy: 0.9312 - val_loss: 0.1825
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9438 - loss: 0.1419 - val_accuracy: 0.9339 - val_loss: 0.1727
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9494 - loss: 0.1313 - val_accuracy: 0.9262 - val_loss: 0.1819
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9530 - loss: 0.1208 - val_accuracy: 0.9249 - val_loss: 0.1933
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9255 - loss: 0.1869
Test Loss: 0.1770
Test Accuracy: 0.9303
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0.1
Training Accuracy
Validation Accuracy
0.94
0.92
0.90
0.88
0.86
Accuracy
0
2
4
6
8
Epochs



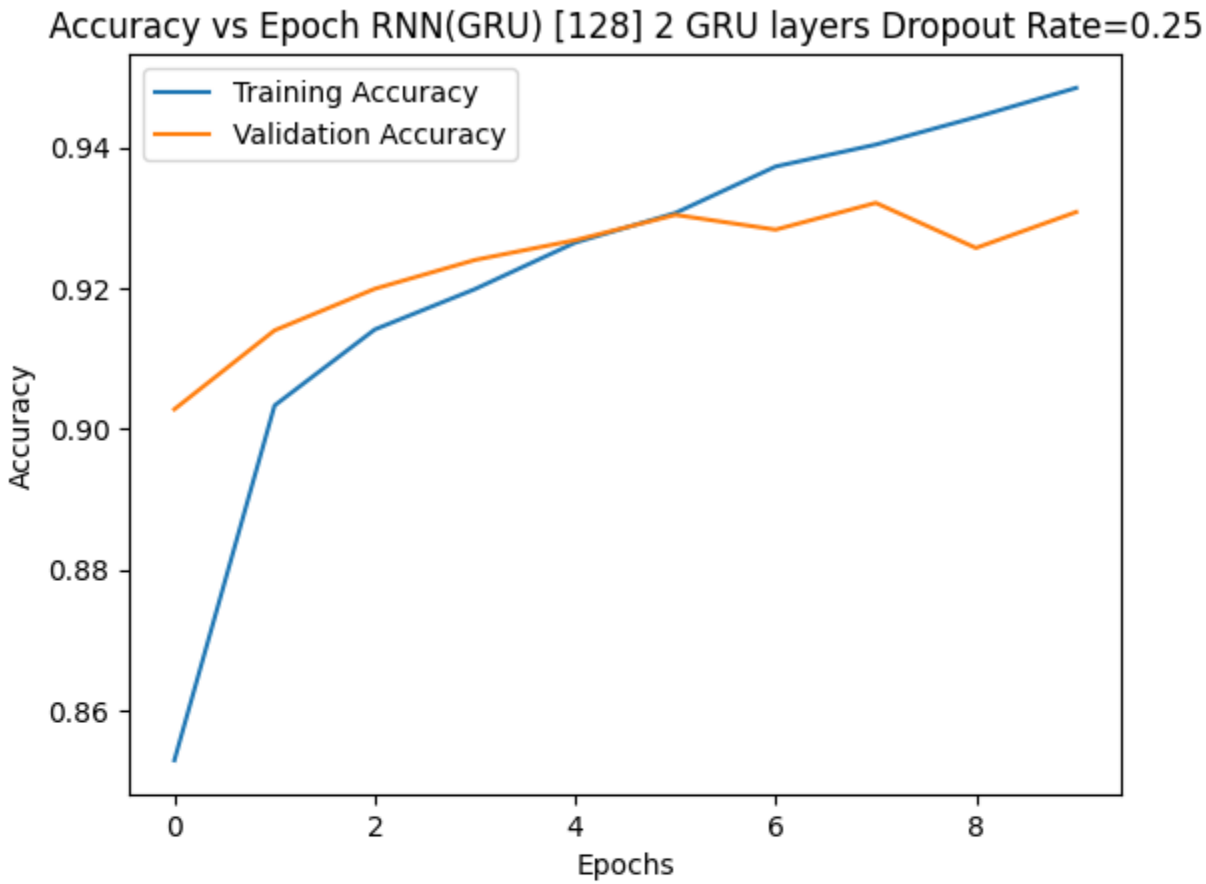
Model: "sequential_23"

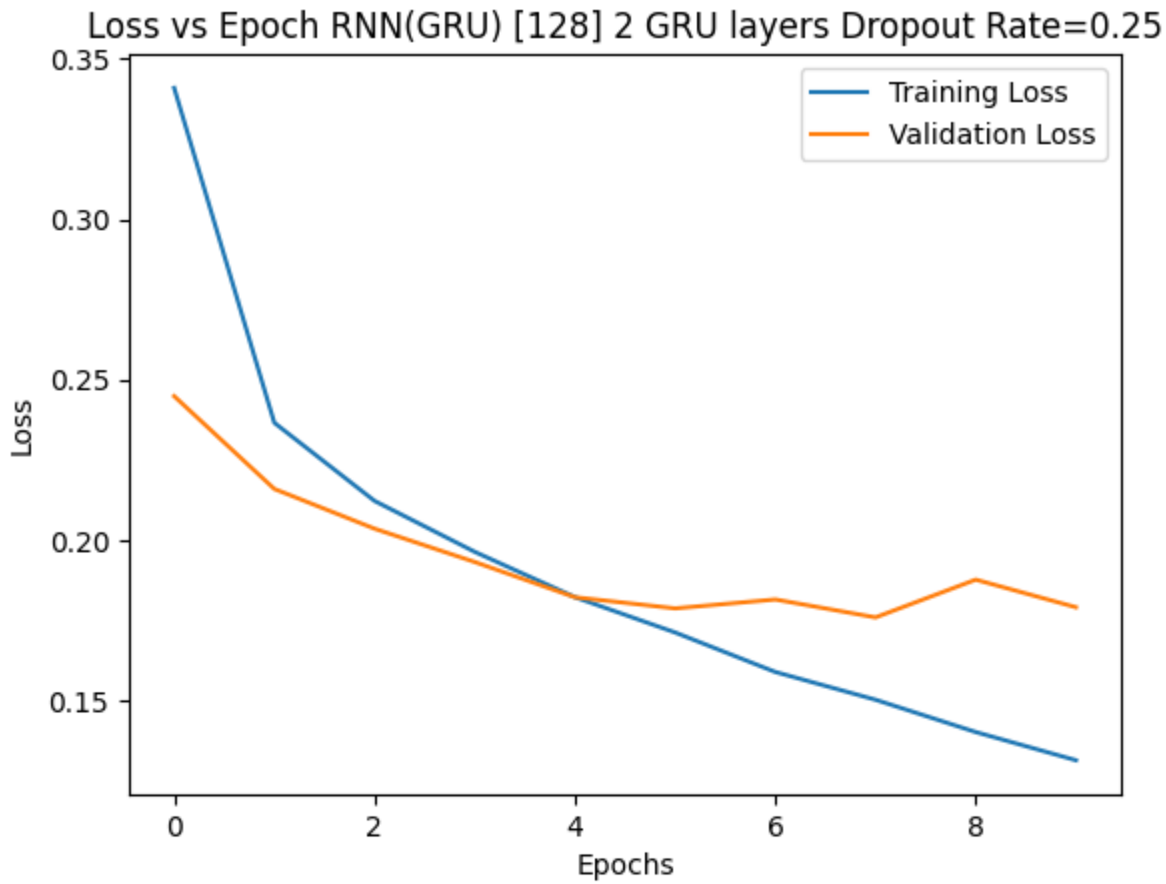
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_64 (GRU)	?	0 (unbuilt)
dropout_10 (Dropout)	?	0 (unbuilt)
gru_65 (GRU)	?	0 (unbuilt)
dropout_11 (Dropout)	?	0 (unbuilt)
dense_23 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 94s 70ms/step - accuracy: 0.8121 - loss: 0.4303 - val_accuracy: 0.9028 - val_loss: 0.2448
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 86s 69ms/step - accuracy: 0.9017 - loss: 0.2406 - val_accuracy: 0.9140 - val_loss: 0.2159
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 86s 68ms/step - accuracy: 0.9144 - loss: 0.2141 - val_accuracy: 0.9199 - val_loss: 0.2035
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9194 - loss: 0.1993 - val_accuracy: 0.9240 - val_loss: 0.1931
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9268 - loss: 0.1816 - val_accuracy: 0.9268 - val_loss: 0.1821
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9300 - loss: 0.1725 - val_accuracy: 0.9304 - val_loss: 0.1787
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9387 - loss: 0.1577 - val_accuracy: 0.9283 - val_loss: 0.1814
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9403 - loss: 0.1483 - val_accuracy: 0.9321 - val_loss: 0.1758
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9461 - loss: 0.1366 - val_accuracy: 0.9257 - val_loss: 0.1876
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9488 - loss: 0.1281 - val_accuracy: 0.9308 - val_loss: 0.1790
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9238 - loss: 0.1920
Test Loss: 0.1813
Test Accuracy: 0.9282
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0.25
Training Accuracy
Validation Accuracy
0.94
0.92
0.90
0.88
0.86
Accuracy
0
2
4
6
8
Epochs



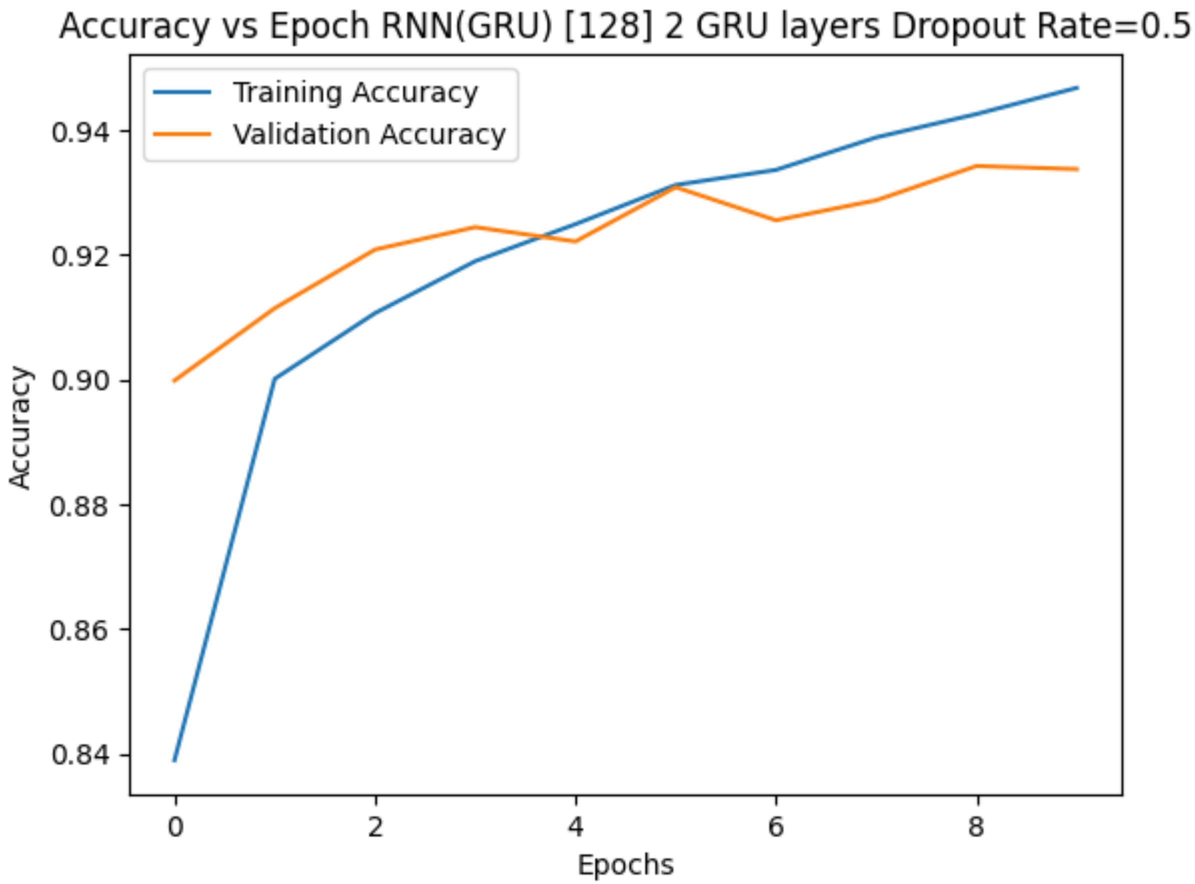
Model: "sequential_24"

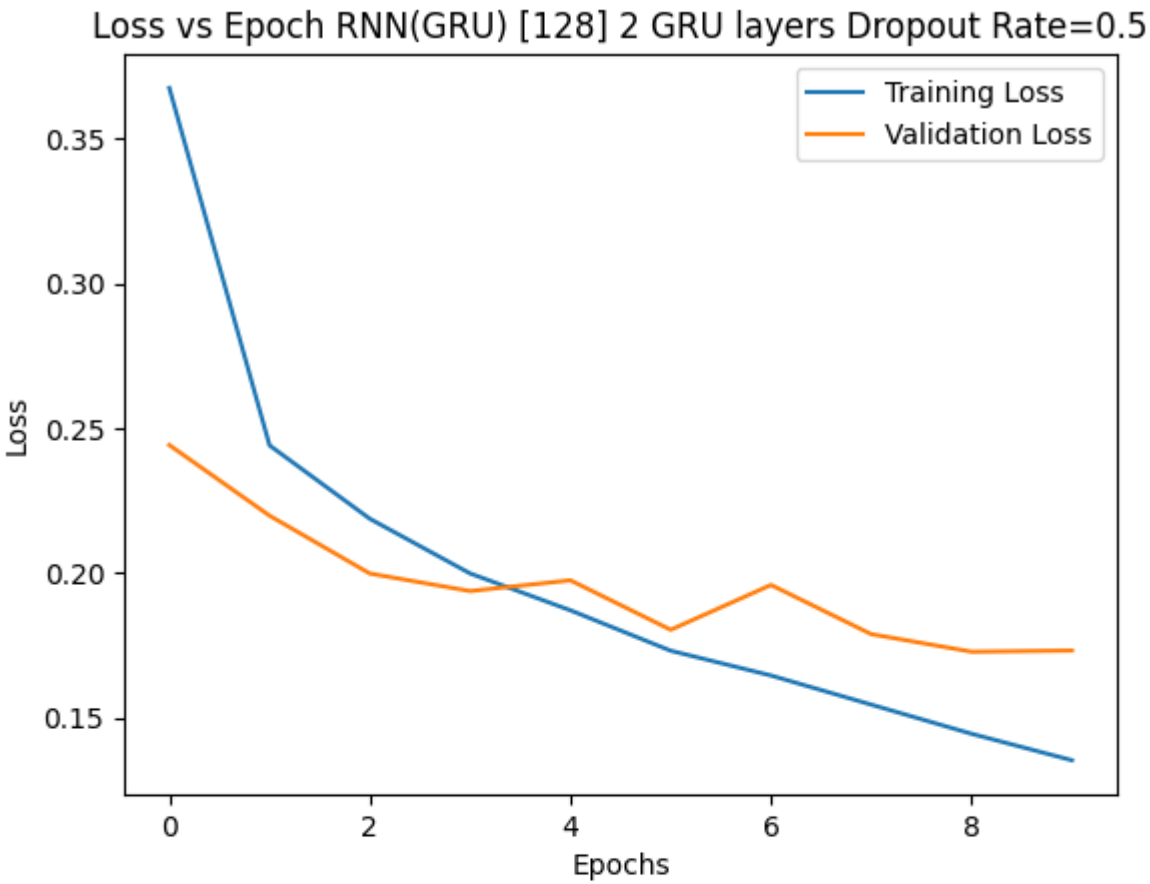
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_66 (GRU)	?	0 (unbuilt)
dropout_12 (Dropout)	?	0 (unbuilt)
gru_67 (GRU)	?	0 (unbuilt)
dropout_13 (Dropout)	?	0 (unbuilt)
dense_24 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 93s 69ms/step - accuracy: 0.7961 - loss: 0.4558 - val_accuracy: 0.8998 - val_loss: 0.2441
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.8965 - loss: 0.2533 - val_accuracy: 0.9114 - val_loss: 0.2197
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9087 - loss: 0.2246 - val_accuracy: 0.9208 - val_loss: 0.1997
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9189 - loss: 0.2007 - val_accuracy: 0.9244 - val_loss: 0.1937
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9266 - loss: 0.1855 - val_accuracy: 0.9221 - val_loss: 0.1974
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9303 - loss: 0.1716 - val_accuracy: 0.9308 - val_loss: 0.1803
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9339 - loss: 0.1641 - val_accuracy: 0.9255 - val_loss: 0.1958
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9374 - loss: 0.1545 - val_accuracy: 0.9287 - val_loss: 0.1788
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9429 - loss: 0.1432 - val_accuracy: 0.9342 - val_loss: 0.1727
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9479 - loss: 0.1314 - val_accuracy: 0.9337 - val_loss: 0.1731
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9263 - loss: 0.1916
Test Loss: 0.1790
Test Accuracy: 0.9320
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0.5
Training Accuracy
Validation Accuracy
Accuracy
0.94
0.92
0.90
0.88
0.86
0.84
0
2
4
6
8
Epochs



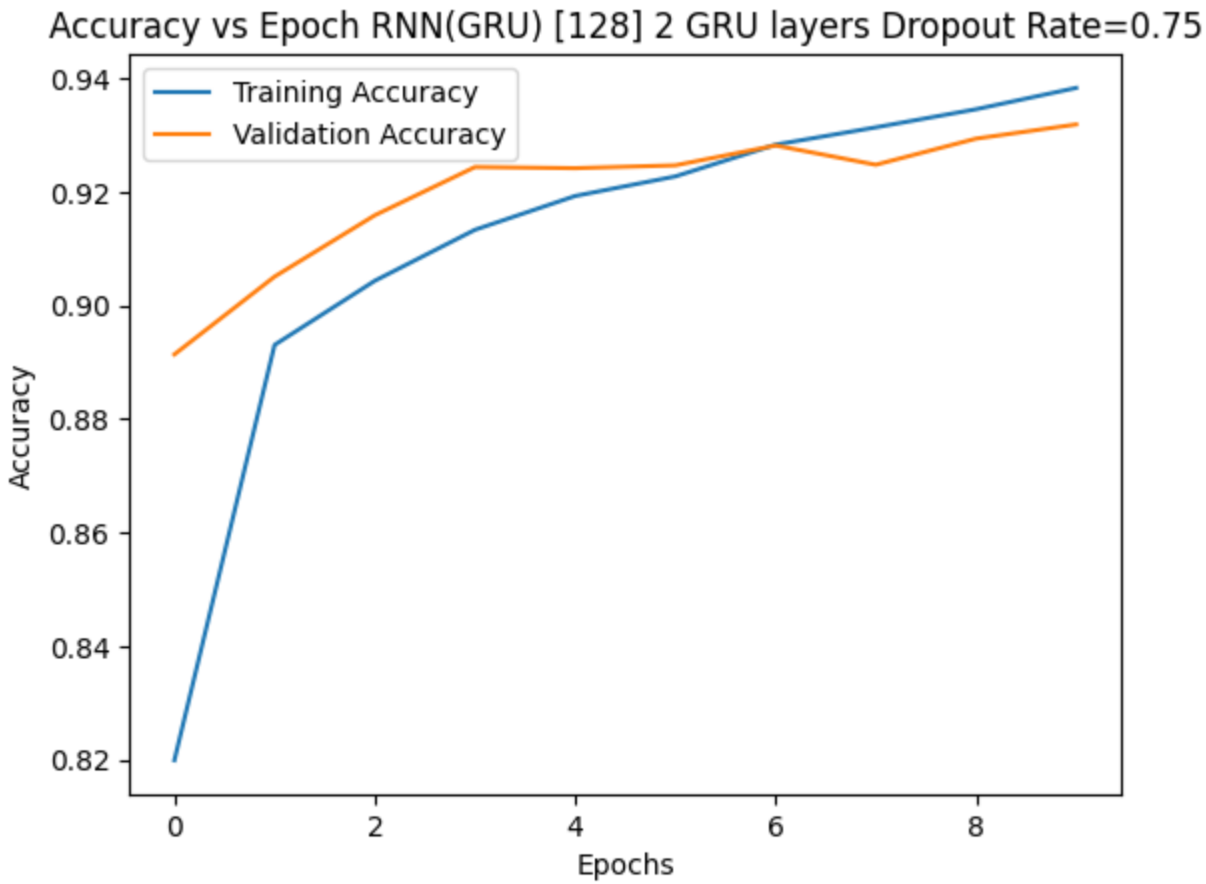
Model: "sequential_25"

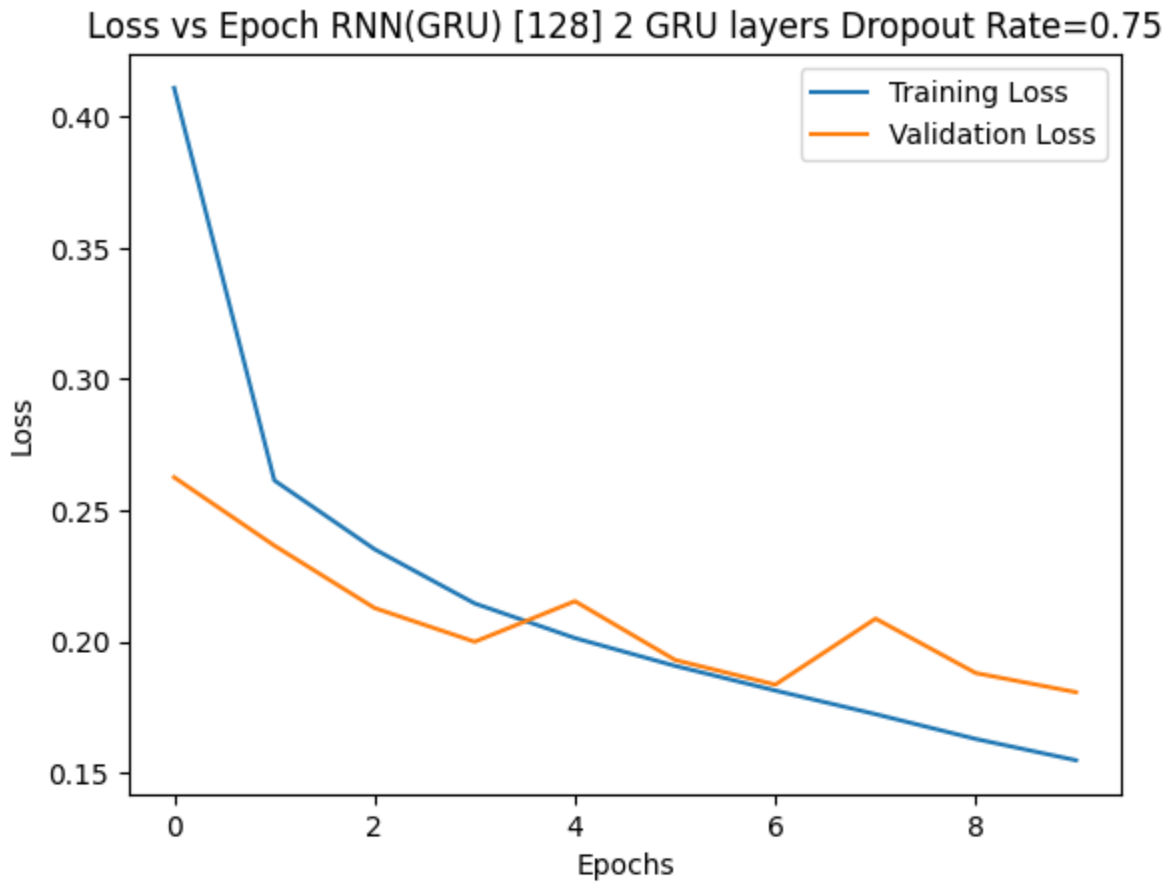
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_68 (GRU)	?	0 (unbuilt)
dropout_14 (Dropout)	?	0 (unbuilt)
gru_69 (GRU)	?	0 (unbuilt)
dropout_15 (Dropout)	?	0 (unbuilt)
dense_25 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 91s 68ms/step - accuracy: 0.7827 - loss: 0.4974 - val_accuracy: 0.8914 - val_loss: 0.2626
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.8894 - loss: 0.2673 - val_accuracy: 0.9051 - val_loss: 0.2367
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 68ms/step - accuracy: 0.9034 - loss: 0.2372 - val_accuracy: 0.9159 - val_loss: 0.2129
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9108 - loss: 0.2205 - val_accuracy: 0.9244 - val_loss: 0.2001
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 86s 69ms/step - accuracy: 0.9199 - loss: 0.2015 - val_accuracy: 0.9242 - val_loss: 0.2155
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9236 - loss: 0.1882 - val_accuracy: 0.9247 - val_loss: 0.1931
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9269 - loss: 0.1822 - val_accuracy: 0.9282 - val_loss: 0.1837
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9325 - loss: 0.1718 - val_accuracy: 0.9248 - val_loss: 0.2089
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9353 - loss: 0.1633 - val_accuracy: 0.9294 - val_loss: 0.1882
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.9397 - loss: 0.1524 - val_accuracy: 0.9319 - val_loss: 0.1809
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.9251 - loss: 0.2018
Test Loss: 0.1886
Test Accuracy: 0.9277
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0.75
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0
2
4
6
8



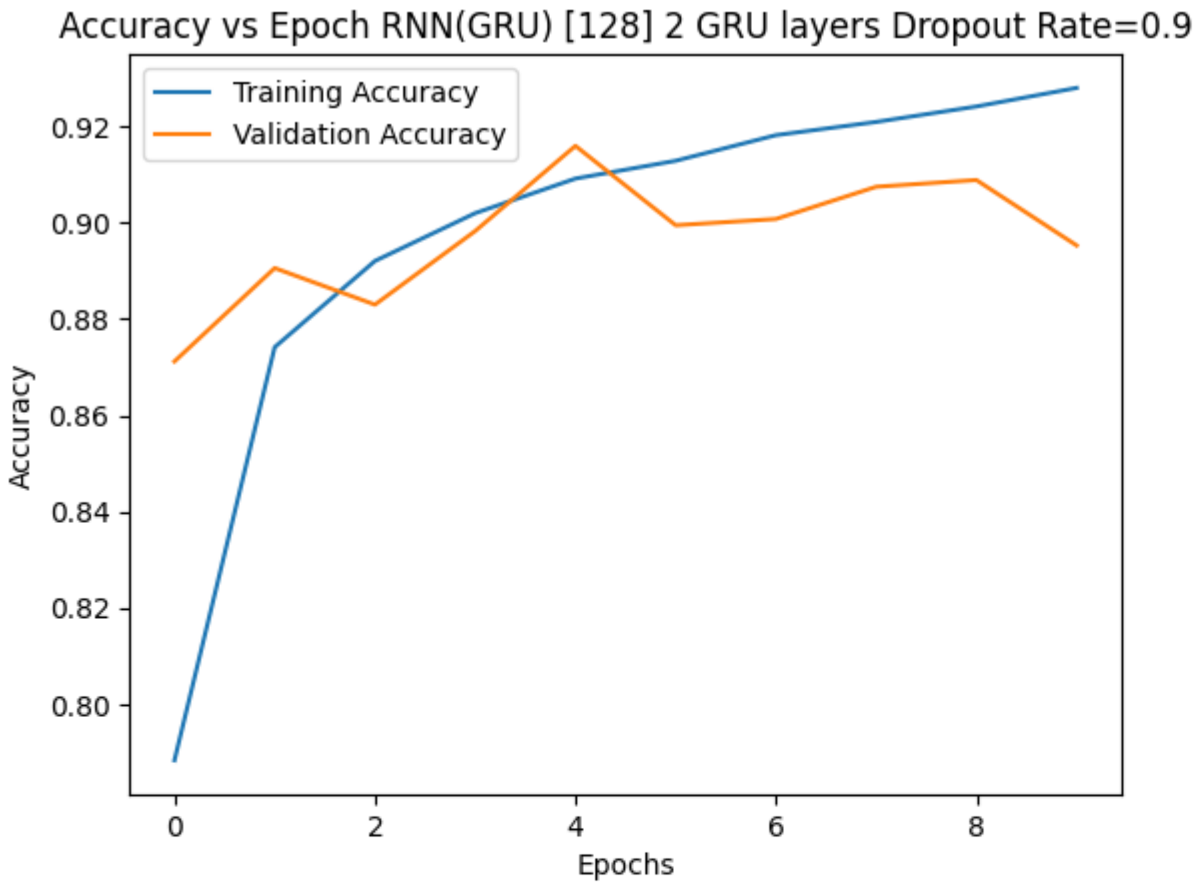
Model: "sequential_26"

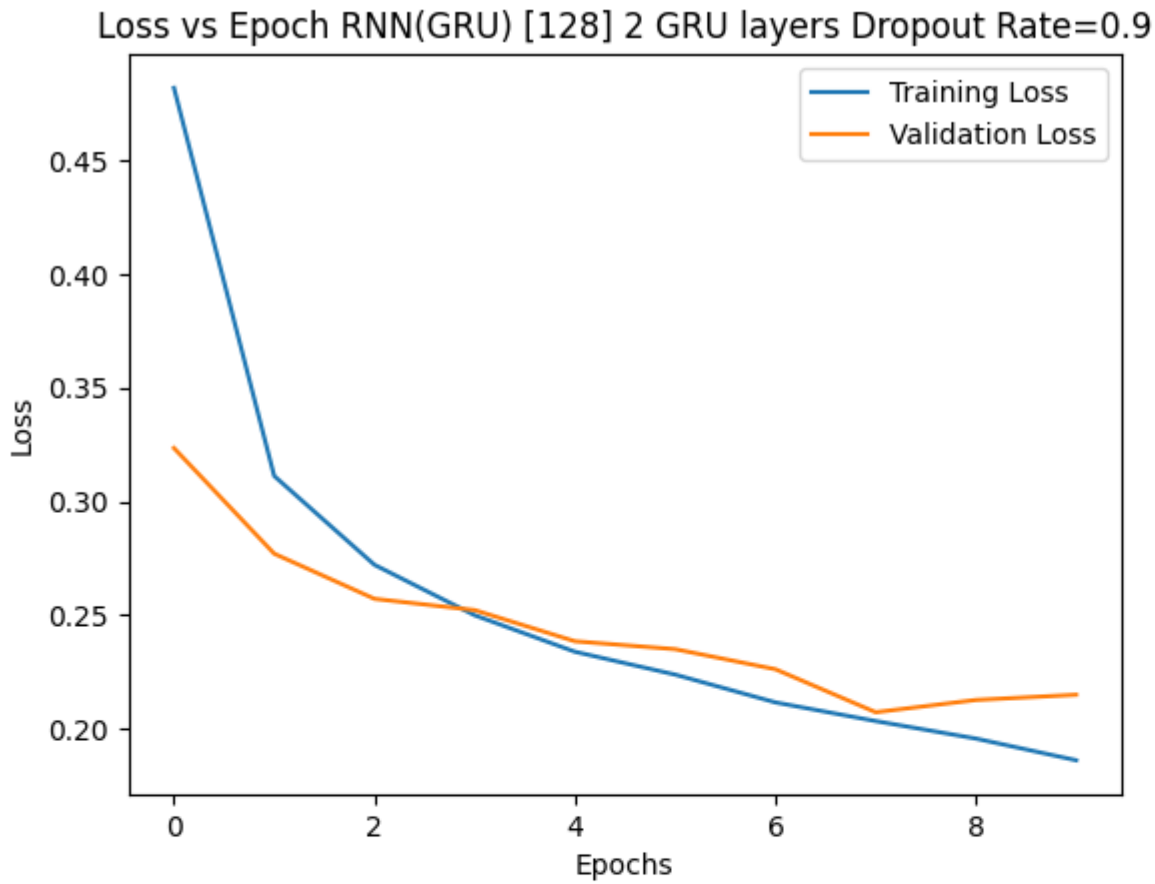
Layer (type)	Output Shape	Param #
embedding (Embedding)	(64, 300, 100)	1,000,000
gru_70 (GRU)	?	0 (unbuilt)
dropout_16 (Dropout)	?	0 (unbuilt)
gru_71 (GRU)	?	0 (unbuilt)
dropout_17 (Dropout)	?	0 (unbuilt)
dense_26 (Dense)	?	0 (unbuilt)

Total params: 1,000,000 (3.81 MB)

Trainable params: 0 (0.00 B)

```
Non-trainable params: 1,000,000 (3.81 MB)
Epoch 1/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 92s 68ms/step - accuracy: 0.7573 - loss: 0.5597 - val_accuracy: 0.8712 - val_loss: 0.3234
Epoch 2/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.8668 - loss: 0.3290 - val_accuracy: 0.8906 - val_loss: 0.2770
Epoch 3/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 85s 68ms/step - accuracy: 0.8894 - loss: 0.2777 - val_accuracy: 0.8830 - val_loss: 0.2571
Epoch 4/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 68ms/step - accuracy: 0.8996 - loss: 0.2538 - val_accuracy: 0.8983 - val_loss: 0.2522
Epoch 5/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9070 - loss: 0.2358 - val_accuracy: 0.9160 - val_loss: 0.2385
Epoch 6/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9132 - loss: 0.2254 - val_accuracy: 0.8995 - val_loss: 0.2350
Epoch 7/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 68ms/step - accuracy: 0.9194 - loss: 0.2104 - val_accuracy: 0.9008 - val_loss: 0.2262
Epoch 8/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 68ms/step - accuracy: 0.9199 - loss: 0.2031 - val_accuracy: 0.9075 - val_loss: 0.2073
Epoch 9/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 67ms/step - accuracy: 0.9248 - loss: 0.1929 - val_accuracy: 0.9089 - val_loss: 0.2126
Epoch 10/10
1250/1250 ━━━━━━━━━━━━━━━━━━━━ 84s 68ms/step - accuracy: 0.9277 - loss: 0.1852 - val_accuracy: 0.8953 - val_loss: 0.2149
313/313 ━━━━━━━━━━━━━━━━━━━━ 4s 13ms/step - accuracy: 0.8982 - loss: 0.2221
Test Loss: 0.2133
Test Accuracy: 0.9031
```


Accuracy vs Epoch RNN(GRU) [128] 2 GRU layers Dropout Rate=0.9
Training Accuracy
Validation Accuracy
Accuracy
Epochs
0.80
0.82
0.84
0.86
0.88
0.90
0.92
0
2
4
6
8



Dropout Rate 0.5 performs better than others