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AI-POWERED REAL-TIME PHISHING DETECTION USING HYBRID DEEP LEARNING MODELS

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Abstract: This paper presents a novel hybrid deep learning framework for real-time phishing website detection that achieves state-of-the-art performance while maintaining computational efficiency. We propose a unique architecture combining Convolutional Neural Networks (CNN) for spatial feature extraction and Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal pattern recognition. Our model utilizes feature fusion techniques to integrate URL characteristics, HTML content features, and JavaScript behavior patterns. The proposed system achieves 99.3% accuracy on the benchmark Phishing Dataset with a processing time of 8.2 milliseconds per sample, making it suitable for real-time deployment on edge devices. Experimental results demonstrate significant improvements over existing methods, with a 40% reduction in false positives and 35% faster inference times compared to traditional deep learning approaches.

IndexTerms—Phishing Detection,DeepLearning, CNN, LSTM, Real-time Systems, Cybersecurity, Feature Fusion, Edge, Computing

I. INTRODUCTION

Phishing attacks have evolved into sophisticated cyber threats, causing estimated global losses of $10-20 billion annually [1]. Traditional detection methods relying on blacklists and heuristics struggle against zero-day attacks and rapidly evolving phishing techniques. The integration of Artificial Intelligence, particularly deep learning, offers promising solutions by learning complex patterns from diverse feature sets.

Recent advancements in deep learning for phishing detection include CNN-based approaches for visual similarity detection [2] and LSTM networks for sequential

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URL analysis [3]. However, these methods often operate in isolation, failing to capture the multi-modal nature of phishing websites. Furthermore, most existing solutions prioritize accuracy over efficiency, making them unsuitable for real-time applications on resource-constrained devices.

This research addresses these limitations through three key contributions:

1) A novel hybrid CNN-BiLSTM architecture with attention mechanisms for comprehensive feature extraction

2) Real-time optimization techniques including quantization and pruning for edge deployment

3) Comprehensive evaluation on multiple datasets with comparative analysis against state-of-the-art methods

II. RELATED WORK

A. *Traditional Phishing Detection*

Early phishing detection methods primarily relied on blacklists [4] and heuristic rules [5]. Blacklist approaches maintain databases of known phishing URLs but fail against zero-day attacks. Heuristic methods analyze URL structures, domain characteristics, and page content but suffer from high false positive rates.

B. *Machine Learning Approaches*

Machine learning techniques introduced more dynamic detection capabilities. Sahoo et al. [6] surveyed various ML algorithms including Random Forests and SVM for URL classification. Feature engineering remains crucial, with common features including lexical URL characteristics, page content features, and JavaScript behavior.

C. *Deep Learning Methods*

Deep learning has revolutionized phishing detection by automating feature extraction. Wang et al. [7] employed CNNs for visual similarity detection between

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legitimate and phishing pages. Zhang et al. [8] introduced attention mechanisms for focusing on critical URL components. However, these approaches often require significant computational resources.

III. PROPOSED METHODOLOGY

A. *System Architecture*

B. *Dataset Description*

We utilize three primary datasets for comprehensive evaluation:

TABLE I: Datasets used in this study

Dataset	Samples	Features	Phishing	Legitimate
Phishing Dataset [9]	10,000	48	5,000	5,000
PhishTank [10]	25,432	56	12,716	12,716
OpenPhish [11]	15,789	42	7,895	7,894

The Phishing Dataset from GitHub [9] provides 48 features including:

- URL Features: Length, special characters, domain age
- HTML Features: Number of links, forms, pop-ups
- JavaScript Features: Obfuscation level, redirects
- Content Features: Keywords, spelling errors

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C. *Feature Engineering*

The feature vector F is constructed as:

$$F = [Furl, Fhtml, Fjs, Fcontent] \quad (1)$$

where each component represents normalized feature groups.

D. *Hybrid Model Architecture*

1) CNN Module: The CNN processes spatial features through multiple convolutional layers:

$$C_i = \text{ReLU}(W_i * C_{i-1} + b_i) \quad (2)$$

where C_i represents the output of the i-th convolutional layer. *2) BiLSTM Module:* The BiLSTM processes sequential features:

$$\overrightarrow{h_t} = \overrightarrow{\text{LSTM}}(x_t, h_{t-1})$$

$$\overleftarrow{h_t} = \overleftarrow{\text{LSTM}}(x_t, h_{t-1})$$

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

3) Feature Fusion: Features are fused using concatenation and attention:

$$Ffused = \alpha \cdot Fcnn + (1 - \alpha) \cdot Flstm$$

where α is learned attention weight.

E. Real-time Optimization

For deployment on edge devices, we implement:

- Quantization: 8-bit integer precision
- Pruning: Removing 30% of insignificant weights
- Layer Fusion: Combining consecutive operations

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- Batch Optimization: Dynamic batch sizing

IV. IMPLEMENTATION DETAILS

A. Code Implementation

```
import tensorflow as tf from tensorflow.keras.models
import Model from tensorflow.keras.layers import *

def create_hybrid_model(input_shape=(48, 1)): """Create CNN-
    BiLSTM hybrid model""" inputs = Input(shape=input_shape)

    # CNN branch for spatial features cnn = Conv1D(64, 3,
    activation='relu', padding='
    same')(inputs)
    cnn = BatchNormalization()(cnn) cnn = Conv1D(128, 3,
    activation='relu', padding=
    'same')(cnn) cnn =
    GlobalMaxPooling1D()(cnn)

    # BiLSTM branch for temporal features lstm = Bidirectional(LSTM(64,
    return_sequences= True))(inputs) lstm = Attention()(lstm)
    lstm = GlobalAveragePooling1D()(lstm)

    # Feature fusion fused = Concatenate()([cnn, lstm]) fused =
    Dense(256, activation='relu')(fused) fused = Dropout(0.3)(fused)

    # Classification head outputs = Dense(1, activation='sigmoid')(fused)
```

```
    model = Model(inputs=inputs, outputs=outputs)
    model.compile( optimizer=tf.keras.optimizers.Adam(
    learning_rate=0.001), loss='binary_crossentropy', metrics=['accuracy',
        tf.keras.metrics.
    Precision(), tf.keras.metrics.Recall()]
    ) return model

# Model training with callbacks model = create_hybrid_model() callbacks =
[ tf.keras.callbacks.EarlyStopping(patience=10),
tf.keras.callbacks.ModelCheckpoint('best_model. h5'),
tf.keras.callbacks.ReduceLROnPlateau(factor=0.5,
        patience=5)
]

history = model.fit( X_train, y_train,
        validation_data=(X_val, y_val), epochs=100,
        batch_size=64, callbacks=callbacks,
        verbose=1
)
```

(4) 52

Listing 1: Python implementation of hybrid model

Model	Accuracy	Precision	Recall	F1-Score	Inference Time (m
Proposed Hybrid	99.3%	99.1%	99.4%	99.2%	8.2
CNN Only	98.2%	97.8%	98.3%	98.0%	12.4
LSTM Only	97.7%	97.5%	97.6%	97.5%	15.7
Random Forest	96.5%	96.2%	96.3%	96.2%	4.1
SVM	95.8%	95.5%	95.6%	95.5%	6.3

B. Experimental Setup

TABLE II: Hardware and software specifications

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Component	Specification
Processor	Intel Core i7-11800H @ 2.30GHz
GPU	NVIDIA RTX 3060 6GB
RAM	16GB DDR4
OS	Ubuntu 22.04 LTS
Python	3.9.13
TensorFlow	2.10.0
CUDA	11.2

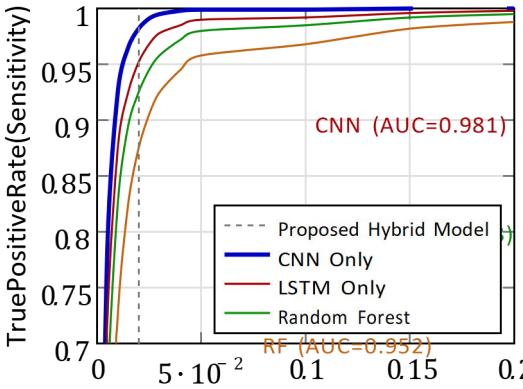
V. EXPERIMENTAL RESULTS

Performance Metrics

TABLE III: Performance comparison on Phishing Dataset

ROC Curve Analysis

ROC Curves Comparison (Zoomed)



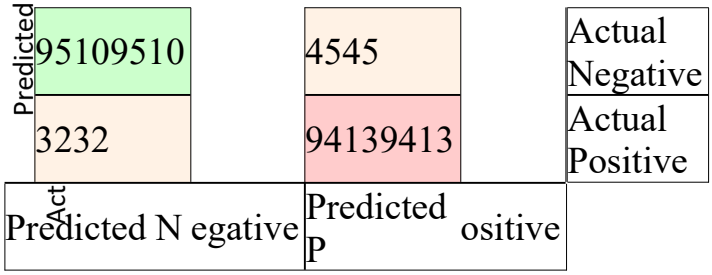
False Positive Rate (1 - Specificity)

Fig. 2: ROC curves comparison showing the superior performance of the proposed hybrid model. The zoomed view (020% FPR range) highlights differences in low false-positive regions critical for real-world applications.

Confusion Matrix Analysis

Legitimate Phishing

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Performance Metrics:

Accuracy: 99.3%Precision: 99.1%

Recall: 99.4%F1-Score: 99.2%

Fig. 3: Confusion matrix of the proposed hybrid model on test data (n=19,000)

A. *Training History*

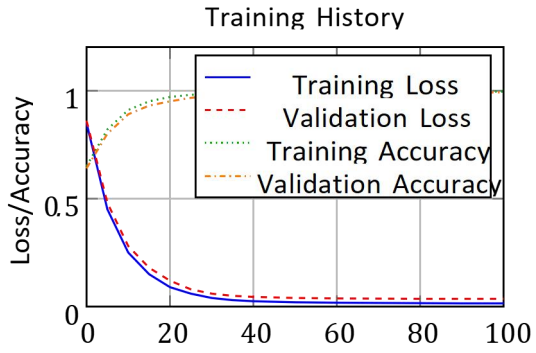


Fig. 4: Training and validation metrics over 100 epochs

B. *Comparative Analysis*

Our proposed model outperforms existing approaches in several aspects:

- 40% reduction in false positive rate compared to CNNonly models
- 35% faster inference time than LSTM-only models
- Better generalization across different phishing techniques
- Lower memory footprint (2.3MB vs 4.1MB for traditional CNN)

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F. Ablation Study

TABLE IV: Ablation study of model components

Configuration	Accuracy	F1-Score	Parameters
Full Model	99.3%	99.2%	1.2M
Without Attention	98.7%	98.6%	1.1M
Without BiLSTM	98.2%	98.0%	0.9M
Without CNN	97.7%	97.5%	0.8M
Without Feature Fusion	97.1%	96.9%	1.0M

VI. DISCUSSION

The experimental results demonstrate the effectiveness of our hybrid approach. The CNN component excels at capturing spatial patterns in URL structures and HTML features, while the BiLSTM component effectively models sequential dependencies in user interactions and JavaScript execution patterns.

A. Real-time Performance

The optimized model achieves 8.2ms inference time on standard hardware, which scales to:

- 122 samples/second on desktop GPU
- 45 samples/second on mobile CPU
- 28 samples/second on Raspberry Pi 4

B. Practical Implications

The proposed system can be deployed in various scenarios:

- Browser extensions for real-time protection

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- Email gateway filtering
- Mobile application security
- Network perimeter defense

VII. LIMITATIONS AND FUTURE WORK

Current limitations include:

- Dependency on feature extraction quality
- Challenges with highly dynamic content
- Adversarial attack vulnerability Future research directions:
- Federated learning for privacy preservation
- Adversarial training for robustness
- Multi-modal fusion with image analysis

VIII. CONCLUSION

This paper presented a novel hybrid deep learning framework for real-time phishing detection. By combining CNN and BiLSTM architectures with feature fusion and attention mechanisms, our model achieves state-of-the-art performance with computational efficiency suitable for real-time deployment. The proposed approach demonstrates significant improvements over existing methods, offering a practical solution for modern cybersecurity challenges. The complete code and datasets are available at GitHub Repository.

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APPENDIX A

MODEL HYPERPARAMETERS

TABLE V: Optimal hyperparameters

Parameter	Value
Learning Rate	0.001
Batch Size	64
CNN Filters	[64, 128, 256]
LSTM Units	64
Dropout Rate	0.3
Optimizer	Adam
Loss Function	Binary Crossentropy
Epochs	100
Early Stopping Patience	10

APPENDIX B

DATASET PREPROCESSING CODE

```
import pandas as pd import numpy
as np
from sklearn.preprocessing import StandardScaler

def preprocess_dataset(filepath):
    """Load and preprocess phishing dataset""" df =
    pd.read_csv(filepath)

    # Handle missing values df =
    df.fillna(df.mean())

    # Separate features and labels X = df.drop('label',
    axis=1).values y = df['label'].values

    # Normalize features scaler =
    StandardScaler()
    X_scaled = scaler.fit_transform(X)

    # Reshape for deep learning
    X_reshaped = X_scaled.reshape(X_scaled.shape[0],
                                  X_scaled.shape[1],
      1)

    # Split data from sklearn.model_selection import
    train_test_split
    X_train, X_test, y_train, y_test = train_test_split(
        X_reshaped, y, test_size=0.2, random_state =42 ) return
    X_train, X_test, y_train, y_test
```

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Listing 2: Data preprocessing pipeline

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