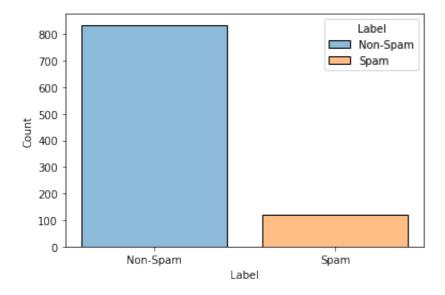
```
In [1]:
          # Load the modules that are useful for solving this problem
          import numpy as np
          import pandas as pd
          from matplotlib import pyplot as plt
          import seaborn as sns
          import spacy
          from sklearn.feature_extraction.text import TfidfVectorizer
          from sklearn.base import BaseEstimator, TransformerMixin
          from sklearn.pipeline import Pipeline
          from sklearn.model selection import GridSearchCV
          from sklearn.metrics import classification report as clt
          from sklearn.svm import LinearSVC
          from sklearn.linear model import LogisticRegression
          from sklearn.ensemble import RandomForestClassifier
In [4]:
          # Load the data
          my data = pd.read csv('SMS train.csv', encoding = 'latin')
          data test = pd.read csv('SMS test.csv', encoding = 'latin')
In [5]:
          # Overview the data
          my data.head(10)
            S. No.
Out[5]:
                                                Message_body
                                                                  Label
                                         Rofl. Its true to its name Non-Spam
         0
                1
         1
                       The guy did some bitching but I acted like i'd... Non-Spam
                        Pity, * was in mood for that. So...any other s... Non-Spam
         2
                3
         3
                4
                               Will ü b going to esplanade fr home? Non-Spam
                       This is the 2nd time we have tried 2 contact u...
                                                                  Spam
                6 REMINDER FROM 02: To get 2.50 pounds free call...
         5
                                                                  Spam
                7
                                                    Huh y lei... Non-Spam
         6
         7
                8
                       Why don't you wait 'til at least wednesday to ... Non-Spam
         8
                                               Ard 6 like dat lor. Non-Spam
         9
               10
                       Ok lor... Sony ericsson salesman... I ask shuh... Non-Spam
In [6]:
          # Measure the number of each class
          sns.histplot(x = my_data['Label'], hue = my_data['Label'], shrink = 0.8)
          plt.show()
          my data.groupby('Label').count()
```



Out[6]:

S. No. Message_body

Label		
Non-Spam	835	835
Spam	122	122

```
In [7]: # Measure 3 different dataset: imbalanced, oversampling, undersampling
    data_ini = my_data.copy()

df1 = my_data.query("Label == 'Spam'")
    df2 = my_data.query("Label == 'Non-Spam'")
    indover = np.random.choice(df1.index, 835, replace = True)
    dfover = my_data.iloc[indover]
    indunder = np.random.choice(df2.index, 122, replace = False)
    dfunder = my_data.iloc[indunder]

data_over = pd.concat([df2, dfover], axis = 0, ignore_index = True)
    data_under = pd.concat([df1, dfunder], axis = 0, ignore_index = True)
```

```
In [8]:
         # Word Embedding Function
         nlp = spacy.load("en core web lg", disable = ["parser", "ner"])
         class PairedSentenceVectorizer(BaseEstimator, TransformerMixin):
             def init (self):
                 pass
             def fit(self, X, y=None):
                 return self
             # Vectorize a single sentence.
             def _transform1(self, sentence):
                 words = sentence.split()
                 vectors = np.zeros(nlp.vocab.vectors.shape[1])
                 for i in words:
                     vectors = vectors + nlp.vocab[i].vector
                 return vectors
             # Vectorize a single row of the dataframe.
             def transform2(self, row):
                 vector1 = np.zeros(nlp.vocab.vectors.shape[1])
                 vector1[0 : nlp.vocab.vectors.shape[1]] = self._transform1(row[2])
                 return vector1
             def transform(self, X):
                 return np.concatenate(
                     [self. transform2(row).reshape(1, -1) for row in X.itertuples(
```

```
In [9]:
         # Method 1 Logistic Regression, Tf-idf to determine the best parameters, o
         def my_lr(data1, data2):
             pipe 1 = Pipeline(
                 [('tfidf', TfidfVectorizer()),
                  ('lr', LogisticRegression())])
             param_1 = {
                 'tfidf__binary': (True, False),
                 'tfidf__ngram_range': ((1, 1), (1, 2)),
                 'lr solver': ('newton-cg', 'lbfgs'),
                 'lr C': (1, 3)}
             grid 1 = GridSearchCV(pipe 1, param 1, cv = 5, verbose = 0, n jobs = -
             grid_1.fit(data1['Message_body'], data1['Label'])
             test = grid 1.predict(X = data2['Message body'])
             print("The best model :")
             print(grid_1.best_params_)
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
```

```
my lr(data ini, data test)
        The best model:
        {'lr__C': 3, 'lr__solver': 'newton-cg', 'tfidf__binary': True, 'tfidf__ngra
        m range': (1, 1)}
        The result :
                      precision
                                   recall f1-score
                                                       support
                            0.65
                                      1.00
                                                0.79
                                                            49
            Non-Spam
                Spam
                            1.00
                                      0.66
                                                0.79
                                                            76
            accuracy
                                                0.79
                                                           125
           macro avg
                            0.83
                                      0.83
                                                0.79
                                                           125
        weighted avg
                            0.86
                                      0.79
                                                0.79
                                                           125
In [ ]:
         # Method 1 Logistic Regression, Tf-idf, best parameters
         def my lr best(data1, data2):
             tfidfvec = TfidfVectorizer(binary = True)
             logr = LogisticRegression(C = 3, solver = 'newton-cg')
             pipe = Pipeline(
                 [('tfidf', tfidfvec),
                  ('lr', logr)))
             pipe.fit(data1['Message_body'], data1['Label'])
             test= pipe.predict(X = data2['Message_body'])
             print("The result :")
             print(clt(y true = data2['Label'], y pred = test))
In []:
         # Method 1 Logistic Regression, Tf-idf, best parameters, oversampling data
         my_lr_best(data_over, data_test)
        The result:
                      precision
                                    recall f1-score
                                                       support
                                      0.96
                                                0.88
                                                             49
            Non-Spam
                            0.81
                Spam
                            0.97
                                      0.86
                                                0.91
                                                            76
            accuracy
                                                0.90
                                                           125
           macro avg
                            0.89
                                      0.91
                                                0.89
                                                           125
        weighted avg
                            0.91
                                      0.90
                                                0.90
                                                           125
In [ ]:
         # Method 1 Logistic Regression, Tf-idf, best parameters, undersampling date
         my_lr_best(data_under, data_test)
```

```
The result :
              precision
                          recall f1-score
                                               support
                   0.92
                             0.96
                                        0.94
                                                    49
    Non-Spam
        Spam
                   0.97
                              0.95
                                        0.96
                                                    76
                                        0.95
    accuracy
                                                   125
                                        0.95
                   0.95
                             0.95
                                                   125
   macro avq
weighted avg
                   0.95
                              0.95
                                        0.95
                                                   125
```

```
In []:
         # Method 1 Logistic Regression : words embedding to determine the best para
         # original dataset
         def my lr em(data1, data2):
             psv = PairedSentenceVectorizer()
             x em1 = psv.fit transform(data1)
             x em2 = psv.fit transform(data2)
             pipe_1 = Pipeline(
                 [('lr', LogisticRegression(max_iter = 200))])
             param 1 = {
                 'lr_solver': ('newton-cg', 'lbfgs'),
                 'lr C': (0.1, 1)}
             grid_1 = GridSearchCV(pipe_1, param_1, cv = 5, verbose = 0, n_jobs = -
             grid 1.fit(x em1, data1['Label'])
             test = grid 1.predict(X = x em2)
             print("The best model :")
             print(grid_1.best_params_)
             print("The result :")
             print(clt(y true = data2['Label'], y pred = test))
```

```
In []: my_lr_em(data_ini, data_test)
The best model:
```

```
{'lr__C': 0.1, 'lr__solver': 'newton-cg'}
The result:
              precision
                           recall f1-score
                                               support
                   0.79
                             1.00
                                        0.88
                                                    49
    Non-Spam
                             0.83
                                        0.91
        Spam
                   1.00
                                                    76
    accuracy
                                        0.90
                                                   125
   macro avg
                   0.90
                             0.91
                                        0.89
                                                   125
weighted avg
                   0.92
                             0.90
                                        0.90
                                                   125
```

```
In [ ]:
         # Method 1 Logistic Regression, wrod embedding, best parameters
         def my_lr_em_best(data1, data2):
             psv = PairedSentenceVectorizer()
             x em1 = psv.fit transform(data1)
             x em2 = psv.fit transform(data2)
             logr = LogisticRegression(C = 0.1, solver = 'newton-cg', max iter = 50
             pipe = Pipeline([('lr', logr)])
             pipe.fit(x_em1, data1['Label'])
             test= pipe.predict(X = x_em2)
             print("The result :")
             print(clt(y true = data2['Label'], y pred = test))
In [ ]:
         # Method 1 Logistic Regression, word embedding, best parameters, oversampl.
         my_lr_em_best(data_over, data_test)
        The result:
                      precision
                                   recall f1-score
                                                       support
            Non-Spam
                            0.83
                                      1.00
                                                0.91
                                                            49
                Spam
                            1.00
                                      0.87
                                                0.93
                                                            76
            accuracy
                                                0.92
                                                           125
           macro avg
                                      0.93
                                                0.92
                                                           125
                            0.92
        weighted avg
                            0.93
                                      0.92
                                                0.92
                                                           125
In [ ]:
         # Method 1 Logistic Regression, word embedding, best parameters, undersamp.
         my_lr_em_best(data_under, data_test)
        The result:
                      precision
                                   recall f1-score
                                                       support
                                      0.98
                                                0.92
            Non-Spam
                            0.87
                                                            49
                Spam
                            0.99
                                      0.91
                                                0.95
                                                            76
                                                0.94
                                                           125
            accuracy
           macro avg
                            0.93
                                      0.94
                                                0.93
                                                           125
        weighted avg
                           0.94
                                      0.94
                                                0.94
                                                           125
```

```
In []:
         # Method 2 Support Vector Machine, Tf-idf to determine best parameters, or
         def my_svm(data1, data2):
             pipe_1 = Pipeline(
                 [('tfidf', TfidfVectorizer()),
                  ('svm', LinearSVC())])
             param 1 = {
                 'tfidf__binary': (True, False),
                 'tfidf__ngram_range': ((1, 1), (1, 2)),
                 'svm loss': ('hinge', 'squared hinge'),
                 'svm C': (1, 3)}
             grid_1 = GridSearchCV(pipe_1, param_1, cv = 5, verbose = 0, n_jobs = -
             grid_1.fit(data1['Message_body'], data1['Label'])
             test = grid_1.predict(X = data2['Message_body'])
             print("The best model :")
             print(grid 1.best params )
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
In []:
         my svm(data ini, data test)
        The best model:
        {'svm_C': 3, 'svm_loss': 'hinge', 'tfidf_ binary': True, 'tfidf_ ngram_ra
        nge': (1, 2)}
        The result :
                      precision
                                   recall f1-score
                                                       support
                           0.83
                                     1.00
                                                0.91
                                                            49
            Non-Spam
                                     0.87
                                                0.93
                           1.00
                                                            76
                Spam
                                                0.92
                                                           125
            accuracy
                           0.92
                                     0.93
                                                0.92
                                                           125
           macro avg
        weighted avg
                           0.93
                                     0.92
                                                0.92
                                                           125
In []:
         # Method 2 Support Vector Machine, Tf-idf, best parameters
         def my_svm_best(data1, data2):
             tfidfvec = Tfidfvectorizer(binary = True, ngram_range = (1, 2))
             lsvm = LinearSVC(C = 3, loss = 'hinge')
             pipe = Pipeline(
                 [('tfidf', tfidfvec),
                  ('svm', lsvm)])
             pipe.fit(data1['Message body'], data1['Label'])
             test= pipe.predict(X = data2['Message_body'])
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
```

```
In [ ]:
         # Method 2 Support Vector Machine, Tf-idf, best parameters, oversampling de
         my svm best(data over, data test)
        The result:
                       precision
                                    recall f1-score
                                                       support
                            0.80
                                      1.00
                                                0.89
            Non-Spam
                                                            49
                Spam
                            1.00
                                      0.84
                                                0.91
                                                            76
            accuracy
                                                0.90
                                                           125
                            0.90
                                      0.92
                                                0.90
                                                           125
           macro avg
                                      0.90
        weighted avg
                            0.92
                                                0.91
                                                           125
In [ ]:
         # Method 2 Support Vector Machine, Tf-idf, best parameters, undersampling
         my svm best(data under, data test)
        The result:
                      precision
                                  recall f1-score
                                                       support
                                      0.96
                            0.94
                                                0.95
                                                            49
            Non-Spam
                Spam
                            0.97
                                      0.96
                                                0.97
                                                            76
                                                0.96
                                                           125
            accuracy
                                                0.96
           macro avg
                            0.96
                                      0.96
                                                           125
        weighted avg
                            0.96
                                      0.96
                                                0.96
                                                           125
In []:
         # Method 2 Support Vector Machine: words embedding, best parameters, original
         def my svm em(data1, data2):
             psv = PairedSentenceVectorizer()
             x_em1 = psv.fit_transform(data1)
             x em2 = psv.fit transform(data2)
             pipe 1 = Pipeline([('svm', LinearSVC(max iter = 6000))])
             param 1 = {
                 'svm__loss': ('hinge', 'squared_hinge'),
                 'svm_C': (0.1, 1)}
             grid 1 = GridSearchCV(pipe 1, param 1, cv = 5, verbose = 0, n jobs = -
             grid 1.fit(x em1, data1['Label'])
             test = grid_1.predict(X = x_em2)
             print("The best model :")
             print(grid 1.best params )
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
In [ ]:
         my svm em(data ini, data test)
```

```
The best model:
        {'svm_C': 0.1, 'svm_loss': 'hinge'}
        The result:
                      precision
                                   recall f1-score
                                                       support
            Non-Spam
                            0.76
                                      0.98
                                                0.86
                                                             49
                                      0.80
                Spam
                            0.98
                                                0.88
                                                             76
                                                0.87
                                                            125
            accuracy
           macro avg
                            0.87
                                      0.89
                                                0.87
                                                            125
                            0.90
                                                0.87
                                                            125
        weighted avg
                                      0.87
In []:
         # Method 2 Support Vector Machine : words embedding, best parameters
         def my svm em best(data1, data2):
             psv = PairedSentenceVectorizer()
             x em1 = psv.fit transform(data1)
             x em2 = psv.fit transform(data2)
             lsvm = LinearSVC(C = 0.1, loss = 'hinge', max_iter = 5000)
             pipe = Pipeline([('svm', lsvm)])
             pipe.fit(x em1, data1['Label'])
             test= pipe.predict(X = x em2)
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
In [ ]:
         # Method 2 Support Vector Machine, word embedding, best parameters, oversal
         my_svm_em_best(data_over, data_test)
        The result:
                       precision
                                    recall f1-score
                                                       support
            Non-Spam
                            0.79
                                      0.98
                                                0.87
                                                             49
                 Spam
                            0.98
                                      0.83
                                                0.90
                                                             76
            accuracy
                                                0.89
                                                            125
                            0.89
                                      0.90
                                                0.89
                                                            125
           macro avg
        weighted avg
                            0.91
                                      0.89
                                                0.89
                                                            125
In [ ]:
         # Method 2 Support Vector Machine, word embedding, best parameters, unders
         my svm em best(data under, data test)
        The result:
                       precision
                                    recall f1-score
                                                       support
                            0.85
                                      0.94
                                                0.89
            Non-Spam
                                                             49
                                      0.89
                                                0.93
                            0.96
                Spam
                                                             76
            accuracy
                                                0.91
                                                            125
                            0.90
                                      0.92
                                                0.91
                                                            125
           macro avg
        weighted avg
                            0.92
                                      0.91
                                                0.91
                                                            125
```

```
In []:
         # Method 3 Random Forest: Tf-idf to determine best parameters, original determine
         def my_rf(data1, data2):
             pipe_1 = Pipeline(
                 [('tfidf', TfidfVectorizer()),
                  ('rf', RandomForestClassifier())])
             param 1 = {
                 'tfidf__binary': (True, False),
                 'tfidf__ngram_range': ((1, 1), (1, 2)),
                 'rf__max_features': ('sqrt', 'log2'),
                 'rf__ccp_alpha': (0.0, 0.5),
                  'rf _random_state' : (0, 1)}
             grid_1 = GridSearchCV(pipe_1, param_1, cv = 5, verbose = 0, n_jobs = -
             grid_1.fit(data1['Message_body'], data1['Label'])
             test = grid_1.predict(X = data2['Message_body'])
             print("The best model :")
             print(grid 1.best params )
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
In []:
        my rf(data ini, data test)
        The best model:
        {'rf_ccp_alpha': 0.0, 'rf_max_features': 'sqrt', 'rf_random_state': 0, '
        tfidf__binary': True, 'tfidf__ngram_range': (1, 1)}
        The result :
                      precision
                                    recall f1-score
                                                       support
                                      1.00
            Non-Spam
                            0.69
                                                0.82
                                                             49
                Spam
                            1.00
                                      0.71
                                                0.83
                                                            76
                                                0.82
                                                           125
            accuracy
           macro avq
                            0.85
                                      0.86
                                                0.82
                                                           125
```

weighted avg

0.88

0.82

0.83

125

```
In []:
         # Method 3 Random Forest : Tf-idf, best parameters
         def my_rf_best(data1, data2):
             tfidfvec = TfidfVectorizer(binary = True, ngram range = (1, 1))
             rdf = RandomForestClassifier(ccp alpha = 0.0, max features = 'sqrt', re
             pipe = Pipeline(
                 [('tfidf', tfidfvec),
                  ('rf', rdf)])
             pipe.fit(data1['Message body'], data1['Label'])
             test= pipe.predict(X = data2['Message_body'])
             print("The result :")
             print(clt(y_true = data2['Label'], y_pred = test))
In [ ]:
         # Method 3 Random Forest: Tf-idf, best parameters, oversampling
         my_rf_best(data_over, data_test)
        The result :
                      precision
                                   recall f1-score
                                                       support
            Non-Spam
                           0.69
                                      1.00
                                                0.82
                                                            49
                                      0.71
                                                0.83
                            1.00
                                                            76
                Spam
                                                0.82
                                                           125
            accuracy
           macro avg
                           0.85
                                      0.86
                                                0.82
                                                           125
        weighted avg
                            0.88
                                      0.82
                                                0.83
                                                           125
In [ ]:
         ## Method 3 Random Forest: Tf-idf. best parameters, undersampling
         my_rf_best(data_under, data_test)
        The result :
                      precision
                                   recall f1-score
                                                       support
            Non-Spam
                            0.75
                                      1.00
                                                0.86
                                                            49
                            1.00
                                      0.79
                                                0.88
                                                            76
                Spam
            accuracy
                                                0.87
                                                           125
           macro avg
                           0.88
                                      0.89
                                                0.87
                                                           125
                           0.90
        weighted avg
                                      0.87
                                                0.87
                                                           125
```

```
In []:
                      # Method 3 Random Forest: words embedding, best parameters, original data
                      def my_rf_em(data1, data2):
                                psv = PairedSentenceVectorizer()
                                x em1 = psv.fit transform(data1)
                                x em2 = psv.fit transform(data2)
                                pipe_1 = Pipeline([('rf', RandomForestClassifier())])
                                param_1 = {
                                          'rf_ max_features': ('sqrt', 'log2'),
                                          'rf ccp alpha': (0.0, 0.5),
                                          'rf__random_state' : (1, 2)}
                                grid_1 = GridSearchCV(pipe_1, param_1, cv = 5, verbose = 0, n_jobs = -
                                grid_1.fit(x_em1, data1['Label'])
                                test = grid_1.predict(X = x_em2)
                                print("The best model :")
                                print(grid 1.best params )
                                print("The result :")
                                print(clt(y_true = data2['Label'], y_pred = test))
In []:
                      my rf em(data ini, data test)
                    The best model:
                     {'rf_ccp_alpha': 0.0, 'rf_max_features': 'sqrt', 'rf_random_state': 2}
                    The result:
                                                      precision recall f1-score
                                                                                                                                     support
                                                                                           1.00
                                                                                                                     0.82
                              Non-Spam
                                                                   0.69
                                                                                                                                                  49
                                                                   1.00
                                                                                                                     0.83
                                        Spam
                                                                                            0.71
                                                                                                                                                  76
                                                                                                                     0.82
                                                                                                                                               125
                              accuracy
                                                                                                                     0.82
                            macro avg
                                                                   0.85
                                                                                            0.86
                                                                                                                                               125
                    weighted avg
                                                                   0.88
                                                                                            0.82
                                                                                                                     0.83
                                                                                                                                               125
In [ ]:
                      # Method 3 Random Forest : words embedding, best parameters
                      def my rf em best(data1, data2):
                                psv = PairedSentenceVectorizer()
                                x_em1 = psv.fit_transform(data1)
                                x_em2 = psv.fit_transform(data2)
                                rdf = RandomForestClassifier(ccp alpha = 0.0, max features = 'sqrt', randomForestClassifier(ccp alpha = 0.0, max features = 0.0, max features = 'sqrt', randomForestClassifier(ccp alpha = 0.0, max features = 0.0, max f
                                pipe = Pipeline([('rf', rdf)])
                                pipe.fit(x_em1, data1['Label'])
                                test= pipe.predict(X = x em2)
                                print("The result :")
                                print(clt(y true = data2['Label'], y pred = test))
```

```
In [ ]:
          # Method 3 Random Forest, word embedding, best parameters, oversampling da
          my_rf_em_best(data_over, data_test)
         The result :
                        precision
                                     recall f1-score
                                                         support
                                       1.00
                                                 0.82
             Non-Spam
                             0.69
                                                              49
                 Spam
                             1.00
                                       0.71
                                                 0.83
                                                              76
             accuracy
                                                  0.82
                                                             125
                                       0.86
                                                  0.82
                                                             125
            macro avg
                             0.85
         weighted avg
                             0.88
                                       0.82
                                                  0.83
                                                             125
In []:
          # Method 3 Random Forest, word embedding, best parameters, undersampling de
          my_rf_em_best(data_under, data_test)
         The result:
                                     recall f1-score
                       precision
                                                         support
             Non-Spam
                             0.90
                                       0.96
                                                 0.93
                                                              49
                 Spam
                             0.97
                                       0.93
                                                 0.95
                                                              76
             accuracy
                                                  0.94
                                                             125
                             0.94
                                       0.95
                                                 0.94
                                                             125
            macro avg
         weighted avg
                             0.95
                                       0.94
                                                  0.94
                                                             125
In [11]:
          # Method 4 RNN-LSTM : with pre trained words embedding from spacy
          import os
          import warnings
          # Ignore FutureWarning from numpy
          warnings.simplefilter(action='ignore', category=FutureWarning)
          import keras.backend as K
          import tensorflow as tf
          os.environ["CUDA_DEVICE_ORDER"]="PCI_BUS_ID";
          # The GPU id to use, usually either "0" or "1";
          os.environ["CUDA VISIBLE DEVICES"]="0";
          # Allow growth of GPU memory, otherwise it will always look like all the me
          physical devices = tf.config.experimental.list physical devices('GPU')
          tf.config.experimental.set_memory_growth(physical_devices[0], True)
```

```
In [12]:
          def word index(data):
              word_to_index = {}
              for sentence in data['Message_body']:
                  for word in sentence.split():
                      if word not in word to index:
                          word to index[word] = len(word to index) + 1
              return word to index
In [13]:
          def word_embedding(data):
              embedding_matrix = np.zeros((len(data) + 1, 300))
              for i, j in data.items():
                  embedding_matrix[j] = nlp.vocab[i].vector
              return embedding matrix
In [14]:
          # Method 4 RNN-LSTM with original dataset
          word_to_index_ini = word_index(data_ini)
          matrix weight = word embedding(word to index ini)
In [62]:
          from tensorflow.keras.preprocessing.sequence import pad sequences
          from tensorflow.keras.utils import to_categorical
          def encode(tagged sentences, y, word to index):
              X = []
              for s in tagged sentences:
                  Xcurrent = []
                  for p in s.split():
                      if p in word_to_index.keys():
                          Xcurrent.append(word_to_index[p])
                      else:
                          Xcurrent.append(0)
                  X.append(Xcurrent)
              X = pad sequences(X)
              Y = np.where(y == 'Spam', 1, 0)
              Y = to categorical(Y, num classes = 2)
              return X, Y
          X, Y = encode(data_ini['Message_body'], data_ini['Label'], word_to_index_in
          N, M = X.shape
```

In [63]: from tensorflow.keras import Sequential from tensorflow.keras.layers import Embedding, Bidirectional, LSTM, Dense, from keras.optimizers import rmsprop_v2 from keras.optimizers import adam_v2 from keras.losses import categorical crossentropy embedding dim = 300 hidden dim = 100 model = Sequential() model.add(Embedding(len(word_to_index_ini) + 1, embedding_dim, weights = [matrix_weight], trainable = False, input_length = M)) model.add(Bidirectional(LSTM(hidden_dim))) model.add(Dense(2, activation = 'softmax')) model.compile(optimizer = 'rmsprop', loss = categorical crossentropy, metr: model.summary()

Model: "sequential 3"

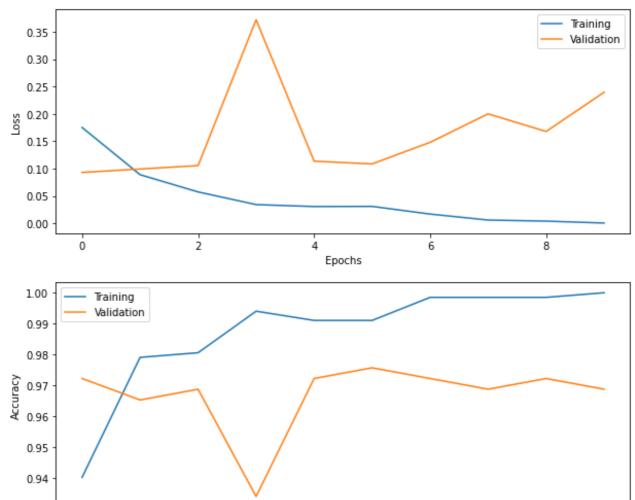
```
Layer (type)
                       Output Shape
embedding_3 (Embedding)
                       (None, 96, 300)
                                             1458300
bidirectional 3 (Bidirectio (None, 200)
                                             320800
nal)
dense 3 (Dense)
                        (None, 2)
                                             402
______
Total params: 1,779,502
Trainable params: 321,202
Non-trainable params: 1,458,300
```

```
In [64]:
```

```
P = int(0.7 * N)
X_val = X[P : ]
Y \text{ val} = Y[P:]
X \text{ train} = X[0 : P]
Y_train = Y[0 : P]
batch No = 10
epo_No = 10
history = model.fit(x = X_train, y = Y_train, batch_size = batch_No,
                     epochs = epo_No, verbose = 1, validation_data = (X_val
```

```
Epoch 1/10
     c: 0.9402 - val loss: 0.0929 - val acc: 0.9722
     Epoch 2/10
     c: 0.9791 - val_loss: 0.0992 - val_acc: 0.9653
     c: 0.9806 - val_loss: 0.1054 - val_acc: 0.9688
     Epoch 4/10
     c: 0.9940 - val_loss: 0.3723 - val_acc: 0.9340
     Epoch 5/10
     c: 0.9910 - val_loss: 0.1135 - val_acc: 0.9722
     Epoch 6/10
     67/67 [============= ] - 10s 157ms/step - loss: 0.0308 - ac
     c: 0.9910 - val_loss: 0.1084 - val_acc: 0.9757
     Epoch 7/10
     c: 0.9985 - val loss: 0.1480 - val acc: 0.9722
     Epoch 8/10
     c: 0.9985 - val_loss: 0.2000 - val_acc: 0.9688
     Epoch 9/10
     c: 0.9985 - val_loss: 0.1678 - val_acc: 0.9722
     - acc: 1.0000 - val loss: 0.2396 - val acc: 0.9688
In [17]:
      import matplotlib.pyplot as plt
      def plot_results(history):
        val loss = history.history['val loss']
        acc = history.history['acc']
        loss = history.history['loss']
        val acc = history.history['val acc']
        plt.figure(figsize=(10,4))
        plt.xlabel('Epochs')
        plt.ylabel('Loss')
        plt.plot(loss)
        plt.plot(val loss)
        plt.legend(['Training','Validation'])
        plt.figure(figsize=(10,4))
        plt.xlabel('Epochs')
        plt.ylabel('Accuracy')
        plt.plot(acc)
        plt.plot(val acc)
        plt.legend(['Training','Validation'])
        plt.show()
```





6

8

Epochs

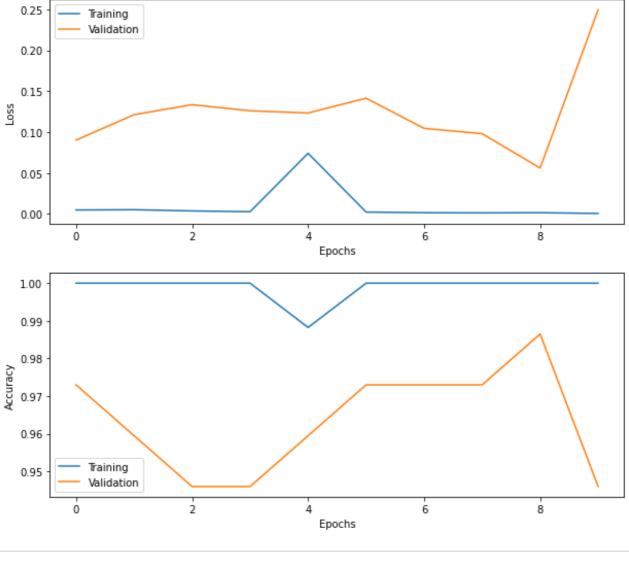
ż

Ó

```
Epoch 1/5
         67/67 [==============] - 11s 157ms/step - loss: 5.3126e-06
         - acc: 1.0000 - val loss: 0.3933 - val acc: 0.9722
         Epoch 2/5
         67/67 [============= ] - 10s 156ms/step - loss: 3.4640e-07
         - acc: 1.0000 - val_loss: 0.3882 - val_acc: 0.9722
         67/67 [============= ] - 10s 156ms/step - loss: 2.6710e-07
         - acc: 1.0000 - val_loss: 0.3653 - val_acc: 0.9722
         Epoch 4/5
         67/67 [===========] - 11s 158ms/step - loss: 1.6055e-07
         - acc: 1.0000 - val_loss: 0.3797 - val_acc: 0.9757
         Epoch 5/5
         67/67 [============= ] - 10s 156ms/step - loss: 8.3036e-08
         - acc: 1.0000 - val_loss: 0.3837 - val_acc: 0.9757
In [78]:
         X test, Y test = encode(data test['Message body'], data test['Label'], word
          X_{\text{test}_1} = \text{np.concatenate}((X_{\text{test}}, \text{np.zeros}((125, 44))), \text{ axis} = 1)
          score = model.evaluate(X_test_1, Y_test, verbose = 0)
          print('Test loss: %.4f' % score[0])
          print('Test accuracy: %.4f' % score[1])
         Test loss: 0.9669
         Test accuracy: 0.9200
In [18]:
          # Method 4 RNN-LSTM with undersampling dataset
          word to index under = word index(data under)
         matrix weight under = word embedding(word to index under)
          X_under, Y_under = encode(data_under['Message_body'], data_under['Label'],
          N_under, M_under = X_under.shape
In [19]:
         model under = Sequential()
          model under.add(Embedding(len(word to index under) + 1, embedding dim,
                             weights = [matrix weight under], trainable = False,
                             input_length = M_under))
          model under.add(Bidirectional(LSTM(hidden dim)))
          model_under.add(Dense(2, activation = 'softmax'))
          model_under.compile(optimizer = 'rmsprop', loss = categorical_crossentropy
```

```
In [27]:
     P \text{ under} = int(0.7 * N \text{ under})
     X_val_under = X_under[P_under : ]
     Y_val_under = Y_under[P_under: ]
     X_train_under = X_under[0 : P_under]
     Y train under = Y under[0 : P under]
     batch No = 10
     epo No = 10
     history under = model_under.fit(x = X train_under, y = Y train_under, batcl
                 epochs = epo No, verbose = 1,
                 validation_data = (X_val_under, Y_val_under))
     Epoch 1/10
     1.0000 - val loss: 0.0902 - val acc: 0.9730
     Epoch 2/10
     1.0000 - val_loss: 0.1213 - val_acc: 0.9595
     Epoch 3/10
     1.0000 - val_loss: 0.1334 - val_acc: 0.9459
     Epoch 4/10
     1.0000 - val_loss: 0.1260 - val_acc: 0.9459
     Epoch 5/10
     0.9882 - val loss: 0.1233 - val acc: 0.9595
     Epoch 6/10
     1.0000 - val loss: 0.1414 - val acc: 0.9730
     Epoch 7/10
     1.0000 - val_loss: 0.1045 - val_acc: 0.9730
     Epoch 8/10
     1.0000 - val_loss: 0.0981 - val_acc: 0.9730
     Epoch 9/10
     1.0000 - val loss: 0.0561 - val acc: 0.9865
     Epoch 10/10
     acc: 1.0000 - val_loss: 0.2495 - val_acc: 0.9459
```

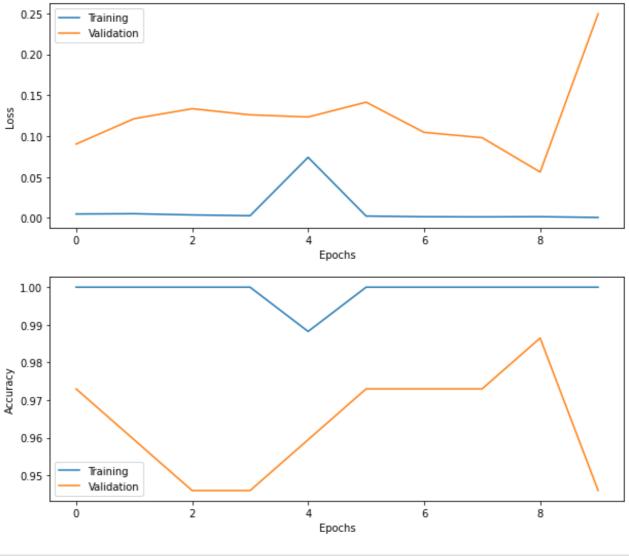
```
In [28]: plot_results(history_under)
```



```
Epoch 1/8
       : 1.0000 - val loss: 0.1888 - val acc: 0.9459
       Epoch 2/8
        acc: 1.0000 - val_loss: 0.1516 - val_acc: 0.9459
       17/17 [============= ] - 2s 91ms/step - loss: 2.9108e-04 -
       acc: 1.0000 - val_loss: 0.1002 - val_acc: 0.9730
       Epoch 4/8
       acc: 1.0000 - val_loss: 0.0711 - val_acc: 0.9865
       Epoch 5/8
       acc: 1.0000 - val loss: 0.3662 - val acc: 0.9459
       17/17 [===========] - 1s 89ms/step - loss: 6.6754e-05 -
       acc: 1.0000 - val_loss: 0.2804 - val_acc: 0.9459
       Epoch 7/8
       17/17 [============= ] - 1s 87ms/step - loss: 1.7313e-05 -
       acc: 1.0000 - val loss: 0.2052 - val acc: 0.9595
       Epoch 8/8
       17/17 [==============] - 1s 87ms/step - loss: 1.0597e-05 -
       acc: 1.0000 - val loss: 0.2698 - val acc: 0.9595
       <keras.callbacks.History at 0x7fef9d933c90>
Out[32]:
In [33]:
        X test, Y test = encode(data test['Message body'], data test['Label'], word
        X test under = np.concatenate((X test, np.zeros((125, 9))), axis = 1)
        score_under = model_under.evaluate(X_test_under, Y_test, verbose = 0)
        print('Test loss: %.4f' % score_under[0])
        print('Test accuracy: %.4f' % score_under[1])
       Test loss: 0.3748
       Test accuracy: 0.9600
In [79]:
        # Method 4 RNN-LSTM with oversampling dataset
        word_to_index_over = word_index(data_over)
        matrix weight over = word embedding(word to index over)
        X over, Y over = encode(data over['Message body'], data over['Label'], word
        N_over, M_over = X_over.shape
In [80]:
        model_over = Sequential()
        model over.add(Embedding(len(word to index over) + 1, embedding dim,
                         weights = [matrix weight over], trainable = False,
                         input length = M over))
        model over.add(Bidirectional(LSTM(hidden dim)))
        model over.add(Dense(2, activation = 'softmax'))
        model_over.compile(optimizer = 'rmsprop', loss = categorical_crossentropy,
```

```
In [81]:
     P \text{ over} = int(0.7 * N \text{ over})
     X_val_over = X_over[P_over : ]
     Y_val_over = Y_over[P_over: ]
     X_train_over = X_over[0 : P_over]
     Y train over = Y over[0 : P over]
     batch No = 10
     epo No = 10
     history_over = model_over.fit(x = X_train_over, y = Y_train_over, batch_si
                 epochs = epo No, verbose = 1,
                 validation_data = (X_val_over, Y_val_over))
     Epoch 1/10
     acc: 0.9401 - val loss: 0.0526 - val acc: 0.9721
     Epoch 2/10
     acc: 0.9795 - val_loss: 0.2366 - val_acc: 0.9082
     Epoch 3/10
     acc: 0.9897 - val_loss: 0.0542 - val_acc: 0.9900
     Epoch 4/10
     acc: 0.9914 - val loss: 0.0039 - val acc: 1.0000
     Epoch 5/10
     acc: 0.9991 - val loss: 2.6830e-04 - val acc: 1.0000
     Epoch 6/10
     acc: 0.9966 - val loss: 0.0019 - val acc: 1.0000
     Epoch 7/10
     acc: 0.9983 - val_loss: 0.0136 - val_acc: 0.9820
     Epoch 8/10
     4 - acc: 1.0000 - val_loss: 0.0185 - val_acc: 0.9940
     Epoch 9/10
     acc: 0.9983 - val loss: 0.0248 - val acc: 0.9880
     Epoch 10/10
     5 - acc: 1.0000 - val_loss: 0.1009 - val_acc: 0.9820
```

```
In [82]: plot_results(history_under)
```



```
Epoch 1/8
     acc: 0.9991 - val loss: 0.2115 - val acc: 0.9820
     Epoch 2/8
     6 - acc: 1.0000 - val_loss: 0.1815 - val_acc: 0.9820
     acc: 0.9991 - val_loss: 5.2347e-08 - val_acc: 1.0000
     Epoch 4/8
     acc: 0.9983 - val_loss: 4.5053e-06 - val_acc: 1.0000
     Epoch 5/8
     7 - acc: 1.0000 - val loss: 2.7713e-06 - val acc: 1.0000
     acc: 0.9966 - val_loss: 0.0887 - val_acc: 0.9820
     Epoch 7/8
     7 - acc: 1.0000 - val loss: 0.0799 - val acc: 0.9940
     Epoch 8/8
     7 - acc: 1.0000 - val_loss: 0.0699 - val_acc: 0.9940
     <keras.callbacks.History at 0x7fef994b5950>
Out[83]:
In [84]:
      X test, Y test = encode(data test['Message body'], data test['Label'], word
      X test over = np.concatenate((X test, np.zeros((125, 44))), axis = 1)
      score over = model over.evaluate(X test over, Y test, verbose = 0)
      print('Test loss: %.4f' % score_over[0])
      print('Test accuracy: %.4f' % score_over[1])
```

Test loss: 0.9282
Test accuracy: 0.9280