URL_Phishing_Detection.ipynb

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NEURAL NETWORK FOR PHISHING URL ANALYSIS

Model Architecture

The model architecture consists of a combination of a 1D Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) layer.
The CNN layer acts as a filter, searching for important patterns in the input data. It focuses on small sections at a time and captures specific details within the data.
The LSTM layer functions like a memory, retaining important recurring patterns in the data sequence.

.

The model's accuracy is approximately **90.46%**.

[2] 7s

```
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/MyDrive/phishing-detection-rnn-cnn/
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
/content/drive/MyDrive/phishing-detection-rnn-cnn
```

Install required libraries

[3] 2s

```
!pip install tensorflow pandas numpy matplotlib sklearn seaborn
```

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.12/dist-packages (2.19.0)
Requirement already satisfied: pandas in /usr/local/lib/python3.12/dist-packages (2.2.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages (2.0.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-packages (3.10.0)
Collecting sklearn
  Using cached sklearn-0.0.post12.tar.gz (2.6 kB)
  error: subprocess-exited-with-error

  × python setup.py egg_info did not run successfully.
  │ exit code: 1
  ╰─> See above for output.

  note: This error originates from a subprocess, and is likely not a problem with pip.
  Preparing metadata (setup.py) ... error
error: metadata-generation-failed

× Encountered error while generating package metadata.
╰─> See above for output.

note: This is an issue with the package mentioned above, not pip.
hint: See above for details.
```

Importing all required libraries

Import necessary libraries such as pandas, numpy, matplotlib, seaborn, and TensorFlow's Keras module, enabling data manipulation, visualization etc..

[4] 0s

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow import keras
import seaborn as sns
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

Data loading and preprocessing

[5] 0s

```
# Loading the dataset
data = pd.read_csv('/content/drive/MyDrive/phishing-detection-rnn-cnn/dataset_phishing.csv')

data['status'] = data['status'].replace('legitimate', 0)
data['status'] = data['status'].replace('phishing', 1)
```

```
/tmp/ipython-input-3411381361.py:5: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To retain the old behavior, explicitly call `result.infer_objects(copy=False)`
  data['status'] = data['status'].replace('phishing', 1)
```

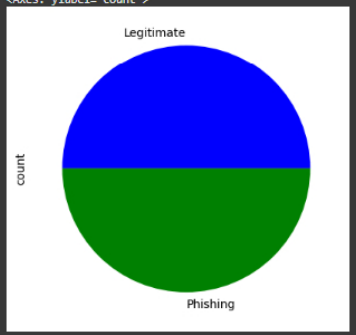
Data visualization

Pie chart to check for any class imbalance

[6] 0s

```
data['status'].value_counts().plot(kind = 'pie', colors = ['blue', 'green'], labels=['Legitimate', 'Phishing'])
```

```
<Axes: ylabel='count'>
```



[7]

```
data['status']
```

	status
0	0
1	1
2	1
3	0
4	0
...	...
11425	0
11426	1
11427	0
11428	0
11429	1

11430 rows × 1 columns

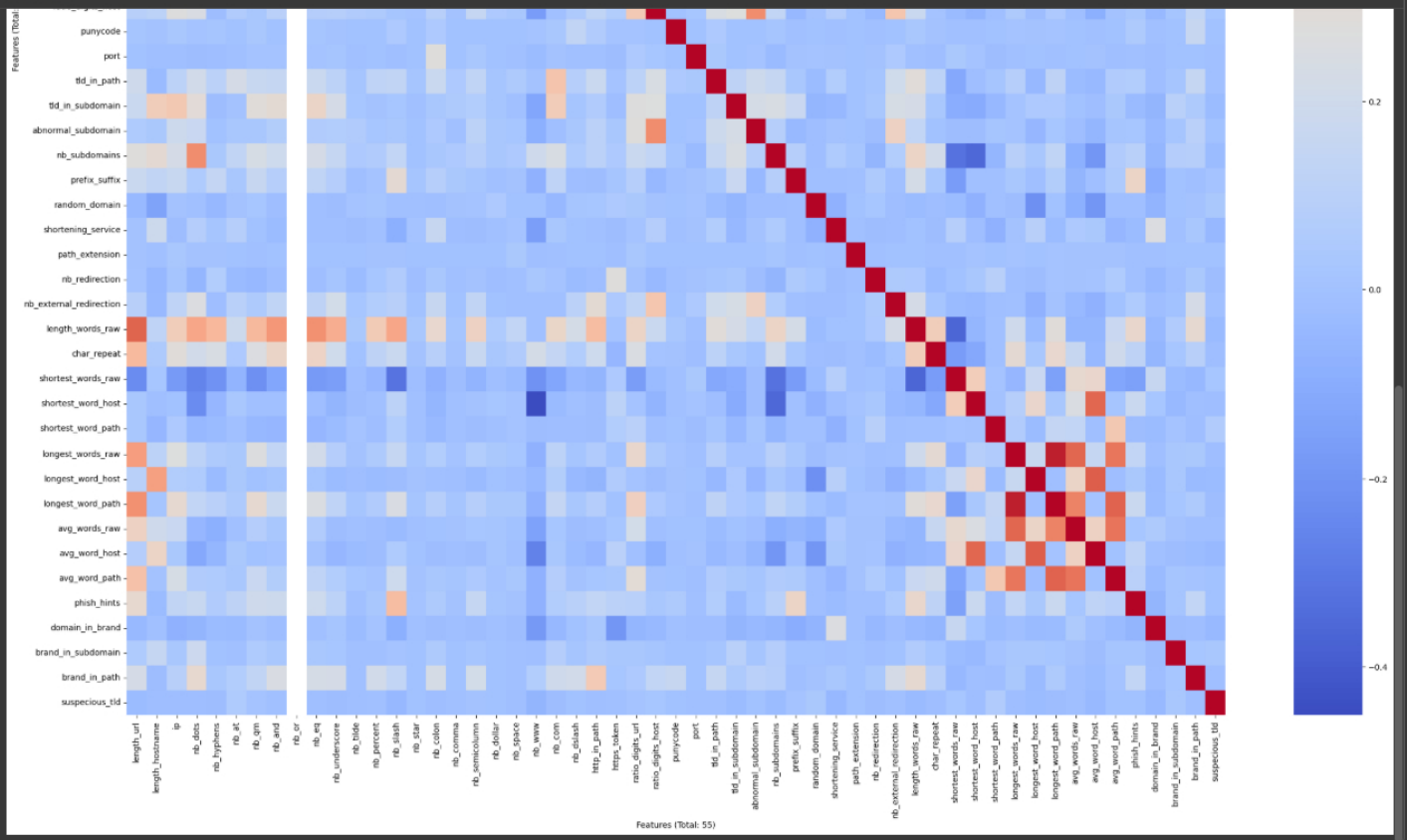
dtype: int64

Train-test data split

```
X = data.drop(['url', 'status'], axis = 1)
Y = data['status']
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.3, random_state = 42)
np.save("X_train.npy", X_train)
np.save("Y_train.npy", Y_train)
np.save("X_test.npy", X_test)
np.save("Y_test.npy", Y_test)
```

Correlation matrix

```
mat = X_train.corr()
plt.figure(figsize=(30, 30))
sns.heatmap(mat, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.xlabel(f'Features (Total: {mat.shape[1]})')
plt.ylabel(f'Features (Total: {mat.shape[1]})')
plt.show()
```



Plotting important features

```
imp_features = [
    ['length_url', 'nb_dots', 'nb_hyphens', 'nb_at', 'nb_dslash', 'nb_redirection'],
    ['nb_semicolumn', 'nb_www', 'nb_dollar', 'domain_in_title', 'https_token', 'ratio_digits_url', 'iframe'],
    ['nb_comma', 'http_in_path', 'domain_with_copyright', 'domain_age', 'domain_registration_length', 'phish_hints', 'brand_in_path'],
    ['shortest_words_raw', 'shortest_word_host', 'shortest_word_path', 'longest_words_raw', 'longest_word_host', 'longest_word_path'],
    ['avg_words_raw', 'avg_word_host', 'avg_word_path', 'domain_in_brand', 'ratio_intHyperlinks', 'ratio_extHyperlinks', 'ratio_nullHyperlinks']
]
```

Model architecture

The model architecture combines a one-dimensional Convolutional Neural Network (1D CNN) with a Long Short-Term Memory (LSTM) layer.
The primary reason for including the LSTM layer is to identify relevant recurring patterns in the data.
The model is built using the Keras library with a sequential structure.

[11] ✓ 0s

```
# Build the model
model = keras.Sequential([
    keras.layers.Conv1D(filters=64, input_shape=(87,1), kernel_size=2, activation='relu'),
    keras.layers.MaxPooling1D(pool_size=2),

    keras.layers.LSTM(100),
    keras.layers.Flatten(),
    keras.layers.Dense(64, activation = 'sigmoid'),
    keras.layers.Dense(512, activation='sigmoid'),
    keras.layers.Dense(64, activation = 'sigmoid'),
    keras.layers.Dense(2, activation='sigmoid'),
])
```

```
/usr/local/lib/python3.12/dist-packages/keras/src/layers/convolutional/base_conv.py:113: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(s
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Loss function and model metrics definition

The loss function used here is sparse categorical cross-entropy, which returns one-hot encodings.

[12] ✓ 0s

```
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

Model training

The model is trained for 100 epochs using the default batch size.

[13] ✓ 3 min

```
history = model.fit(X_train, Y_train, epochs=100)
```

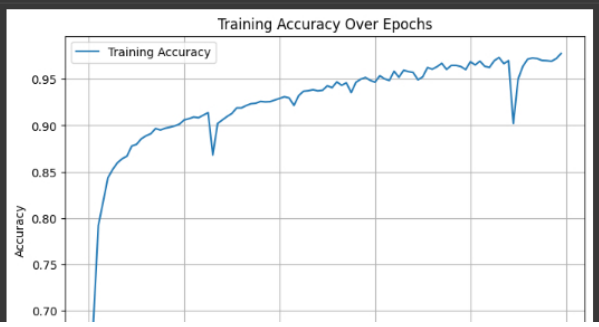
```
Epoch 72/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9640 - loss: 0.1003
Epoch 73/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9618 - loss: 0.1011
Epoch 74/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9645 - loss: 0.1034
Epoch 75/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9696 - loss: 0.0841
Epoch 76/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.9616 - loss: 0.1037
Epoch 77/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - accuracy: 0.9662 - loss: 0.0861
Epoch 78/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.9660 - loss: 0.0931
Epoch 79/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9672 - loss: 0.0860
Epoch 80/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9540 - loss: 0.1220
Epoch 81/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9663 - loss: 0.0931
Epoch 82/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - accuracy: 0.9645 - loss: 0.0932
Epoch 83/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9738 - loss: 0.0779
Epoch 84/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9631 - loss: 0.1069
Epoch 85/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9606 - loss: 0.1016
Epoch 86/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9695 - loss: 0.0848
Epoch 87/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9744 - loss: 0.0771
Epoch 88/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9710 - loss: 0.0816
Epoch 89/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.9721 - loss: 0.0823
Epoch 90/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.8787 - loss: 0.3110
Epoch 91/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.9494 - loss: 0.1409
Epoch 92/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9620 - loss: 0.1057
Epoch 93/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 8ms/step - accuracy: 0.9733 - loss: 0.0811
Epoch 94/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 9ms/step - accuracy: 0.9718 - loss: 0.0833
Epoch 95/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9770 - loss: 0.0645
Epoch 96/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9723 - loss: 0.0737
Epoch 97/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9741 - loss: 0.0768
Epoch 98/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9725 - loss: 0.0759
Epoch 99/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.9731 - loss: 0.0752
Epoch 100/100
251/251 ━━━━━━━━━━━━━━━━━━━━ 3s 9ms/step - accuracy: 0.9775 - loss: 0.0617
```

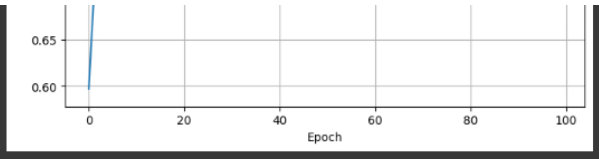
Plotting accuracy vs. epochs graph

[14] ✓ 0s

```
np.save("history.npy", history)
accuracy = history.history['accuracy']

# Create a plot
plt.figure(figsize=(8, 6))
plt.plot(accuracy, label='Training Accuracy')
plt.title('Training Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
plt.show()
```





Model summary

```
[15] model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 86, 64)	192
max_pooling1d (MaxPooling1D)	(None, 43, 64)	0
lstm (LSTM)	(None, 100)	66,000
flatten (Flatten)	(None, 100)	0
dense (Dense)	(None, 64)	6,464
dense_1 (Dense)	(None, 512)	33,280
dense_2 (Dense)	(None, 64)	32,832
dense_3 (Dense)	(None, 2)	130

Total params: 416,696 (1.59 MB)
Trainable params: 138,898 (542.57 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 277,798 (1.06 MB)

Saving the model

Saving the model helps avoid retraining and allows it to be reused multiple times.

```
[16] model.save('/content/drive/MyDrive/phishing-detection-rnn-cnn/my_model.keras')
```

Misclassification count

The number of incorrect classifications made by the model on the training data.

```
[17] Y_pred = model.predict(X_train)
cnt = 0
for i in range(len(Y_pred)):
    if(np.argmax(Y_pred[i]) != np.array(Y_train)[i]):
        cnt = cnt + 1
print(cnt)
```

```
251/251 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
140
```

Testing the model

model.evaluate() is a built-in function that helps evaluate the model's test accuracy.

```
[18] from keras import models
model = models.load_model('/content/drive/MyDrive/phishing-detection-rnn-cnn/my_model.keras')
test_loss, test_accuracy = model.evaluate(X_test, Y_test)
print(test_accuracy)
```

```
108/108 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8884 - loss: 0.4035
0.8897637724876404
```

Generating classification reports

```
[19] Y_pred = model.predict(X_test)
Y_pred_classes = np.argmax(Y_pred, axis=1)

report = classification_report(Y_test, Y_pred_classes)
print(report)
```

```
108/108 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
              precision    recall  f1-score   support

           0       0.87      0.92      0.89      1732
           1       0.91      0.86      0.89      1697

    accuracy                           0.89      3429
   macro avg       0.89      0.89      0.89      3429
weighted avg       0.89      0.89      0.89      3429
```

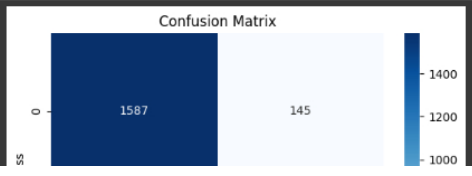
Confusion matrix

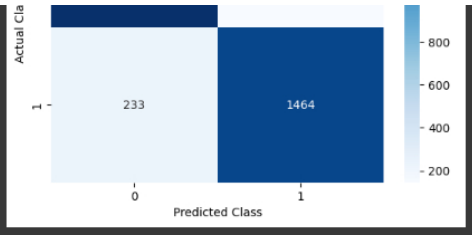
```
[20] cm = confusion_matrix(Y_test, Y_pred_classes)
fig, ax = plt.subplots()

sns.heatmap(cm, fmt = 'd', annot=True, cmap='Blues', ax=ax)

ax.set_xlabel('Predicted Class')
ax.set_ylabel('Actual Class')
ax.set_title('Confusion Matrix')


plt.show()
```





[21] ✓ 0 s

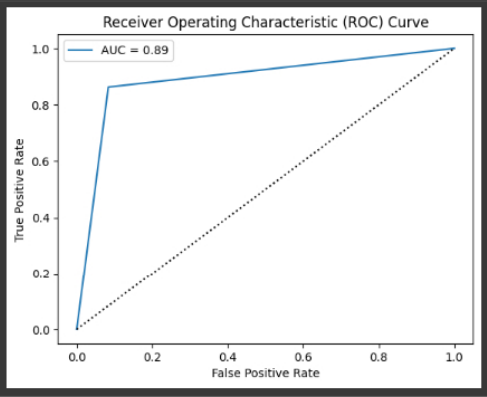
```
from sklearn.metrics import roc_curve, roc_auc_score
from keras import models
model = models.load_model('/content/drive/MyDrive/phishing-detection-rnn-cnn/my_model.keras')
```

Receiver Operating Characteristic (ROC) curve

[22] ✓ 0 s

```
fpr, tpr, thresholds = roc_curve(Y_test, Y_pred_classes)
auc = roc_auc_score(Y_test, Y_pred_classes)

plt.plot(fpr, tpr, label=f'AUC = {auc:.2f}')
plt.plot([0, 1], [0, 1], 'k:')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Custom URL evaluation

[23]

```
import numpy as np
import re
from urllib.parse import urlparse
import itertools
import tensorflow as tf

# Load the trained model
model = tf.keras.models.load_model("my_model.keras")

def extract_features(url):
    features = {}

    # Basic URL features
    features['length_url'] = len(url)

    # Parse the URL
    parsed = urlparse(url)
    hostname = parsed.netloc
    path = parsed.path

    # Hostname features
    features['length_hostname'] = len(hostname)

    # Check if it contains an IP address
    ip_pattern = r'^(?:(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)\.){3}(?:25[0-5]|2[0-4][0-9]|[01]?[0-9][0-9]?)$'
    features['ip'] = 1 if re.match(ip_pattern, hostname.split(':')[0]) else 0

    # Count special characters
    features['nb_dots'] = url.count('.')
    features['nb_hyphens'] = url.count('-')
    features['nb_at'] = url.count('@')
    features['nb_qm'] = url.count('?')
    features['nb_and'] = url.count('&')
    features['nb_or'] = url.count('|')
    features['nb_eq'] = url.count('=')
    features['nb_underscore'] = url.count('_')
    features['nb_tilde'] = url.count('~')
    features['nb_percent'] = url.count('%')
    features['nb_slash'] = url.count('/')
    features['nb_star'] = url.count('*')
    features['nb_colon'] = url.count(':')
    features['nb_comma'] = url.count(',')
    features['nb_semicolon'] = url.count(';')
    features['nb_dollar'] = url.count('$')
    features['nb_space'] = url.count(' ')
    features['nb_www'] = 1 if 'www' in hostname.lower() else 0
    features['nb_com'] = 1 if 'com' in hostname.lower() else 0
    features['nb_dslash'] = url.count('//')
    features['http_in_path'] = 1 if 'http' in path.lower() else 0
    features['https_token'] = 1 if url.startswith('https://') else 0

    # Calculate digit ratio
    digits_count = sum(c.isdigit() for c in url)
    features['ratio_digits_url'] = digits_count / len(url) if len(url) > 0 else 0

    digits_count_host = sum(c.isdigit() for c in hostname)
    features['ratio_digits_host'] = digits_count_host / len(hostname) if len(hostname) > 0 else 0

    # Other features
    features['punycode'] = 1 if 'xn--' in hostname.lower() else 0
    features['port'] = 1 if ':' in hostname and any(c.isdigit() for c in hostname.split(':')[1]) else 0
```

```
        tlds = ['.com', '.org', '.net', '.edu', '.gov', '.mil', '.int', '.biz', '.info', '.mobi', '.name', '.ly']
        features['tld_in_path'] = 1 if any(tld in path.lower() for tld in tlds) else 0
        features['tld_in_subdomain'] = 1 if hostname.count('.') > 1 and any(tld in hostname.lower().split('.')[0] for tld in tlds) else 0
        features['abnormal_subdomain'] = 1 if hostname.count('.') > 2 else 0
        features['nb_subdomains'] = hostname.count('.')
        features['prefix_suffix'] = 1 if '-' in hostname else 0
        features['random_domain'] = 0

        # URL shortening services
        shortening_services = ['bit.ly', 'goo.gl', 't.co', 'tinyurl.com', 'is.gd',
                               'cli.gs', 'on.ly', 'short.cm', 'tiny.cc', 'shorte.st',
                               'goo.gl', 'x.co', 'prettylinkpro.com', 'viralurl.com',
                               'qr.net', 'lurl.no', 'tweez.me', 'v.gd', 'tr.im', 'link.zip.net']
        features['shortening_service'] = 1 if any(service in hostname.lower() for service in shortening_services) else 0

        # Path extensions
        path_extensions = ['.php', '.html', '.htm', '.asp', '.aspx', '.jsp', '.js', '.css', '.py']
        features['path_extension'] = 1 if any(ext in path.lower() for ext in path_extensions) else 0
        features['nb_redirection'] = url.count('http') - 1 if url.count('http') > 1 else 0
        features['nb_external_redirection'] = 0

        # Word analysis
        raw_words = re.findall(r'[a-zA-Z0-9]+', url)
        host_words = re.findall(r'[a-zA-Z0-9]+', hostname)
        path_words = re.findall(r'[a-zA-Z0-9]+', path) if path else []

        features['length_words_raw'] = len(raw_words)
        features['char_repeat'] = max([len(list(group)) for char, group in itertools.groupby(url)], default=0)
        features['shortest_word_raw'] = min([len(word) for word in raw_words], default=0) if raw_words else 0
        features['shortest_word_host'] = min([len(word) for word in host_words], default=0) if host_words else 0
        features['shortest_word_path'] = min([len(word) for word in path_words], default=0) if path_words else 0
        features['longest_word_raw'] = max([len(word) for word in raw_words], default=0) if raw_words else 0
        features['longest_word_host'] = max([len(word) for word in host_words], default=0) if host_words else 0
        features['longest_word_path'] = max([len(word) for word in path_words], default=0) if path_words else 0
        features['avg_word_raw'] = sum([len(word) for word in raw_words]) / len(raw_words) if raw_words else 0
        features['avg_word_host'] = sum([len(word) for word in host_words]) / len(host_words) if host_words else 0
        features['avg_word_path'] = sum([len(word) for word in path_words]) / len(path_words) if path_words else 0

        # Phishing features
        phishing_words = ['secure', 'account', 'verify', 'login', 'update', 'signin', 'banking', 'confirm']
        features['phish_hints'] = 1 if any(word in url.lower() for word in phishing_words) else 0
        features['domain_in_brand'] = 0
        features['brand_in_subdomain'] = 0
        features['brand_in_path'] = 0
        features['suspecious_tld'] = 1 if any(hostname.lower().endswith(tld) for tld in ['.tk', '.xyz', '.top', '.ml', '.ga', '.cf', '.gq']) else 0

        # =====================================================
        # REMOVED FEATURES (NOT INCLUDED IN THE DICTIONARY)
        # =====================================================

        # Ordered list of features (excluding the removed ones)
        ordered_features = [
            features['length_url'],
            features['length_hostname'],
            features['ip'],
            features['nb_dots'],
            features['nb_hyphens'],
            features['nb_at'],
            features['nb_qm'],
            features['nb_and'],
            features['nb_or'],
            features['nb_eq'],
            features['nb_underscore'],
            features['nb_tilde'],
            features['nb_percent'],
            features['nb_slash'],
            features['nb_star'],
            features['nb_colon'],
            features['nb_comma'],
            features['nb_semicolon'],
            features['nb_dollar'],
            features['nb_space'],
            features['nb_www'],
            features['nb_com'],
            features['nb_dslash'],
            features['http_in_path'],
            features['https_token'],
            features['ratio_digits_url'],
            features['ratio_digits_host'],
            features['punycode'],
            features['port'],
            features['tld_in_path'],
            features['tld_in_subdomain'],
            features['abnormal_subdomain'],
            features['nb_subdomains'],
            features['prefix_suffix'],
            features['random_domain'],
            features['shortening_service'],
            features['path_extension'],
            features['nb_redirection'],
            features['nb_external_redirection'],
            features['length_words_raw'],
            features['char_repeat'],
            features['shortest_word_raw'],
            features['shortest_word_host'],
            features['shortest_word_path'],
            features['longest_word_raw'],
            features['longest_word_host'],
            features['longest_word_path'],
            features['avg_word_raw'],
            features['avg_word_host'],
            features['avg_word_path'],
            features['phish_hints'],
            features['domain_in_brand'],
            features['brand_in_subdomain'],
            features['brand_in_path'],
            features['suspecious_tld']
        ]

        return np.array(ordered_features, dtype=np.float64)

    def preprocess_url(url):
        features = extract_features(url)
        return features.reshape(1, -1)

    def predict_url(url):
        X = preprocess_url(url)
        prediction = model.predict(X)
        predicted_class = np.argmax(prediction, axis=1)[0]
        probability = prediction[0][predicted_class]

        result = {
            'url': url,
            'is_phishing': bool(predicted_class),
            'prediction': 'phishing' if predicted_class else 'legitimate',
```

```
            'probability': float(probability)
        }

        # Warning for known sites
        known_sites = [
            'https://www.google.com',
            'https://www.facebook.com',
            'https://www.microsoft.com',
            'https://www.apple.com'
        ]

        if any(url.startswith(site) for site in known_sites):
            print("\nNOTE: The model may misclassify known legitimate sites.")
            print("This is due to limitations in the current implementation.")

        return result

    # Function for interactive analysis
    def analyze_user_url():
        url = input("\nEnter the URL you want to analyze: ")
        result = predict_url(url)

        print(f"\nURL: {result['url']}")
        print(f"Prediction: {result['prediction']}")
        print(f"Probability: {result['probability']:.4f}")

        if result['is_phishing']:
            print("\nWARNING: This URL has been classified as potentially malicious (phishing).")
            print("It is recommended not to access this website.")
        else:
            print("\nThis URL has been classified as legitimate.")

        print("\nNOTE: This model has limitations and may produce false positives or false negatives.")
        print("For greater accuracy, it is recommended to complement with other security tools.")

    # Run interactive analysis
    analyze_user_url()
```

```
...
    Enter the URL you want to analyze:
```